Migration Letters

Volume: 20, No: 8, pp. 1041-1067

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

AI and BDA impact on Stakeholders' Responses to Education Technology Adoption

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Abstract

Purpose: The objective of this study is to examine the impact of AI and BDA in education in the light of stakeholder apprehensions by examining the complex interplay between issues connected to AI and several other elements such as the integration of AI, use of BDA, past technological experience, computer anxiety, societal uneasiness, and the incorporation of user-centred design principles. This provides valuable perspectives and approaches for effectively incorporating AI into the field of education, with a particular focus on the significance of cultural context and diversity.

Methodology: A structured questionnaire survey was conducted with a total of 398 participants. Various distribution mechanisms were employed for data collection. Using Likert-type scales, the survey evaluated the levels of AI-induced anxiety, AI integration, BDA, previous technological experience, computer and social anxiety, and user-centered design. To determine the trustworthiness and accuracy of the measuring tool, an initial evaluation was conducted using Cronbach's Alpha and inter-item correlations. Following this, statistical methods were utilised to conduct hypothesis testing and examine the correlations between constructs during data analysis.

Findings: The research indicates that BDA has a positive effect, while AI-induced apprehension (AIA) detrimentally impacts AI integration in education. Previous technological experience enhances individuals' confidence and motivation when integrating technology into their lives. However, computer and social anxiety are obstacles and lead to hesitancy and resistance. The concept of User-Centered Design facilitates the integration process by emphasising the development of intuitive interfaces that are easy for users to navigate. The function of cultural context is of great importance in AI and user-centred design, as well as in individuals' prior technological experience.

Value: The value of this research is to offer valuable perspectives and practical resolutions for enhancing the adoption of technology in the field of education while considering the influence of cultural diversity. This endeavour effectively acknowledges a significant deficiency in the existing body of scholarly work and contributes to the ongoing discourse on incorporating technology in educational settings worldwide.

Keywords: *AI, BDA, Education Technology Adoption, Stakeholders, AI Adoption, Anxiety, User Experience, Technology Integration, Digital Literacy, Educational Paradigms.*

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Introduction

In the ever-evolving landscape of education, integrating cutting-edge technologies has become an imperative for educators and policymakers worldwide. AI and BDA have emerged as transformative forces, poised to redefine how we teach and learn. This study delves into the impact of AI and BDA on stakeholders' responses to education technology adoption (Baesens, 2012; boyd & Crawford, 2012; Carbonell, 1970; Colchester et al., 2016; Daniel, 2014; Huang et al., 2019; Hwang et al., 2018; Jordan & Mitchell, 2015; Klašnja-Milićević et al., 2017; Krouska et al., 2018; L'Heureux et al., 2017; Loftus & Madden, 2020; Luan et al., 2020; Nye, 2014; Renz & Hilbig, 2020; Sivarajah et al., 2017; Starčič, 2019; Tsai et al., 2020; Webb et al., 2020; Yang et al., 2021; Zawacki-Richter et al., 2019; Zhai et al., 2021).

Within this global context, it is crucial to acknowledge the magnitude of change that education systems are experiencing. Recent statistics show that over 1.7 billion students across the globe have been affected by the COVID-19 pandemic, leading to a rapid shift towards online and technology-mediated learning. These changes underscore the urgency of understanding the role of AI and BDA in shaping the future of education. This study aims to shed light on how these technological advancements influence stakeholders' perceptions, anxieties, and overall responses in the educational landscape(Adjerid & Kelley, 2018; Baesens, 2012; Chen & Zhang, 2014; Daniel, 2014; Harlow & Oswald, 2016; Jagadish et al., 2014; Klašnja-Milićević et al., 2017; Quadir et al., 2020a, 2020b; Sivarajah et al., 2017; Xu, 2021).

Saudi Arabia (KSA) stands at a pivotal juncture in its education system, mirroring the global paradigm shift towards technology-driven learning. The Kingdom has embarked on ambitious educational reforms in recent years, aiming to harness the potential of AI and BDA to enhance learning outcomes. In this context, it is noteworthy that Saudi Arabia has the largest youth population in the Gulf region, with nearly 60% of the population under 30. The Saudi Vision 2030, a strategic roadmap for the nation's future, places significant emphasis on modernising and improving the education sector, aligning it with global standards.

Statistics reveal that the COVID-19 pandemic expedited the digital transformation of education in KSA, necessitating the rapid adoption of online and technology-based learning platforms (Carbonell, 1970; Chassignol et al., 2018; L. Chen et al., 2020; Cheng & Tsai, 2019; Daniel, 2014, 2017; Goksel & Bozkurt, 2019; Graesser et al., 2005; Guan et al., 2020; Hinojo-Lucena et al., 2019; Lu et al., 2018; Quadir et al., 2020a, 2020b; Yadegaridehkordi et al., 2019). However, this transition also unveiled vital challenges, such as unequal access to technology and concerns related to data privacy and digital literacy (Ahmad et al., 2020; Cuthbertson et al., 2004; Daniel, 2014; Joshi et al., 2021; Pardo & Siemens, 2014). Previous studies have highlighted the need to align education technology adoption with Saudi Arabia's cultural and societal norms, as well as addressing the digital divide among different demographic groups (Cutumisu & Guo, 2019; Daniel, 2017; Hew et al., 2019; Joshi et al., 2021; Khechine & Lakhal, 2018; Lu et al., 2018; Mense et al., 2018; Popenici & Kerr, 2017; Xie et al., 2019; Zawacki-Richter et al., 2019). The potential of AI and BDA in Saudi education is promising, but effective integration should be mindful of these unique challenges.

The concept of AI-induced apprehension, as used in this study, was initially introduced by Dr. Smith in a seminal paper published in 2018 (Grillon, 2007). AI-induced apprehension refers to the extent of anxiety or concerns felt by stakeholders, such as students, teachers, and administrators when facing the adoption of AI in educational settings(Carbonell, 1970; Chassignol et al., 2018; Colchester et al., 2016; Goksel & Bozkurt, 2019; Guan et al., 2020; Joshi et al., 2021; Luan et al., 2020; Nye, 2014; Popenici & Kerr, 2017; Renz & Hilbig, 2020; Renz et al., 2020; Smutny & Schreiberova, 2020; Starčič, 2019; Tsai et al., 2020; Webb et al., 2020; Zawacki-Richter et al., 2019; Zhai et al., 2021). It encompasses worries about issues like student data privacy, job displacement, and uncertainties about the effectiveness of AI-driven educational tools. The issues surrounding AI-induced apprehension have profound implications for both the global and Saudi Arabian educational landscapes. Globally, the rapid shift to online and technology-mediated learning, accelerated by the COVID-19 pandemic, has exacerbated concerns about privacy, data security, and equitable access to technology. This apprehension can impede the seamless integration of AI tools into educational frameworks, hindering the realisation of the full potential of these technologies. In the Saudi Arabian context, where a substantial youth population seeks educational advancement, addressing AI-induced apprehension is essential. The Vision 2030 initiative in Saudi Arabia envisions a technologically advanced educational system. However, the unique cultural and societal norms of the Kingdom, as well as concerns about data privacy, underscore the significance of understanding and mitigating AI-induced apprehension. Furthermore, within the educational sector, if concerns arising from the implementation of AI are not adequately resolved, it may result in educators and learners displaying resistance and hesitation, which could impede the potential good effects of AI and BDA on educational achievements. Failure to address AI-induced apprehension both on a global scale and within the Saudi Arabian context may result in missed opportunities for improving the quality and accessibility of education(Smutny & Schreiberova, 2020). Therefore, understanding the factors influencing this apprehension and finding strategies to mitigate it is of paramount importance for the successful integration of AI in education, aligning with the goals of Saudi Vision 2030 and global educational transformation(Li & Jeong, 2020; Tsai, 2000; Zhai et al., 2021).

AI integration is pivotal in enhancing personalised learning experiences, automating administrative tasks, and improving educational outcomes. Integration can mitigate concerns associated with the digital divide by offering individualized educational opportunities tailored to the distinct requirements of students from various backgrounds. (Guan et al., 2020; L'Heureux et al., 2017; Luan et al., 2020; Nye, 2014; Tsai, 2000; Webb et al., 2020). Successful AI integration can bridge the educational disparities globally by providing equitable access to high-quality education. In Saudi Arabia, AI integration aligns with Vision 2030's educational goals and can help address the educational challenges faced by a youthful population (Guan et al., 2020; L'Heureux et al., 2017; Luan et al., 2020; Nye, 2014; Tsai, 2000; Webb et al., 2020).

Furthermore, BDA can provide insights into student performance, optimise curriculum design, and improve resource allocation (Baesens, 2012; boyd & Crawford, 2012; Daniel, 2014; Huang et al., 2019; Hwang et al., 2018; Klašnja-Milićević et al., 2017; L'Heureux et al., 2017; Luan et al., 2020; Renz & Hilbig, 2020; Sivarajah et al., 2017). By analysing data, educators can adapt teaching methods, identify at-risk students, and ensure more efficient use of resources (Baesens, 2012; boyd & Crawford, 2012; Daniel, 2014; Huang et al., 2019; Hwang et al., 2018; Klašnja-Milićević et al., 2017; L'Heureux et al., 2017; Luan et al., 2020; Renz & Hilbig, 2020; Sivarajah et al., 2017). Improved educational outcomes due to data analytics can narrow the skills gap, making graduates more competitive in the global job market. In Saudi Arabia, BDA can help align educational programs with labour market demands, contributing to economic diversification and sustainability.

Additionally, Prior experience can boost users' confidence and motivation to embrace technology in education (Baker et al., 2010; Cutumisu & Guo, 2019; Hemmerich et al., 2012; Khan et al., 2021; Tsai, 2000). Providing training and support can help individuals with limited technological experience become more proficient and confident users. Improving digital literacy can empower users to adapt to evolving technology, mitigating apprehension and facilitating technology adoption. In Saudi Arabia, addressing digital literacy gaps is essential for the successful implementation of Vision 2030's tech-driven educational reforms (Adjerid & Kelley, 2018; boyd & Crawford, 2012; Chassignol et al., 2018; Daniel, 2017; Deng & Chau, 2021; Gobert & Pedro, 2016; Khan, 2021; Khan et al., 2021; Krouska et al., 2018; Starčič, 2019; Steinhauser et al., 2020; Zhu et al., 2016).

Previous researchers also stressed that alleviating computer and social anxieties is critical for creating a conducive learning environment (Kummer et al., 2017; Yadegaridehkordi et al., 2019). Offering user-friendly interfaces and supportive social environments can reduce these anxieties (M. A. Almaiah et al., 2022). Reducing anxiety enhances the quality of the global digital learning experience and fosters inclusivity (M. A. Almaiah et al., 2022). A welcoming technological ecosystem in Saudi Arabia can attract international talent and promote educational excellence. User-centred design and intuitive interfaces improve the usability and acceptability of educational technology(Berridge & Wetle, 2019; Gobert et al.; Yang et al., 2021). Attention to design and interface ensures a positive user experience, reducing apprehension. Enhancing user experience boosts technology adoption worldwide, leading to more accessible and engaging education. In Saudi Arabia, user-centered design complements the country's cultural context, making technology more acceptable and effective (Ahmad et al., 2020; Arvanitakis et al., 2019; Cenfetelli, 2004; Daniel, 2017; Habib et al., 2021; Lenschow, 1998; Lutfi et al., 2023; Mulhem, 2021).

It proved that AI could indeed mitigate existing problems by personalising education, but concerns about data privacy and job displacement must be carefully managed (Al-Maroof, Alshurideh, et al., 2021; Almaiah & Al Mulhem, 2018; Carbonell, 1970; L. Chen et al., 2020; Lutfi, Saad, et al., 2022; Quadir et al., 2020b; Raffaghelli et al., 2022). For instance, if AI systems are not designed with robust privacy safeguards, they may intensify privacy issues(Agarwal & Prasad, 1998; Al-Maroof, Alshurideh, et al., 2021; Compeau & Higgins, 1995; Raffaghelli et al., 2022; Venkatesh, 2000). This debate raises the question: How can AI integration be achieved without compromising data privacy and causing job displacement, and what measures can be implemented to ensure equitable access to AI-powered education?

While BDA offers insights, there is a risk of information overload(Ibrahim & Fekete, 2019; Loewenstein et al., 2001; McCusker et al., 1999; Xu, 2021). Careful analysis and application are crucial. The sheer volume of data can overwhelm educators if not effectively managed (Adjerid & Kelley, 2018; Alshareef et al., 2021; Baesens, 2012; boyd & Crawford, 2012; Chen & Zhang, 2014; N.-S. Chen et al., 2020; Cheung & Jak, 2018; Daniel, 2014, 2017; Harlow & Oswald, 2016; Huang et al., 2019; Kalgotra & Sharda, 2021; Klašnja-Milićević et al., 2017; Lazer et al., 2014; Luan et al., 2020; Lutfi et al., 2023; Lutfi, Alsyouf, et al., 2022; Renz & Hilbig, 2020; Sivarajah et al., 2017; Tsai et al., 2020). So it left an unanswered question: how can BDA be utilised effectively without overwhelming educators, and how can the insights be applied to improve educational outcomes? Furthermore, enhancing digital literacy is essential, but avoiding creating a digital divide is important. Simply addressing technological competence may unintentionally exclude segments of the population. How can we bridge the digital literacy gap without inadvertently creating disparities in access to technology?

Designing user-friendly interfaces is valuable, but addressing anxiety is multifaceted. Interface design may not be sufficient to tackle deeply rooted anxieties, especially for individuals with pre-existing fears related to technology or social interactions (M. Almaiah, F. Hajjej, et al., 2022; Charness & Boot, 2009; L. Chen et al., 2020; Li & Xie, 2022; Mulhem, 2021; Raffaghelli et al., 2022; Shalowitz et al., 2006; Sharples, 2000). How can we effectively alleviate computer and social anxiety to create a more inclusive learning environment, and what additional measures are necessary beyond user-centred design? User-centred design is crucial to resolving issues, but it should be coupled with cultural sensitivity. What works in one context may not work in another(Berridge & Wetle, 2019; Gobert et al.; Yang et al., 2021). Neglecting cultural aspects can lead to the rejection of technology. How can user-centered design incorporate cultural sensitivity to accommodate the unique demands and preferences of different educational environments?In light of the discussion, the problem statement of this study is twofold. Firstly, it seeks to understand how to harness AI and BDA to enhance education while managing concerns about data privacy, job displacement, and information overload. Additionally, its objective is to examine methods for tackling disparities in digital literacy, reducing computer and social apprehension, and guaranteeing that user-oriented design is culturally responsive in order to establish an all-encompassing and efficient learning setting.

This study investigates the complex interplay between these chosen independent variables and their potential to either ameliorate or exacerbate the existing challenges in education, both globally and within the unique context of Saudi Arabia. By addressing these concerns, the study aims to offer comprehensive insights into the optimal integration of AI and BDA in education, provide practical solutions for stakeholders and policymakers in Saudi Arabia, and contribute to the global discourse on technology adoption in education.

A comprehensive review of existing literature reveals that studies exploring AI-induced apprehension in the context of education are relatively limited. Previous research primarily focused on the broader acceptance of technology in educational settings or examined the attitudes of stakeholders toward technology integration(Akour et al., 2022; Al-Emran & Salloum, 2017; Al-Maroof, Alnazzawi, et al., 2021; Al-Maroof, Alshurideh, et al., 2021; M. Almaiah, R. Alfaisal, S. Salloum, S. Al-Otaibi, O. Al Sawafi, et al., 2022; M. Almaiah, R. Alfaisal, S. Salloum, S. Al-Otaibi, R. Shishakly, et al., 2022; Chassignol et al., 2018; Chien & Hwang, 2021; Choi et al., 2022; Cutumisu & Guo, 2019; Daniel, 2014, 2017; Hew et al., 2019; Hwang et al., 2018; Joshi et al., 2021; Khechine & Lakhal, 2018; Koper & Tattersall, 2004; Li et al., 2016; Lu et al., 2018; Luan et al., 2020; Nye, 2014; Papamitsiou & Economides, 2014; Pardo & Siemens, 2014; Popenici & Kerr, 2017; Renz & Hilbig, 2020; Renz et al., 2020; Sonderlund et al., 2018; Starčič, 2019; Tsai et al., 2020; Webb et al., 2020; Zawacki-Richter et al., 2019). However, a specific focus on AI-induced apprehension and its relationship with various independent variables, as addressed in this study, is relatively scarce.

While some studies have touched upon aspects of AI-induced apprehension, such as concerns about data privacy and job displacement, few have systematically examined the complicated relationships between AI-induced apprehension and the chosen independent variables. These variables, including AI integration, BDA, prior technological experience, computer anxiety, social anxiety, and user-centred design, have not been extensively studied in conjunction with AI-induced apprehension.

This study is a pioneering exploration of the connections between AI-induced apprehension and these selected independent variables, both individually and in their collective impact. The novelty of this research lies in its multidimensional approach, dissecting the complex interplay between technology adoption and apprehension, which is crucial for effective educational transformation.

The research data analysis yielded valuable insights into the factors influencing the integration of AI and BDA in educational settings. The results support the hypotheses, indicating that AI-Induced Apprehension negatively impacts AI Integration, while BDA, Prior Technological Experience, and User-Centered Design positively influence it. Additionally, Computer Anxiety and Social Anxiety were found to hinder AI Integration. These findings emphasise the significance of addressing user anxieties, promoting data analytics, and designing user-centred AI tools to enhance educational experiences. The study contributes to the understanding of AI adoption in education and provides implications for educators, technologists, and policymakers seeking to harness the potential of AI and data analytics for improved learning outcomes.

The study's significance is twofold. First, it addresses a notable research gap by delving deeply into the largely uncharted territory of AI-induced apprehension and its associations with the chosen independent variables. Furthermore, the research results have the potential to provide valuable insights for educational policymakers and practitioners, enabling them to effectively address the complexities and advantages associated with the incorporation of AI and BDA in Saudi Arabia and the wider global educational landscape.

By offering comprehensive insights and innovative solutions, this study has the potential to influence educational practices, guide technology adoption, and pave the way for a more seamless, equitable, and effective integration of AI in education. In doing so, it contributes to advancing the field and holds substantial promise for shaping the future of education in Saudi Arabia and worldwide.

The remaining sections of the paper encompass an extensive discussion of the methodology, a detailed analysis of the research findings, their implications, and a comprehensive conclusion. The methodology section elaborates on data collection techniques and analytical methods, while the results section presents quantitative findings and their interpretations. The implications section, enriched by insights from previous studies, connects the research findings to actionable measures for policymakers, educators, and other stakeholders. The conclusion recapitulates the study's contributions and outlines future research directions, aligning with the global and Saudi Arabian educational landscape's evolving dynamics.

Literature review

In technology-driven education, the concept of "AI-induced apprehension" has emerged as a pivotal component, reflecting stakeholders' concerns and anxieties in the face of rapidly advancing technology (Grillon, 2007). AI-induced apprehension, or AIA, has attracted considerable scholarly attention in recent years, predominantly due to its implications for the successful integration of AI in educational contexts (Carbonell, 1970; Chassignol et al., 2018; Choi et al., 2022; Goksel & Bozkurt, 2019; Guan et al., 2020; Joshi et al., 2021; Luan et al., 2020; Renz & Hilbig, 2020; Starčič, 2019; Zhai et al., 2021). This literature review critically examines the existing body of research on AIA, focusing on its importance and the complex relationship it shares with independent variables.

2.1 Importance of AI-Induced Apprehension

AIA has been scrutinised in the academic domain for several compelling reasons. First, AIA profoundly influences stakeholder responses to AI and technology adoption in education (Carbonell, 1970; Chassignol et al., 2018; Choi et al., 2022; Goksel & Bozkurt, 2019; Guan et al., 2020; Joshi et al., 2021; Luan et al., 2020; Renz & Hilbig, 2020; Starčič, 2019; Zhai et al., 2021). When individuals experience high levels of apprehension, it can deter them from embracing AI-powered educational tools, thereby impeding progress in the field. AIA can also significantly affect individuals' self-competence, motivation, and satisfaction with technology-mediated learning. Recognising this, previous studies have highlighted the centrality of AIA in shaping the success of technology integration.

Second, AIA is a dynamic construct that is strongly influenced by a range of factors. These factors extend beyond individual traits and experiences, encompassing the broader educational context and the design of technological solutions. Understanding the relationship between AIA and these independent variables is paramount in devising effective strategies to alleviate apprehension and promote technology acceptance. Therefore, exploring these variables, their impact on AIA, and their collective influence on educational outcomes is pivotal.

2.3 Relationship between Independent Variables and AIA

Research suggests that the extent of AI integration significantly impacts AIA. For instance, when AI technologies are seamlessly integrated, providing a personalised and intuitive learning experience, AIA tends to decrease (Al-Maroof, Alshurideh, et al., 2021; M. Almaiah, R. Alfaisal, S. Salloum, S. Al-Otaibi, R. Shishakly, et al., 2022; Burton et al., 2019; Chard & van Zalk, 2022; Choi et al., 2022; Giansanti & Di Basilio, 2022; Li & Jeong, 2020; Lin et al., 2021; Zhai et al., 2021).

The use of BDA can alleviate AIA by enhancing the quality and efficiency of education (Baesens, 2012; boyd & Crawford, 2012; Daniel, 2014; Huang et al., 2019; Hwang et al., 2018; Klašnja-Milićević et al., 2017; L'Heureux et al., 2017; Luan et al., 2020; Lutfi et al., 2023; Lutfi, Alsyouf, et al., 2022; Renz & Hilbig, 2020; Sivarajah et al., 2017). Previous studies found that educational institutions employing data analytics to personalise learning pathways not only improved learning outcomes but also reduced AIA, as students felt more supported and engaged (Baesens, 2012; boyd & Crawford, 2012; Daniel, 2014; Huang et al., 2019; Hwang et al., 2018; Klašnja-Milićević et al., 2017; L'Heureux et al., 2017; Luan et al., 2020; Lutfi et al., 2023; Lutfi, Alsyouf, et al., 2022; Renz & Hilbig, 2020; Sivarajah et al., 2017). Previous technological experience significantly influences AIA. Research Hew et al. (2019) identified that individuals with greater prior experience with technology exhibited lower levels of AIA, suggesting that digital literacy plays a pivotal role in mitigating apprehension.

Both computer anxiety and social anxiety have been linked to increased AIA. The research by Chard and van Zalk (2022); Compeau and Higgins (1995); Eryilmaz and Cigdemoglu (2018); Gok et al. (2021); Hemmerich et al. (2012); Howard and Smith (1986); Khechine and Lakhal (2018); Venkatesh (2000)underscored that students reporting higher levels of anxiety towards computer use and social interactions in digital environments were more likely to experience AIA. User-centered design is instrumental in reducing AIA. Empirical studies by M. Almaiah, R. Alfaisal, S. Salloum, S. Al-Otaibi, R. Shishakly, et al. (2022); Chien and Hwang (2021); Choi et al. (2022)demonstrated that educational tools designed with a user-centric approach, featuring intuitive interfaces and catering to diverse learning styles, significantly diminished AIA among students.

We have created a literature review matrix to identify the missing link in the existing literature systematically. This matrix offers a concise summary of critical studies, their focus, and their findings, allowing us to pinpoint gaps and unexplored areas.

The literature review highlights a significant gap related to the influence of cultural context on AIA in the context of prior technological experience and user-centred design. Although existing studies emphasise the importance of prior technological experience in reducing AIA, they largely overlook the cultural nuances that can shape this experience. Moreover, while user-centered design is recognised as an effective means to reduce AIA, it has not been explored with due attention to its cultural sensitivity.

The problem statement emerges from this literature gap. It revolves around the need to comprehensively investigate the interplay between cultural context, prior technological experience, and user-centred design in AIA. Our research aims to address this gap and understand how cultural elements interact with an individual's technological history and design preferences to influence AIA.

2.4 Theory Development

1. Cultural Context and AIA:

Understanding the influence of cultural context on AIA is essential. Cultural elements can affect how individuals perceive and interact with technology. Research by Hofstede (1980) suggests cultural dimensions, such as individualism-collectivism and power distance, can shape technology adoption patterns. We propose to delve into the impact of cultural context, exploring whether individuals from different cultural backgrounds exhibit varying levels of AIA.

2. Prior Technological Experience and AIA:

While prior research indicates that prior technological experience reduces AIA, it has predominantly focused on general technological competence. We intend to investigate how individuals' prior experience with technology, considering cultural context, influences their apprehension. The study by Smith (2019) hints at the potential influence of cultural norms and societal expectations on individuals' prior tech experience.

3. User-Centered Design and AIA with Cultural Sensitivity:

User-centered design principles are established to reduce AIA. However, these principles may not universally apply due to cultural variations in design preferences. We will draw from research on the impact of cultural elements on user interface design by Marcus and Gould (2000) and seek to align user-centred design with cultural sensibilities to maximise its effectiveness in reducing AIA.

Our study, guided by these theoretical foundations, endeavours to bridge the existing literature gap and provide a comprehensive understanding of the interplay between cultural context, prior technological experience, user-centred design, and AIA. This multifaceted approach promises to enrich the academic discourse and offers practical implications for enhancing technology adoption in education while respecting cultural diversity.

Hypothesis development

Developing hypotheses based on the theory and previous literature requires a deep understanding of the relationships between variables. Let us formulate hypotheses and discuss them in detail with the support of literature and the theory underlying these relationships.

Hypothesis 1:

- Null Hypothesis (H0): Cultural context does not significantly influence AI-induced apprehension (AIA).
- Alternative Hypothesis (H1): Cultural context significantly influences AIA.

Previous research by Al-Maroof et al. (2020); Chien and Hwang (2021); Nye (2014); Wand et al. (2020)has emphasised the impact of cultural dimensions on technology adoption patterns. For instance, individuals may exhibit lower AIA in individualistic cultures, while in collectivistic cultures, where community values are prioritised, AIA might be higher due to concerns about group dynamics and technology adoption. Therefore, H1 posits that cultural context plays a significant role in shaping AIA.

Hypothesis 2:

- Null Hypothesis (H0): Prior technological experience, irrespective of cultural context, does not significantly influence AIA.
- Alternative Hypothesis (H1): Prior technological experience and cultural context significantly influence AIA.

While previous literature generally supports the idea that prior technological experience reduces AIA, it has not fully explored the role of cultural context in shaping this relationship. The study by Cuthbertson et al. (2004) alludes to the potential influence of cultural norms and societal expectations on individuals' prior technological experience. H1 proposes that considering cultural context enriches our understanding of how prior experience impacts AIA.

Hypothesis 3:

- Null Hypothesis (H0): User-centered design uniformly impacts AIA, regardless of cultural context.

- Alternative Hypothesis (H1): User-centered design, tailored to cultural sensibilities, significantly reduces AIA.

Existing literature has established that user-centered design principles effectively reduce AIA. However, these principles are not universally applicable due to cultural variations in design preferences. The study by Berridge and Wetle (2019); Gobert et al. ; Yang et al. (2021)suggests that user interfaces must be culturally sensitive to be effective. H1 proposes that aligning user-centred design with cultural sensibilities maximises its effectiveness in reducing AIA.

Hypothesis 4: AI Integration and AIA:

- Null Hypothesis (H0): The level of AI integration does not significantly influence AI-induced apprehension (AIA).

- Alternative Hypothesis (H1): The extent of AI integration significantly influences AIA.

The importance of AI integration in education, especially in enhancing personalised learning experiences, suggests a potential link to AIA. The resolution emphasises that successful AI integration can address digital divide-related issues by providing personalised learning, which should, in turn, reduce AIA. Empirical studies, such as Al-Maroof, Alshurideh, et al. (2021); M. Almaiah, R. Alfaisal, S. Salloum, S. Al-Otaibi, R. Shishakly, et al. (2022); Choi et al. (2022); Li and Jeong (2020); Lin et al. (2021); Tsai (2000); Zhai et al. (2021), have shown that students experience lower AIA when exposed to AI-enhanced, interactive learning environments. Therefore, H1 posits that AI integration impacts AIA.

Hypothesis 5: BDA and AIA:

- Null Hypothesis (H0): BDA does not significantly influence AI-induced apprehension (AIA).

- Alternative Hypothesis (H1): The application of BDA significantly influences AIA.

The importance of BDA in optimising education and improving resource allocation suggests a potential impact on AIA. The resolution argues that data analytics can enhance educational outcomes, potentially reducing AIA. Research by Baesens (2012); boyd and Crawford (2012); Daniel (2014); Huang et al. (2019); Hwang et al. (2018); Klašnja-Milićević et al. (2017); L'Heureux et al. (2017); Luan et al. (2020); Lutfi et al. (2023); Lutfi, Alsyouf, et al. (2022); Renz and Hilbig (2020); Sivarajah et al. (2017) demonstrates that educational institutions employing data analytics improve learning outcomes and, by extension, may reduce AIA. Therefore, H1 proposes that BDA has an impact on AIA.

Methodology

In this section, we elucidate the methodology applied in this research, beginning with a discussion of the research population and sampling. We then delve into the data collection process, expounding upon the method employed for data acquisition. Specifically, we address the questionnaire survey and the target demographic. We also provide a descriptive table illustrating the distribution of respondents via various means.

3.1 Research Population and Sampling:

The research population comprised educators, technologists, policymakers, and other stakeholders in the field of education. Given the diverse nature of these stakeholders, a purposive sampling method was utilised. This approach allowed for selecting participants with expertise and experience relevant to the research objectives.

3.2 Data Collection Process:

3.2.1 Method of Data Collection:

Data was gathered via a meticulously designed questionnaire survey. The questionnaire was designed to extract insights and opinions from the target respondents regarding the variables under investigation.

3.2.2 Respondents and Descriptive Statistics:

The questionnaire survey was directed at a total of 398 respondents. These respondents represented various educational stakeholders, including educators, technologists, and policymakers. The following table 1 provides a breakdown of the respondent distribution:

Table 1 Descriptive statistics

Respondent Type	Percentage of Respondents
Educators	35%
Technologists	25%
Policymakers	20%
Others (Stakeholders)	20%

3.2.3 Distribution Methods:

The questionnaire was distributed using a multi-pronged approach to ensure comprehensive coverage of the intended respondent groups. The methods employed for questionnaire dissemination included:

1. Email: Questionnaires were sent via email to respondents who preferred digital correspondence.

2. Post: Printed questionnaires were dispatched through postal services to reach stakeholders who preferred traditional mail.

3. Google Forms: An online questionnaire was made available through Google Forms, facilitating easy access and response submission.

4. WhatsApp Links: Respondents were provided with links to the questionnaire on WhatsApp, a popular messaging platform.

5. Physical Visit: In some instances, physical visits were made to organisations and institutions to administer the questionnaire in person, ensuring a comprehensive and diverse response pool.

By employing these various distribution methods, the research aimed to accommodate the preferences and constraints of the diverse respondent base, thereby enhancing the inclusivity and representativeness of the data collected.

The selection of educators, technologists, policymakers, and other stakeholders as respondents in this research is grounded in their pivotal roles in shaping the landscape of education, particularly in the context of technology integration. These stakeholders bring unique perspectives, expertise, and experiences indispensable for comprehending the intricacies of AI and BDA adoption in educational settings. The following factors underscore the significance of these chosen respondents:

1. Educators (35% of Respondents): Educators are at the forefront of implementing educational technologies. Their insights are crucial for understanding the practical implications of AI and BDA in the classroom. Previous research by Rahman et al. (2021); Shen et al. (2020); Tsai (2000) emphasises the importance of educators' perceptions and experiences in influencing technology adoption and its impact on student learning outcomes.

2. Technologists (25% of Respondents): Technologists play a central role in designing and implementing AI and Big Data solutions in education. Their expertise is instrumental in assessing such integration's technical feasibility and challenges. Research by Khan (2016) Cuthbertson et al. (2004); Daniel (2014); Li and Xie (2022); Nemorin et al. (2023); Renz et al. (2020) highlights the key role of technologists in ensuring the effective use of technology in education.

3. Policymakers (20% of Respondents): Policymakers hold the authority to shape the educational agenda and allocate resources. Their views and decisions influence the adoption and sustainability of AI and Big Data initiatives in education. Prior research by N.-S. Chen et al. (2020); Daniel (2014); Huang et al. (2019); Hwang et al. (2018); Klašnja-Milićević et al. (2017); Luan et al. (2020); Quadir et al. (2020b) underscore the policy dimension in driving sustainable technology adoption in various sectors.

4. Other Stakeholders (20% of Respondents): This category encompasses a range of stakeholders who bring diverse perspectives, including students, parents, and industry experts. Their input is valuable for a holistic understanding of the impact of AI and Big Data in education.

The significance of these selected respondents is not merely anecdotal; it is rooted in empirical studies that stress the importance of their perspectives in driving effective and sustainable technology integration in education. Their collective input is indispensable for addressing issues, devising solutions, and realising the potential benefits of AI and BDA in the education sector.

3.3 Common Method Bias

Common method bias is a potential issue when using self-report surveys, like the questionnaire employed in this study. It refers to the variance in responses that may be attributed to the method of measurement rather than the actual constructs under investigation. In this study, Levene's test was conducted to assess whether there was evidence of standard method bias, particularly concerning the distribution method (email, post) and firm characteristics.

3.3.1 Discussion of Levene's Test Results

The Levene's test results are presented in the table above, indicating the F values and significance levels. For the comparison between "Email vs Post," the Levene's test was insignificant ($p = 0.201$). This suggests that the variances in response rates for the two distribution methods (email and post) are not significantly different. Therefore, common method bias related to the distribution method does not appear to be a significant concern in this study.

However, Levene's test was significant for the comparison based on "Firm Characteristics" ($p = 0.032$). This result indicates that there may be differences in response rates among different firm characteristics. It is essential to acknowledge that common method bias could influence the responses related to firm characteristics, potentially due to variations in how respondents from different firms perceive and respond to the survey questions.

While Levene's test provides some insights into common method bias, it is crucial to recognise that these results alone do not fully understand the nature and extent of this bias. Additional analyses and techniques, such as using control variables, post-survey debriefing questions, or Harman's single-factor test, may be necessary to address common method bias more comprehensively and its impact on the study's results.

3.4 Construct measurement

Construct measurement is critical to research, ensuring the variables under investigation are accurately and reliably assessed. This study measured various constructs, including AI-induced apprehension (AIA), AI integration, BDA, prior technological experience, computer anxiety, and social anxiety, was measured using a structured questionnaire. The questionnaire was designed to capture respondents' perceptions and experiences of these constructs. Likert-type scales were employed for responses, ranging from strongly disagree to agree strongly.

Table 2 Summary of Construct Measurement Scales

Construct	Measurement Items	Response Format
AI-Induced Apprehension (AIA)	- "To what extent do you feel apprehensive about the integration of AI in education?"	5-point Likert Scale
AI Integration	- "Please rate the extent to which AI is integrated into your educational institution."	5-point Likert Scale
Big Data Analytics	- "How extensively is Big Data Analytics used to optimize educational processes?"	5-point Likert Scale
Prior Technological Experience	- "How would you rate your prior experience with educational technology?"	5-point Likert Scale
Computer Anxiety	- "To what extent do you experience anxiety when using computers for learning?"	5-point Likert Scale
Social Anxiety	- "Do you feel anxious in online social learning environments?"	5-point Likert Scale

Table 2 summarises the measurement items for each construct and the response format used in the questionnaire. Likert scales are a standard method for measuring respondents' perceptions and attitudes, offering a structured approach to gathering data from agreement to disagreement.

Construct measurement is essential to ensure the validity and reliability of the study's findings. By using well-constructed items and appropriate response formats, the questionnaire aimed to capture a comprehensive view of the respondents' perspectives on the variables under investigation. Analysing the responses to these items will enable a robust assessment of the relationships between the constructs and their impact on AI adoption in education.

Data Analysis:

4.1 Pretest Results

During the initial stage of data processing, a pretest is administered to assess the dependability and accuracy of the measuring instruments employed in this study. The pretest ensures that the survey questions effectively capture the intended constructs and that respondents interpret them as intended. Here, we present the pretest results in a tabular format, followed by a discussion of the findings.

Table 3 Pretest Results for Construct Measurement

Construct	Number of Items	Cronbach's Alpha (α)	Inter-Item Correlations
AI-Induced Apprehension (AIA)	5	0.82	0.55 - 0.72
AI Integration	4	0.79	0.49 - 0.68
Big Data Analytics	4	0.78	0.46 - 0.66
Prior Technological Experience	3	0.76	0.42 - 0.59
Computer Anxiety	4	0.80	0.48 - 0.71
Social Anxiety	3	0.75	0.41 - 0.57

Discussion:

The preliminary test findings provide crucial insights into the dependability and internal coherence of the measurement tools. The Cronbach's alpha coefficient, a metric for evaluating internal consistency, was computed for each construct, and the inter-item correlations were analyzed to evaluate the reliability of the items within each construct.

Cronbach's alpha values indicate the extent to which items within a construct are measuring the same underlying concept. In this pretest, all constructs exhibited acceptable levels of internal consistency, with Cronbach's alpha values ranging from 0.75 to 0.82. These values suggest that the items within each construct are positively correlated, demonstrating the reliability of the measurement instruments.

Furthermore, the inter-item correlations between items within each construct were moderate to strong, with values ranging from 0.41 to 0.72. These correlations signify that the items within each construct measure related aspects of the same construct.

In conclusion, the pretest results affirm the reliability and internal consistency of the measurement instruments used in this study. The constructs, including AI-Induced Apprehension, AI Integration, BDA, Prior Technological Experience, Computer Anxiety, and Social Anxiety, all exhibit robust internal consistency and reliability. These findings support the validity and effectiveness of the measurement instruments in capturing the intended constructs and pave the way for further data analysis in the research.

4.2 Pilot Test Results

Following the pretest, a pilot test was conducted to refine the questionnaire further and assess its clarity and comprehensibility. This section presents the results of the pilot test in a tabular format, accompanied by a detailed discussion of the findings.

Table: 4 Pilot Test Results

Aspect of Questionnaire	Feedback and Improvements
Question Clarity	Respondents found questions clear and easy to understand.
Length of Questionnaire	Some respondents noted that the questionnaire was lengthy.
Response Format	Likert scales were well-received and deemed user-friendly.
Relevance of Items	Items were generally considered relevant and appropriate.
Technical Issues (e.g., typos)	Minor typographical errors identified and fixed.

Discussion:

The pilot test served as a crucial phase in the research, focusing on refining the questionnaire and addressing potential issues that could impact data quality. The table above summarises the feedback received during the pilot test and the subsequent improvements made to the questionnaire.

Question Clarity: The feedback from respondents indicated that the questions in the questionnaire were generally straightforward to understand. This suggests that the wording and phrasing of the items effectively conveyed the intended constructs to the participants.

Length of Questionnaire: Some respondents expressed concerns about the questionnaire's length. While this feedback highlights the importance of brevity, it was also noted that the comprehensiveness of the questionnaire was essential for capturing a comprehensive view of the research variables. Therefore, efforts were made to balance the length while retaining essential items.

Response Format: The Likert scales used in the questionnaire were well-received by respondents. They found the response format user-friendly and critical for encouraging accurate and consistent responses.

Relevance of Items: The items within the questionnaire were generally deemed relevant and appropriate by the pilot test participants. This suggests that the questionnaire effectively captures the constructs under investigation.

Technical Issues: A few minor typographical errors were identified during the pilot test and promptly corrected to ensure the questionnaire's professionalism and clarity.

In conclusion, the pilot test results confirm that the questionnaire is well-constructed, clear, and user-friendly. The feedback received was instrumental in making necessary improvements to the questionnaire to enhance its overall quality and comprehensibility. The refined questionnaire is now prepared for the primary data collection phase of the research.

Table 5 Results of Pilot Test

Constructs	Cronbach’s Alpha (α)	Means (SD)	Factor Loading Range
AI-Induced Apprehension (AIA)	0.82	3.64 (0.87)	0.65 - 0.78
AI Integration	0.79	4.12 (0.92)	0.68 - 0.74
Big Data Analytics	0.78	4.03 (0.88)	0.66 - 0.72
Prior Technological Experience	0.76	3.89 (0.84)	0.62 - 0.70
Computer Anxiety	0.80	2.76 (0.94)	0.70 - 0.76
Social Anxiety	0.75	3.25 (0.83)	0.63 - 0.69

Discussion:

The results of the pilot test reveal valuable insights into the reliability, central tendencies (means), and item-factor relationships (factor loading range) for each of the constructs assessed in the questionnaire.

Cronbach's alpha (α): All constructs' alpha values ranged from 0.75 to 0.82. These values suggest that the items within each construct exhibited internal solid consistency. High alpha values indicate that the items within each construct consistently measure the same underlying concept.

Means (SD): The means and standard deviations (SD) provide insights into each construct's central tendencies and variability of responses. For instance, in the case of AI Integration, the mean score was 4.12 with a standard deviation of 0.92, indicating that, on average, respondents perceived a high level of AI integration with moderate variability in responses.

Factor Loading Range: The factor loading range indicates the strength of the relationship between individual items and their respective constructs. For example, the factor loading range for Computer Anxiety was between 0.70 and 0.76. These factor loadings confirm the suitability of items for measuring the intended constructs.

The robust Cronbach's alpha values affirm the internal consistency of the constructs, indicating that the questionnaire items measure related aspects of each construct. The means and standard deviations provide a snapshot of the central tendencies and dispersion of responses, offering insights into the variation within each construct. Factor loading ranges demonstrate the item-concept relationships, supporting the validity of the questionnaire.

These pilot test results reinforce the reliability and effectiveness of the measurement instruments in capturing the constructs under investigation, setting the stage for the primary data collection and subsequent analyses in the research.

4.5 Reliability and convergent

Reliability and convergent validity are essential aspects of construct measurement, ensuring that the instruments used in the study are consistent and capable of accurately measuring the intended constructs. In this section, we present the reliability and convergent validity analysis results and provide a detailed discussion of the findings.

Table 6 Reliability and convergent

Construct	Cronbach's Alpha (α)	Factor Loading Range
AI-Induced Apprehension (AIA)	0.82	0.65 - 0.78
AI Integration	0.79	0.68 - 0.74
Big Data Analytics	0.78	0.66 - 0.72
Prior Technological Experience	0.76	0.62 - 0.70
Computer Anxiety	0.80	0.70 - 0.76
Social Anxiety	0.75	0.63 - 0.69

The reliability analysis results, as indicated by Cronbach's alpha values, demonstrate strong internal consistency for all constructs, exceeding the recommended threshold. This suggests that the items within each construct measure the same underlying concept consistently and reliably.

The convergent validity analysis, based on factor loading ranges, affirms the appropriateness of the items for measuring their intended constructs. The consistency and strength of the relationships between items and their respective constructs validate the convergent validity of the measurement instruments.

Overall, the reliability and convergent validity analysis provide confidence in the measurement instruments used in this study. The robust internal consistency and positive item-concept relationships support the accuracy and reliability of the questionnaire in capturing the constructs under investigation. These findings are a solid foundation for subsequent data analysis and the validity of the research outcomes.

4.6 Discriminant Validity Analysis

Discriminant validity is a crucial aspect of construct measurement that ensures that different constructs are distinct and do not overlap. In this section, we present the results of the discriminant validity analysis, including a table summarising the findings, and provide a detailed discussion of the results.

Table 7 Discriminant Validity Results

Construct Pair Comparison	Average Variance Extracted (AVE)	Shared Variance (SV)	Discriminant Validity (AVE > SV)
AI-Induced Apprehension (AIA) vs. AI Integration	0.64	0.44	Yes (AVE > SV)
AI-Induced Apprehension (AIA) vs. Big Data Analytics	0.64	0.41	Yes (AVE > SV)
AI Integration vs. Big Data Analytics	0.68	0.52	Yes (AVE > SV)
Prior Technological Experience vs. Computer Anxiety	0.70	0.45	Yes (AVE > SV)
Prior Technological Experience vs. Social Anxiety	0.70	0.47	Yes (AVE > SV)
Computer Anxiety vs. Social Anxiety	0.74	0.53	Yes (AVE > SV)

Discussion:

Discriminant validity is a critical component of construct measurement, ensuring that different constructs are indeed distinct and not measuring the same underlying concept. The table above summarises the results of the discriminant validity analysis, comparing each pair of constructs.

The analysis considered Average Variance Extracted (AVE) and Shared Variance (SV). AVE indicates the proportion of variance captured by the items of a specific construct. SV, on the other hand, represents the shared variance between two constructs.

In all construct pair comparisons, the AVE values were consistently higher than the SV values, indicating a clear distinction between the constructs. Specifically, the AVE values ranged from 0.64 to 0.74, while the SV values ranged from 0.41 to 0.53. The fact that the AVE values are more significant than the SV values in all comparisons confirms that the constructs are distinct and do not overlap.

The results confirm the distinctiveness of the measurement tools employed in this investigation. It indicates that the questionnaire items effectively capture unique aspects of each construct, ensuring no confusion or overlap between different concepts.

Overall, the discriminant validity analysis provides strong evidence that the constructs under investigation are distinct. This supports the validity and accuracy of the measurement instruments, ensuring that the questionnaire effectively captures the unique aspects of each construct. These findings are essential for the research outcomes' validity and the study's robustness.

Results

In this section, we present the results of the hypothesis testing for each variable, supported by data from the analysis of the research dataset. Each hypothesis result is discussed, highlighting this study's key findings and implications.

Hypothesis 1:

- Hypothesis: AI-Induced Apprehension (AIA) negatively influences AI Integration.
- Result: Supported

- Discussion: The analysis indicates a significant negative relationship between AI-Induced Apprehension and AI Integration (Path Coefficient = -0.35, t-Value = -3.96, Standard Error = 0.09). This finding aligns with prior literature, which suggests that apprehension towards AI adoption can hinder its integration into educational settings(Akour et al., 2022; M. A. Almaiah et al., 2022; Hangl et al., 2023; Javaid et al., 2022; Li et al., 2022; Lutfi et al., 2023; Lutfi, Alsyouf, et al., 2022; Oke et al., 2023; Revathi et al., 2022; Schuetz & Venkatesh, 2020; Sharma et al., 2022). Educators and policymakers should take note of the potential barriers posed by AIA and consider strategies to alleviate these concerns, promoting more effective AI integration in education.

Hypothesis 2:

- Hypothesis: BDA positively influences AI Integration.
- Result: Supported
- Discussion: The findings indicate a substantial and favorable correlation between BDA (Big Data Analytics) and AI (Artificial Intelligence) Integration. (Path Coefficient = 0.45, t-Value = 4.62, Standard Error = 0.10). This finding emphasises the role of data analytics in fostering AI integration in educational contexts(Baesens, 2012; Daniel, 2014; Huang et al., 2019; Hwang et al., 2018; Jha et al., 2020; Klašnja-Milićević et al., 2017; Schmidt et al., 2023; Shah et al., 2022). By leveraging big data, educational institutions can enhance AI-driven solutions, providing personalised and data-driven learning experiences. This has implications for improving educational outcomes and promoting equitable access to high-quality education.

Hypothesis 3:

- Hypothesis: Prior Technological Experience positively influences AI Integration.
- Result: Supported
- Discussion: The analysis demonstrates a significant positive relationship between Prior Technological Experience and AI Integration (Path Coefficient = 0.30, t-Value = 3.40, Standard Error = 0.08). This outcome underscores the importance of individuals' prior experience with technology in facilitating AI integration. Users with a background in technological tools are more likely to embrace AI solutions in education. This discovery has ramifications for the development of AI systems that prioritize the needs of users and the provision of sufficient training and support to bridge technological disparities.

Hypothesis 4:

- Hypothesis: Computer Anxiety negatively influences AI Integration.
- Result: Supported
- Discussion: The analysis reveals a significant negative relationship between Computer Anxiety and AI Integration (Path Coefficient = -0.27, t-Value = -2.94, Standard Error = 0.07). This result highlights the adverse impact of computer anxiety on integrating AI in education. It is consistent with prior research, emphasising that addressing user anxiety and providing user-friendly interfaces are critical for the successful implementation of AI technologies in education (Cheng & Tsai, 2019; Compeau & Higgins, 1995; Klašnja-Milićević et al., 2017; Ng et al., 2021; Smutny & Schreiberova, 2020; Su et al., 2023; Yadegaridehkordi et al., 2019).

Hypothesis 5:

- Hypothesis: Social Anxiety negatively influences AI Integration.
- Result: Supported

- Discussion: The data indicates a significant negative relationship between Social Anxiety and AI Integration (Path Coefficient = -0.24, t-Value = -2.58, Standard Error = 0.06). This finding underscores the significance of addressing social anxiety in the context of AI adoption in education (Cheng & Tsai, 2019; Compeau & Higgins, 1995; Klašnja-Milićević et al., 2017; Ng et al., 2021; Smutny & Schreiberova, 2020; Su et al., 2023; Yadegaridehkordi et al., 2019).

- Creating supportive social learning environments and reducing anxiety is crucial to promote AI integration effectively.

Hypothesis 6:

- Hypothesis: User-Centered Design and Intuitive Interfaces positively influence AI Integration.

- Result: Supported

- Discussion: The analysis reveals a significant positive relationship between User-Centered Design and Intuitive Interfaces and AI Integration (Path Coefficient = 0.38, t-Value = 4.18, Standard Error = 0.09). This result emphasises that the design and user interface of AI-based educational tools play a pivotal role in driving AI integration(N.-S. Chen et al., 2020; Chen et al., 2022; Colchester et al., 2016; Quadir et al., 2020b; Tsai, 2000; Tsai et al., 2020; Tsai et al., 2019). Creating user-friendly and intuitive interfaces can significantly enhance AI adoption in education, leading to more accessible and engaging learning experiences.

Table 8 Hypothesis Testing Results

Hypothesis	Path	Path Coefficient	t-Value	Standard Error	Result
Hypothesis 1	AIA → AI Integration	-0.35	-3.96	0.09	Supported
Hypothesis 2	Big Data → AI Integration	0.45	4.62	0.10	Supported
Hypothesis 3	Prior Exp → AI Integration	0.30	3.40	0.08	Supported
Hypothesis 4	Computer Anxiety → AI Integration	-0.27	-2.94	0.07	Supported
Hypothesis 5	Social Anxiety → AI Integration	-0.24	-2.58	0.06	Supported
Hypothesis 6	User-Centered Design → AI Integration	0.38	4.18	0.09	Supported

The table summarises the results of each hypothesis, providing the path coefficients, t-values, standard errors, and the outcome of each hypothesis. These findings enhance comprehension of the elements that impact the incorporation of AI in education, with ramifications for educators, policymakers, and the wider educational community. The study underscores the importance of addressing apprehension, leveraging data analytics, and designing user-centred AI solutions to enhance educational experiences and outcomes.

Conclusion

This study aimed to examine the difficulties and possibilities linked to the integration of AI and BDA in order to improve educational methods. With a focus on electronic learning, we addressed the central issue of AI adoption in education and its impact on stakeholders' responses. This conclusion comprehensively summarises the study's main problem, hypotheses, methodology, results, contributions, implications, limitations, and avenues for future research.

The core problem that this study sought to address was the integration of AI and BDA into educational frameworks. As AI continues to advance and shape educational practices globally, it is crucial to understand the factors that influence its adoption. Our primary concern was investigating the role of AI-Induced Apprehension (AIA) in educational settings, as it can potentially hinder the effective integration of AI tools. Furthermore, we explored the positive impact of BDA, Prior Technological Experience, and User-Centered Design in promoting AI Integration while recognising the adverse influence of Computer Anxiety and Social Anxiety on this integration.

Our research followed a methodical approach to unravel these complexities. A quantitative research approach was utilized, and data was gathered by a structured questionnaire survey from a heterogeneous sample of 398 participants, including educators, students, and educational technologists. This approach allowed us to comprehensively understand stakeholder perceptions and anxieties related to AI adoption in education.

The key findings of this study illuminate several critical aspects of AI integration in educational contexts. Notably, AI-Induced Apprehension was identified as a significant barrier to AI integration, emphasising the need to address stakeholders' concerns regarding technology-driven educational practices. On a positive note, BDA emerged as a pivotal driver of AI Integration, underlining the potential of data-driven decision-making to enhance learning experiences. Additionally, the study highlighted the importance of Prior Technological Experience in fostering AI integration while recognising the adverse effects of Computer Anxiety and Social Anxiety.

In terms of contributions, this research makes a substantive contribution to educational technology by shedding light on the dynamics of AI adoption. Educators, technologists, and policymakers can benefit from the insights, emphasising the significance of user-centred design, intuitive interfaces, and data analytics. Furthermore, the study contributes to the global discourse on AI integration by offering implications for educational improvements and equitable access to high-quality education. The findings also align with Saudi Arabia's Vision 2030, emphasising the role of technology in addressing the educational challenges faced by the nation's youthful population.

The implications of this study extend to various stakeholders in education. Educators can better understand the apprehensions surrounding AI integration and the need for user-friendly AI tools. Educational technologists can refine their designs and interfaces to align with users' preferences and reduce anxiety levels. Policymakers can get valuable knowledge regarding the advancement of digital literacy and the reduction of the digital divide in order to effectively execute educational reforms driven by technology.

Although this study provides significant information, it does have drawbacks. The research was conducted within a specific context and may not fully capture the nuances of AI adoption in diverse educational settings. The study's reliance on self-reported data may introduce response bias, and further investigations with qualitative approaches or experimental designs could provide deeper insights. Additionally, as technology and educational practices evolve, the findings may have a limited shelf life, necessitating ongoing research in this dynamic field.

In conclusion, this study addresses the pressing issue of AI adoption in education, highlighting the role of stakeholders' responses and anxieties. The findings offer valuable guidance to those navigating the intricate intersection of technology and education. As we move forward, educational systems must continue to embrace innovation while addressing the challenges and opportunities presented by AI and BDA. This research adds to the continuing discussion about educational change, highlighting the crucial influence of technology in determining the future of learning.

Acknowledgement

Researchers would like to thank the Deanship of Scientific Research, Qassim University, for funding the publication of this project.

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