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Article

Adoption and impact of AI-enhanced learning platforms in education

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Abstract: The integration of artificial intelligence (AI) in education is rapidly transforming learning environments, and the adoption of AI-based e-learning platforms (AI-ELP) is gaining momentum. However, understanding the factors influencing AI-ELP adoption is crucial to ensure its effective implementation. This research study aims to extend the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating technophobia, technophilia, content quality, and functional quality. By examining the psychological tendencies of users toward technology and the quality aspects of AI-ELP, this study seeks to provide a comprehensive understanding of the adoption process. Through a quantitative study involving research scholars at IIT Kharagpur, the research will identify key factors influencing the acceptance and use of AI-ELP. The findings will have significant implications for educational practitioners, policymakers, and platform developers, enabling them to tailor strategies that address user concerns, enhance platform quality, and promote successful AI-ELP adoption in educational settings.

Keywords: artificial intelligence; e-learning platforms; UTAUT; technophobia; technophilia; content quality; functional quality; education technology adoption

1. Introduction

In recent years, the field of education has undergone substantial changes due to technological developments. The combination of computers, networks, multimedia, and information technology has generated e-learning [1]. This method integrates multiple technological components to create an interactive and engaging learning environment. There have been four distinct technological transformations within the domain of e-learning: "E-learning itself, m-learning (mobile learning), u-learning (ubiquitous learning), and smart learning" [2]. Each of these transformations has presented educational institutions with new opportunities and possibilities. M-learning, also known as mobile learning, takes advantage of the capabilities of mobile devices to facilitate learning. In contrast, ubiquitous learning uses digital content, mobile devices, pervasive components, and wireless connectivity to provide anytime, anywhere teaching and learning experiences [3]. In addition, technological progress has led to smart learning, which uses intelligent technologies such as the Internet of Things and wearables [4]. These technologies provide learners with greater flexibility, effectiveness, adaptation, engagement, motivation, and feedback [1].

The development of AI technology has had a significant impact on the future of education. AI-powered systems can provide pupils with individualized instruction, assistance, and feedback, as well as aid teachers and policymakers in decision-making processes [5]. This potential includes not only augmenting the learning experience for students but also redefining how educators approach education [6]. An artificial intelligence-powered e-learning platform (AI-ELP) can cater to the diverse requirements of all student demographics, providing a truly individualized and customized approach to education [7].

However, adopting and implementing AI-ELPs in educational institutions depends on several factors, including educators' acceptance and adoption of these technologies, which are crucial in facilitating their integration into the learning process [8]. When new technologies are introduced, they frequently bring enthusiasm and promise, presenting innovative and stimulating opportunities. Nevertheless, technology can elicit negative emotional responses, anxiety, and concerns in some individuals who perceive it as a danger to proven norms and behavior patterns that help us adapt to our environment [9]. As a result, individuals' reactions to new technologies can range from technophilia, which is an attraction to and ardent embrace of technology, to technophobia, which is a rejection or avoidance of technology.

In addition to psychological factors such as technophobia and technophilia, the content quality [10] and functional quality [11] of an AI-ELP are crucial adoption factors. The content quality of AI-enabled e-learning products is the practical evaluation by users of whether the content and personalization satisfy their learning needs [1]. Functional quality, on the other hand, encompasses the design and technical implementation of the interface and examines whether it meets users' requirements more effectively than conventional e-learning products [1].

There has been limited research on the combined effects of psychological factors such as technophobia and technophilia with physical characteristics such as content quality and functional quality. This study investigates the relationship between content quality, functional quality, technophobia, and technophilia and their influence on future teachers' behavioral intention to adopt an AI-ELP. The existence of a study gap highlights the necessity to address differences in theories by investigating how psychological characteristics (such as technophobia and technophilia) and physical characteristics (such as content and functional quality) interact in the context of AI-ELP adoption. From a psychological perspective, it explores the complex relationship between fear and excitement toward technology, providing an understanding of users' cognitive and emotional responses. Behaviorally, the study scrutinizes future teachers' intentions, a crucial precursor to actual adoption. This study aims to reveal the practical consequences of this combination, promoting a more profound comprehension of how these interconnected aspects influence educators' readiness to adopt AI-ELP in their teaching methods.

To accomplish this goal, we propose extending the Unified Theory of Acceptance and Use of Technology (UTAUT) [12] by incorporating technophobia, technophilia, content quality, and functional quality. The UTAUT model is widely recognized for analyzing the acceptability of technology in numerous disciplines, including education [8,13] According to the UTAUT model, user usage and acceptance behavior are predominantly influenced by four direct factors: expected performance, expected effort, facilitating conditions, and social influence.[14] The model also identifies four moderating constructs: experience, voluntariness, gender, and age [12]. This study investigates the relationships between the extended UTAUT model, which includes technophobia, technophilia, content quality, and functional quality, and the behavioral intention to embrace an AI-ELP. To conduct this study, research scholars (future academicians) of IIT Kharagpur should be considered as a study point. Due to their academic prowess, technological expertise, and different academic backgrounds, as well as their representation of social, cultural, and economic diversity, IIT Kharagpur research scholars are perfect study participants. Doctoral students have strong analytical and critical thinking skills, broad academic resources, and a passion for knowledge development [15]. We may use IIT Kharagpur research researchers' intellectual talents, research rigor, and interdisciplinary viewpoints to acquire deep insights [16] on AI-ELP acceptance and inform the development of effective educational technology. However, as AI-ELP has not yet been implemented at IIT Kharagpur, it is essential to note that we will evaluate the behavioral intention to adopt AI-ELP as an indicator of usage intention.

Therefore, the primary aims of this study are as follows:

1) To determine the main influencing factors of AI-ELP adoption using the UTAUT framework;
2) To investigate the impact of technophobia, technophilia, content quality, and functional quality on AI-ELP adoption.

The organization of this paper is as follows. First, a comprehensive examination of the existing literature will be undertaken, focusing on AI-ELP, UTAUT, technophobia, and technophilia. We will construct hypotheses and research models based on our findings from the literature review. Following the description of the research methodology, we will analyze the data collected from 350 questionnaires distributed to research scholars at the Indian Institute of Technology, Kharagpur. The findings and their implications will be discussed. Finally, we conclude the paper by emphasizing its limitations and proposing future research directions.

2. Literature review

2.1. Artificial intelligence-e-learning platform (AI-ELP)

Artificial intelligence (AI), which simulates intelligent human behaviors such as inference, analysis, and decision-making, has advanced rapidly due to improvements in computational power and information processing capabilities [5]. These advancements enable AI technologies to support a variety of functions across educational programs, including personalized learning, decision support, and adaptive assessments. AI in education is now recognized for its potential to transform learning environments by providing individualized support tailored to each student's learning profile [17,18].

AI-based e-learning platforms (AI-ELPs) focus on "prevention and intervention" by analyzing learner behaviors to enable responsive, adaptive learning systems. These platforms aim to function like intelligent instructors by leveraging teachers' expertise within decision-making processes and enhancing students' engagement and outcomes. The concept of "adaptive learning systems" has evolved, modifying aspects like user interfaces, instructional materials, and learning pathways to adapt to the specific needs and progress of individual learners. Such systems are categorized based on their functionality and roles, including the Intelligent Tutor, Intelligent Tutee, Intelligent Learning Tool, and Policy-Making Advisor [5].

Intelligent tutors, such as personalized learning systems and intelligent tutoring systems like AutoTutor, deliver tailored educational experiences [20]. Intelligent tutees actively engage students by allowing them to teach AI systems, thereby developing higher-order thinking skills (e.g., Microsoft Tay) [19]. Intelligent learning tools help students collect and analyze data efficiently, promoting deeper insights and critical thinking [19]. At a broader level, AI systems can also support education policymakers by identifying trends and evaluating the effectiveness of educational initiatives from both macro and micro perspectives, facilitating data-driven policymaking [20].

For an AI-ELP to have its intended impact, however, adoption by educators is critical, as their role is central in fostering students' acceptance and effective use of these technologies. This study aims to examine the factors influencing AI-ELP adoption, focusing specifically on psychological factors (e.g., technophobia, technophilia) and quality attributes (e.g., content and functional quality), which prior studies have shown to significantly shape technology adoption intentions. The insights from this research seek to inform targeted strategies for AI-ELP design and implementation in educational settings.

2.2. AI-adoption

The adoption of AI technology in organizational settings involves the integration of both new and existing technologies, resulting in innovative and transformative systems [21–24]. Effective adoption requires institution-wide implementation and ongoing tracking post-deployment to ensure successful integration. A clear understanding of technology's functions and capabilities is essential, as it facilitates smoother deployment and acceptance of AI by end-users, especially within educational contexts [25]. The adoption process typically unfolds in three key phases: (a) initiation, where organizations recognize the need for technological change and allocate necessary resources; (b) adoption, involving the organization's readiness and acceptance of the innovation; and (c) implementation, the active integration of the technology into routine operations [21].

However, research identifies several obstacles to AI adoption. First, reliance on AI for critical decision-making can lead to scrutiny and resistance, particularly within education, where decisions impact learning outcomes and data security [24]. Privacy, security, and transparency concerns present significant hurdles, as algorithms are often "black boxes" that lack visibility into their processing logic. This opacity can result in hesitancy among users, particularly educators and administrators, to fully trust the technology [21]. Additionally, fears around job displacement complicate AI adoption, as individuals may perceive AI as a threat to traditional educational roles, though it is argued that creativity and human ingenuity will remain invaluable [24].

The adoption of AI is also complicated by demographic factors. For instance, older users may prefer direct human interactions over AI-based systems, a preference that poses challenges for the widespread acceptance of AI in educational settings. Furthermore, resistance to technological changes remains a barrier, especially among employees who may be unfamiliar or uncomfortable with AI's capabilities [24].

To assess the factors influencing AI adoption in this study, we extend the "Unified Theory of Acceptance and Use of Technology" (UTAUT) to include constructs such as technophobia and technophilia, reflecting both barriers and enablers specific to AI-Enhanced Learning Platforms (AI-ELP). This approach allows a comprehensive analysis of psychological and practical adoption factors. By identifying and addressing these barriers, this study aims to inform strategies that can facilitate smoother AI-ELP adoption among educators and educational institutions.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

This study's theoretical foundation is based on the UTAUT model. We choose UTAUT as a base because it has a wide range of uses and can explain how people adopt or accept technology [24]. The UTAUT model is considered to have the ability to explain technology acceptance better than other technology acceptance models [25]. The UTAUT model suggests that performance expectancy, effort expectancy, facilitating conditions, and social influence directly affect user use and acceptability. The model suggests that experience, voluntariness, gender, and age moderate these main factors [24]. **Table 1** gives the definitions of the constructs.

Table 1. UTAUT construct definitions.

Constructs	**Definitions** [24]
Performance Expectance	To what extent will technology help individuals do specific tasks
Effort Expectance	User ease of use with technology
Social Influence	Users believe that important persons recommend a specific technology.
Facilitating Conditions	Perception of resources and support for behavior
Behavioral Intention	The stronger the will to execute, the more likely the behavior will be performed.

The UTAUT is powerful; however, it is a context-independent technology adoption model [24]. According to UTAUT studies on different technologies, their major predictors may affect technology use behavior differently [25]. To understand AI-ELP acceptance among IIT Kharagpur researchers, we extend UTAUT utilizing technophobia, technophilia, perceived content, and function quality. Since IIT Kharagpur has not established an AI-ELP, students will not have any exposure to it. Thus, moderators' experience and voluntariness can be removed.

2.4. Technophobia

This study focuses on the fear of technology or technophobia. Technophobia is "an irrational fear and/or anxiety that individuals form as a response to a new stimulus that comes in the form of a technology that modifies and/or changes the individual's normal or previous routine in performing a certain task. Individuals may display active, physical reactions (fear) such as avoidance and/or passive reactions (anxiety) such as distress or apprehension" [26]. Technophobia is due to "a past, present, or anticipated interaction with a computer; a negative attitude towards computers in general; or a self-critical internal interchange in the presence of a computer" [27]. Technophobia is a significant problem in modern society because many people have negative views of new technology and resist embracing it despite the widespread use of technological improvements in every aspect of life [28].

For fear of looking incompetent, many people stick to tried-and-true methods of accomplishing their work or limit themselves to using high-powered tools just for the most fundamental operations [9]. Fear of new technologies, especially artificial intelligence (AI), is a significant problem today since it can cause people to be less productive at work, more likely to call out sick, and more susceptible to cyberattacks [29]. Luquire states, "Technology developments should always be considered from an attitudinal or psychological standpoint. Because adopting new technology at work throws folks into an environment with which they are unaccustomed". This lack of familiarity produces worry and anxiety, which are frequently associated with technology [30]. Although a technological accomplishment, this innovation generates technophobia and discourages employees from adopting new technologies [30].

Technophobia is characterized by techno-paranoia ("unjustified fear and mistrust that individuals form toward a technology that leads individuals to avoid that technology; their fear and avoidance of technology might not be supported with evidence or facts")[31],Techno-Fear ("unpleasant feeling of fear that an individual experience in the presence of technology where it might be perceived as a threat to his/her current norm"), Techno-Anxiety ("feeling of nervousness and unease an individual might feel about the potential use of technology"), Cybernetic-Revolt ("fear of technology an individual feel because he/she believes that technology is collecting his/her information and one-day it may become self-aware, and for a malicious or defensive reason, and take over the world"), Techno-avoidance ("individuals' avoidance of technology which might result from individuals' fear or anxiety regarding the unintended consequences of this technologies") [28]. This study intends to understand the role of technophobia in adopting a highly technological system like AI-ELP and how it interacts with other technology adoption factors.

2.5. Technophilia

Technophilia is a favorable attitude towards new technology, highlighting the "pleasure and emotional" aspects that precede the acceptance of novel technologies [32]. Technophilia "generally refers to the enthusiasm generated by the use of technology. It is expressed by easily adapting to the social changes brought by technological innovations" [33]. It highlights how technology can evoke strong, futuristic positive feelings. In a nutshell, technophilia is a way of looking at the world in which all new technology is seen as naturally good and helpful to people. A technophile likes technology and wants to learn more about it. Technophiles love technology and see it as good for society [28].

Technophilia can be characterized by enthusiasm, dependency, and techno-reputation [9]. Technophilia involves a strong interest or enthusiasm for technology, especially emerging technologies like desktops and laptops, the internet, cell phones, and other devices [32]. Schien et al. [33] reported that a solution becomes a reality when a group of people (or society) uses it regularly to address a problem. Thus, people view reality that way and cannot envision acting otherwise (for example, the internet or messaging apps). Because of this, people become dependent on technology, which makes them anxious when they can't use it. So, dependency is another type of technophilia, described as the repeated use of technology because of a strong desire to feel its effects [9]. Since technophiles view technologies as natural societal developments, improvements to daily life, or forces that will transform reality for the better, they combine their enthusiasm and reliance with a fear of falling behind and missing the chance to join the technological advance. This is termed techno-reputation [34]. High techno-reputation can cause someone to spend a lot of money on unnecessary electronics merely to have the latest models. Long-term adoption and use of technology result from technophilia, which emphasizes an attitude to technology that embodies the characteristics of that particular technology [35]. Thus, this study includes technophilia as a construct to use the adoption characteristics of an AI-ELP [36].

2.6. Perceived content quality and functional quality

Any ELP, whether AI-enabled or natural, will be judged by its effectiveness, the quality of its content, and the functions it can perform. This study will determine how much the content quality and functional quality of the AI-ELP Package will affect the adoption decision of its users [37]. Content quality is a measure of how good the course content is. It looks at how accurate, factual, accessible, well-designed, and suitable the course content is. Content quality provides enough material for the target audience, i.e., students, to accomplish the course's objectives [38]. Content quality plays a crucial role in user satisfaction that could ultimately lead to the system's adoption. Content quality has two dimensions, "content richness" and "update frequency" [36]. Content richness has a positive effect on students' course satisfaction. It is determined by how the users can adapt to the system in comparison to traditional methods of teaching [36]—for example, the internet. The internet has more information than any other form of technology, and all of that information can be used as course material. Links and interactivity on the internet allow students and teachers to interact and utilize many tools besides the basic course materials. The update frequency dimension is also of equal importance. Any new technology is only applicable if it is abreast of the latest offerings. Ronit [37] found that learners would be much happier if they had access to regularly updated e-learning material.

Functional quality is defined as "the functional interface design and technical implementation and whether it meets the needs of the users more than traditional e-learning products" [11]. AI-enabled education solutions provide immersive learning using conversations, graphics, and cinematic scenarios to simulate real-life learning [1]. After initial adoption, the user interface can influence the user's sentiments and assumptions compared to the conventional printed reading method. In their experiment with e-learning portals, [11] stated that the portal can determine the student's learning style and tailor the content and user interface to accommodate that learning style. The student's potential for learning will increase as a result of this. Because the student usually lacks sufficient time to go through all the different kinds of material that pertain to a specific subject, the portal will personalize and offer just those items that will improve the student's overall satisfaction with learning. The functions comprise the GUI and its overall layout.

3. Theoretical underpinnings and hypothesis development

The research study is based on carefully chosen theoretical frameworks, each of which plays a crucial role in enhancing our comprehension of the intricate process of implementing AI-ELP in educational institutions. The core framework of this theoretical foundation is the Unified Theory of Acceptance and Use of Technology (UTAUT) [24]. The UTAUT model, well-known for its capacity to understand the dynamics of technology adoption, emphasizes the crucial significance of perceived ease of use and perceived usefulness. Within the scope of our research, this implies that UTAUT serves as a reliable framework for understanding how users perceive the ease of using AI-ELP and their evaluation of its usefulness [39,40]. These factors greatly influence their attitudes and intentions toward adopting AI-ELP.

The Task-Technology Fit (TTF) Theory [41], an essential context in our theoretical framework, builds upon UTAUT by highlighting the importance of aligning technology with the specific educational tasks it aims to support. The TTF Theory emphasizes that the quality of AI-ELP content and its practical characteristics are crucial in guaranteeing a smooth alignment with educational goals [42]. This alignment is congruent with UTAUT's emphasis on perceived utility, as it guarantees that the AI-ELP efficiently facilitates and improves educational tasks, resulting in increased user approval.

The Information Systems Success Model [43] enhances our understanding of AI-ELP adoption by emphasizing the importance of content and functional quality. This approach emphasizes the significance of both system and information quality, along with UTAUT's emphasis on the perception of utility. The presence of high content and functional quality is crucial for a successful information system. These qualities immediately contribute to improved user satisfaction and, as a result, boost the overall performance of the system [44].

Cognitive load theory contributes a cognitive aspect [41] to our theoretical framework. This theory emphasizes the significant influence of material quality on cognitive load, which in turn has a substantial effect on the adoption of AI-ELP. Cognitive load theory posits that the use of well-organized and captivating material can reduce the mental strain on learners, thereby enhancing the efficiency of the learning process [41]. This aligns precisely with the research's focus on the quality of content, as improving the quality of content in AI-ELP materials efficiently reduces the mental effort required and promotes higher user approval [45].

The Expectancy-Value Theory focuses on user attitudes, specifically highlighting their expectations and perceived value regarding adopting technology [46]. This theory elucidates the substantial impact of technophobia and technophilia on users' attitudes and perceptions. This assertion suggests that technophobia can lower user expectations and perceived value while technophilia can increase these expectations and value perceptions, which is in line with UTAUT.

Finally, the social cognitive theory emphasizes the influence of peers and instructors in molding user attitudes [43] toward the adoption of AI-ELP, highlighting the significant role played by the social aspect. Negative comments from peers may influence individuals who have a fear or aversion to technology. In contrast, those who have strong enthusiasm for technology are more inclined to adopt AI-ELP because of positive peer influence.

3.1. Direct impact on behavioral intention to adopt AI-ELP

Most research based on UTAUT claims that performance expectancy is the primary variable influencing consumers' willingness to use a product [29]. In implementing information technology systems, performance expectancy refers to the extent to which the system increases work performance. The performance expectancy is defined in this study in the context of using AI-enabled goods; thus, the PE suggests that users can obtain improved learning performance [1]. The convenience offered by e-learning is another topic covered in the practical experience. Mobile phones, particularly in this age of the mobile web, are frequently used to acquire new information and to further one's education [3]. So, it is clear that users' willingness to use AI-ELP systems will increase when they believe that doing so will enhance their professional productivity or provide them with benefits. Hence

H1. Performance expectance positively influences behavioral intention to adopt AI-ELP.

According to the Effort Expectance concept, consumers do not want to devote excessive time and effort to becoming familiar with a new system [1]. EE can also refer to the extent to which artificial intelligence-powered educational solutions are simple. Users' perceptions of a new product or system's ease of use are major factors in determining how well it will be accepted [45]. Venkatesh et al. [24] define effort expectancy as the user's subjective estimate of the new technology system's ease of running. This appraisal is a relationship between human beings and technologies and is one of the underlying motives influencing usage behavior [46]. Hence

H2. Effort expectancy positively influences behavioral intention to adopt AI-ELP.

Social Influence (SI) refers to the belief held by consumers that influential individuals deem it necessary for them to utilize a particular technology [24]. Social norms, observable behavioral patterns commonly exhibited among members of a social group, serve as a powerful motivator for individuals to embrace innovative solutions like artificial intelligence (AI) to gain social recognition and status [47]. Users can use AI-based customer relationship management (AI-CRM) to enhance their perceived societal image and attain the desired social recognition and status [48]. The continued adoption of AI technology can be seen as a means for individuals to conform to group membership and establish a sense of identification through the image associated with the technology [45]. Hence, in the case of AI-ELP, we propose that

H3. Social influence positively influences behavioral intention to adopt AI-ELP.

Venkatesh et al. [24] explain that facilitating conditions (FC) refer to the perception individuals have regarding the presence of a suitable technological framework that enables the adoption of new technologies like AI-integrated eLearning Platforms (AI-ELP) systems. Previous research, as indicated by Chen et al. [49], has highlighted the significant role of FC in determining the acceptance of technology, thereby influencing its adoption and usage patterns. If the existing technical infrastructure is user-friendly and encourages system usage among employees [24], it becomes easier for staff members to utilize the AI-integrated ELP system. In simpler terms, users with better support and resources are more inclined to embrace the adoption of AI-ELP

H4. Facilitating conditions positively influence behavioral intention to adopt AI-ELP.

According to Papp [38], content quality describes how well-done a course's materials are regarding the correctness, authenticity, accessibility, design, and suitability for the target audience. Its primary goal is to give students access to enough material to complete the course's objectives, essential for user satisfaction and system adoption [50]. According to Lee [39], "content richness" and "update frequency" are the two dimensions that make up content quality. Compared to conventional teaching approaches, content richness measures how well users can adapt to the system [39]. The update frequency dimension is also crucial because the usefulness of any new technology depends on how well it keeps up with contemporary developments [37]. Learners who have access to frequently updated e-learning resources report feeling more satisfied [37]. Thus, we hypothesize that

H5. Content quality positively influences behavioral intention to adopt AI-ELP.

AI-enabled educational products use voice interaction, animation, and movies to create immersive learning experiences. These features engage users by simulating learning. Liu and Sun [51] stressed the importance of mobile reading services. After early acceptance, the interface may significantly alter users' experiences and expectations relative to paper-based reading. Kolekar et al. [11] stressed the relevance of learning preferences and user interface customization in e-learning site frameworks. This strategy improves students' learning by providing materials that match their learning styles. Due to time restrictions, students use the portal's personalized information to boost learning [39]. Functional interface, including layout and user interface design, was positively correlated with user enjoyment [52]. Hence

H6. Functional quality positively influences behavioral intention to adopt AI-ELP.

Khasawneh [30] defines technophobia as an irrational fear and anxiety about unknown or new technologies. Fear and anxiety hinder the adoption of AI-related technologies [32]. New technology can be difficult for personnel without prior familiarity. Unfamiliarity causes anxiety [53]. Uncertainty comes from not knowing how to use the technology or how it will affect their work [54]. Anxiety can lead to technophobia [30]. Technophobia can lead to reluctance, resistance, or avoidance of new technology, particularly AI-based systems [32]. Technophobia generally stems from worries about ineptitude, loss of control, or adverse effects of modern technology [55]. Technophobia may cause employees to refuse or reject new technology, slowing or halting adoption [32,56]. Technophobia can make workers wary of AI-based solutions in the workplace. Hence

H7. Technophobia inversely impacts behavioral intention to adopt AI-ELP.

Technophilia is a personality trait that increases a person's propensity for adopting positive attitudes, a sense of curiosity, and openness [55]. A stronger intention to interact with AI technology may result from this positive outlook and passion for technology [57]. Technophiles frequently see the positive, engaging, and important aspects of technology. They are more likely to welcome new technical developments and think AI-powered technologies can improve their educational experience [32]. This favorable perception makes them more motivated and willing to accept and use these platforms. Technological self-efficacy is the degree to which a person believes they can utilize and interact with technology successfully [10]. Technophiliacs frequently exhibit higher levels of this self-efficacy. As a result of their increased self-efficacy, they have more confidence in their ability to operate and use AI-powered devices, which supports their decision to adopt them [35]. A proactive and adventurous mindset is frequently linked to technophilia. Technophiles are more inclined to actively seek out possibilities for learning and development, use new technologies, and participate in technology-related activities [58]. Hence, we hypothesize that

H8. Technophilia positively influences behavioral intention to adopt AI-ELP.

3.2. Moderation effects

Venkatesh et al. [24] found that the relationships between performance expectancy, effort expectancy, social influence, and facilitating conditions were influenced by age and gender. However, no existing literature explicitly explores the impact of age or gender on technophobia, technophilia, content quality, or functional quality. Hence, this study examines the moderating effect of age and experience on technophobia, technophilia, content quality, or functional quality. Thus, we hypothesize that.

H9a: Age moderates the impact of PE, EE, SI, FC, technophobia, technophilia, content quality, and functional quality on behavioral intention to adopt AI-CRM.

H9b: Gender moderates the impact of PE, EE, SI, FC, technophobia, technophilia, content quality, and functional quality on behavioral intention to adopt AI-CRM.

3.3. Inter relationships between constructs

Technophobia is the dread of technology, while performance expectation (PE) is the perceived benefits consumers expect from a system. Existing literature does not explicitly link technophobia with PE. However, “computer anxiety” reduces technology’s perceived utility [58]. Technophobia, fear, and anxiety about technology may prevent people from seeing AI-ELP systems’ benefits. Technophobia may deter users from adopting and using the system. Due to their fears and concerns, employees with higher technophobia levels may oppose or shun AI-ELP systems. Therefore, their opinions of the system’s utility and potential benefits may decrease. Thus, we propose

H10. Technophobia inversely impacts performance expectancy.

“Effort expectancy” refers to the perceived ease of use connected with any given technology. Brosnan [58], in his study of word processor acceptance, said that computer anxiety (technophobia) caused users to perceive that the system was not easy to operate and harder to learn. Even though a direct correlation between technophobia and effort expectancy has not been reported in the existing literature. However, we propose that technophobes find working with AI-ELP difficult. Thus

H11. Technophobia inversely impacts the effort expectancy.

According to Venkatesh et al. [24], a user's psychology might be significantly influenced to use new technology if they perceive that influential people want them to adopt a specific technology. Social influence is another term for this perception. Important people in an organization can play a role in encouraging their peers and subordinates to take advantage of a relatively new technical solution. According to Meyer-Waarden and Cloarec [47], social norms push people to accept new technologies to gain social recognition and prestige. According to Moore and Benbasat [59], early technology adoption can help promote the "image" of personnel. Because of this motive, an employee's perception of the dangers of technology may improve, making it more likely that they will readily adopt new technologies such as AI-CRM. By giving consumers the desired social recognition and improved social status, AI-CRM has the potential to help users improve their image as seen by society [48]. Thus,

H12. Social influence inversely influences technophobia.

The support and resources that employees believe to be available to use a system are known as "facilitating conditions". Venkatesh et al. [24] state that organizations create "facilitating conditions" to reduce obstacles preventing people from using technology. Venkatesh and colleagues [45] claim that certain "task-related behaviors would not be possible without infrastructure of conditions capable of facilitating the interactions necessary for task completion." In other words, if a support structure is provided to the user to understand and utilize any technology, including technical help, they are more eager to use it [53]. According to research by Baptista and Oliveira [44] and Dwivedi and his colleagues [24], this is true. According to Galiveeti et al. [60], the facilitating conditions consist of technical information, technical support, hardware and software, training, guidance, and on-the-job assistance. It is possible to conclude from this information that if an employee perceives that all of the necessary facilitating conditions are present, their level of anxiety around the use of innovative technology such as AI-CRM will significantly decrease. Hence

H13: Facilitating conditions inversely impact technophobia.

Technophobia is an unreasonable fear and worry about technology, while AI e-learning system content quality is the quality and applicability of educational content. There is no existing literary connection between technophobia and content quality. High content quality in an AI e-learning system means accurate, well-designed, accessible, and acceptable for the intended audience [38]. High-quality content meets students' needs and interests. Technophobia is technology-related anxiety. Technophobia can complicate using technology, notably AI-ELP [30]. Technophobes' fear and anxiety about technology [61] will decrease as an AI-ELP perceived content quality. High-quality information can make learning more accessible and more supportive by reducing technology-related worries. We propose that an AI e-learning system with well-designed and compelling content can ease technophobia. It can help them feel comfortable and confident utilizing the system, reducing their nervousness. Thus H14. Content quality inversely impacts technophobia.

Technophobia is people's fear and anxiety when using technology [30], whereas an AI-ELP's functional quality refers to the platform's functionality, usability, and user interface. No academic research has linked functional quality to technophobia. An AI-ELP's excellent functional quality denotes the platform's user-friendliness, effectiveness, and efficiency in enabling learning. It delivers seamless user experiences, interactive features, intuitive interfaces, and a wealth of resources [11]. Technophobia, on the other hand, is characterized by fear and worry about technology. Higher technophobic individuals may show resistance, reluctance, or avoidance when interacting with technology [32], especially AI-ELPs. We suggest that people with technophobia are more likely to experience a decrease in their fear and anxiety towards using the platform as the functional quality of an AI-ELP increases. A platform with excellent functional quality may help users get over their reservations and develop confidence when using the technology. We propose

H16. Functional quality inversely impacts technophobia.

Technophilia [62] is a great affinity or enthusiasm for technology, whereas technophobia is people's fear and worry about it. An aversion or fear of using technology is known as technophobia [30]. When using technology, people with high degrees of technophobia frequently show fear, discomfort, or avoidance [63]. Technophilia, on the other hand, is characterized by an optimistic outlook and a keen interest in technology [63]. Technophiles are eager, inquisitive, and receptive to learning about and embracing technology. People are more open to the advantages and potential of technology when they can get past their fear and anxiety about it [55]. They grow to embrace technology as a tool to improve their productivity, communication, learning, and several other facets of their lives [35]. On the contrary, those with high degrees of technophobia may resist or reject technology because of the perceived dangers, difficulties, or uncertainties involved in using it [64]. Their nervousness and fear prevent them from adequately engaging with and appreciating the benefits of technology. A positive outlook and a desire to engage with and absorb technological developments may be fostered through overcoming technophobia, which may result in a higher acceptance and appreciation of technology's potential advantages. Higher degrees of technophobia may result in a reduced propensity to embrace and adopt new technologies. In contrast, lower levels of technophobia are more likely to show higher levels of technophilia. Hence

H17. Technophobia inversely impacts technophilia.

4. Research methodology

4.1. Sample size

We used Daniel Soper's a priori sample size calculator for structural equation modeling (SEM) to determine the sample size [65]. This tool considers the number of observable and latent variables, the expected effect size, and the desired levels of statistical significance and power [66]. It provides two key outputs: the minimum sample size to detect the given effect and the minimum sample size for statistical significance [67]. Setting the estimated effect size at 0.3, desired statistical power at 0.9, and p at 0.05, with ten latent and 43 observed variables, the calculator recommended a minimum sample size of 120 for model structure and 232 to detect the given effect. Adding a safety factor of 50%, we determined a sample size of 350. (see **Figure 1**)

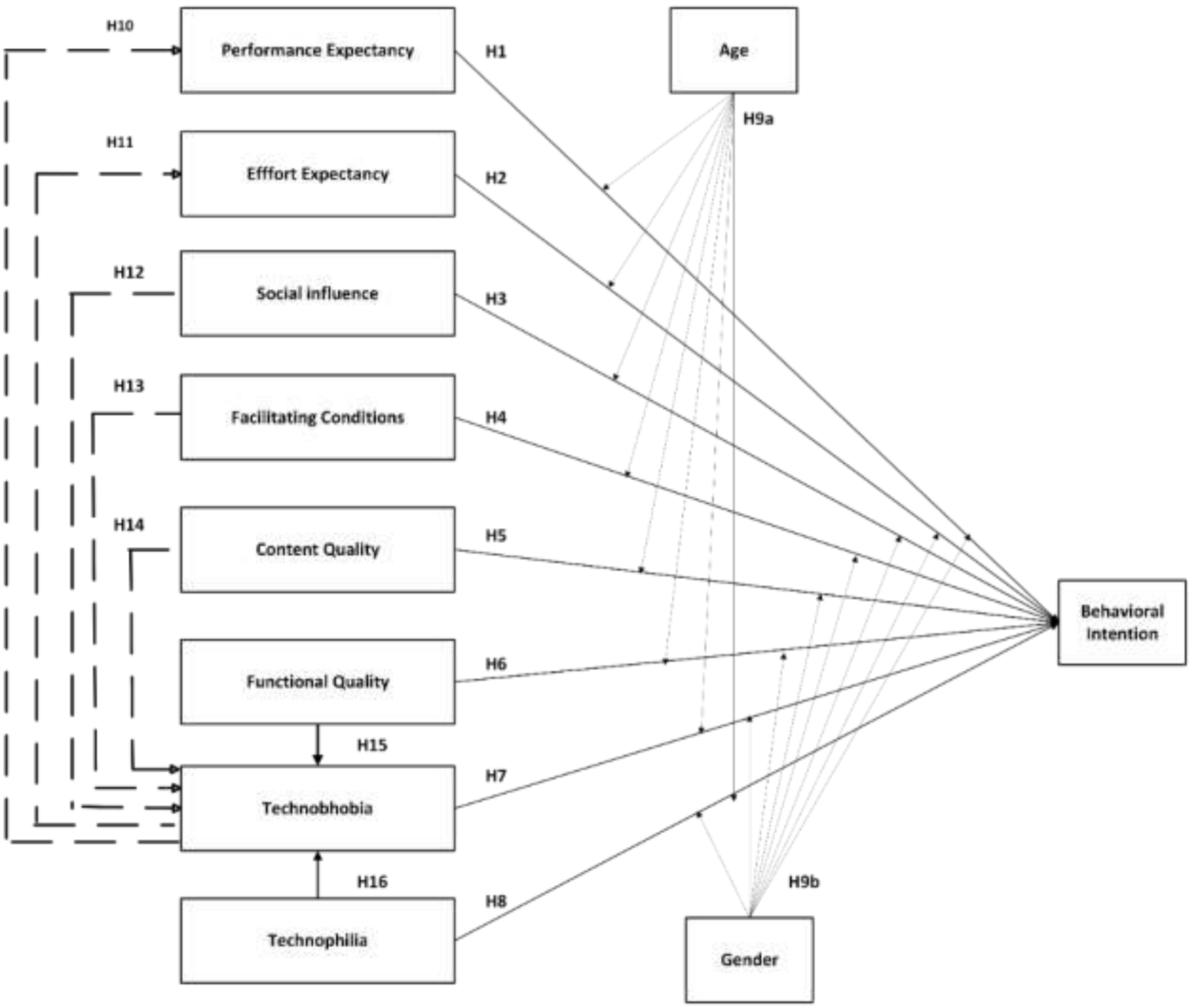

Figure 1. The conceptual model.

4.2. Procedure, questionnaire, and data collection

We developed a questionnaire with two parts: sociodemographic characteristics and construct-specific items related to AI-ELP adoption factors. The construct-specific section included questions designed around UTAUT variables (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions), as well as technophobia, technophilia, content quality, and functional quality. Each question was formulated based on validated scales from previous research to ensure reliability and relevance to the AI-ELP context. The sources of these questionnaire items are mentioned in **Table 2**. Responses were recorded using a five-point Likert scale (strongly disagree to strongly agree) across 42 questions. The questionnaire targeted research scholars at IIT Kharagpur, leveraging their academic expertise and technological proficiency to yield insightful data on AI-ELP adoption. To enhance content validity, we conducted a pilot test with a small group from the target population, refining questions based on feedback for clarity and appropriateness. Data collection spanned from March to April 2023, with in-person distribution ensuring response accuracy and completeness. Participants volunteered without compensation, fostering genuine responses and minimizing bias.

Table 2. Demographics of the respondents.

	n	**M (years)**	**Responses**				
Age Distribution	414	28	18–24	25–29	30–34	35–39	40+
			18%	65%	14%	1%	2%
Gender			Male	Female			
			64%	36%			

4.3. Data filtering

From 450 responses, we implemented rigorous filtering to ensure data integrity. Incomplete responses were discarded, and those with a standard deviation of 0.25 or below were excluded for potential inconsistencies (Collier). This process yielded 414 reliable responses, surpassing the threshold of 350.

4.4. Data analysis and results

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SMARTPLS4 software for data analysis. PLS-SEM was chosen due to its suitability for exploratory research models and its flexibility in handling complex models that include both reflective and formative constructs. This method allows us to analyze multiple dependent variables simultaneously and capture the relationships between latent constructs in our AI-ELP adoption model. PLS-SEM performs robustly with smaller sample sizes and non-normal data distributions, making it ideal for our sample of research scholars [68]. SMARTPLS4's user-friendly interface, ability to handle various data types, and advanced features like bootstrapping and Monte Carlo simulations make it a popular choice for PLS-SEM. This software's robustness and continuous updates make it a reliable tool for deriving essential insights from data, particularly in research contexts requiring detailed structural analysis.

4.5. Validity and reliability tests

We calculated the factor loadings to evaluate each item's convergent validity and assessed the validity, consistency, reliability, and multicollinearity of each construct. This involved measuring the average variance extracted (AVE), Cronbach's alpha (α), composite reliability (CR), and variance inflation factor. All estimates were within acceptable ranges, indicating good validity and reliability. According to Fornell and Larcker [69], the square roots of AVEs exceeded the corresponding bi-factor correlation coefficients, confirming discriminant validity. Additionally, the HTMT ratio was below 0.9 [70], further confirming discriminant validity. Detailed results are presented in **Tables 3–5**.

Table 3. Factor loadings, composite reliability, internal reliability, and convergent validity.

Constructs/Items	***λ***	**CR**	***α***	**AVE**
Performance Expectancy (Adapted from Venkatesh et al. [22])		0.86	0.79	0.61
PerEx1: Using AI-ELP would help me improve my productivity.	0.83			
PerEx2: Using AI-ELP would enhance effectiveness on the job	0.77			
PerEx3: The use of AI-ELP can significantly increase the quality of output on my job	0.8			
PerEx4: Using AI-ELP, I can accomplish my tasks more quickly.	0.72			
Effort Expectancy (Adapted from Venkatesh et al. [22])		0.84	0.72	0.64
EffEx1: Learning to use AI-ELP would be easy for me.	0.76			
EffEx2: Using AI-ELP would take too much time from my regular duties	0.87			
EffEx3: I would find AI-ELP easy to use	0.77			
Social Influence (Adapted from Venkatesh et al. [22])		0.84	0.72	0.64
SoIf1: People who are important to me think I should use AI-ELP	0.75			
SoIf2: I would use AI-ELP if a proportion of my co-workers use it.	0.82			
SoIf3: People who use AI-ELP have more prestige.	0.83			
Facilitating Conditions (Adapted from Venkatesh et al. [22])		0.78	0.71	0.54
FaCo1: I will have the necessary resources to use AI-ELP	0.72			
FaCo2: I will have the necessary knowledge to use AI-ELP	0.74			
FaCo3: Technical support will be available for difficulties using AI-ELP.	0.74			
Content Quality (Adapted from Lee [15])		0.86	0.75	0.67
CQ1: I believe that using AI-ELP would enable students to access study information more quickly.	0.79			
CQ2: I believe that using AI-ELP makes it easier for students to visualize content	0.8			
CQ3: I believe students would find AI-ELP to be a useful option for acquiring curriculum knowledge.	0.84			
Functional Quality (Adapted from Kolekar et al. [11])		0.89	0.82	0.74
FQ2: I believe the AI-ELP will have all the cues that will help students easily understand the media content.	0.86			
FQ3: I believe the AI-ELP will have all the cues that will help students better understand the media content.	0.87			
FQ4: I believe the AI-ELP will have all the cues that will help students quickly understand the media contents	0.84			
Technophobia (Adapted from Khasawneh and Technophobia [31])		0.8	0.73	0.57
TP3: I am afraid of AI because it may interfere with my file emotionally, physically, and psychologically.	0.76			
TP4: I feel more comfortable dealing with humans rather than AI	0.76			
TP5: Thinking about using AI makes me nervous and anxious.	0.76			
Technophilia (Adapted from Martínez-Córcoles et al. [9])		0.77	0.75	0.53
TPH1: I am excited about AI-ELP as it is a new technology.	0.74			
TPH2: I am afraid of being left behind if I cannot use the latest equipment or technology.	0.71			
TPH3: I enjoy using new equipment or technology.	0.72			

Table 3. (*Continued*).

Constructs/Items	*λ*	CR	*α*	AVE
Behavioral Intention (Adapted from Venkatesh et al. [22])		0.87	0.77	0.69
BevInt1: I intend to use AI-ELP in the future.	0.86			
BevInt2: If I have access to AI-ELP, I predict that I will use it	0.85			
BevInt4: I predict using AI-ELP for daily work	0.77			

AVE = Average Variance Extracted; α = Cronbach's Alpha; λ = Factor Loadings; CR = Composite Reliability.

Table 2. Fornell–larker criteria to determine discriminant validity.

Construct	PerEx	EffEx	SoIf	FaCo	CQ	FQ	TP	TPH	BevInt
PerEx	0.6118								
EffEx	0.1672	0.6417							
SoIf	0.1901	0.0891	0.6388						
FaCo	0.1891	0.2442	0.1064	0.5393					
CQ	0.2748	0.1209	0.1058	0.1985	0.665				
FQ	0.1594	0.1018	0.0894	0.1783	0.28	0.7351			
TP	0.0314	0.0341	0.1905	0.0049	0.0139	0.0018	0.5739		
TPH	0.1878	0.0871	0.0754	0.1421	0.2703	0.1475	0.0338	0.5264	
BevInt	0.2104	0.0833	0.0983	0.1714	0.2573	0.1737	0.0334	0.257	0.6868

PerEx = Performance Expectancy; EffEx = Effort Expectancy; SoIf = Social Influence; FaCo = Facilitating Conditions; CQ = Content Quality; FQ = Functional Quality; TP = Technophilia; TPH = Technophilia; BevInt = behavioral intention.

Table 3. HTMT ratio to determine discriminant validity.

Construct	PerEx	EffEx	SoIf	FaCo	CQ	FQ	TP	TPH	BevInt
PerEx									
EffEx	0.552								
SoIf	0.5674	0.4012							
FaCo	0.6366	0.7567	0.4831						
CQ	0.683	0.4606	0.4323	0.6567					
FQ	0.4983	0.4091	0.3898	0.6021	0.6645				
TP	0.2446	0.2828	0.0159	0.0985	0.1624	0.0547			
TPH	0.6492	0.453	0.3976	0.6645	0.8078	0.5658	0.3044		
BevInt	0.586	0.3776	0.4131	0.6062	0.6561	0.5263	0.2543	0.7678	

4.6. Common method bias

Table 4. VIF values of the inner model.

	PerEx	EffEx	SoIf	FaCo	CQ	FQ	TP	TPH
BevInt	3.184	2.939	2.347	2.763	2.962	2.86	1.885	2.812

This study uses self-reported data, which may cause common method bias (CMB). Applying the inner model's variance inflation factor (VIF), the CMB was analyzed. Since all values in the current analysis are below 3.33, the model has no common method bias [71]. **Table 6** illustrates inner model path VIFs.

4.7. Structural equation modeling for hypothesis testing

The suggested model was tested using a blindfolded method while considering an accelerated bootstrapping approach using 5000 resamples. The R^2 value was estimated to be 0.399, confirming that the model has predictive capacity [72]. This approach provided robust statistical analysis, considering the non-normal data distribution and small sample size. Our calculation of the Stone-Geisser Q^2 measure indicates a value of 0.32, confirming the results' significant predictive relevance [73]. Standardized root mean square residual (SRMR) has been used as an index to evaluate the model's fit [74]. The SRMR values are 0.0722, which is ≤ 0.08 [75].

Following the PLS-SEM analysis, the results show that all eight hypotheses were validated. The results highlight that the effect of PerEx on BevInt (H1) was significant, with a β of 0.1239 and a significance level of $p < 0.01$(**). The effect of FaCo on BevInt (H4) was also significant, with a β of 0.12871 and a significance level of $p < 0.01$(**). The results highlight that CQ positively impacted BevInt (H5) with a β of 0.1761 and a significance level of $p < 0.001$ (***). The effect of TP on BevInt (H7) was significant, with a β of −0.0871 and a significance level of $p < 0.05$ (*). The impact of TPH on BevInt (H8) was significant, with a β of 0.2433 and a significance level of $p < 0.001$(***). However, the effects of SocInf on BevInt (H3), EffEx on BevInt (H2), and FQ on BevInt (H6) were insignificant. The results are shown in **Table 7**.

Table 7. Direct effects of constructs on behavioral intention.

Path	Hypothesis	*β*-value	*T*-value	*p*-value	Remarks
PerEx → BevInt	H1	0.1289	2.5631	0.0053	Significant**
EffEx → BevInt	H2	−0.0325	−0.6257	0.2658	Insignificant
SoIf → BevInt	H3	0.0685	1.3161	0.0942	Insignificant
FaCo → BevInt	H4	0.1287	2.4691	0.0069	Significant**
CQ → BevInt	H5	0.1761	3.0982	0.001	Significant***
FQ → BevInt	H6	0.1104	1.6776	0.0469	Insignificant
TP → BevInt	H7	−0.0871	−2.1332	0.0166	Significant*
TPH → BevInt	H8	0.2433	3.9014	0.0001	Significant***

Note: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***).

Age as a moderator showed no significant impact on the relationship between the constructs and behavioral intention to adopt AI-ELP. However, gender shows partial moderation in the relationship between the constructs and behavioral intention to adopt AI-ELP. The effect of gender: x EffEx on BevInt was significant, with a β of −0.263 and a significance level of $p < 0.05$ (*). The effect of gender: x FaCo on BevInt was also significant, with a β of 0.461 and a significance level of $p < 0.01$ (**). This is shown in **Table 8**.

The inter-relationships are as shown in **Table 9**.

Table 8. Moderating effects of age and gender.

Path	Hypothesis	*β*-value	*T*-value	*p*-value	Remarks
Age: x CQ → BevInt	9a	0.014	0.149	0.881	Insignificant
Age: x EffEx → BevInt		−0.215	1.898	0.058	
Age: x FaCo → BevInt		0.161	1.703	0.089	
Age: x FQ → BevInt		0.123	1.117	0.264	
Age: x PerEx → BevInt		0	0.001	0.999	
Age: x SoIf → BevInt		−0.063	0.685	0.493	
Age: x TP → BevInt		−0.039	0.527	0.598	
Age: x TPH → BevInt		−0.038	0.389	0.697	
Gender: x CQ → BevInt	9b	−0.021	0.135	0.893	Partially supported
Gender: x EffEx → BevInt		−0.263	1.994	0.046*	
Gender: x FaCo → BevInt		0.461	3.019	0.003**	
Gender: x FQ → BevInt		−0.027	0.186	0.852	
Gender: x PerEx → BevInt		0.051	0.297	0.767	
Gender: x SoIf → BevInt		−0.016	0.127	0.899	
Gender: x TP → BevInt		0.122	1.074	0.283	
Gender: x TPH → BevInt		−0.027	0.178	0.859	

Note: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***).

Table 9. Inter-relationship amongst constructs.

Path	Hypothesis	*β*-value	*T*-value	*p*-value	Remarks
TP → PerEx	H10	−0.1979	−4.0123	0.0001	Significant***
TP→ EffEx	H11	−0.21	−3.9915	0	Significant***
SoIf → TP	H12	0.1644	1.0395	0.1494	Insignificant
FaCo→ TP	H13	−0.1307	−1.8993	0.0289	Insignificant
CQ → TP	H14	−0.1459	−2.2459	0.0125	Significant*
FQ → TP	H15	0.0223	0.2326	0.408	Insignificant
TP → TPH	H16	−0.2252	−5.3172	0	Significant***

Note: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***).

5. Discussion

5.1. Direct paths

The significant positive relationship between performance expectancy and behavioral intention aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), which asserts that perceived usefulness is a primary predictor of technology adoption [24]. In our context, individuals were more likely to engage with AI-ELP if they believed it would enhance their academic performance. This finding also reflects the Theory of Planned Behavior (TPB), where an individual's belief in the benefits of a behavior, such as improved efficiency or success, enhances motivation and commitment to perform it. The literature confirms that when the expected outcomes are positive, individuals are motivated to invest effort and resources [44], supporting the view that performance expectancy is crucial for behavioral intention in educational technologies.

The positive impact of facilitating conditions on behavioral intention reinforces UTAUT's premise that adequate support structures reduce perceived obstacles and increase technology adoption likelihood. This finding suggests that users with access to necessary resources, such as technical support and training, feel more confident using AI-ELP, which is consistent with Social Cognitive Theory [43]. The perception of available support fosters a sense of control over new technology, promoting engagement and reducing anxiety, as previous research has shown [54]. This confirms that users are more inclined to use AI-ELP when the environment supports seamless integration, reinforcing the relationship between facilitating conditions and behavioral intention.

The strong positive association between content quality and behavioral intention highlights that users are motivated to engage with AI-ELPs when they perceive the content as high-quality, relevant, and valuable. This finding aligns with Cognitive Load Theory [41], suggesting that well-organized and relevant content reduces cognitive load, enhancing the learning experience and encouraging repeated engagement. High-quality content meets users' informational needs, capturing their attention and promoting consistent use, as shown in studies on content-rich educational platforms.

The role of technophilia in enhancing behavioral intention toward AI-ELP highlights the importance of users' intrinsic motivation, as described by Self-Determination Theory [76]. Enthusiastic users are drawn to AI-ELP for exploration and enjoyment, exhibiting proactive adoption behavior due to positive emotional engagement. This aligns with findings from previous studies, where technophilia facilitates technology acceptance by reducing perceived barriers and promoting sustained interaction [56]. Technophiles' proactive use of technology aligns with the UTAUT model's notion of personal innovativeness as a facilitator of behavioral intention, underscoring that positive attitudes toward technology drive sustained engagement.

Interestingly, effort expectancy did not significantly impact behavioral intention, diverging from traditional UTAUT findings. This could indicate that users prioritize the anticipated benefits of AI-ELP (performance expectancy) or intrinsic enjoyment (technophilia) over the perceived ease of use. Similarly, the lack of impact from social influence suggests an independent decision-making approach among our sample, potentially due to their high academic proficiency, which aligns with previous research indicating that autonomous individuals are less swayed by social cues [45]. The non-significant role of functional quality implies that users may focus more on content relevance than technical attributes, which aligns with findings in educational technology where content quality often overshadows technical aspects [11].

5.2. Moderation's impact

Our analysis revealed that age did not significantly moderate the adoption factors, supporting findings from Venkatesh et al. [24], where age effects diminish in contexts with standardized technological skills, as seen in our sample of research scholars. Gender, however, moderated the relationship between effort expectancy and behavioral intention, indicating that perceptions of ease of use vary between genders, possibly influenced by sociocultural factors. This finding is consistent with Social Role Theory [28], which explains how gender differences in comfort with technology can arise due to prior experiences. Gender also moderated the influence of facilitating conditions on behavioral intention, suggesting that external support has a variable impact based on gender-related preferences and experiences, in line with findings that highlight gender-based differences in technology support utilization [12].

5.3. Inter-relationships

The significant negative relationship between technophilia and performance expectancy suggests that high enthusiasm for technology can lead to overly optimistic expectations, potentially resulting in disappointment when technology does not perform as anticipated. This finding is supported by expectation-confirmation theory [77], where unmet expectations can diminish perceived usefulness. Technophiles may hold inflated beliefs about AI-ELP capabilities, which may not align with reality, leading to a gap between expected and actual performance [34].

The negative link between technophilia and effort expectancy indicates that technophiles perceive tasks as easier due to their familiarity and confidence with technology, echoing findings from cognitive psychology where familiarity reduces perceived difficulty [33]. Their strong technological affinity may lead them to underestimate the required effort, potentially leading to complacency or reduced preparation for task challenges, as previously noted in studies on tech-savvy individuals.

A similar negative relationship between facilitating conditions and technophilia shows that technophiles may rely on their technical skills over external support, reflecting self-reliance and comfort in navigating technological environments. This finding is consistent with self-efficacy theory [43], which posits that self-confident individuals rely less on external support, perceiving themselves as capable of overcoming challenges independently [35].

The negative relationship between content quality and technophilia suggests that technophiles prioritize technological sophistication over content quality, indicating that novelty and interactivity may take precedence. This aligns with technology acceptance theory [78], where users focused on technology may prioritize innovation over content substance. These findings highlight that while technophiles are eager adopters, they may undervalue content quality when the technology itself is engaging.

Finally, the inverse relationship between technophilia and technophobia confirms that enthusiasm for technology generally diminishes fears associated with it, aligning with dual process theory [79], where positive attitudes can counteract anxiety. As previous studies suggest, technophiles' comfort and familiarity with technology act as buffers against technophobic tendencies, allowing them to view technology positively, even in potentially intimidating situations [30].

6. Implications

6.1. Theoretical contributions

This study offers significant theoretical contributions by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model, incorporating unique factors such as technophobia, technophilia, content quality, and functional quality.

Firstly, technophobia acknowledges users' apprehensions and concerns regarding AI technology adoption in AI-enhanced e-learning platforms (AI-ELP). These worries may encompass privacy, security, job loss, and other negative impacts associated with AI-ELP adoption. Addressing users' concerns and devising solutions to alleviate technophobia is paramount.

Secondly, technophilia recognizes individuals' positive attitudes towards technology, highlighting their curiosity and eagerness to engage with AI-ELP. Technophiles exhibit openness to new technologies, thereby enhancing adoption rates. Leveraging users' positive attitudes can significantly improve their learning experiences and bolster AI-ELP platform adoption.

Thirdly, content quality explains how instructional content influences AI-ELP adoption and use. Users value the relevance, correctness, credibility, interactivity, and overall quality of the platform's learning content. High-quality content enhances user engagement, satisfaction, and intent to use AI-ELP, thereby improving learning outcomes.

Lastly, the study's modified UTAUT model incorporates functional quality, encompassing aspects such as usability, performance, dependability, and system functionality of AI-ELP. Ensuring a user-friendly, effective, and trustworthy platform is crucial for promoting adoption. Technical issues or deficiencies can diminish users' tolerance and usage intentions, highlighting the importance of providing a seamless user experience and addressing technical challenges.

Moreover, this study adopts a user-centric approach, acknowledging individual differences and technology psychology. It emphasizes the significance of addressing both positive and negative attitudes and preferences to influence users' perceptions and usage of AI-ELP platforms. Additionally, the study underscores the contextual relevance of AI in education and its impact on users' opinions.

Furthermore, the research's unique aspect lies in its exploration of the interconnectedness of variables. By studying the interplay between technophobia, technophilia, content quality, and functional quality, the study unveils the complex dynamics shaping AI-ELP adoption. This holistic approach, previously unexplored in extant literature, provides a nuanced understanding of technology acceptance in educational contexts.

The study conducted at IIT Kharagpur adds to its theoretical value, capturing the diverse dynamics of technology adoption prevalent across India. As a prestigious institute with students from all corners of the country, IIT Kharagpur offers a comprehensive perspective, enriching the study's theoretical framework and enhancing its applicability on a national scale.

Thus, by integrating psychological and practical variables and exploring their interconnectedness, this study significantly advances our understanding of AI-ELP adoption dynamics. It offers valuable insights into the multifaceted factors influencing technology acceptance in educational settings, thereby contributing to the evolution of theoretical frameworks such as the UTAUT model.

6.2. Practical implications

The practical implications of this study are multifaceted, offering valuable insights for educators, policymakers, technology developers, and other stakeholders involved in the design, implementation, and promotion of AI-enhanced e-learning platforms (AI-ELP).

Firstly, by recognizing and addressing users' concerns and fears regarding AI technology adoption, educators and platform developers can implement strategies to alleviate technophobia. This may involve providing transparent information about data privacy and security measures, offering reassurances regarding job security, and demonstrating the positive impacts of AI-ELP adoption on learning outcomes. By proactively addressing these concerns, educators can cultivate a supportive environment conducive to technology adoption among users.

Secondly, leveraging users' positive attitudes towards technology, such as technophilia, can significantly enhance AI-ELP adoption rates. Educators and platform developers can capitalize on users' curiosity and eagerness to engage with new technologies by incorporating innovative features, interactive content, and user-friendly interfaces into AI-ELP platforms. By aligning platform design with users' preferences and inclinations, stakeholders can enhance user engagement and satisfaction, ultimately driving adoption and usage.

Thirdly, prioritizing content quality is essential for fostering user engagement and improving learning outcomes on AI-ELP platforms. Educators and content creators should focus on developing high-quality instructional materials that are relevant, accurate, credible, and interactive. By investing in the creation of compelling and enriching content, stakeholders can enhance user satisfaction, retention, and intent to use AI-ELP platforms, thereby maximizing the educational impact of these technologies.

Furthermore, ensuring functional quality, including usability, performance, dependability, and system functionality, is crucial for promoting user acceptance and adoption of AI-ELP platforms. Educators and platform developers should prioritize user-centered design principles, conducting usability testing and gathering feedback to identify and address any usability issues or technical challenges. By providing a seamless user experience and reliable system performance, stakeholders can instill confidence in users and enhance their willingness to adopt and utilize AI-ELP platforms.

Moreover, adopting a user-centric approach and acknowledging individual differences in technology psychology is essential for promoting technology acceptance and adoption. Educators and policymakers should consider users' diverse attitudes, preferences, and learning needs when designing and implementing AI-ELP initiatives. By tailoring interventions to accommodate users' unique characteristics and circumstances, stakeholders can enhance the relevance, accessibility, and effectiveness of AI-ELP platforms for a wide range of users.

7. Limitations and future research directions

Although the research paper on adopting an AI-e-learning platform (AI-ELP) and the extension of UTAUT with factors such as technophobia, technophilia, content quality, and functional quality offers insightful information, it has some limitations. First, because of the specific setting or the user group that was the focus of the research, the generalizability of the findings may be constrained. Technophobia, technophilia, content quality, and functional quality are variables that can change between user demographics and educational settings. Therefore, to improve generalizability, future studies should examine the applicability of these findings in various contexts and user groups. Second, it can be challenging to prove causation and establish the directionality of correlations between the extended UTAUT variables and the adoption of AI-ELP. While the research study examines the relationship between these variables, it is crucial to consider any potential for reverse causation or bidirectional correlations. The correlations could be better understood through longitudinal or experimental studies. Third, the research study focuses on individual elements, which may not adequately convey the complexity of interactions between humans and technology. To gain a more profound knowledge of the adoption process for AI-ELPs, exploring additional variables related to the adoption's social and contextual elements may be necessary. Finally, although they are not fully considered in the research, external factors, including institutional support, instructor qualities, social impact, and cultural factors, may affect the adoption of AI-ELP. These broader contextual elements should be considered in future research to understand AI-ELP adoption better.

Future research objectives could include examining the long-term impacts of the extended UTAUT model on the steady uptake and use of AI-ELP systems. Additionally, a greater comprehension of the social dynamics influencing AI-ELP adoption would result from examining the effect of environmental and social factors, such as peer influence and organizational culture. Qualitative research techniques could also be used to learn more about how users perceive and experience adoption hurdles for AI-ELP. The differences in AI-ELP adoption trends may also be revealed by comparing research across various academic levels or fields of study, which might be used to guide targeted initiatives. Researchers can further develop their understanding of the adoption of AI-ELP in different educational settings by addressing these limitations and exploring these future research initiatives.

8. Conclusion

The objective of this study was to increase our understanding of the adoption of an AI-e-learning platform (AI-ELP) by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) with factors such as technophobia, technophilia, content quality, and functional quality. Several key findings emerged from the empirical investigation and analysis of the collected data, shedding light on the complex dynamics influencing users' acceptance and use of AI-ELP platforms.

Technophobia was identified as a significant factor influencing the adoption of AI-ELP by users. Users with greater technophobia were less likely to adopt and use the platform because of concerns about privacy, job displacement, and artificial intelligence technology. Users with greater technophilia demonstrated greater enthusiasm, curiosity, and motivation to interact with the AI-ELP, resulting in greater acceptance and use intentions. Second, content quality emerged as a crucial factor influencing users' perceptions and adoption of AI-ELP. Users rated the relevance, integrity, credibility, and interactivity of the platform's learning materials as extremely important. Greater perceived content quality increased user satisfaction, engagement, and intent to continue using AI-ELP. In addition, functional quality plays a vital role in the acceptance and utilization of AI-ELP by users. AI-ELP adoption and usage were more likely among users who perceived the platform as user-friendly, efficient, and trustworthy. User acceptance and use intentions were adversely affected by technical issues, bugs, or a lack of functionality. These findings highlight the significance of addressing technophobia, capitalizing on technophilia, enhancing content quality, and enhancing the functional aspects of AI-ELP platforms. By reducing technophobia and capitalizing on technophilia, educational practitioners and policymakers can alleviate user concerns, improve content quality and platform functionality, and increase user acceptability and engagement with AI-ELP platforms.

In conclusion, this study contributes to the existing body of knowledge by offering a comprehensive framework for comprehending AI-ELP adoption. By extending the UTAUT model and incorporating factors such as technophobia, technophilia, content quality, and functional quality, this study provides valuable insights into the complex interaction between user perceptions, attitudes, and platform characteristics in adopting AI-ELP. These findings have practical implications for the design and implementation of AI-ELP platforms, thereby facilitating their adoption and use in educational settings. Future research can build upon these findings to investigate additional factors and contexts, thereby advancing our comprehension of technology adoption in the e-learning and AI integration landscape.

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