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# Integrating TAM and IS success model: exploring the role of blockchain and AI in predicting learner engagement and performance in e-learning

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This study innovatively intertwines technology adoption and e-learning by integrating blockchain and AI, offering a novel perspective on how cutting-edge technologies revolutionize learning processes. The present study investigates the factors that influence the behavioral use of learners to use blockchain and artificial intelligence (AI) in e-learning. The study proposes the integrated model of Technology Acceptance Model (TAM) and Information System (IS) success Model that include perceived usefulness, perceived ease of use, system quality, information quality, and service quality as antecedents to behavioral use of blockchain and AI in e-learning. The model also examines the moderating effect of learner self-efficacy on the relationship between behavioral use and e-learning engagement and performance. The study collected data from 322 respondents and analyzed the data using partial least squares structural equation modeling (PLS-SEM) with a bootstrapping technique. The results show that the factors of TAM model and IS model have the significant and positive effects on behavior to use blockchain and AI in e-learning. Additionally, learner self-efficacy has a significant positive effect on e-learning engagement and performance, but it does not moderate the relationship between behavior to use blockchain or AI and e-learning engagement and performance. Overall, the study provides insights into the factors that influence the adoption of blockchain and AI in e-learning and offers practical implications for educators and policymakers.

KEYWORDS

**Information System (IS) Success model, Technology Acceptance Model (TAM), blockchain adoption, AI adoption, e-learning engagement, e-learning performance**

## 1. Introduction

The rapid evolution of technology has driven the growth of e-learning, making it an essential component of modern education. With this growth, understanding and predicting learner performance and engagement has become increasingly important for ensuring the success of online educational platforms (Klašnja-Milićević et al., 2017; Klašnja-Milicevic and Ivanovic, 2018; Holmes et al., 2019). In recent years, researchers have focused on leveraging cutting-edge technologies like blockchain (Ocheja et al., 2018; Saadati et al., 2021) and artificial intelligence (AI) (Klašnja-Milićević et al., 2017; Chen et al., 2020) to create personalized, efficient, and engaging learning experiences. In recent years, e-learning has become an increasingly popular form of education. However, ensuring learner engagement (Halverson and Graham, 2019) and performance in e-learning can be challenging, and educators are always looking for new ways to improve the quality and effectiveness of e-learning (Lalitha and Sreeja, 2021). In this context, emerging technologies such as blockchain and artificial intelligence (AI) have shown the potential to predict learner performance and engagement in e-learning. Recent research has explored the possibility of blockchain and artificial intelligence (AI) in predicting learner performance and engagement in e-learning. Li et al. (2019) proposed a blockchain-based e-learning system that uses AI to analyze learner data and provide personalized recommendations to improve learning outcomes. Another study by Tang et al. (2021) used machine learning algorithms to predict learner engagement based on various factors such as course content, learner behavior, and social interaction.

Several studies have explored the potential of AI in e-learning. Li et al. (2019) used machine-learning algorithms to predict learner engagement based on various factors such as course content, learner behavior, and social interaction. The study found that machine-learning algorithms could accurately predict learner engagement and identify factors that contribute to learner engagement. Similarly, Riad et al. (2009) reviewed the applications of AI in intelligent e-learning systems. Other studies have explored the potential of blockchain technology in e-learning. Lin et al. (2021) proposed a blockchain-based e-learning system that verifies educational credentials and achievements using smart contracts. The system also provides a decentralized platform for sharing educational content and resources. Similarly, Chilambarasan and Kangaiammal (2021) proposed a blockchain-based e-learning system that uses cryptography to ensure data privacy and security. The system also provides a decentralized platform for peer-to-peer learning and sharing of educational resources.

Blockchain technology is a distributed ledger technology that allows for secure and transparent data sharing across a network (Swan, 2015). The technology can potentially revolutionize various industries, including education, by providing a secure and decentralized platform for storing and sharing educational credentials and achievements (Ocheja et al., 2018; Lin et al., 2021). In the context of e-learning, blockchain technology can be used to create a secure and decentralized platform for sharing and verifying educational credentials and achievements. This can help ensure the authenticity of educational certificates and prevent fraud and misrepresenting qualifications (Li et al., 2019). Additionally, blockchain technology can facilitate peer-to-peer learning by enabling learners to share and exchange educational content and resources without intermediaries (Halverson and Graham, 2019). On the other hand, AI refers to the ability of machines to perform tasks that typically require human intelligence, such as learning, reasoning, and problem-solving (Russell, 2010). In the context of e-learning, AI can be used to analyze large amounts of learner data and provide personalized and adaptive learning experiences. One way AI can be used in e-learning is through machine learning algorithms (Tang et al., 2021). Machine learning algorithms can be trained on large datasets of learner data to predict learner performance and engagement based on various factors such as past performance, learning style, and interaction patterns (Li et al., 2019; Lin et al., 2019). For example, AI makes educational platforms individualized (Al-Azawei et al., 2017, 2019). AI systems adjust content to the learner's behavior, response times, correct/incorrect answers, and interests to improve learning. AI-based learning analytics monitor and forecast student performance and engagement, enabling early intervention and increased learner engagement (Klašnja-Milićević et al., 2017; Klašnja-Milicevic and Ivanovic, 2018). Massive Open Online Courses use AI to scale learning. Alraimi et al. (2015) recommend courses, monitor discussion boards, and grade assignments automatically. AI-powered chatbots or virtual assistants can answer common questions, provide resources, and remind students to stay on course (Chilambarasan and Kangaiammal, 2021).

The use of blockchain and AI in e-learning has the potential to improve learner performance and engagement by providing personalized and adaptive learning experiences (Halverson and Graham, 2019; Saadati et al., 2021). However, some challenges and limitations need to be addressed, such as low academic performance and engagement, the potential for bias in e-learning (Junco, 2012; Lee, 2014), and the need for more research to explore the full potential of these technologies (i.e., AI and blockchain) in e-learning engagement and performance. Despite the growing interest in using blockchain and AI in e-learning, there is a lack of empirical research on their effectiveness in improving learner performance and engagement. There are a limited number of studies in this field due to the wide application of TAM and IS in numerous research studies to measure behavioral use in learner engagement and academic performance.

This study pays an interesting contributions how emerging technologies (i.e., Blockchain and AI), affect e-learning engagement and performance in the South African education institutions. These emerging technologies are at the developing stage in South Africa and still need to be addressed. These technologies are used to some extent; in particular, the education sector is using these technologies to project data and enhance management capability and skills. The understanding of how perceived usefulness, ease of use, and various service quality factors affect behavioral use toward AI is deepened as a result of this research, which is essential for the effective design of e-learning platforms. This builds a bridge between the adoption of AI, blockchain and the academic results from them because it investigates how these goals influence engagement and performance in online learning environments. Notably, it is the first study to investigate the moderating effect of learner self-efficacy on this relationship (Prifti, 2022). This research provides a comprehensive viewpoint that combines educational, technological, and psychological factors in the context of e-learning. Therefore, the research gap in this area is the need for empirical research to explore the academic effectiveness and self-efficacy of blockchain and AI in improving learner performance and engagement in e-learning by using these technologies in e-learning. For this purpose, the study integrated the TAM, including perceived usefulness, ease of use, and behavior to use (Davis, 1989; Venkatesh et al., 2003) and IS success model, including system quality, information quality, and service quality (DeLone and McLean, 1992, 2003) to explore the factors that influence the acceptance and use of AI and blockchain in learner academic performance and engagement in e-learning. Finally, the study designs the research objectives:

1. To examine the influence of perceived usefulness and ease of use on behavior to use blockchain and AI in e-learning in South Africa.
2. To examine the influence of system quality, information quality, and service quality on behavior to use blockchain and AI in e-learning in South Africa.
3. To examine the influence of behavior to use AI and blockchain on e-learning engagement and performance in South Africa.
4. To examine the moderating effect of learner self-efficacy on the relationship between behavior to use blockchain and AI in e-learning and learner engagement and academic performance in South Africa.

## 2. Literature review and hypotheses development

### 2.1. Applications of blockchain and AI in education

The integration of emerging technologies like blockchain and artificial intelligence (AI) into the educational domain holds significant promise. Traditionally known for its application in cryptocurrency, blockchain is now being explored for its potential in certifying and verifying educational credentials. Li et al. (2019) delved into a blockchain system for e-learning assessment and certification, ensuring tamper-proof, transparent records that can be seamlessly verified. Additionally, Chilambarasan and Kangaiammal (2021) explored the security aspects of e-learning in the cloud, utilizing blockchain to guarantee secure access and data management.

On the other hand, AI is reshaping how students interact with content, offering personalized learning experiences and robust analytics to track progress. Chen et al. (2020) pinpointed potential gaps in the application and theory during the rise of AI in education, emphasizing the need for a bridge between potential and practice. Furthermore, Holmes et al. (2019) discussed learning analytics' crucial role in online distance learning, highlighting the advantages of AI-driven analytics in enhancing learning design.

Blockchain and AI have emerged as transformative technologies in e-learning, and their impact on engagement and performance is undeniable. Blockchain's ability to provide secure, transparent, and immutable records of learners' achievements enhances trust and credibility in the e-learning ecosystem. This fosters a sense of confidence in learners, leading to increased engagement as they actively participate in courses, knowing their accomplishments are verified and cannot be altered (Chen et al., 2020). Moreover, blockchain's decentralized nature enables the creation of personalized learning paths for individual learners, optimizing their educational experiences. Learners can receive tailor-made content and assignments that align with their interests, preferences, and skill levels. This personalization fosters a stronger connection between learners and the learning materials, resulting in improved engagement and motivation (Sharples and Domingue, 2016).

On the other hand, AI-powered applications in e-learning have revolutionized the learning experience by providing adaptive learning systems that dynamically adjust content difficulty based on learners' performance. These systems ensure learners are continuously challenged appropriately, preventing boredom or frustration and promoting sustained engagement (Zhou and Feng, 2017). AI also facilitates personalized content recommendations, making accessing relevant resources that align with their learning goals easier for learners. As AI analyzes learners' interactions with the platform, it can suggest courses, modules, or peer interaction opportunities that cater to their preferences. This targeted approach keeps learners motivated and engaged, as they feel more invested in their learning journey (Conde et al., 2019).

Another significant contribution of AI to e-learning is its capacity for automated assessment and feedback. Through machine learning and natural language processing, AI tools can provide instant feedback on assignments and quizzes, enabling learners to promptly identify and address their mistakes. This feedback loop enhances learning efficiency, as learners can understand and correct their errors in real time, leading to improved performance (Holstein et al., 2019). Combining blockchain and AI in e-learning creates a powerful synergy, addressing critical challenges like trust, personalization, and feedback mechanisms. Learners benefit from personalized learning experiences, secure credentials, and constant access to targeted resources, resulting in heightened engagement and improved performance. As these technologies continue to evolve and integrate further into e-learning platforms, the future of education promises to be more inclusive, efficient, and learner-centric (Kulik and Fletcher, 2016).

Therefore, blockchain and AI radically impact e-learning engagement and performance. The transparency, security, and trust blockchain provides enhance learners' confidence in the system, leading to increased engagement. With its adaptive learning systems and personalized content recommendations, AI further enhances engagement and promotes sustained motivation. Additionally, AI's automated assessment and feedback mechanisms improve learners' performance by providing timely guidance. These technologies revolutionize e-learning, making education more accessible and practical for learners worldwide.

### 2.2. Integration of TAM and IS success models

An integrated model for understanding the acceptance and use of AI in e-learning, the study integrates the Technology Acceptance Model (TAM) and the Information Systems (IS) Success model. The TAM focuses on users' technological adoption and behavioral objectives. According to research (Venkatesh et al., 2003; Lee, 2010), perceived usefulness and perceived simplicity of use are important factors in user acceptance and adoption. This is consistent with other research (Liaw, 2008; Holmes et al., 2019; Humida et al., 2022) that highlight the importance of these parameters in the context of e-learning. The system quality, information quality, and service quality characteristics that affect system use and user satisfaction are examined by the IS model in addition to the TAM (Ramayah et al., 2010; Udo et al., 2010). These have been demonstrated in the research to have an impact on behavioral intents to use e-learning systems (Martin et al., 2010; Khalilzadeh et al., 2017; Latip et al., 2020).

Zarifis and Efthymiou (2022) outlined four business models for AI adoption in education, substantiating our study's premise that AI integration into e-learning has significant potential and diverse application possibilities. Furthermore, Li et al.'s (2022) study used the Theory of Planned Behavior and the Expectation–Confirmation Model to examine continuance use in online learning during the COVID-19 pandemic. This study supports our findings about the significance of perceived usefulness and ease of use in encouraging the adoption and continued use of AI and blockchain in e-learning.

Al-Emran et al. (2018) systematically reviewed the TAM's application in the context of M-learning. The study emphasized integrating TAM with other models, such as IS, to understand the factors affecting users' behavioral use. Al-Samarraie et al. (2018) did a systematic literature review on e-learning continuance satisfaction using a unified model integrating TAM and IS. The study found that integrating the two models effectively captures factors influencing instructors and students' use to continue using e-learning systems. Park and Kim (2014) proposed an integrated adoption model for mobile cloud services by incorporating TAM and IS. The findings demonstrated that the integrated model significantly improved the prediction of users' behavioral use in adopting mobile cloud services. Pai and Huang (2011) integrated the TAM (i.e., perceived usefulness, ease of use and attitude) and IS (i.e., system quality, information quality, and service quality) in the context of healthcare information systems has yielded a comprehensive understanding of the factors influencing user acceptance and system success. This combined approach has proven to be a valuable tool for identifying the key determinants of healthcare professionals' behavioral use and informing such systems' design, implementation, and improvement. Therefore, the study integrates technology models to test behavioral use in e-learning engagement and performance.

## 2.3. Conceptual framework

Incorporating insights from the Technology Acceptance Model (TAM) and the Information Systems (IS) Success model, our study seeks to understand the adoption and use of AI in e-learning. The TAM, supported by research such as Venkatesh et al. (2003) and Lee (2010), emphasizes the significance of perceived usefulness and ease of use, while the IS model, as investigated by Udo et al. (2010) and Ramayah et al. (2010), explores the impacts of system, information, and service quality. Prior research from Zarifis and Efthymiou (2022) and Li et al. (2022) provides additional context for the potential of AI in education and the continued use of e-learning. The integration of these models provides a comprehensive understanding of the determinants of e-learning engagement and performance.

According to the literature (Al-Adwan et al., 2021, 2022; Li et al., 2022; Zarifis and Efthymiou, 2022), the integration of AI and blockchain technology into e-learning has significantly transformed the education sector. However, this study and its worth to readers is enhanced by a more thorough examination of how they are used in practice. For instance, Zarifis and Efthymiou's paper from 2022 explains many economic models for how AI and other technologies are already used in education, from individualized instruction to administrative chores. As a result, a thorough analysis of these models give readers specific instances of how AI and related technologies are used in e-learning. In-depth discussions about the use of blockchain in e-learning, notably its function in producing transparent and secure learning records (Al-Adwan et al., 2021), further shed light on the advantages of this technology. The importance of perceived usefulness, service quality measures, and self-efficacy in the context of these emerging technologies are also highlighted by incorporating studies like that of Li et al. (2022), which examine behavioral use toward continuous online learning use. Finally, the study offers the following hypotheses with the help of literature pieces of evidence:

### 2.3.1. Perceived usefulness, perceived ease of use, behavior to use blockchain and AI

The effect of PU and PEOU on behavior to use e-learning has been studied in recent years, but the studies did not target blockchain and AI in e-learning. Such as Zhou and Feng (2017) investigated the effect of PU and PEOU on the behavioral use of subscribers to use 4G mobile services in e-learning contexts. Their findings suggest that PU and PEOU significantly impact users' to adopt e-learning services. Al-Azawei et al. (2016) extended the TAM to incorporate learning styles in a blended e-learning system. The study revealed that PU and PEOU significantly influence behavioral use, with the relationship being moderated by individual learning styles. Khalilzadeh et al. (2017) extended the UTAUT model to include security-related factors in the context of NFC-based mobile payments for e-learning. The results suggest that PU and PEOU are significant predictors of behavioral uses, highlighting the importance of these factors in technology acceptance. Tarhini et al. (2017) investigated the moderating effect of individual-level cultural values on users' acceptance of e-learning in developing countries. The study confirmed that PU and PEOU significantly influence behavioral uses. In the context of e-learning, PU has been found to positively influence behavioral intentions to use e-learning platforms (Al-Adwan et al., 2013). In addition, many studies have demonstrated that PEOU positively affects behavioral uses to use e-learning platforms (Al-Gahtani et al., 2007; Sun et al., 2008). Based on the literature evidence, the study proposes the research hypotheses to measure the technology adoption of blockchain and AI in e-learning.

**$H_1$.** Perceived usefulness significantly and positively influences behavior to use blockchain (a) and AI (b) in e-learning.

**$H_2$.** Perceived ease of use significantly and positively influences behavior to use blockchain (a) and AI (b).

### 2.3.2. System quality and behavior to use blockchain and AI

System quality refers to the extent to which e-learning platforms are perceived to be technically and functionally sound (Davis, 1989). One study by Al-Fraihat et al. (2020) found that system quality significantly predicted behavior to use e-learning in higher education. The study used a structural equation model to analyze data from 514 students in Austria. Another study by Alalwan et al. (2017) found that system quality significantly influenced behavior to use e-learning in the context of higher education in Saudi Arabia. The study used data from 276 students. Furthermore, a study by Udo et al. (2010) investigated the impact of system quality on behavior to use. The study found that system quality significantly predicted behavior to use information technology. Finally, a recent study by Jameel et al. (2021) investigated the relationship between system quality and behavior to use e-learning platforms in the context of COVID-19. The study found that system quality significantly predicted behavior to use e-learning platforms. Park et al. (2012) found that system accessibility significantly predicted behavior to use e-learning among university students. Efiloglu Kurt (2019) investigated the impact of system quality on behavior to use e-learning in the context of higher education. The study found that system quality significantly influenced behavior to use e-learning. Therefore, the study proposes the research hypotheses:

**H$_3$.** System quality significantly and positively influences behavior to use blockchain (a) and AI (b).

### 2.3.3. Information quality and behavior to use blockchain and AI

Information quality is an important factor influencing the adoption and use of e-learning platforms (Davis, 1989). It refers to how e-learning materials are perceived to be accurate, complete, relevant, and up-to-date. Ramayah et al. (2010) investigated the impact of information quality on behavior to use e-learning platforms among postgraduate students in Malaysia. The study found that information quality significantly predicted behavior to use e-learning platforms. The studies by Tung and Chang (2008), Li et al. (2012), and Tsai et al. (2018) also provide insights into the impact of information quality on behavior to use e-learning. Tung and Chang (2008) found that information quality was a significant predictor of nursing students' behavior to use online courses. Li et al. (2012) found that information quality positively affected the behavior to reuse e-learning systems in rural China. Tsai et al. (2018) found that information quality had a significant and positive effect on nursing staff's use to continuously use a blended e-learning system. Overall, these studies suggest that information quality is an important factor that influences students' and healthcare professionals' attitudes to use e-learning. These findings highlight the need to provide accurate, complete, and relevant information to enhance users' engagement and use them. The studies suggest that e-learning platforms should provide accurate, complete, relevant, and up-to-date information to enhance students' and healthcare professionals' engagement and usage. Therefore, the study proposes the research hypotheses:

**H$_4$.** Information quality significantly and positively influences behavior to use blockchain (a) and AI (b).

### 2.3.4. Service quality and behavior to use blockchain and AI

The impact of service quality on behavior to use e-learning platforms has also been studied in the literature. The studies by Ramayah et al. (2010), Li et al. (2012), Mailizar et al. (2021), and Li et al. (2021) provide insights into this relationship. Ramayah et al. (2010) found that service quality significantly influenced the use to continue using an e-learning system among university students in Malaysia. Li et al. (2012) found that service quality had a positive effect on the behavior to reuse e-learning systems in rural China. Mailizar et al. (2021) found that service quality had a significant impact on university students' behavior to use e-learning during the COVID-19 pandemic. Li et al. (2021) found that service quality significantly affected customer satisfaction with bank services that included e-learning. Overall, these studies suggest that service quality is an important factor that influences students and customers' behavior to use e-learning platforms. The findings highlight the need to provide high-quality services that meet users' expectations to enhance their engagement and use of e-learning platforms. Finally, the literature consistently shows that service quality has a significant impact on behavior to use e-learning platforms. The studies suggest that e-learning platforms and other services that include e-learning should provide high-quality services to enhance users' engagement and use of them. Therefore, the study proposes the research hypotheses:

**H$_5$.** Service quality significantly and positively influences behavior to use blockchain (a) and AI (b).

### 2.3.5. Behavior to use blockchain, AI, and e-learning engagement

The integration of blockchain technology into e-learning has garnered attention due to its potential to revolutionize the trustworthiness and security of online educational platforms. Chilambarasan and Kangaiammal (2021) propose a blockchain-based secure access control system for e-learning in cloud environments, ensuring data integrity and credentials' legitimacy. Similarly, Lin et al. (2021) have explored the practical implementations of blockchain in e-learning, indicating that with these advancements, learners could be more engaged in a system where credentials are verifiable, and content is immutable. Such a secure and transparent learning environment significantly increases learners' trust and, consequently, their engagement levels. Behavioral use and engagement are two important factors influencing the adoption and use of e-learning platforms. Behavioral use refers to the individual's attitude to use the e-learning platform. In contrast, engagement refers to the level of involvement, interest, and attention the individual has toward the e-learning platform. The studies by Liaw (2008), Abbas (2017), Al-Azawei et al. (2019), and Yang et al. (2021) provide insights into the determinants of learning engagement and behavior to use e-learning platforms. Yang et al. (2021) found that environmental stimuli, such as online learning resources and social interactions, significantly influenced learning engagement and behavior to use e-learning platforms during the COVID-19 pandemic. Abbas (2017) found that perceived usefulness, perceived ease of use, and subjective norms significantly influenced university hospitality and tourism students' behavior to use e-learning platforms in Egypt and the UK. Al-Azawei et al. (2019) found that universal learning design (UDL) applications significantly affected e-learning acceptance among university students. Liaw (2008) found that students' perceived satisfaction and effectiveness of e-learning positively influenced their behavior to use the Blackboard system.

Overall, these studies user intentions and effectiveness are important factors influencing students' learning engagement and behavior to use e-learning platforms. The findings highlight the need to design user-friendly e-learning platforms, offer diverse and high-quality resources, and facilitate social interactions to enhance learning engagement and behavioral to use them. Finally, the literature consistently shows that various factors influence learning engagement and behavior to use e-learning platforms. Therefore, the study proposes the research hypotheses:

**$H_6$.** Behavior to use blockchain (a) and AI (b) significantly and positively influence e-learning engagement.

### 2.3.6. Behavior to use blockchain, AI, and e-learning performance

Artificial intelligence (AI) has emerged as a transformative force in e-learning. The rise of AI holds the promise of highly personalized learning experiences by analyzing extensive educational datasets. Tang et al. (2021) conducted a systemic review, shedding light on the evolving trends in AI-supported e-learning. Additionally, Chen et al. (2020) have identified gaps and potential opportunities for incorporating AI into education. The application of AI promises tailored content delivery and immediate feedback, elements that Lee (2014) suggests directly impact academic performance. Behavioral uses play a crucial role in e-learning performance. Several studies have established the relationship between behavioral use and e-learning performance, highlighting the importance of understanding and promoting factors influencing these uses. Lee (2010) extends the Expectation-Confirmation Model (ECM) to explain and predict users' continuance use of e-learning. The findings reveal that satisfaction, PU, and confirmation of expectations are significant factors influencing continuance use. In addition, Alraimi et al. (2015) investigate factors that influence users' continuance use of MOOCs (Massive Open Online Courses). The results show that openness and reputation are crucial factors affecting users' behavioral use, which in turn, affect their learning performance. Furthermore, Liaw (2008), Li et al. (2014), and (Hamida et al., 2022) emphasize the importance of understanding students' perceived satisfaction, behavioral use, and the effectiveness of e-learning systems. Liaw (2008) investigates students' satisfaction and behavioral use in the context of the Blackboard system, finding that perceived satisfaction is a significant predictor of behavioral use, which in turn affects learning performance. Humida et al. (2022) explore factors influencing behavior to use e-learning systems in a university setting in Bangladesh, identifying that PEOU, PU, and social influence are key determinants of students' use. Lastly, Li et al. (2014) compare traditional classroom settings with e-learning environments, highlighting that students' behavioral engagement differs, with e-learning showing potential for higher performance when designed effectively. These findings underline the need to consider various factors influencing students' behavioral uses, as they directly affect e-learning performance and the effectiveness of e-learning systems. Therefore, the study proposes the research hypotheses:

**$H_7$.** Behavior to use blockchain (a) and AI (b) significantly and positively influence e-learning performance.

### 2.3.7. Moderating role of learner self-efficacy between behavior to use blockchain and AI and e-learning engagement

Academic self-efficacy can be defined as *the level of confidence of the students in their ability to accomplish academic activities*. For instance, Alqurashi (2016) conducted a comprehensive review of self-efficacy in online learning environments, where self-efficacy significantly influences engagement and participation in digital platforms (Wang et al., 2022). Wang and Li (2022) further investigated this concept, suggesting that online learning self-efficacy mediated the relationship between interaction and learning engagement in online platforms. Wolverton et al. (2020) also found that computer self-efficacy, a close concept to learning self-efficacy in the digital age, substantially affected student engagement in online business courses. Even though the cited studies do not directly mention blockchain and AI, given the ever-increasing role of these technologies in modern e-learning systems, self-efficacy will likely influence behavior to use such advanced technologies about e-learning engagement. Rathnasekara et al. (2023) explore the impact of self-efficacy beliefs on contextual issues of online learning among employees in the banking sector in Sri Lanka. Their findings indicate that self-efficacy is crucial in determining employees' engagement and success in online learning. Wang and Li (2022) delve into the relationship between interaction, learning engagement, and the mediating roles of e-learning self-efficacy and academic emotions in online learning. Their results show that e-learning self-efficacy and academic emotions significantly mediate the relationship between interaction and learning engagement, emphasizing the importance of fostering self-efficacy and addressing students' emotional needs in e-learning environments. Collectively, these studies underscore the critical role of self-efficacy in determining students' engagement and satisfaction in online and blended learning contexts. Therefore, the study proposes the research hypotheses:

**$H_8$.** Learner self-efficacy significantly and positively moderates the relationship between behavior to use blockchain (a), AI (b) and e-learning engagement.

### 2.3.8. Moderating role of learner self-efficacy between behavior to use blockchain and AI and e-learning performance

The studies conducted by Martin et al. (2010), Alqurashi (2016), and Latip et al. (2020) emphasize the importance of self-efficacy in influencing e-learning performance and students' acceptance of e-learning platforms. Martin et al. (2010) found that students with higher learning management systems self-efficacy tend to perform better in e-learning environments. Similarly, Latip et al. (2020) discovered that self-efficacy is crucial in determining students' acceptance of e-learning in Malaysia. Alqurashi's (2016) literature review on self-efficacy in online learning environments further supports the notion that self-efficacy is essential to e-learning success. It impacts students' motivation, engagement, and persistence in online courses. Chuo et al. (2011) expanded upon the relationship between self-efficacy and e-learning by examining the role of organizational support, self-efficacy, and computer anxiety in determining the usage of e-learning systems in hospitals. The influence of self-efficacy on e-learning performance is another area of interest among researchers. Martin et al. (2010) indicated that Learning Management Systems Self-efficacy directly affects E-Learning Performance. In their research on Malaysian students, Latip et al. (2020) found that self-efficacy notably impacted students' acceptance of e-learning and, subsequently, their performance in these settings. In a specific context, Rathnasekara et al. (2023) studied the banking sector in Sri Lanka and deduced that the self-efficacy beliefs of employees significantly influenced various contextual issues related to online learning, which could indirectly impact their e-learning performance. Again, while the direct link between blockchain and AI use and performance is not highlighted, the consistent pattern in the literature supports the premise that learner self-efficacy would likely moderate the use-performance relationship, especially when using advanced technologies like blockchain and AI. Therefore, the study proposes the research hypotheses:

**$H_9$.** Learner self-efficacy significantly and positively moderates the relationship between behavior to use blockchain (a), AI (b) and e-learning performance.

Therefore, the study develops a conceptual framework (Figure 1) to test the research hypotheses.

# 3. Research methodology

## 3.1. Research method

This study employs a quantitative research design to investigate the relationships among PU, PEOU, system quality, information quality, service quality, behavior to use blockchain and AI, e-learning engagement, e-learning performance, and learner self-efficacy. A survey questionnaire is used as the primary data collection tool, with the data subsequently analyzed using Structural Equation Modeling (SEM) in Smart PLS 4.0.

## 3.2. Sample and data collection procedure

The target population for this study includes university students and professionals engaged in e-learning environments that incorporate blockchain and AI technologies in e-learning. Therefore, this study was based on measuring use about using technologies in education, and the study targeted institutions involved in such practices. The study targeted the schools, colleges, and universities in the region of South Africa to measure the use of blockchain and AI in the schools and colleges in South Africa, in turn, e-learning engagement and performance. A purposive sampling technique is used to select participants with experience using blockchain and AI in e-learning contexts. The focus of this study is on the use of e-learning technologies; therefore, the use of purposive sampling enables researchers to choose participants based on their knowledge and experiences linked to the phenomenon under study (Palinkas et al., 2015). An online survey questionnaire is distributed to the participants through email, social media platforms, and e-learning forums. The data collection period lasts 4 weeks, with reminder emails sent after 2 weeks to maximize the response rate. The survey questionnaire includes a cover letter briefly describing the study's purpose, ensuring the respondents' anonymity and confidentiality.

First, the pilot testing of this study was conducted on a sample of 55 students, and aimed at examining the validity and reliability of the survey items. Additionally, the students who participated in the pilot study affirmed that the items were clear and understandable, establishing face validity. The reliability of the instrument was assessed using Cronbach's alpha. All constructs demonstrated alpha values above the commonly accepted threshold of 0.7, indicating good internal consistency among the items within each construct. This pilot testing signifies that the survey instrument is both valid; capturing the constructs it is intended to measure, and reliable, producing consistent results. This ensures the robustness of the subsequent main study and its findings.

Second, a final questionnaire was posed before collecting whether the students experienced blockchain and AI in e-learning (1 = Yes, 2 = No), then the data was obtained from the respondents with the response "Yes". The study received 206 responses on 12 January 2023. A reminder was sent to the respondents, so the study received 133 responses on 20 February 2023. After cleaning the data, the study found that 17 responses were not fully answered, so they were removed from the model. Finally, the study used 322 responses for final testing. The sample size of 322, which exceeds the minimal requirements for the robust application of statistical approaches like structural equation modeling, which frequently proposes a 10:1 ratio of cases to variables (Wong, 2015), is a sizable sample size.

The study includes the demographic information of the students, including age (1 = 20–25 Years, 2 = 26–30 years, and 3 = 31-above Years), gender (1 = Male, 2 = Female), University (1 = Private, 2 = Public), student technology experience (1 = 1 year of experience, 2 = 2 years of experience, 3 = 3 and more years of experience), and student experience in block chain and AI (1 = 1 year of experience, 2 = 2 years of experience, 3 = 3 and more years of experience).

## 3.3. Measurement scales

The survey questionnaire consists of multiple sections, with each section measuring a specific construct. The measurement scales are adapted from existing literature and are modified to fit the study's context. All items are measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) constructs were evaluated using four adapted items each from the studies by Liaw (2008) and Zhou and Feng (2017). System Quality, Information Quality, and Service Quality were measured using three items each, adapted from the works of Liaw (2008) and Tarhini et al. (2019). For the construct of Behavior to Use Blockchain and AI, we incorporated three items adapted from Liaw (2008). Moreover, E-learning Engagement was assessed through four items adopted from Yang et al. (2021), while the construct of E-learning Performance was gauged using three items each from the studies by Lee (2010) and Alraimi et al. (2015). Finally, the Learner Self-Efficacy construct was measured using three items adapted

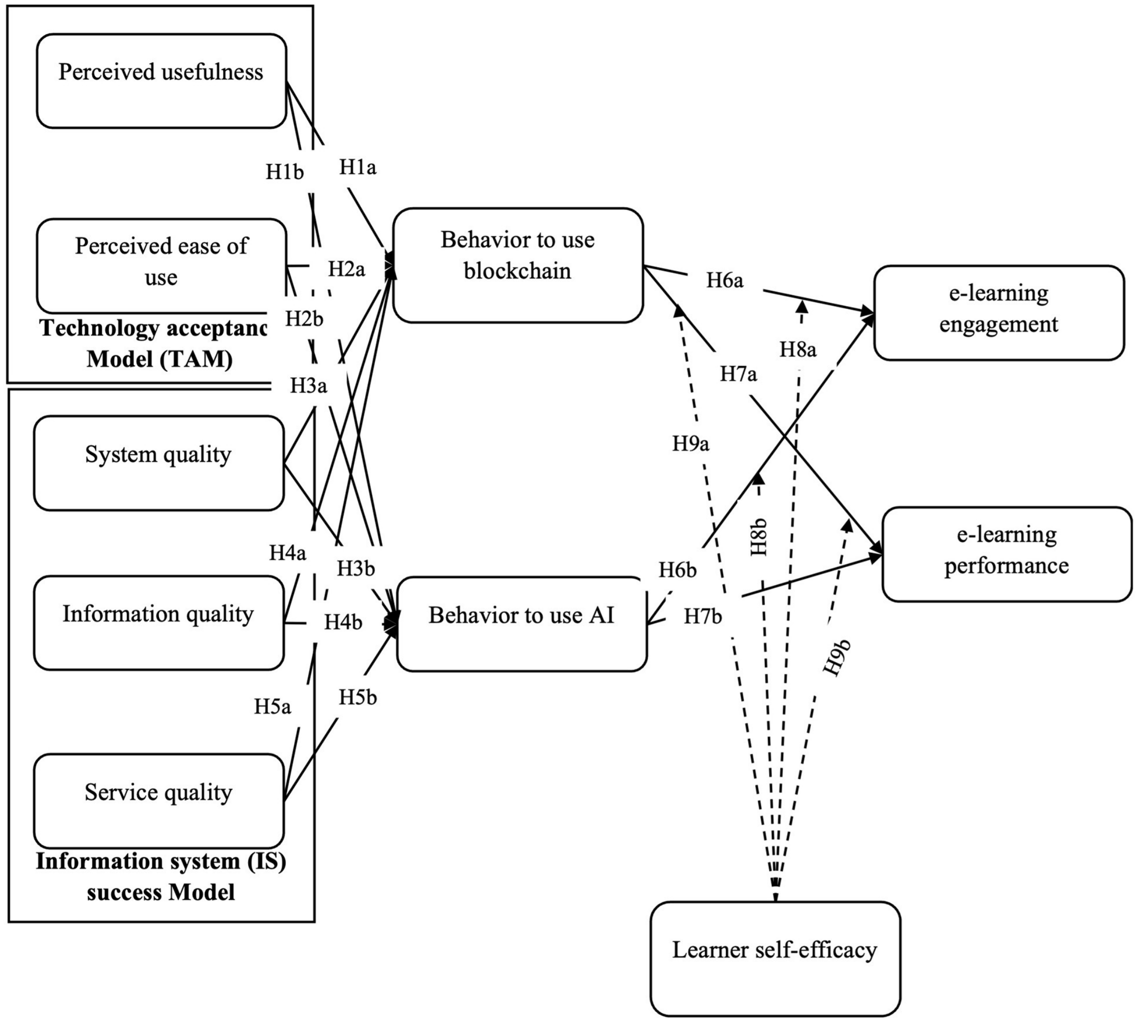


FIGURE 1
Conceptual framework.

from Liaw (2008). This amalgamation of scales from renowned studies serves to provide a comprehensive and robust measurement framework for our research.

## 3.4. Data analysis

The collected data are analyzed using Structural Equation Modeling (SEM) in Smart PLS 4.0 software. The study employed PLS-SEM because it handles non-normal data better than covariance-based SEM and requires fewer assumptions about variable distribution (Hair et al., 2017). It effectively predicts structural models with multiple constructs and indicators (Ringle et al., 2015). When theory is still emerging, PLS-SEM is a great technique for exploring important driving constructs, pathways, and interactions (Hair et al., 2017). SEM allows for the simultaneous examination (Henseler et al., 2015; Ringle et al., 2015) of multiple relationships among the constructs and enables the assessment of both the measurement model (reliability and validity) and the structural model (hypothesis testing) (Hair et al., 2017; Sharif et al., 2022). The data analysis process involves the following steps:

1. Data screening: checking missing values, outliers, and normality (Hair et al., 2017).
2. Assessment of the measurement model: examining the reliability (Cronbach's alpha, composite reliability) and validity (convergent validity, discriminant validity) of the measurement scales (Henseler et al., 2015; Hair et al., 2017).
3. Assessment of the structural model: testing the proposed research hypotheses by examining the path coefficients, *t*-values, and R-squared values (Hair et al., 2017; Sharif et al., 2021, 2022).
4. Assessment of the moderating effect: investigating the moderating role of learner self-efficacy on the relationships between behavior to use blockchain and AI in e-learning.

In this study, the 10 factors under consideration were subjected to a Harman's single factor test in order to evaluate common method bias (CMB). According to the findings, just 34.14% of the total variance was accounted for by a single factor, well-below the cutoff point of 50%. The research findings are more robust and

TABLE 1 Demographic information ($N = 322$).

| Demographic information | | Frequency | Percent |
|---|---|---|---|
| Age | 20–25 years | 81 | 25.2 |
| | 26–30 years | 212 | 65.8 |
| | 31-above years | 29 | 9.0 |
| Gender | Male | 283 | 87.9 |
| | Female | 39 | 12.1 |
| University | Private | 140 | 43.5 |
| | Public | 182 | 56.5 |
| Student technology experience | 1 year of experience | 29 | 9.0 |
| | 2 years of experience | 119 | 37.0 |
| | 3 years of experience | 99 | 30.7 |
| | 4 and more years of experience | 75 | 23.3 |
| Student experience in blockchain and AI | 1 year of experience | 15 | 4.7 |
| | 2 years of experience | 63 | 19.6 |
| | 3 years of experience | 113 | 35.1 |
| | 4 and more years of experience | 131 | 40.7 |

reliable as a result of this finding, which indicates that CMB is unlikely to be a serious problem in this study (Podsakoff et al., 2003).

# 4. Results

## 4.1. Demographic information

The sample consisted of primarily male students (87.9%) from South African universities, with only 12.1% female students (Table 1). The majority of the students were between the ages of 26–30 years (65.8%) with 25.2% of students being between the ages of 20–25 years, and only 9% of the sample being 31 years or older. Furthermore, 56.5% of the students attended public universities, while 43.5% attended private universities. In terms of technology experience, the majority of students (67.7%) had two or more years of experience, while only 9% had 1 year of experience. In terms of blockchain and AI experience, 76.9% of students had three or more years of experience, with only 4.7% having 1 year of experience.

## 4.2. Multi-collinearity statistics

The finding presents multi-collinearity between various factors affecting e-learning, such as behavior to use AI and blockchain, information quality, learner self-efficacy, perceived ease of use, perceived usefulness, service quality, and system quality, which result in stable and correct estimates of regression coefficients (O'brien, 2007) because value for each factor is lower than 5 (Hair et al., 2010). Therefore, the data is free from multi-collinearity issues.

## 4.3. Assessment of measurement model

The study runs a series of an algorithm technique with 5,000 sub-samples. The study assesses convergent validity [Factor-loadings and Average variance extracted (AVE)], discriminant validity [Cross-loadings and Heterotrait-Monotrait HTMT (Ratio)] (Henseler et al., 2015; Hair et al., 2021). Table 2 provides the factor loadings, Cronbach Alpha, and AVE values for the different scales and items used in the study. To evaluate the acceptance of these measures, we can use the threshold values proposed by several authors in the literature. According to Hair et al. (2021), it is suggested to adopt a consistent reference for all criteria that all factor loadings exceed 0.7, which is deemed acceptable in terms of indicator reliability. Adhering to this criterion reveals that all factor loadings are considered acceptable. In this study, most factor loadings are above 0.75, indicating that the constructs are being measured effectively. It can be found that all the factor loadings are >0.7, which is considered acceptable in terms of indicator reliability, according to (Hair et al., 2016).

For internal consistency reliability, Sharif et al. (2022) suggest that a Cronbach Alpha above 0.7 is acceptable, while Henseler et al. (2015) suggest a more stringent threshold of 0.8. In this study, most scales have a Cronbach Alpha above 0.7, indicating good internal consistency reliability. However, the Cronbach Alpha for perceived usefulness is lower than the acceptable threshold, suggesting that the items may not be measuring the construct effectively.

For convergent validity, Hair et al. (2016) suggested that AVE value should be higher than 0.5. From the results in the table, all scales demonstrated an AVE above 0.5, indicating satisfactory convergent validity.

Based on Hair et al. (2016), it's seen that all the indicators meet the criteria without any need for data manipulation to meet the required standards, including factor loadings, Cronbach Alpha, and AVE. These findings align with previous research on technology acceptance and provide valuable insights for practitioners and researchers seeking to develop and evaluate technology acceptance models.

The Table 3 shows the cross-loadings for the different items in the model. According to Hair et al. (2021), cross-loadings above 0.4 indicate potential problems with discriminant validity, suggesting that the item may be measuring more than one construct. Sarstedt et al. (2014) suggest that cross-loadings should be lower than the loadings of the primary construct. Finally, the study proved that the cross-loadings of one construct are higher with itself and higher than the cross-loadings of another construct.

Table 4 presents the Heterotrait-Monotrait (HTMT) ratio values for a set of constructs in a research study. HTMT is commonly used to assess discriminant validity in partial least squares structural equation modeling (PLS-SEM). The HTMT ratio should be <0.90 to indicate discriminant validity between constructs. In this table, all the HTMT ratios are below the threshold of 0.90, indicating that discriminant validity is established

TABLE 2 Validity and reliability.

| Scales | Items | Factor loadings | Cronbach alpha | AVE |
|---|---|---|---|---|
| System quality (SQ) | | | 0.788 | 0.701 |
| | SQ1 | 0.845 | | |
| | SQ2 | 0.856 | | |
| | SQ3 | 0.811 | | |
| Information quality (IQ) | IQ1 | 0.769 | 0.789 | 0.703 |
| | IQ2 | 0.861 | | |
| | IQ3 | 0.881 | | |
| Service quality (SEQ) | | | 0.838 | 0.756 |
| | SEQ1 | 0.831 | | |
| | SEQ2 | 0.904 | | |
| | SEQ3 | 0.872 | | |
| Perceived usefulness (PU) | | | 0.707 | 0.630 |
| | PU2 | 0.803 | | |
| | PU3 | 0.747 | | |
| | PU4 | 0.828 | | |
| Perceived ease of use (PEOU) | PEOU1 | 0.782 | 0.773 | 0.594 |
| | PEOU2 | 0.785 | | |
| | PEOU3 | 0.702 | | |
| | PEOU4 | 0.810 | | |
| Learner self-efficacy (SE) | | | 0.841 | 0.760 |
| | SE1 | 0.911 | | |
| | SE2 | 0.895 | | |
| | SE3 | 0.805 | | |
| Behavior to use AI (BIAI) | BIAI1 | 0.795 | 0.773 | 0.688 |
| | BIAI2 | 0.855 | | |
| | BIAI3 | 0.836 | | |
| Behavior to use blockchain (BIB) | BIB1 | 0.839 | 0.774 | 0.686 |
| | BIB2 | 0.771 | | |
| | BIB3 | 0.873 | | |
| E-learning performance (ELP) | | | 0.808 | 0.722 |
| | ELP1 | 0.829 | | |
| | ELP2 | 0.868 | | |
| | ELP3 | 0.852 | | |
| E-learning engagement (ELE) | | | 0.820 | 0.649 |
| | ELE1 | 0.779 | | |
| | ELE2 | 0.824 | | |
| | ELE3 | 0.788 | | |
| | ELE4 | 0.830 | | |

among the constructs. This finding is consistent with the guidelines proposed by Henseler et al. (2015) and Hair et al. (2017) that HTMT values should be below 0.90 for adequate discriminant validity. Overall, the results suggest that the study's constructs are distinct and do not measure the same underlying construct. The study has followed the recommended guidelines for assessing discriminant validity using HTMT. The results suggest that the measures are sufficiently distinct from each other, allowing valid inferences to be drawn about the relationships between the constructs.

## 4.4. Assessment of path model (direct effects)

Table 5 presents the results of hypothesis testing using a 5% significance level and 95% confidence interval based on a sample size of 322 respondents and using a bootstrapping technique with 5,000 sub-samples. The results show that the hypotheses are significant except for H2b,, H3a, H4a, and H7a (Figure 2). Specifically, H1a and H1b are both significant with beta values of 0.179 and 0.240, *t*-values of 2.816 and 3.513, and *p*-values of 0.005 and 0.000, respectively. This suggests that perceived usefulness has a positive and significant effect on behavior to use blockchain and AI. H2a is also significant with a beta value of 0.141, *t*-value of 2.192, and *p*-value of 0.028, suggesting that perceived ease of use has a positive and significant effect on behavior to use blockchain. H3b is significant with a beta value of 0.215, *t*-value of 3.121, and *p*-value of 0.002, indicating that system quality has a positive and significant effect on behavior to use blockchain. H4a is not statistical significant however, H4b is significant with *p*-values of 0.090 and 0.005, respectively. These hypotheses suggest that information quality has a positive effect on behavior to use blockchain and AI. H5a and H5b are both significant with beta values of 0.177 and 0.271, *t*-values of 3.069 and 5.128, and *p*-values of 0.002 and 0.000, respectively, indicating that service quality has a positive and significant effect on behavior to use blockchain and AI. H6 and H6b are significant with beta values of 0.173 and 0.326, *t*-values of 2.431 and 4.544, and *p*-values of 0.015 and 0.000, respectively, indicating that behavior to use blockchain and AI have a positive and significant effect on e-learning engagement. H7a is not statistical significant and H7b is significant with beta values of 0.052 and 0.248, *t*-values of 0.778 and 3.720, and *p*-values of 0.437 and 0.000, respectively, indicating that behavior to use blockchain and AI have a positive and significant effect on e-learning performance. Overall, the results of the study are consistent with the theoretical framework and previous empirical studies, suggesting that the proposed model can be used to explain the factors that influence behavior to use blockchain and AI in e-learning.

## 4.5. Assessment of path model (moderating effects)

Table 6 presents the results of the moderating effects of learner self-efficacy on the relationship between behavior to use blockchain and AI and e-learning engagement and performance. The results

TABLE 3 Cross loadings.

| Cross-loadings | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| BIAI1 | 0.795 | 0.689 | 0.414 | 0.442 | 0.449 | 0.457 | 0.460 | 0.421 | 0.408 | 0.482 |
| BIAI2 | 0.855 | 0.649 | 0.482 | 0.593 | 0.426 | 0.480 | 0.498 | 0.421 | 0.490 | 0.555 |
| BIAI3 | 0.836 | 0.630 | 0.403 | 0.514 | 0.357 | 0.459 | 0.382 | 0.384 | 0.589 | 0.520 |
| BIB1 | 0.634 | 0.839 | 0.473 | 0.611 | 0.461 | 0.508 | 0.447 | 0.552 | 0.567 | 0.545 |
| BIB2 | 0.597 | 0.771 | 0.285 | 0.412 | 0.302 | 0.341 | 0.310 | 0.362 | 0.370 | 0.414 |
| BIB3 | 0.725 | 0.873 | 0.527 | 0.603 | 0.496 | 0.529 | 0.472 | 0.491 | 0.467 | 0.527 |
| ELE1 | 0.489 | 0.456 | 0.408 | 0.432 | 0.417 | 0.443 | 0.428 | 0.362 | 0.779 | 0.440 |
| ELE2 | 0.414 | 0.446 | 0.511 | 0.451 | 0.456 | 0.478 | 0.410 | 0.453 | 0.824 | 0.497 |
| ELE3 | 0.522 | 0.467 | 0.371 | 0.442 | 0.370 | 0.477 | 0.304 | 0.386 | 0.788 | 0.418 |
| ELE4 | 0.502 | 0.483 | 0.395 | 0.448 | 0.431 | 0.444 | 0.316 | 0.411 | 0.830 | 0.408 |
| ELP1 | 0.435 | 0.435 | 0.388 | 0.560 | 0.477 | 0.405 | 0.448 | 0.375 | 0.377 | 0.829 |
| ELP2 | 0.577 | 0.578 | 0.531 | 0.630 | 0.530 | 0.473 | 0.495 | 0.517 | 0.542 | 0.868 |
| ELP3 | 0.573 | 0.519 | 0.435 | 0.639 | 0.404 | 0.414 | 0.479 | 0.375 | 0.460 | 0.852 |
| IQ1 | 0.367 | 0.376 | 0.769 | 0.392 | 0.406 | 0.398 | 0.371 | 0.508 | 0.372 | 0.429 |
| IQ2 | 0.442 | 0.451 | 0.861 | 0.378 | 0.522 | 0.484 | 0.397 | 0.560 | 0.476 | 0.416 |
| IQ3 | 0.494 | 0.500 | 0.881 | 0.397 | 0.468 | 0.545 | 0.440 | 0.644 | 0.455 | 0.499 |
| PEOU1 | 0.373 | 0.401 | 0.357 | 0.429 | 0.782 | 0.481 | 0.391 | 0.368 | 0.377 | 0.470 |
| PEOU2 | 0.358 | 0.388 | 0.491 | 0.331 | 0.785 | 0.534 | 0.394 | 0.448 | 0.393 | 0.454 |
| PEOU3 | 0.330 | 0.306 | 0.346 | 0.257 | 0.702 | 0.462 | 0.230 | 0.279 | 0.296 | 0.327 |
| PEOU4 | 0.445 | 0.478 | 0.503 | 0.444 | 0.810 | 0.557 | 0.382 | 0.482 | 0.502 | 0.441 |
| PU2 | 0.420 | 0.470 | 0.466 | 0.336 | 0.560 | 0.803 | 0.406 | 0.554 | 0.442 | 0.419 |
| PU3 | 0.395 | 0.392 | 0.404 | 0.373 | 0.473 | 0.747 | 0.341 | 0.464 | 0.426 | 0.367 |
| PU4 | 0.511 | 0.480 | 0.488 | 0.453 | 0.539 | 0.828 | 0.459 | 0.489 | 0.489 | 0.422 |
| SE1 | 0.592 | 0.606 | 0.455 | 0.911 | 0.476 | 0.467 | 0.544 | 0.429 | 0.526 | 0.680 |
| SE2 | 0.566 | 0.631 | 0.466 | 0.895 | 0.400 | 0.435 | 0.461 | 0.442 | 0.498 | 0.659 |
| SE3 | 0.467 | 0.498 | 0.262 | 0.805 | 0.384 | 0.372 | 0.362 | 0.306 | 0.403 | 0.531 |
| SEQ1 | 0.464 | 0.466 | 0.357 | 0.428 | 0.426 | 0.490 | 0.831 | 0.462 | 0.386 | 0.416 |
| SEQ2 | 0.479 | 0.431 | 0.457 | 0.460 | 0.385 | 0.429 | 0.904 | 0.475 | 0.383 | 0.502 |
| SEQ3 | 0.459 | 0.417 | 0.444 | 0.493 | 0.384 | 0.410 | 0.872 | 0.446 | 0.406 | 0.542 |
| SQ1 | 0.390 | 0.456 | 0.519 | 0.377 | 0.443 | 0.552 | 0.432 | 0.845 | 0.416 | 0.384 |
| SQ2 | 0.450 | 0.531 | 0.578 | 0.377 | 0.412 | 0.526 | 0.431 | 0.856 | 0.429 | 0.417 |
| SQ3 | 0.389 | 0.455 | 0.625 | 0.391 | 0.457 | 0.513 | 0.475 | 0.811 | 0.410 | 0.456 |

1, behavior to use AI; 2, behavior to use blockchain; 3, information quality; 4, learner self-efficacy; 5, perceived ease of use; 6, perceived usefulness; 7, service quality; 8, system quality; 9, e-learning engagement; 10, e-learning performance.

show that learner self-efficacy has a significant positive effect on e-learning engagement (Beta = 0.254, $t$-value = 4.596, $p$-value = 0.000) and e-learning performance (Beta = 0.515, $t$-value=11.063, $p$-value = 0.000), indicating that learners who have a high level of self-efficacy are more likely to engage in e-learning activities and perform better. However, the interaction effects between learner self-efficacy and behavior to use blockchain or AI are not significant for e-learning engagement (Beta = 0.046, $t$-value = 0.690, $p$-value = 0.490 for blockchain and Beta = 0.008, $t$-value = 0.112, $p$-value = 0.911 for AI) or e-learning performance (Beta = 0.038, $t$-value = 0.448, $p$-value = 0.654 for blockchain and Beta = −0.081, $t$-value = 0.936, $p$-value = 0.349 for AI). This suggests that learner self-efficacy does not influence the relationship between behavior to use blockchain or AI and e-learning engagement and performance.

## 5. Discussion

The findings of this study contribute to the existing literature on technology adoption in e-learning by providing empirical evidence supporting the relationships among PU, PEOU, system quality,

TABLE 4 Heterotrait-Monotrait (HTMT) ratio.

| Constructs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Behavior to use AI | | | | | | | | | |
| Behavior to use block chain | 0.820 | | | | | | | | |
| Information quality | 0.662 | 0.655 | | | | | | | |
| Learner self-efficacy | 0.767 | 0.805 | 0.559 | | | | | | |
| Perceived ease of use | 0.634 | 0.644 | 0.702 | 0.586 | | | | | |
| Perceived usefulness | 0.753 | 0.745 | 0.757 | 0.629 | 0.890 | | | | |
| Service quality | 0.669 | 0.612 | 0.591 | 0.623 | 0.562 | 0.657 | | | |
| System quality | 0.629 | 0.719 | 0.863 | 0.554 | 0.657 | 0.849 | 0.655 | | |
| e-learning engagement | 0.748 | 0.707 | 0.647 | 0.658 | 0.639 | 0.749 | 0.546 | 0.623 | |
| e-learning performance | 0.785 | 0.749 | 0.664 | 0.864 | 0.695 | 0.670 | 0.679 | 0.624 | 0.666 |

information quality, service quality, behavior to use blockchain and AI, e-learning engagement, e-learning performance, and learner self-efficacy. The results are consistent with the theoretical underpinnings of the Technology Acceptance Model (TAM) (Davis, 1989) and the DeLone and McLean Information Systems Success Model (DeLone and McLean, 2003), which have been widely used to study technology adoption in various contexts. Perceived usefulness (PU) and perceived ease of use (PEOU) were found to have significant positive effects on behavior to use blockchain and AI in e-learning. These findings align with previous research suggesting that PU and PEOU are key determinants of users' attitude to adopt new technologies (Davis, 1989; Liaw, 2008; Zhou and Feng, 2017). By demonstrating the applicability of these relationships in the context of blockchain and AI technologies in e-learning, the study extends the generalizability of the TAM to these emerging technologies. In addition, Al-Adwan et al. (2021) developed a holistic success model for sustainable e-learning using structural equation modeling, which also underscores the significance of technological and quality, perceived usefulness, and ease of use in determining the success of e-learning platforms. In another relevant study, Al-Adwan et al. (2022) highlighted the crucial role of self-directed learning in the sustainable adoption of e-learning systems. The findings are consistent with regarding the importance of learner self-efficacy in driving behavior to use AI and blockchain in e-learning.

The results also support the significance of system quality, information quality, and service quality in shaping behavior to use blockchain and AI in e-learning. These findings are consistent with the IS model which posits that system quality, information quality, and service quality are essential factors contributing to the success of information systems (DeLone and McLean, 2003; Pai and Huang, 2011; Efiloglu Kurt, 2019). By demonstrating the relevance of these factors in the context of blockchain and AI technologies in e-learning, the study contributes to the understanding of the factors that drive the adoption of these novel technologies in educational settings. The study also found that behavior to use blockchain and AI have a positive and significant effect on e-learning engagement and e-learning performance. These results are in line with prior research suggesting that users' attitude to adopt and use technology can influence their actual usage behavior and subsequent outcomes (Al-Azawei et al., 2017; Tarhini et al., 2017; Efiloglu Kurt, 2019; Mailizar et al., 2021). By establishing these relationships in the context of blockchain and AI technologies in e-learning, the study highlights the potential benefits of promoting the adoption of these technologies to enhance learner engagement and performance.

On the other hand, Learner self-efficacy was found to have a significant positive effect on e-learning engagement and performance but did not significantly moderate the relationship between behavior to use blockchain and AI and e-learning engagement or performance. These findings are consistent with Bandura's Social Cognitive Theory (Bandura, 1986), which posits that self-efficacy can influence individuals' behavior and performance. However, the lack of a significant moderating effect suggests that the influence of self-efficacy on the relationship between uses and outcomes might be context-specific or influenced by other factors not considered in this study.

## 5.1. Theoretical contributions

The study contributes to the existing body of knowledge on technology adoption in e-learning by examining the adoption of emerging technologies like blockchain and AI. The findings confirm the applicability of the Technology Acceptance Model (TAM) (Davis, 1989) and the DeLone and McLean Information Systems Success Model (DeLone and McLean, 1992) in explaining the adoption of these technologies in e-learning settings. For practitioners, the study provides valuable insights into the factors that drive the adoption of blockchain and AI in e-learning environments. Understanding these factors can help educators, administrators, and policymakers develop strategies to promote adopting and effectively using these technologies, ultimately leading to improved e-learning outcomes. Additionally, the results highlight the importance of learner self-efficacy in influencing e-learning engagement and performance. As such, e-learning providers must create learning environments that foster learner self-efficacy, as it can lead to better engagement and performance outcomes. In conclusion, this study provides valuable insights into the factors influencing the adoption of blockchain and AI

TABLE 5 Direct effects.

| Hypotheses testing | Beta | *t*-value | *p*-value |
|---|---|---|---|
| H1a. Perceived usefulness -> behavior to use blockchain | **0.179** | 2.816 | 0.005 |
| H1b. Perceived usefulness -> behavior to use AI | **0.240** | 3.513 | 0.000 |
| H2a. Perceived ease of use -> behavior to use blockchain | **0.141** | 2.192 | 0.028 |
| H2b. Perceived ease of use -> behavior to use AI | 0.096 | 1.545 | 0.122 |
| H3b. System quality -> behavior to use blockchain | **0.215** | 3.121 | 0.002 |
| H3a. System quality -> behavior to use AI | 0.015 | 0.230 | 0.818 |
| H4a. Information quality -> behavior to use blockchain | 0.119 | 1.698 | 0.090 |
| H4b. Information quality -> behavior to use AI | **0.191** | 2.823 | 0.005 |
| H5a. Service quality -> behavior to use blockchain | **0.177** | 3.069 | 0.002 |
| H5b. Service quality -> behavior to use AI | **0.271** | 5.128 | 0.000 |
| H6. Behavior to use blockchain -> e-learning engagement | **0.173** | 2.431 | 0.015 |
| H6b. Behavior to use AI -> e-learning engagement | **0.326** | 4.544 | 0.000 |
| H7a. Behavior to use blockchain -> e-learning performance | 0.052 | 0.778 | 0.437 |
| H7b. Behavior to use AI -> e-learning performance | **0.248** | 3.720 | 0.000 |

technologies in e-learning environments and their impact on e-learning engagement and performance. The findings contribute to the understanding of technology adoption in e-learning and have practical implications for educators, administrators, and policymakers.

Universities should provide opportunities for learners to develop their self-efficacy in using blockchain and AI technologies, such as offering training sessions, workshops, or tutorials. Encouraging learners to take ownership of their learning process and providing constructive feedback on their progress can also help to build their confidence and self-efficacy. Universities, administrators, and policymakers should collaborate to raise awareness about the potential benefits of blockchain and AI technologies in e-learning among learners, instructors, and institutions. Offering training programs, workshops, and seminars can help build the necessary skills and knowledge to adopt and use these technologies in e-learning settings effectively. Sharing success stories and best practices can also inspire and motivate stakeholders to embrace the potential of blockchain and AI in e-learning.

The findings underscore the pivotal role of perceived usefulness in determining users' behavioral use toward blockchain and AI in e-learning settings. With significant beta values and *p*-values below the 0.05 threshold, the data suggests that when users see blockchain and AI as useful, they are more inclined to use them. This reaffirms the established theoretical proposition in the technology acceptance model (TAM) and extends its application to emerging technologies like blockchain and AI in e-learning contexts. While perceived ease of use significantly affects the behavior to use blockchain, its impact on AI is insignificant. This hints at the nuanced differences in user perceptions of ease when navigating different technological innovations. It adds a layer of complexity to the literature, which predominantly assumes ease of use to be a universal determinant for technology acceptance. The study also brings forward the significant influence of system quality on behavior to use blockchain, though the same was not observed for AI. Similarly, information quality significantly affected the behavioral use toward both AI and blockchain. These findings emphasize the need for high-quality systems and information when integrating emerging technologies into e-learning platforms.

With strong beta values and significant *p*-values, service quality emerges as a paramount factor affecting behavioral use toward blockchain and AI. This supports the argument for service quality being a foundational element for effective e-learning, especially when advanced technologies are in play. The research establishes a direct and significant relationship between behavior to use blockchain and AI and e-learning engagement. However, only the relationship between AI and e-learning performance was found significant, pointing toward AI's superior potential in enhancing e-learning outcomes. While learner self-efficacy was found to have a significant direct effect on e-learning engagement and performance, its moderating role between behavioral use (for both blockchain and AI) and e-learning outcomes was not established. This nuanced finding nuance our understanding of self-efficacy's role, suggesting that while it directly affects e-learning dynamics, its interaction with technology-specific behavioral use is less pronounced.

## 5.2. Practical implications

Given the significance of perceived usefulness in determining behavioral use toward blockchain and AI, e-learning platform developers and educators should prioritize features that enhance the practical value of these technologies for users. As perceived ease of use affects the use of blockchain, there is a clear mandate for designers to ensure that blockchain-based e-learning interfaces are user-friendly. This could involve intuitive designs, onboarding tutorials, and readily available support to enhance user experience and encourage adoption. The positive relationship between system quality and behavior to use blockchain suggests that investments in robust and reliable system infrastructure bolster user confidence and encourage the adoption of blockchain in e-learning. The significance of information quality for both technologies underscores the need for e-learning platforms

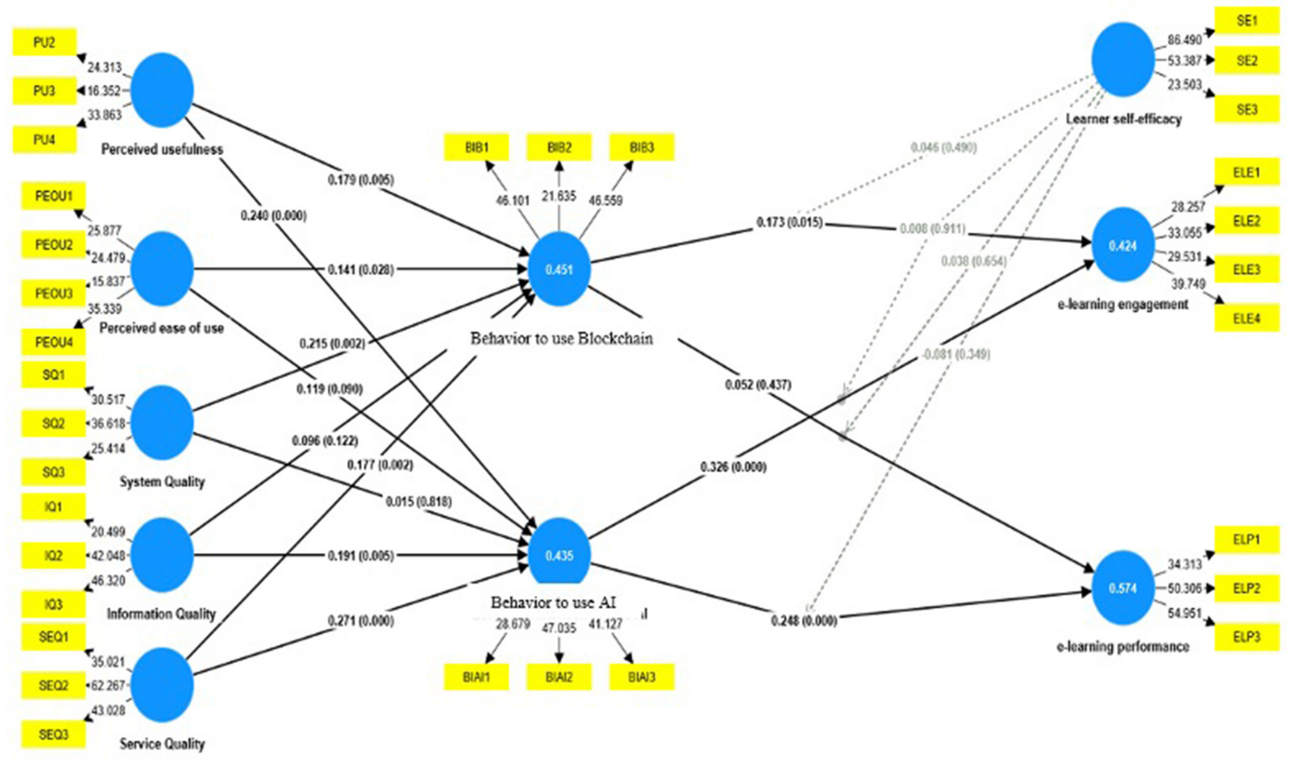


FIGURE 2
Structural equation modeling.

TABLE 6 Moderating effects.

| Moderating effects | Beta | *t*-value | *p*-value |
|---|---|---|---|
| Learner self-efficacy -> e-learning engagement | 0.254 | 4.596 | 0.000 |
| Learner self-efficacy -> e-learning performance | 0.515 | 11.063 | 0.000 |
| Learner self-efficacy × behavior to use blockchain -> e-learning engagement | 0.046 | 0.690 | 0.490 |
| Learner self-efficacy × behavior to use blockchain -> e-learning performance | 0.038 | 0.448 | 0.654 |
| Learner self-efficacy × behavior to use AI -> e-learning engagement | 0.008 | 0.112 | 0.911 |
| Learner self-efficacy × behavior to use AI -> e-learning performance | −0.081 | 0.936 | 0.349 |

to prioritize accurate, updated, and relevant content. Course creators should be meticulous in content curation, ensuring that blockchain and AI information is reliable and pertinent to the learning objectives.

The robust impact of service quality on behavioral use of blockchain and AI emphasizes the importance of offering strong after-sales service, technical support, and responsive customer service. This enhances user trust and drives more widespread adoption of these technologies in e-learning contexts. With a clear link between the use of AI and e-learning performance, there is an implication for educators and tech developers to focus on how AI can be specifically tailored to enhance learning outcomes. The study indicates that learner self-efficacy directly affects e-learning engagement and performance. As such, there is a strong practical implication to nurture and boost self-efficacy among learners. Initiatives include confidence-building exercises, providing consistent feedback, offering skills-building resources, or creating supportive online communities where learners can share experiences and challenges. Despite the prevailing thought that, self-efficacy might moderate the relationship between technology adoption and e-learning outcomes, the findings suggest otherwise. Practitioners should be aware that while fostering self-efficacy is crucial, it does not amplify behavioral use' impact on e-learning metrics as previously assumed.

Blockchain technology secure and transparently track student credentials, achievements, and personalized learning paths, transforming e-learning. This decentralized system controls students' educational records, promoting student-centered learning. Monitoring progress and authenticating certifications improves education trust and accountability. Students are motivated to learn since their performance are recorded and recognized globally actively. AI personalizes and adapts e-learning.

AI-powered algorithms tailor content to individual learning styles and abilities, providing targeted support and challenges. Students engage and perform better when they learn at their pace and level. AI-driven analytics and feedback systems offer continuous insights into student progress, allowing educators to intervene and help when needed. AI and blockchain ensure a customized, transparent, and secure learning experience that meets the education needs and opportunities.

### 5.3. Limitations and future directions

This study has some limitations. First, the sample was predominantly university students and professionals engaged in e-learning environments, which may limit the generalizability of the findings to other populations. Future research should explore the adoption of blockchain and AI technologies in different educational settings, such as K-12 education and vocational training. Second, the study used a cross-sectional design, which may not capture the dynamic nature of technology adoption. Longitudinal research could provide insights into how the factors influencing the adoption of blockchain and AI technologies evolve over time. Lastly, the study did not examine the potential barriers to the adoption of blockchain and AI technologies in e-learning environments. Future research should explore these barriers and identify strategies for overcoming them to facilitate the widespread adoption of these technologies in e-learning settings. Despite its limitations, this study provides a solid foundation for future research on the adoption of blockchain and AI technologies in different educational settings and populations. Additionally, exploring potential barriers to adoption and identifying strategies to overcome them can further facilitate the widespread adoption of these technologies in e-learning environments.

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

## Author contributions

The author confirms being the sole contributor of this work and has approved it for publication.

## Conflict of interest

DN was employed by Dynatech Information Systems.

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## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fcomp.2023.1227749/full#supplementary-material

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