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Exploring the Acceptance and User Satisfaction of AI-Driven e-Learning Platforms (Blackboard, Moodle, Edmodo, Coursera and edX): An Integrated Technology Model

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Abstract: As e-learning platforms gain traction globally, understanding students' perceptions and intentions towards these platforms is paramount, especially within the context of Saudi universities, where e-learning is rapidly emerging as a transformative educational tool for sustainable development. This study examined the influence of different AI-based social learning networks, personal learning portfolios, and personal learning environments on Saudi university students' perceived usefulness and ease of use regarding AI-driven platforms (Blackboard, Moodle, Edmodo, Coursera and edX). Furthermore, the study explored the direct effects of these perceptions on students' satisfaction and intentions to use e-learning. The study also delved into the moderating effects of individual characteristics like readiness for self-directed e-learning, self-efficacy, and personal innovativeness on students' e-learning intentions. A cross-sectional design was employed, collecting self-reported data from a strong sample of Saudi university students using stratified random sampling. The study targeted 500 students from different universities in Saudi Arabia. Results underscored the significant influence of AI-based social learning networks, personal learning portfolios, and personal learning environments on perceived usefulness and ease of use. Both perceived usefulness and ease of use also significantly and positively influenced satisfaction, influencing students' attitudes toward e-learning but not their intention to use it. Student characteristics, especially self-efficacy, showed notable impacts on e-learning intentions. However, their interaction with satisfaction yielded insignificant effects on intentions.

Keywords: artificial intelligence; e-learning and artificial intelligence powered platforms; higher education; technology acceptance model (TAM); expectation-confirmation model (ECM)

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1. Introduction

As a result of the technological upheaval, artificial intelligence (AI)-based technologies are projected to promote sustainable development over the next decade [1]. Moreover, AI will be the technology of the next decade because of its ability to increase human cognitive capabilities at a low cost [1–4]. AI is projected to add US$15.7 trillion (14%) to the global GDP by the year 2030 [5]. AI technologies are adopted in many domains and industries, such as health care; i.e., disease prevention [6]; customer service, i.e., Personalized Customer Service [7]; education, i.e., intelligent tutor chatbots, individualized teaching, and autonomous learning [8]; manufacturing, i.e., sensor data to discover possible downtimes [9]; and transportation, i.e., automated vehicles [10]. Generally, there has been a boom in research and interest in investigating the antecedents of AI acceptance, and various frameworks and models have been extended. However, studies focusing on using and accepting AI in virtual learning environments in higher education institutions in Gulf countries are scarce [11]. AI-driven e-learning substantially contributes to sustainable development by offering affordable, easily accessible education that supports socioeconomic sustainability objectives. In further investigation of AI in higher education, Kuleto et al. [4] point out that technology personalizes learning experiences, enhancing academic performance, resource efficiency, and sustainability. The ability of AI to analyze data helps to measure, quantify, and track sustainability, providing information for well-informed policy decisions.

Examining the previous literature in the context of Saudi Arabian higher education reveals a glaring absence of thorough research focusing on the integration of the technology acceptance model (TAM) and expectation-confirmation model (ECM) in evaluating the efficacy of AI-based e-learning platforms [12]. Although numerous studies have examined user satisfaction and behavioral intentions in various contexts worldwide [2,12,13], they still need to sufficiently address the particularities of Saudi Arabia's distinctive cultural, technological, and educational landscape [12,14]. In fact, Saudi higher educational institutions are integrating AI-based e-learning platforms to achieve the strategic objectives of the 2030 vision aiming to extensively develop higher education; therefore, there is a need to develop an integrated model for how students view, use, and benefit from these innovations [14,15]. Additionally, the existing literature frequently needs a more nuanced analysis of the effects of AI-based learner characteristics [16,17], both directly and indirectly, on overall satisfaction and subsequent intention to continue using AI-based e-learning systems. Few empirical data and theoretical frameworks contextualize these elements within Saudi Arabia's higher education e-learning domain [14], despite the widespread acceptance of the critical roles played by variables like self-efficacy and personal innovativeness [18,19].

While social learning networks and virtual personal learning portfolios are among the AI characteristics that have been acknowledged as significant [20,21], there is a dearth of research examining their perceived usability and usefulness in raising overall satisfaction and attitude with e-learning in Saudi Arabia. Because of their complexity, AI-enhanced learning environments require a focused investigation to learn user interactions, preferences, and obstacles to their best use [19]. The pedagogical implications of emerging AI applications in e-learning, particularly in a Saudi context, still need to be fully understood and evolve quickly. Lastly, a glaring research gap exists regarding Saudi university students' readiness for self-directed e-learning [22,23]. Students are expected to take control of their learning processes by integrating AI and e-learning [22,24]. There is a need to develop and test an integrated model of TAM and ECM.

This research meets the objectives of developing an integrated model combining TAM and ECM for AI-based e-learning in Saudi Arabian higher education. This research is contextual, integrative, and AI-centric, unlike previous studies [12,25] that examined these models individually or in other contexts. An integrated model reveals the complex overall student satisfaction, perceived usefulness (PU), and intention to use AI-based e-learning, providing actionable insights for policy, curriculum, and technological integration. By examining the role of specific AI characteristics and student traits, this study reveals context-specific insights that have yet to be explored in the previous literature. It shows how AI-enhanced characteristics and student traits affect satisfaction and the intention to use AI-based e-learning. A detailed understanding of user behavior and preferences helps design more user-centric, efficient, and effective AI-based e-learning platforms (Blackboard, Moodle, Edmodo, Coursera and edX), improving higher education learning outcomes and educational experiences. Finally, the study offers research objectives to develop and test an integrated model. The research will achieve the following objectives:

1. To develop an integrated model enhancing university students' learning experience, improving learning outcomes, and increasing the efficiency and effectiveness of instructors.
2. To investigate users' perception regarding the role of AI characteristics (including social learning networks, virtual personal learning portfolios, and the online personal learning environment) and their effect on perceived ease of use and usefulness in increasing overall satisfaction and attitude towards e-learning.

3. To examine the influence of overall satisfaction on the intention to use AI-driven e-learning platforms.
4. To explore if students' traits (including readiness for self-directed e-learning, self-efficacy, and personal innovativeness) strengthen the relationship between overall satisfaction and the intention to use AI-driven e-learning platforms.

Therefore, this study aims to make the first step in understanding students' acceptance and use of AI in the virtual learning environment in Saudi Higher Education Institutions. Moreover, this research aims to develop a comprehensive framework to examine the factors influencing user acceptance of AI in the context of virtual learning.

The following section provides an overview of the relevant literature on the emerging technologies that support students' learning, and theories related to TAM and ECM use regarding AI learning platforms by developing research hypotheses. Section 3 describes in detail the methodological approach employed to conduct this research, followed by a section presenting the results of this study. Section 4 provides the findings of the survey data. Section 5 discusses the findings and provides insights and implications for students' acceptance and use of AI in the virtual learning environment in Saudi HEIs. Finally, conclusions, limitations/future directions, and suggestions for future studies are provided.

2. Literature Review and Hypotheses Testing

2.1. Emerging Technologies and Education

E-learning platforms such as Blackboard, Edmodo, Coursera and Modular Object-Oriented Dynamic Learning Environment (Moodle) are believed to facilitate interaction with online students. Moreover, these platforms are powered by Artificial intelligence (AI) systems such as intelligent tutor chatbots, natural language processing (NLP) algorithms, automated grading of coursework, and predictive analytics to enhance the learning experience, provide timely support, and ultimately enhance the overall effectiveness of online education in universities [8].

The use of AI in supporting students' learning experiences is a growing area of interest in higher education (HE). AI is technology where a computer, robot, or bot engages in tasks primarily performed by humans. In fact, AI-driven e-learning platforms enable learners to obtain quality education at any time and from any location, enhancing efficiency and effectiveness of the learning process. Previous research identified a variety of benefits that AI can offer online learners [8,11]. Figure 1 illustrates a few of the most notable benefits of AI in education.

AI is believed to have the potential to alter, direct, and shift the learning process. In fact, students come at the core of HE system; they are the driver and the target. Enhancing their learning and skills outcomes reflects positively on their placement in the job market. The personalization of learning and learning materials is where AI has the most potential. Personalized learning is an educational method that tailors learning based on students' unique needs and skills. It also draws insight into detecting learning patterns to aid instructors in better decision making and resource optimization in terms of curriculum design. Through using AI in education, educational goals can be better achieved, as instructors can analyze gaps in the educational material, recognize the best pedagogical approaches for each subject area, support student learning, and free their time through automatic and instant grading.

2.2. Integration of Technology Acceptance Model (TAM) and Expectation-Confirmation Model (ECM)

Previous studies missed combining TAM and ECM as a thorough method for users' initial and ongoing use of technology-based learning systems. According to Mohammadi [12], integrating the TAM and IS success model provides insights into users' perspectives on e-learning, highlighting the significance of perceived usability and ease of use but missing using ECT. These constructs serve as the primary components used to examine AI characteristics in e-learning, and are crucial in determining users' behavioral intentions and actual usage. The TAM's PU and usability and the ECT's PU and satisfaction provide a multidimensional perspective on e-learning. Abdullah et al. [14] examined how TAM factors impacted students' perceptions of e-portfolios. Similarly, social learning networks and other aspects of AI are investigated. Student satisfaction and, consequently, their intention to continue using these AI-enhanced platforms are likely influenced by the simplicity of interaction and the value of the content shared within these networks.

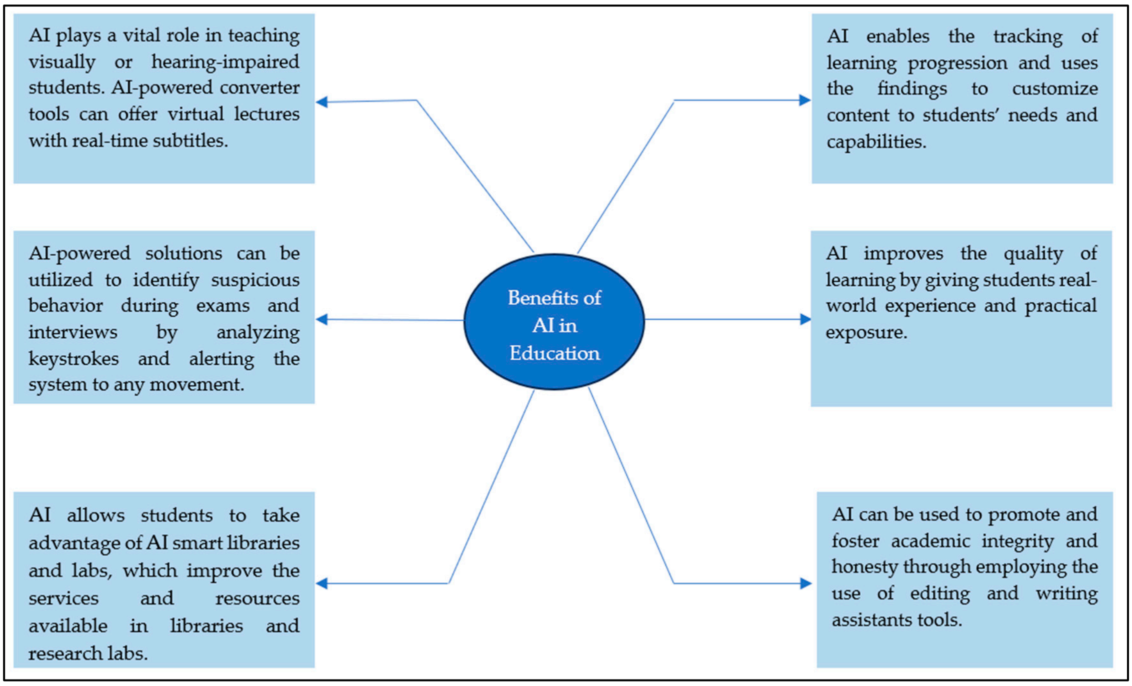

Figure 1. Benefits of AI in education.

In addition, Dai et al. [25] used a modified ECM to analyze students' intentions to continue learning in MOOC environments. ECM is useful in investigating AI traits, which aligns with this. For instance, AI-enabled virtual personal learning portfolios are evaluated under the users' initial expectations, perceived performance, and subsequent satisfaction levels. The satisfaction that results from the agreement between the usefulness of AI features is as expected, and their actual experienced usefulness can be a highly reliable indicator of students' intention to continue their studies. Liu et al. [26] examined variables influencing the intention to use online learning by expanding upon the TAM model. This extension is compared to looking at aspects of AI, like online personalized learning environments. Users' satisfaction levels in these AI-powered environments can be significantly influenced by their perceptions of the environments' usability, perceived ease of navigation, and interactive features. The intention to continue using these AI features can be determined by how well they meet user expectations and contribute to improved learning environments.

In order to analyze mobile learning systems, Alshurideh et al. [27] combined ECM and TAM, but missed all three characteristics of AI-powered e-learning. When evaluating AI traits, this integration is crucial. In order to fully understand the complex dynamics that determine users' intentions to adopt and continue using AI-enhanced e-learning systems, it will be helpful to examine the intersection of perceived usability and usefulness (TAM) with confirmed expectations and subsequent satisfaction (ECT). This integrative theoretical framework should be used to evaluate all aspects of AI from social learning networks to virtual personal learning portfolios, to provide educators, policymakers, and technology developers with insightful analysis and practical advice.

2.3. AI Characteristics, Perceived Usefulness and Perceived Ease of Use

The rapid advancements in information technology have revolutionized e-learning platforms. TAM suggests that users' acceptance of technology is influenced by their perceived usefulness (PU) and perceived ease of use (PEOU) [12,14]. Sun et al. [13] posited that learner satisfaction is critical in e-learning success, and both PU and PEOU play a significant role in influencing this satisfaction. Perceived presence, usefulness, and ease of use predict online students' satisfaction and persistence [15]. Extended models like the general extended technology acceptance model for e-learning, as Chang et al. [28] suggested, offer broader insights considering factors like external variables.

In addition, Holden and Rada [29] pinpointed that technology self-efficacy and perceived usability significantly affect teachers' technology acceptance. Similarly, the relationship between perceived usability and risk has been emphasised, with the latter moderating the intention to use a website [30]. As an integral component of e-learning, E-portfolios have been the subject of multiple studies [31,32]. Research suggests that the TAM framework analyzes students' behavioral intentions toward e-portfolio systems. Readiness for e-learning, especially in a self-directed learning environment, is crucial [33]. According to Al-Adwan et al. [33], these systems promote self-directed learning, strengthening lifelong learning capacities, which are crucial for the changing nature of the labor market. Additionally, by incorporating scientific knowledge into decision-making processes and curricula, AI-driven tools can address sustainability challenges and ensure a comprehensive approach to sustainable development. Studies have explored students' readiness and satisfaction levels in e-learning platforms [22,23]. Yilmaz [34] emphasized the importance of e-learning readiness in the flipped classroom context, suggesting its role in influencing student satisfaction and motivation. In addition, Hansen et al. [21] examined the interplay of PEOU, behavioral control, and trust in predicting consumers' use of social media for transactions. Trust also extends to mobile banking and online shopping environments, impacting user satisfaction and intention [17,35]. Therefore, the study offers the following hypotheses:

2.3.1. Social Learning Network, Perceived Usefulness and Perceived Ease of Use

AI-powered indicators support the use of technology in e-learning services. Both Dai et al. [25] and Yilmaz [34] emphasize the importance of user perceptions in determining ongoing engagement and satisfaction in e-learning environments. Dai et al. [25] emphasize the value of ECM, comparable to how learners anticipate the advantages of social learning networks in raising the perceived value of e-learning platforms. This is consistent with Moussa's [23] investigation into the readiness and satisfaction of students regarding remote learning in higher education, which suggests that when students find a tool or helpful method, it motivates them to keep using it. Such evidence firmly supports H1, which states that incorporating social learning networks increases the perceived value of e-learning systems.

On the other hand, a Taiwanese study by Lai and Wang [24] demonstrated the relationship between public librarians' attitudes toward e-learning and their readiness for self-directed learning. In this context, users are more likely to find e-learning environments intuitive and familiar when combined with social learning networks. This ease of interaction and navigation increases how simple they are perceived to use. Hasim and Yusof's [22] insights on online learning readiness and its relationship to satisfaction, which allude to the crucial role that ease of use plays in defining positive learning experiences, further strengthened this argument. The intersection of technology and user-centric qualities like personal innovativeness was extensively explored in the works of Amoroso and Lim [36] and Joo, Lee, and Ham [37]. According to their research, incorporating social and personal elements into e-learning platforms reduces users' learning curve, making the platforms more approachable and user-friendly. This suggests that social learning networks improve the user experience and make e-learning systems appear easier to use. The importance of fostering social connections in digital learning environments is highlighted by the fact that integrating social learning networks significantly and favorably influences both the PU and PEOU of e-learning platforms. Based on the supported materials, the study creates the research hypotheses:

H1: *A social learning network significantly and positively influences perceived usefulness in enhancing e-learning.*

H2: *A social learning network significantly and positively influences perceived ease of use in enhancing e-learning.*

2.3.2. Electronic Personal Learning Portfolios, Perceived Usefulness, and Perceived Ease of Use

Several studies have investigated the effects of e-portfolios and e-learning resources on educational contexts, including Abdullah et al. [14] and van der Schaaf et al. [32]. According to Abdullah et al. [14] and van der Schaaf et al. [32], incorporating virtual personal learning portfolios improves the educational experience by enabling students to gather and evaluate their work, monitor their development, and highlight their accomplishments. As a result, students view these portfolios as useful resources that aid their learning. This aligns with TAM's notion of PU. Furthermore, Dai et al.'s [25] findings imply that personal innovativeness influences users' satisfaction with e-learning platforms, meaning that people more receptive to cutting-edge learning tools like virtual portfolios are more likely to find them useful. Therefore, it is reasonable to conclude from these studies that virtual personal learning portfolios significantly and favorably influence how useful they are perceived to enhance e-learning.

The body of research is also strong evidence for hypothesis number four. Research by Holden and Rada [29] on teachers' adoption of technology revealed that perceived usability, which is closely related to PEOU, significantly affected the uptake of technology in a learning environment. This suggests that if technology is simple, individuals are more likely to adopt it. Additionally, Shroff, Deneen, and Ng [31] examined students' behavioral intentions to use an e-portfolio system and found that students' perceptions of the system's usability were a significant factor in determining whether they would adopt it. In addition, research by Sumak, Heriko, and Punik [38] and Liu et al. [26] examined the variables influencing users' intentions to use e-learning technologies, and discovered that ease of use was a significant determinant. These results show that virtual personal learning portfolios, as a user-friendly and accessible tool for organizing and presenting educational content, positively affect users' perceptions of e-learning's ease of use.

Therefore, both Hypotheses 3 and 4 receive strong support from the literature review. Virtual personal learning portfolios have been demonstrated to increase PU by assisting students in monitoring their progress and highlighting their accomplishments, aligning with the TAM's principles of PU. Accordingly, virtual personal learning portfolios significantly and positively influence both PU and PEOU to enhance e-learning based on the available research results. Therefore, the study creates the following research hypotheses:

H3: *Electronic personal learning portfolios significantly and positively influences PU in enhancing e-learning.*

H4: *Electronic personal learning portfolios significantly and positively influences PEOU in enhancing e-learning.*

2.3.3. Online Personal Learning Environment, Perceived Usefulness, and Perceived Ease of Use

According to the research hypotheses H5 and H6, online personal learning environments significantly and positively impact enhancing e-learning. Several studies are found in the research literature that back up this hypothesis. Mohammadi [12], for example, investigated users' perspectives on e-learning and found that integrating the TAM and the information systems success model (ISSM) can be applied to understand how PLEs enhance PU. This was discovered after Mohammadi [12] questioned users about their experiences with e-learning. Similarly, Abdullah et al. [14] investigated the influence of the external variables of TAM on students' PEOU and PU of e-portfolios. They discovered that when students have control over their learning environment through using PLEs, they are more likely to perceive the usefulness of e-learning.

The online personal learning environment significantly and favorably influences the perceived ease of use of e-learning. For example, Shroff, Deneen, and Ng [31] analyzed the TAM and found that the PEOU of the system influenced students' behavioral intentions to use an e-portfolio system. This was one of the key findings of the study. E-learning is made simpler, more user-friendly, and more accessible with the help of online PLEs; as a result, students' views of how easy it is to use the technology will improve. In addition, the research by Sumak, Herko, and Punik [38] included a meta-analysis of the acceptance of e-learning technology and highlighted the role of user types. This research demonstrated that PLEs are able to cater to a wide variety of user preferences and contribute to an increased level of usability. Therefore, the research that has been performed so far lends credence to hypotheses H5 and H6, which state that online personal learning environments have a significant impact, both positively and significantly, on the PU of e-learning and the perceived ease with which it can be utilized.

H5: *The online personal learning environment significantly and positively influences PU in enhancing e-learning*.

H6: *The online personal learning environment significantly and positively influences PEOU in enhancing e-learning*.

2.4. Perceived Usefulness, Perceived Ease of Use, and Satisfaction

According to the research hypothesis, H7 states that usefulness significantly and positively influences satisfaction with e-learning. The availability of e-learning and technology acceptance models strongly support e-learning. Numerous studies have demonstrated the close relationship between user satisfaction and PU in e-learning. For instance, Mohammadi [12] combined the IS success model and the TAM to examine user perceptions of e-learning. According to the study, PU is a significant factor affecting users' satisfaction with e-learning platforms. Similarly, perceived usefulness was identified as a significant predictor of satisfaction in the study conducted by Sun et al. [13], which investigated important antecedents influencing learner satisfaction in e-learning.

Additionally, a connection exists between PU and satisfaction in several educational contexts. For instance, Shroff, Deneen, and Ng [31] examined how students used an e-portfolio system and discovered that the students' behavioral intention to use it was significantly influenced by their perception of its usefulness, ultimately leading to higher satisfaction. Holden and Rada [29] looked into how well teachers accepted new technology, and discovered that perceived usability—closely related to PU—significantly influenced their satisfaction. Since learners and educators value systems and technologies perceived as useful for their educational goals, it is reasonable to claim that PU plays a vital role in enhancing satisfaction in online learning environments, drawing on this extensive body of research.

Several studies support hypothesis H8, which states that PEOU significantly and positively affects e-learning satisfaction. E-learning perceived ease of use refers to how easily learners find that the online learning environment and technology are to use [19]. Mohammadi [12] and Sun et al. [13] emphasize user perspectives and learner satisfaction in e-learning. Mohammadi [12] uses the TAM and IS success model to study e-learning users' perspectives. This integration implies that user perceptions of ease of use determine e-learning system success. Sun et al. [13] empirically study the critical factors affecting e-learning learner satisfaction and find that ease of use factors like user interface design and system navigation are important. These findings suggest that easy-to-use e-learning systems improve student satisfaction.

Holden and Rada [29] examine how perceived usability and technology self-efficacy affect teachers' technology acceptance, revealing the link between ease of use and user satisfaction. E-learning technology is more likely to be adopted by teachers if it is perceived as easy to use. E-learning experiences and learner satisfaction can improve with this acceptance. Abdullah et al. [14] examine how external variables affect students' perceptions of e-portfolios' ease of use and usefulness, emphasizing the importance of ease of use in technology perception. Therefore, the study offers the research hypotheses:

H7: *PU significantly and positively influences satisfaction in enhancing e-learning*.

H8: *PEOU significantly and positively influences satisfaction in enhancing e-learning*.

H9: *PEOU significantly and positively influences PU in enhancing e-learning*.

2.5. Satisfaction and Intention to Use e-Learning

A large body of literature supports hypothesis H10, which states that satisfaction significantly and positively influences intention to use to improve e-learning. Several e-learning and technology adoption studies have shown that user satisfaction strongly influences students' intentions to use and adopt technology-driven educational systems; for instance, Sun et al. [13] found that learner satisfaction is a key factor in e-learning system success, as satisfied learners are more likely to use them. Abdullah et al. [14] found that user satisfaction was a key outcome of the TAM and directly affected educational e-portfolio use. In addition, Al-Fraihat et al. [39] found that user satisfaction significantly affects e-learning system success. Students satisfied with their e-learning experiences are more likely to use the platform again. The relationship between satisfaction and intention to use is also supported in studies of mobile banking [40] and mobile shopping applications [41]. These studies consistently show that higher user satisfaction increases technology use. Thus, the literature supports hypothesis H10.

H10: *Satisfaction significantly and positively influences intention to use in enhancing e-learning*.

2.6. Perceived Usefulness, Perceived Ease of Use, and Attitude

This theory is consistent with the findings of several published studies. For instance, when Sun et al. [13] looked into the crucial elements affecting learner satisfaction in e-learning, they discovered that PU was a key factor in determining learners' attitudes. According to Abdullah et al. [14], who also looked at the impact of outside factors on students' expectations of e-portfolio usability and PEOU, PU is a significant factor influencing students' attitudes toward e-learning systems. Furthermore, Kreijns et al. [42] looked into what motivates teachers to incorporate ICT into their pedagogical practices. They found that PU is a key factor in determining whether teachers accept and use educational technologies. These results offer solid evidence in favor of H11. A recurring theme in the literature is the beneficial impact of perceived usefulness on attitude, demonstrating a significant and favorable relationship between these two factors in the context of e-learning.

H11: *PU significantly and positively influences attitude to e-learning*.

On the other hand, Shroff, Deneen, and Ng [31] examined how the TAM affected students' behavioral intention to use an e-portfolio system, and discovered that perceived ease of use positively influences students' attitudes toward e-learning. Chen, Yen, and Hwang [43] found that perceptions of ease of use significantly affect users' intentions to continue using Web 2.0 technologies. The TAM model was further developed by Liu et al. [26] to examine factors influencing users' intentions to engage in online learning communities, and they discovered that perceived usability has a significant positive influence on users' attitudes. These results offer strong evidence in favor of H12. Consistent findings in the literature suggest that perceptions of ease of use are essential in determining learners' attitudes toward and acceptance of e-learning platforms.

H12: *Perceived ease of use significantly and positively influences attitude e-learning.*

2.7. Attitude and Intention to Use e-Learning

The existing literature supports hypothesis H13, which holds that attitude significantly and favorably influences intention to use e-learning. The factors influencing users' acceptance of and intention to use various technology-mediated platforms and systems, including e-learning, have been the subject of numerous studies. Studies like Mohammadi [12], Sun et al. [13], and Abdullah et al. [14] have shown that users are more likely to adopt a positive attitude toward e-learning when they believe it to be practical and straightforward to use. This positive attitude significantly shapes their intention to use e-learning systems. The importance of users' attitudes in predicting their intention to continue using technology-based systems and services is further highlighted by research on technology acceptance, such as Amin et al. [35] and Sumak et al. [38]. Therefore, the body of literature currently in existence offers compelling support for hypothesis H13, highlighting users' intentions.

H13: *Attitude significantly and positively influences intention to use e-learning.*

2.8. The Moderation of Students' Traits between Satisfaction and Intention to Use e-Learning

According to studies on self-directed e-learning readiness, individuals who are more equipped and driven to take charge of their educational experiences in an online setting report feeling more satisfied with their learning [22,33]. This readiness plays a crucial moderating role in the relationship between satisfaction and intention to use e-learning platforms [23]. Individuals with higher readiness levels for self-directed e-learning are more likely to be pleased with their e-learning endeavors and, as a result, are more likely to keep using e-learning tools. Students who are more prepared for self-directed online learning will likely be satisfied with their e-learning opportunities and will therefore be more likely to keep using e-learning tools [23]. This hypothesis is therefore strongly supported by the literature, with readiness for self-directed e-learning significantly moderating the positive relationship between satisfaction and intention to use e-learning.

H14: *Readiness for self-directed e-learning significantly moderates the moderating relationship satisfaction and intention to use in enhancing e-learning.*

Self-efficacy, or a person's confidence in their capacity to complete tasks successfully, has been thoroughly investigated concerning technology acceptance and use. Self-efficacy is a critical moderator of the relationship between satisfaction and intention to use in the context of e-learning. According to Wang et al. [44], self-efficacy influences how long individuals use self-service technologies. Wang et al. [18] also highlighted the importance of self-efficacy in teachers' job satisfaction and their intentions to continue utilizing technology in the class environment. It is most likely that self-efficacy will moderate the relationship between satisfaction with e-learning experiences and the intention to use e-learning platforms. Technology acceptance and use are significantly influenced by self-efficacy, which reflects people's beliefs in their capacity to carry out tasks successfully [18,44]. Higher self-efficacy is associated with greater satisfaction with one's ability to navigate and learn in online learning environments successfully. Because of this, the relationship between satisfaction and intention to use e-learning platforms can be moderated by this sense of self-efficacy [18,44]. According to the hypothesis, self-efficacy significantly moderates the positive relationship between satisfaction and intention to use e-learning.

H15: *Self-efficacy significantly moderates the moderating relationship satisfaction and intention to use in enhancing e-learning.*

The relationship between satisfaction and intention to use e-learning platforms is significantly moderated by personal innovativeness, which is related to a person's willingness to adopt new technologies [23]. Joo et al. [37] have incorporated personal innovativeness into the TAM for mobile learning, and they discovered that it affects users' acceptance and continued use of technology. Similarly, Lu [1] investigated the function of individual inventiveness in mobile commerce and its effects on user satisfaction and recurrent usage. According to these studies, more innovative people personally are more likely to find innovative e-learning technologies satisfying and, as a result, are more likely to keep using them. According to studies [1,37], personal innovativeness, which reflects a person's openness to embracing new technologies, affects how technology is accepted and used in different contexts. Higher levels of personal innovation make people more likely to be pleased with cutting-edge e-learning technologies [37,45]. As individuals with more remarkable personal inventiveness are more likely to continue using these platforms, this increased satisfaction can significantly moderate the relationship between satisfaction and intention to use e-learning platforms. Thus, strong evidence supports the hypothesis that personal innovativeness significantly modifies the positive relationship between satisfaction and intention to use e-learning.

H16: *Personal innovativeness significantly moderates the moderating relationship satisfaction and intention to use in enhancing e-learning.*

The research model is illustrated in Figure 2.

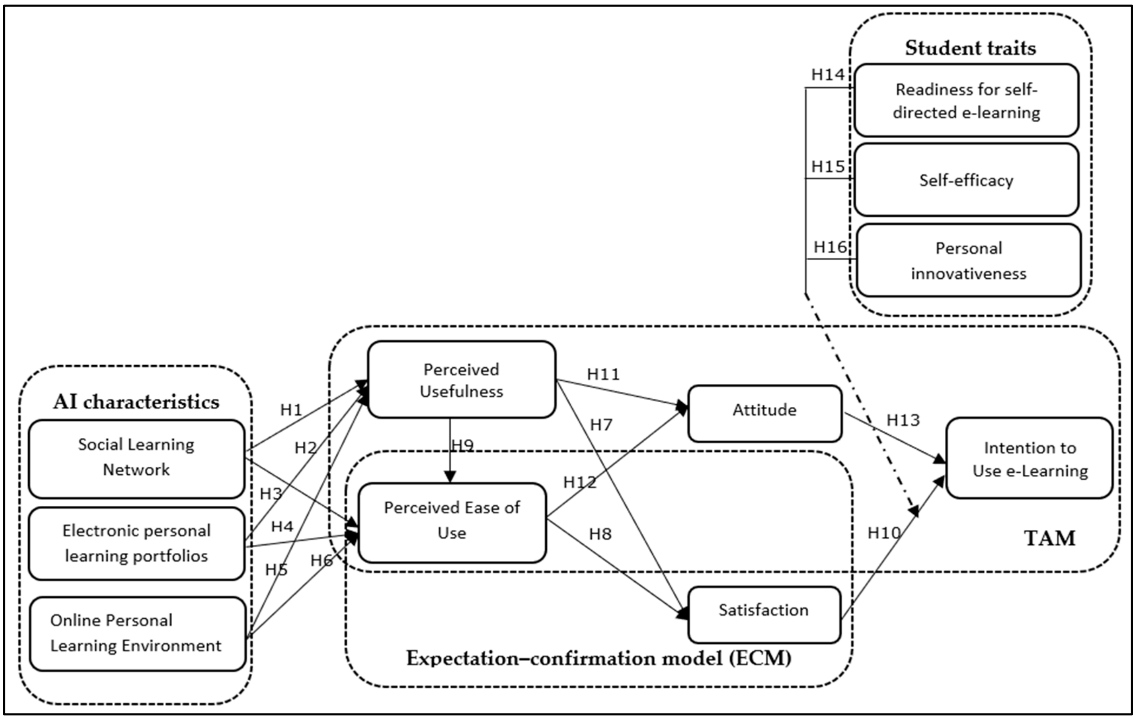

Figure 2. Theoretical Framework.

3. Research Methodology

3.1. Research Design

The research was performed through the use of a quantitative research design, specifically through a survey questionnaire. According to the study, to understand university students' perceptions of AI-based e-learning, it is essential to gather responses from a large and diverse sample. Quantitative data provides a structured and standardized method for collecting responses, ensuring that results can be extrapolated to a broader population [46]. Using integrated models (TAM and ECM), the study proposed research hypotheses for the influence of integrated factors using AI characteristics to enhance e-learning intention among Saudi students. Quantitative research, with its numerical data, is apt for hypothesis testing through statistical methods [47]. Quantitative research, with its controlled conditions, is well suited for such a purpose, facilitating the understanding of moderating or mediating factors [48]. Therefore, the study applied quantitative phenomena by administering a survey questionnaire among university students.

3.2. Sampling and Data Collection Procedure

In a study aimed at Saudi Arabian universities to improve AI-powered e-learning (using Blackboard, Moodle, Edmodo, Coursera and edX), the sample size and data collection procedures would be crucial elements of the research methodology. A representative sample of students was ideally included in a study focusing on Saudi Arabian universities who experienced Blackboard, Moodle, Edmodo, Coursera, and edX in their e-learning journey. According to Creswell [46], the desired significance level should be considered when determining the sample size for quantitative research. Field [47] advises choosing the appropriate sample size for various statistical analyses. The study's results would be statistically significant and representative of the larger university population if the sample size were large enough; therefore, the study used a final clean dataset of 500 survey responses. The necessity of improving AI-powered e-learning in Saudi Arabian universities, which results in better educational outcomes and technological advancements, would frame the study's significance. A survey questionnaire was distributed to students on social media platforms (including Facebook, Twitter, and LinkedIn), and emails were used to collect data for this study. The data collection procedure was carried out over a predetermined time frame to ensure a thorough understanding of the subject.

Through university email systems and other communication channels, the researchers invited students to participate in the survey to collect responses. They employed a stratified sampling strategy to guarantee representation from different Saudi universities and academic disciplines. To gather pertinent information about experiences with AI-powered e-learning, preferences, and suggestions for improvement, the online survey was created following the best practices outlined by Creswell [46]. The research design needs to be very specific about the period for data collection. For instance, to track changes in participants' experiences and perceptions over time, researchers might send out the survey at the start, middle, and end of the academic semester.

Ethical considerations are crucial when gathering data from students in Saudi Arabian universities. All participants consented after being fully informed about the study's objectives, the intended use of their data, and their confidentiality rights. To encourage honest responses, confidentiality and anonymity should be guaranteed. The study should also follow all institutional policies and guidelines, including any institutional review board (IRB) requirements or ethical review. Ethical data collection practices are crucial to protect the well-being and privacy of participants while obtaining insightful data for research purposes.

3.3. Measurement Instruments

The study adapted valid and reliable scales from the previous studies where the validity and reliability indicators showed values >0.70. The measurement scale for the social learning network construct includes 2 items adapted from Kashive et al. [49] and Montebello [50]. The electronic personal learning portfolio measurement scale comprises 2 items that assess participants' use of electronic personal learning portfolios [50]. For the online personal learning environment construct, 2 items were included to assess participants' interactions with online learning environments [49]. The measurement scale for PU consists of 6 items adapted from Liu et al. [26] and Davis [51]. PEOU is measured using a scale with 6 items. These items are adapted from sources such as Liu et al. [26], Maheshwari [52], Salloum and Al-Emran [53], and Davis [51].

On the other hand, the attitude construct is assessed using 3 items borrowed from Kamble et al. [54], Liu et al. [26], and Davis [51]. Intention to use is measured through a scale comprising 6 items adapted from Maheshwari [52], Esterhuyse et al. [55], Venkatesh et al. [56], and Davis [51]. The satisfaction construct is assessed using a scale with 6 items adapted from Esterhuyse et al. [55] and Maheshwari [52]. Readiness for self-directed e-learning is measured through a scale with 6 items adapted from Chau et al. [57]. The self-efficacy construct includes 7 items adapted from Ithriah et al. [58] and Salloum and Al-Emran [53]. Personal innovativeness is measured using a scale comprising 4 items adapted from Twum et al. [59] and Mulyani and Nugraha [60]. All measurement scales were measured on 5-point Likert scales ranging from 1 = strongly disagree to 5 = strongly agree.

3.4. Data Analysis

In order to conduct structural equation modeling (SEM) analysis and ensure the validity and reliability of the constructs, the data for this study were analyzed using various statistical tools and methods. IBM SPSS statistics was initially used for the demographic analysis [46,47]. Smart PLS (Partial Least Squares) was used to evaluate the validity and reliability of the measurement scale used in this study [61]. Smart PLS is an effective tool for SEM, especially when latent constructs and intricate relationships between variables are present. Additionally, reliability analysis utilizing composite reliability (CR) and Cronbach's alpha was carried out to assess the internal consistency of the measurement items [61]. After completing the validation and reliability checks, Smart PLS was used in SEM analysis to examine the structural relationships between the study constructs [61]. This all-encompassing approach made the investigation of intricate dependencies and interactions between variables possible, which is especially pertinent in the context of e-learning systems [62].

4. Results and Findings

4.1. Demographic Information

The demographic breakdown of a sample size of 500 participants is shown in Table 1 by gender, age, and level of education. Female participants comprise 59.6% of the sample, while male participants comprise 40.4%. With 44.2% of respondents, the 36–45 age range has the highest age representation. The age group 18 to 25 has the lowest representation, at just 9%. Regarding education, the majority of participants (41.2%) have a master's degree, while 12.4% have only an intermediate level of education. Individuals with a bachelor's degree account for 35.6% of the population, those with an MS or MPhil degree account for 16.6%, and those with a PhD or postdoctoral degree account for 6.8%.

4.2. Assessing Validity and Reliability

The study used the PLS algorithm to test the validity and reliability of the measurement scales. The study applied a series of algorithm techniques to final good scores of validity measures and reliability thresholds. The study deleted one item of PU (pu6 = 0.610), one item of PEOU (peou2 = 0.684), three items of satisfaction (SAT1 = 0.686, SAT2 = 0.188, SAT6 = 0.640), two items of readiness for self-directed e-learning (Red1 = 0.687, Red2 = 0.692), two items of self-efficacy (SEF3 = 0.688, SEF4 = 0.680), and two items of personal innovativeness (PINN3 = 0.689, PINN = 0.689) due to lower factor loadings than 0.70. According to Table 2, the study's scales have acceptable convergent validity and reliability levels.

Table 1. Demographic information.

Variables	Categories	Frequency	Percent
Gender	Male	202	40.4
	Female	298	59.6
Age	18–25	45	9.0
	26–35	100	20.0
	36–45	221	44.2
	46–55	97	19.4
	56–65	37	7.4
Education	Bachelor	178	35.6
	Master	206	41.2
	MS/MPhil	83	16.6
	PhD/Post Doc	34	6.8

Table 2. Convergent validity and reliability.

Variable	Items	Factor Loadings	Cronbach Alpha	Composite Reliability	Average Variance Extracted (AVE)
Social learning network	SLN1	0.859	0.737	0.882	0.790
	SLN2	0.917			
Electronic personal learning portfolio	Eresource1	0.885	0.790	0.865	0.763
	Eresource2	0.862			
Online personal learning environment	Env1	0.896	0.770	0.897	0.813
	Env2	0.908			
Perceived usefulness	pu1	0.760	0.863	0.900	0.644
	pu2	0.841			
	pu3	0.812			
	Pu4	0.867			
	pu5	0.726			
Perceived ease of use	peou1	0.818	0.890	0.919	0.694
	peou3	0.831			
	peou4	0.909			
	peou5	0.750			
	peou6	0.850			
Attitude	Att1	0.879	0.877	0.924	0.803
	Att2	0.911			
	Att3	0.898			
Intention to use e-learning	INT1	0.906	0.931	0.946	0.746
	INT2	0.833			
	INT3	0.853			
	INT4	0.802			
	INT5	0.916			
	INT6	0.867			
Satisfaction	SAT3	0.842	0.871	0.921	0.796
	SAT4	0.914			
	SAT5	0.919			
Readiness for self-directed e-learning	RED3	0.824	0.907	0.935	0.782
	RED4	0.888			
	RED5	0.932			
	RED6	0.890			
Self-efficacy	SEF1	0.810	0.868	0.903	0.652
	SEF2	0.761			
	SEF5	0.747			
	SEF6	0.881			
	SEF7	0.832			
Personal innovativeness	PINN1	0.915	0.776	0.857	0.750
	PINN2	0.815			

Convergent validity is evaluated by looking at factor loadings and the average variance extracted (AVE). All of the items in the table meet the criteria for factor loadings, which—according to Hair et al. [61]—should ideally be 0.7 or higher, indicating that they share a significant variance with the corresponding latent constructs. Furthermore, an AVE of 0.5 or higher is a generally recognized threshold for determining convergent validity [62]. Each of the constructs listed exceeds this threshold, demonstrating that the items are accurate measures of the corresponding latent variables.

The scales' reliability is assessed using composite reliability (CR) and Cronbach's alpha. According to Hair et al. [61], for satisfactory reliability, Cronbach's alpha values should be greater than 0.7, and ideally, CR should surpass 0.7. These thresholds are met or exceeded by most of the constructs, showing strong internal consistency. Although within acceptable bounds, the "Social Learning Network" has a slightly lower Cronbach's Alpha at 0.737. The results show that the measures used in the study are valid and reliable according to the standards outlined by Henseler et al. [63], ensuring the validity and reliability of subsequent analyses.

The heterotrait–monotrait (HTMT) ratio between the various constructs is shown in Table 3. The HTMT ratio directly evaluates the discriminant validity between pairs of constructs, addressing several limitations of the conventional Fornell–Larcker criteria and cross-loadings [63]. Although the Fornell–Larcker criterion compares the square root of AVE to correlations, it frequently fails to identify the absence of discriminant validity, especially when constructs are highly correlated. Similar to the previous example, cross-loadings compare an indicator's loading on its assigned construct to its loadings on other constructs, which can occasionally produce false results [61]. The HTMT, on the other hand, presents a more precise and exacting approach. Hair et al. [62] state that HTMT values below 0.85 or 0.90 indicate satisfactory discriminant validity. By looking at the provided table, this confirms the appropriateness of applying the HTMT criteria to make sure the examined constructs are distinct from one another.

Table 3. Heterotrait–monotrait (HTMT) ratio.

Constructs	1	2	3	4	5	6	7	8	9	10
Attitude										
Electronic personal learning portfolio	0.768									
Intention to use e-learning	0.848	0.644								
Online personal learning environment	0.662	0.770	0.741							
Perceived ease of use	0.606	0.656	0.699	0.720						
Perceived usefulness	0.706	0.768	0.789	0.895	0.744					
Personal innovativeness	0.728	0.489	0.591	0.452	0.598	0.441				
Readiness for self-directed e-learning	0.820	0.661	0.714	0.549	0.505	0.582	0.869			
Satisfaction	0.786	0.715	0.674	0.694	0.650	0.587	0.671	0.726		
Self-efficacy	0.792	0.761	0.779	0.683	0.661	0.641	0.810	0.765	0.836	
Social learning network	0.815	0.673	0.724	0.666	0.561	0.730	0.643	0.585	0.523	0.603

4.3. Assessing the Path

Table 4 presents the results for the direct effects of the various hypotheses using the bootstrapping technique, employing 5000 subsamples (Table 4). Bootstrapping is a non-parametric statistical method that allows for hypothesis testing without the assumptions of parametric tests, making it particularly suitable for complex models and small sample sizes [61]. Using a 5% significance level with a 95% confidence interval, any p-value less than 0.05 indicates a significant effect, while a p-value greater than 0.05 suggests non-significance.

Table 4. Direct effects.

Direct Effects	Beta Value	*t*-Value	*p*-Value
H1. Social learning network → Perceived usefulness	0.229	6.573	0.000
H2. Social learning network → Perceived ease of use	0.161	3.914	0.000
H3. Electronic personal learning portfolio → Perceived usefulness	0.224	7.137	0.000
H4. Electronic personal learning portfolio → Perceived ease of use	0.222	5.421	0.000
H5. Online personal learning environment → Perceived usefulness	0.502	17.083	0.000
H6. Online personal learning environment → Perceived ease of use	0.399	9.236	0.000
H7. Perceived usefulness → Satisfaction	0.271	6.128	0.000
H8. Perceived ease of use → Satisfaction	0.397	8.328	0.000
H9. Perceived ease of use → Perceived usefulness	0.251	7.950	0.000
H10. Satisfaction →Intention to use e-learning	−0.036	0.901	0.368
H11. Perceived usefulness →Attitude	0.474	11.922	0.000
H12. Perceived ease of use → Attitude	0.232	5.133	0.000
H13. Attitude →Intention to use e-learning	0.500	12.584	0.000

H1: Social learning network → Perceived usefulness: Based on the results, the beta value = 0.229, suggesting a moderate positive relationship between social learning network and perceived usefulness. The effect is statistically significant with a *t*-value = 6.573, which is notably higher than the common threshold of 1.96 for a 95% confidence interval. This statistical significance is further emphasized by the *p*-value = 0.000, which is well below the 0.05 threshold. Consequently, H1 is accepted, underscoring that the social learning network significantly affects perceived usefulness.

H2: Social learning network → Perceived ease of use: For this hypothesis, the beta value = 0.161 indicates a modest positive effect of social learning network on perceived ease of use. The *t*-value = 3.914 surpasses the critical value for significance at the 95% confidence level. The *p*-value = 0.000 confirms the result's statistical significance, falling well below the 0.05 mark. Therefore, H2 is accepted, affirming the positive influence of social learning network on perceived ease of use.

H3: Electronic personal learning portfolio → Perceived usefulness: The analysis yields a beta value = 0.224, pointing towards a moderately positive association between the electronic personal learning portfolio and perceived usefulness. The *t*-value = 7.137 exceeds the standard 95% confidence interval threshold, confirming statistical significance. This is further solidified by the *p*-value = 0.000, which is below 0.05. Thus, H3 is accepted, denoting that the electronic personal learning portfolio significantly boosts perceived usefulness.

H4 to H9 are all accepted based on their respective beta values showing meaningful relationships, *t*-values surpassing the critical threshold, and *p*-values below 0.05. Notably, H10 with a beta value = −0.036, *t*-value = 0.901, and *p*-value = 0.368 is the exception, as the *p*-value exceeds the 0.05 limit. This means that H10 is rejected, indicating that satisfaction does not significantly influence the intention to use e-learning. H11 to H13 are accepted, given their significant beta values, *t*-values well above the benchmark, and *p*-values under 0.05, affirming their respective positive relationships.

The moderating effects table presents the influence of various moderators on the relationship leading to the 'Intention to use e-learning (Table 5)'. Readiness for self-directed e-learning → Intention to use e-learning: The beta value = 0.127 implies a slight positive influence of the readiness for self-directed e-learning on the intention to use e-learning.

The *p*-value = 0.004 below 0.05 further signifies the result's statistical relevance. Self-efficacy → Intention to use e-learning: With a beta value = 0.377, a strong positive relationship exists between self-efficacy and the intention to use e-learning. The *p*-value = 0.000, lower than 0.05, confirms the statistical significance. Consequently, self-efficacy plays a crucial role in fostering the intention to use e-learning. Personal innovativeness → Intention to use e-learning: Despite the negative beta value = −0.094, indicating a slight inverse relationship, the *t*-value = 2.739 signifies a significant effect at the 95% confidence level. The *p*-value = 0.006 further corroborates this significance.

Table 5. Moderating effects.

Moderating Effects	Beta Value	*t*-Value	*p*-Value
Readiness for self-directed e-learning → Intention to use e-learning	0.127	2.896	0.004
Self-efficacy → Intention to use e-learning	0.377	9.251	0.000
Personal innovativeness → Intention to use e-learning	−0.094	2.739	0.006
H14. Readiness for self-directed e-learning × satisfaction → Intention to use e-learning	−0.049	−0.047	0.256
H15. Self-efficacy × satisfaction → Intention to use e-learning	−0.009	−0.010	0.811
H16. Personal innovativeness × satisfaction → Intention to use e-learning	0.040	0.039	0.327

H14. Readiness for self-directed e-learning × Satisfaction → Intention to use e-learning: The interaction effect presents a beta value = −0.049. However, the *t*-value = −0.047 and *p*-value = 0.256, being above 0.05, highlight that the moderating effect of satisfaction on the relationship between readiness for self-directed e-learning and intention to use e-learning is not significant. Therefore, hypothesis H14 is rejected.

H15. Self-efficacy × satisfaction → Intention to use e-learning: For this interaction effect, the beta value is −0.009, pointing to a minimal negative influence. However, the *t*-value = −0.010 and the *p*-value = 0.811 (exceeding the 0.05 limit) confirm that the influence of satisfaction as a moderator between self-efficacy and intention to use e-learning is statistically insignificant. Therefore, hypothesis H15 is rejected.

H16. Personal innovativeness × Satisfaction → Intention to use e-learning: Here, the beta value = 0.040 suggests a modest positive relationship. Nonetheless, the *t*-value = 0.039 and *p*-value = 0.327, being above the threshold, indicate that the moderation effect of satisfaction on the link between personal innovativeness and intention to use e-learning is not statistically valid. As a result, H16 is rejected.

4.4. Model Fitness

In evaluating the model's predictive capacity and fit, R-square (R^2) and adjusted R^2 offer crucial insights. For the "Attitude" construct, a R^2 value of 0.425 implies that the model explains 42.5% of the variance, with a slight adjustment to 42.3% considering the number of predictors, as denoted by the adjusted R^2 value. This suggests a moderate fit for this specific construct. For "Intention to use e-learning", the model appears to be highly predictive, with a R^2 of 0.675, indicating that the model explains 67.5% of the variance in this construct. The slight reduction to 67.0% in the adjusted R^2 still underscores the strong explanatory power of the model for this construct. In the case of "PEOU", the model explains 43.3% of the variance, with a modest decrease to 43.0% after adjusting for the number of predictors. Similarly, for "PU", the model has high explanatory power, with R^2 and adjusted R^2 values of 64.8% and 64.6%, respectively. Lastly, the construct "Satisfaction" has an R^2 of 0.375, meaning the model accounts for 37.5% of its variance. This value slightly drops to 37.2% post-adjustment, suggesting a moderate fit for this construct. Figure 3 illustrates the SEM model.

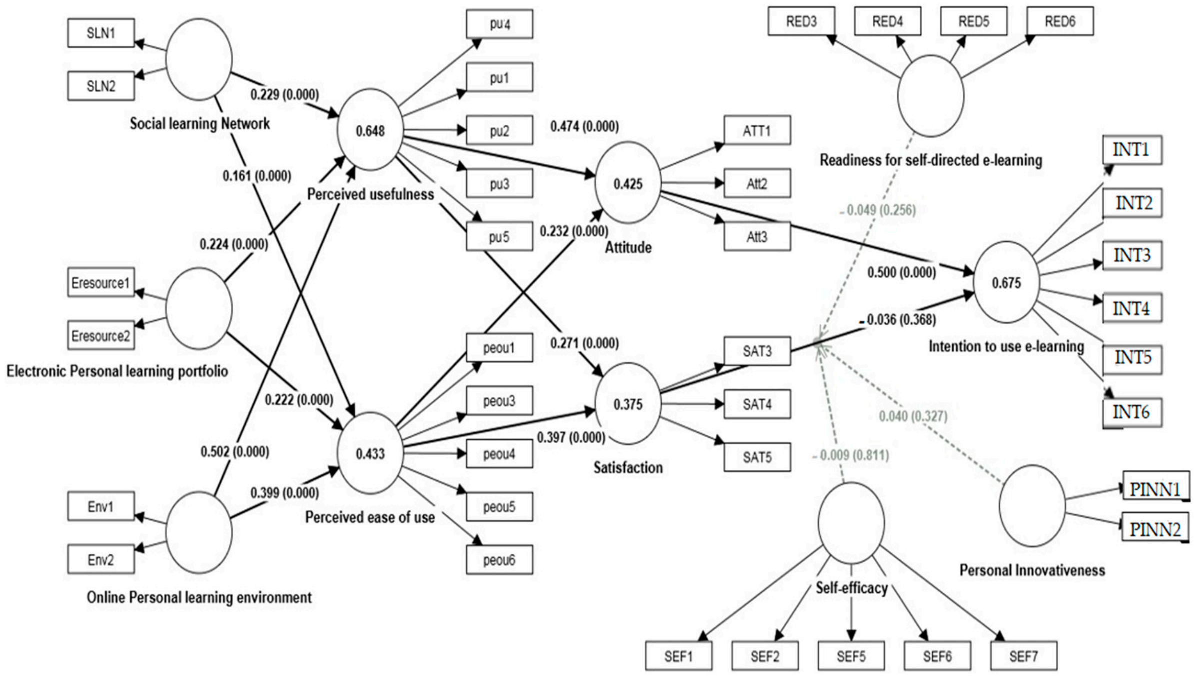

Figure 3. SEM model.

5. Discussion

The study has been carried out in Saudi Arabia by targeting students from universities. The purpose of targeting students was to measure intention to use e-learning from AI-driven platforms, including Blackboard, Moodle, Edmodo, Coursera, and edX. The study's findings show the direct and moderating effects of various technological factors and their effects on students' intentions to use e-learning. These results exhibit notable consistency when compared to earlier literature. Both Mohammadi [12] and Sun et al. [13] highlighted the significance of PU and PEOU in influencing satisfaction and behavioral intention and the importance of these factors in ensuring a successful e-learning experience. To shed light on the user's perspectives on e-learning, Mohammadi [12] specifically integrated the technology acceptance model (TAM) and the IS success model. The author highlighted the importance of PU and PEOU, consistent with our findings. The findings emphasized the critical role of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping user satisfaction and behavioral intentions in e-learning, aligning with findings that integrating the technology acceptance model (TAM) and IS success model is key for e-learning success.

Similarly, Sun et al. [13] examined the factors that influence the success of e-learning and discovered that learner satisfaction is crucial. Our study's high beta values and significant levels for hypotheses like H1, H2, and H9 support these claims. Another recurring effect is self-efficacy, perceived usability, and acceptance of technology. Holden and Rada [29] stressed the importance of perceived usability and technology self-efficacy in influencing technology acceptance, consistent with our findings in H6 and emphasizing the significance of online personal learning environments. Additionally, Abdullah et al. [14] focused on e-portfolios and discovered the importance of the two primary external TAM variables: PEOU and PU. Our study builds on these results by emphasizing how electronic personal learning portfolios affect perceived value and usability.

In addition, Joo, Lim, and Kim [15] also looked into the elements that predicted persistence and satisfaction in online university students. They highlighted the importance of perceived presence, usefulness, and usability; these findings are consistent with H5, H6, and H7. Brady et al. [20] discovered that social learning significantly amplifies moral outrage expression in online social networks and supports the social learning dimension. Our research findings support that a significant association exists between social learning networks and PU and usability (H1 and H2).

Finally, previous studies have found similarities between the moderating effects we identified. As an illustration, Huang et al. [64], (2012) stressed active and passive attitudes about PU and PEOU in their widely used English vocabulary learning system, which is consistent with our findings on the moderating effects of self-efficacy on the intention to use e-learning. Similar to our findings regarding readiness for self-directed e-learning, Sánchez and Hueros [65] identified motivational factors as critical determinants for accepting Moodle using TAM. As a result, our findings, which cover both direct and moderating effects on the intention to use e-learning, align with the majority of the existing research on e-learning, TAM, and related factors. These insights will continue to be crucial in determining future educational strategies and tools as technology-driven learning develops.

5.1. Managerial Implications

The study offers managerial implications for Saudi universities. The results strongly imply that the type of e-learning platform is crucial in determining how students view e-learning. Students' perceptions of the usefulness and usability of online personal learning environments are significantly impacted. In order to meet the unique needs of their students, Saudi universities should invest in creating and implementing robust online personal learning environments. This may increase students' satisfaction levels and, as a result, their desire to use online learning environments. Student satisfaction is directly correlated with PEOU and PU. The significance of ensuring that e-learning platforms are valuable and user-friendly is highlighted by the fact that PEOU influences PU. Students' satisfaction, attitude toward e-learning, and intention to continue using these platforms can all be improved by streamlining the user interface, providing instructions for novice users, and ensuring the system functions properly.

The study emphasizes that personal traits like self-efficacy, personal inventiveness, and readiness for self-directed e-learning are crucial in determining students' intentions to use e-learning. Universities in Saudi Arabia should consider implementing initiatives and programs to increase students' readiness for online learning. Though personal innovativeness favorably affects the intention to use e-learning, its interaction with satisfaction has a negligible impact, which is interesting to note. Therefore, while innovation can be encouraged, the satisfaction-intention relationship may only sometimes be strengthened. Universities must look beyond simple satisfaction, because as demonstrated in H10, it does not significantly predict the intention to use e-learning. Understanding other underlying factors or potential obstacles that might thwart students' intentions should be given priority. Additionally, considering the moderating effects, combining personal traits with satisfaction has little effect on intentions. Therefore, the emphasis should be on enhancing the fundamental elements of the e-learning platform and system while enhancing students' e-learning capacities.

5.2. Limitations and Future Directions

Every study has some limitations and future directions. One significant limitation of the study is the reliance on self-reported data, which can be susceptible to response bias. The study's cross-sectional design means causality was definitively established, even though relationships are evident. Additionally, this study explicitly addresses Saudi university students; therefore, the findings might not be generalizable to students from other cultural or academic backgrounds. Another limitation was that the study did not examine the intention to use e-learning by using students' discipline differences. In addition, the study did not focus on determining intention to use e-learning based on gender differences, job seekers, and degree seekers. Furthermore, while various e-learning platforms and individual characteristics were considered, other potential influential factors, such as technological infrastructure, instructional quality, or external motivations, might have yet to be accounted for. Future research should consider adopting a longitudinal design to trace changes over time and better determine causality in the relationships observed. Additionally, expanding the study to include students from diverse cultural and educational settings would provide insights into the generalizability of the findings. Future studies could incorporate objective measures, such as actual e-learning usage statistics or direct observations, to address the limitations associated with self-reported data. Qualitative methods like interviews or focus groups could provide deeper insights into the nuances behind students' perceptions and intentions regarding e-learning. Lastly, it would be valuable to explore more accurately the interaction effects of various individual and external factors on e-learning outcomes.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Research Committee (REC) of the Faculty of Economics and Administration at King Abdulaziz University (protocol code Ref. REC 1/5 24/5/2023) for studies involving humans.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets generated and analyzed during the current study are not publicly available due to privacy and confidentiality agreements, as well as other restrictions. The datasets, however, are available upon reasonable request. Inquiries related to these may be submitted to the corresponding author.

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Abbreviations

TAM	Technology acceptance model
ECM	Expectation-confirmation model
HEIs	Higher education institutions
HE	Higher education
AI	Artificial intelligence
Moodle	Modular object-oriented dynamic learning Environment
NLP	Natural language processing
ITU	Intentions to use
SLN	Social learning networks
EPLP	Electronic personal learning portfolios
PU	Perceived usefulness
PEOU	Perceived ease of use
PINN	Personal innovativeness
RSDE	Readiness for self-directed e learning
SE	Self-efficacy
OPLE	Online personal learning environment

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