



Artificial Intelligence-Supported Online Learning: Digital Self-Efficacy, Learning Anxiety, Technology Acceptance, and Students' Learning Satisfaction

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ARTICLE INFO	ABSTRACT
Submission: July 09, 2026 Revised: July 25, 2026 Accepted: August 26, 2026 Available Online: September 09, 2026 Keywords: <i>Artificial Intelligence-supported online learning; digital self-efficacy; learning anxiety; technology acceptance; learning satisfaction; higher education; online learning; artificial intelligence.</i> Corresponding author: Zeeshan Ali Email: alirajazeeshan@gmail.com	The present study examined the role of Artificial Intelligence-supported online learning in relation to digital self-efficacy, learning anxiety, technology acceptance, and students' learning satisfaction in higher education. The study was significant because the increasing integration of artificial intelligence into online education has created new opportunities for personalized and flexible learning while also raising concerns regarding students' technological confidence, anxiety, acceptance, and overall learning experience. A quantitative, cross-sectional research design was adopted, and data were collected from 343 university students from higher-education institutions in Pakistan, through a structured adopted questionnaire. The questionnaire was distributed online through Google Forms, and respondents participated voluntarily based on their experience with online learning and AI-supported educational technologies. The collected data were analyzed using IBM SPSS Statistics. Descriptive statistics, Cronbach's alpha reliability analysis, Pearson correlation, multiple linear regression, independent-samples t-test, one-way ANOVA, and Tukey HSD post-hoc analysis were used to examine the study variables and their relationships. The findings demonstrated significant positive relationships between AI-supported online learning, digital self-efficacy, technology acceptance, and learning satisfaction, while learning anxiety was negatively associated with the major positive learning outcomes. Digital self-efficacy positively predicted technology acceptance, whereas learning anxiety negatively predicted technology acceptance. Technology acceptance was also strongly associated with students' learning satisfaction, indicating that students who perceived AI-supported technologies as useful and manageable were more likely to report satisfactory learning experiences. Significant differences were additionally observed across selected demographic and experiential groups, particularly according to gender, academic level, and online-learning experience. Hence, the study concluded that the effectiveness of AI-supported online learning was influenced not only by technological availability but also by students' digital confidence, emotional readiness, and acceptance of AI-based educational technologies. The study highlights the importance of strengthening digital and AI literacy, reducing technology-related learning anxiety, and providing structured institutional support to promote effective, inclusive, and satisfying AI-supported learning environments in higher education.

Introduction

Artificial Intelligence-Supported Online Learning

The growth of Artificial Intelligence (AI) has changed online learning and other digital learning environments in higher education. AI-based technologies support instructors in teaching, evaluating students, and providing timely feedback. In contrast to generic online learning, AI environments can analyze learning activities and provide adaptive feedback, create itself content, support learning activities and complex problems, and address individual learning needs. Current studies show that intelligent tutoring systems, generative AI, automated feedback, predictive analytics, and adaptive learning apps are some technologies that create learning cognitive, behavioral, and emotional effects on students (DIMITRIADOU et al., 2026).

Using AI in education may not lead to the expected learning outcomes unless students' psychological needs and perceptions are also considered. Technology confidence, AI acceptance, and emotional acceptance determine the digital learning experiences. While technology can support personalized and self-assistive learning, students may have negative perceptions toward technology as it can create a digital divide between students and teachers, have information that may be erroneous and invasive, and have the potential to cause dependence. For this reason, Layman-centered studies have become focus areas in AI-supported learning that consider the technology and psychology aspects (Adewale et al., 2024; Lo, 2024).

Confidence in using digital tools is known as digital self-efficacy. Learning anxiety is about feeling uneasy or nervous during learning activities that are mediated by technology. Technology acceptance is about the hesitancy to use a technological system, and satisfaction with learning is the final judgment one makes after having gone through a learning experience. Self-efficacy is looked upon as a precursor to technology acceptance while anxiety about technology is an impediment to using the technology. Finally, the ease of using and the perceived value of the technology play a deciding role in the satisfaction that students obtain from the learning experience (Chen et al., 2024; Jiang et al., 2022). For the purpose of analyzing how students relate to AI in online education, these factors collectively help to bring out a more nuanced picture of how students psychologically and behaviorally engage with AI-driven online learning (Ullah et al., 2026).

Digital Self-Efficacy

Digital self-efficacy describes a person's faith in their ability to successfully use digital tools. According to Bandura's social cognitive theory, self-efficacy alters one's assessment of difficulties, response adjustment, and perseverance amid challenges (Bandura & Wessels, 1997). In the context of online education, having digital self-efficacy means having confidence regarding the use of learning platforms, access to digital resources, online interactions, problem-solving, and task completion. These students are more inclined to view online learning tasks as less challenging and more persistent (Almasri, 2024).

Self-efficacy can be harmful in online learning systems due to students having to learn about new software and tools and how to build prompts, critique AI output, and integrate output into given learning materials. It has been identified that self-efficacy encourages active use of digital technology and can improve students' attitude and acceptance of AI-integrated learning tools. Self-efficacy has been similarly shown to increase students' perceived control of digital learning, persistence, and value-add from online learning (Mohamed Selim et al., 2024).

Digital self-efficacy can help reduce learning anxiety in machines aided learning environments since students with a higher level of digital self-efficacy tend to be less overwhelmed by technology challenges (Ulfert-Blank & Schmidt, 2022). According to Bandura, higher levels of efficacy beliefs tend to decrease perceived threat, improve emotional regulation, and elicit persistence in individuals when faced with obstacles (Maran et al., 2022). New data explored this relation in the context of AI self-efficacy which suggests a positive correlation of AI self-efficacy with AI usage and a negative correlation with AI-related anxiety. Consequently, higher digital self-efficacy is expected to have a positive effect on students' engagement and, at the same time, reduce anxiety in AI aided online learning settings.

Learning Anxiety

Learning anxiety occurs due to difficult or uncertain learning demands and thus prevents learners from engaging and affecting their performance in the classroom. In digital learning environments, anxiety is caused by new technologies, limited digital skills, mistake-aversion, academic pressure, and demands and restrictions of the learning environment in combination with limited instructor support and unpredictable technology. Most of these challenges become even more problematic in AI-based learning environments. The reason is students may interact with information that they cannot even begin to understand and may not even

trust. As a result, anxiety is one of the affective factors that are present and may even foster students' engagement with digital learning environments (Berutu & Mutiawati, 2023).

This type of anxiety caused by learning online may also affect online students cognitively and behaviorally since anxiety tends to consume the students' cognitive and emotional resources that can be required to carry out or sustain academic activities. Students become uncertain about the expectations for learning and the communication and assessment procedures. As a result, students tend to develop negative attitudes and perceptions to the online technologies and their learning. AI-based learning may cause anxiety as students become anxious about the academic integrity of AI, the AI's ease of use, the level of trust in, and the potential reliance on AI. However, AI-based self-efficacy can help reduce AI-based anxiety, and this negative influence may cause students to self-restrict the actual use of AI (Han et al., 2024).

Students with high anxiety may avoid AI tools, consider technology more difficult to use and more distracting, and rate their learning experiences more negatively. Students with low anxiety and high confidence may actively use available AI resources and maintain their engagement in online learning activities. For this reason, anxiety related to the learning process may affect acceptance of technology and satisfaction with learning. This may justify further study of the impact of AI on online learning. (Kao, 2024).

Technology Acceptance

Technology acceptance refers to the inclination to use a technological system for specific purposes. Davis (1989) defines technology acceptance within the Technology Acceptance Model (TAM) as the perceptions of usefulness and ease of use. (Barz et al., 2024) suggest that the perceptions of usefulness and ease of use are crucial factors for the use of educational technologies. In educational technologies, students are like other users. They are motivated to use a given system if they believe that the technology is useful and that the system is easy to use and positively affects their experience.

Technology acceptance is of particular importance in AI-integrated online learning. Students decide whether and how to use AI tools and whether they perceive their output to be useful and trustworthy. AI-integrated educational technologies rely on the self-efficacy of learners, the enjoyment of the systems, social needs, usefulness, and ease of use (García et al., 2024) among other factors. In AI-based educational technologies, learners' AI self-efficacy and AI anxiety are the defining factors of the use of AI technologies. Informality of the technology and learners' expectations separate the usefulness of AI from technology. Therefore, technology acceptance in AI-integrated online learning relates students' psychological characteristics to educational technology.

Students with higher levels of digital self-efficacy may be more inclined to view AI technologies as less complex and more approachable. Deeper anxiety around learning may lead students to think of AI as complex and even threatening. AI-supported learning that is perceived as helpful, user friendly, and matching the needs of the user is more likely to be engaged with and used to create positive learning experiences. Therefore, the acceptance of technology is an essential component through which digital self-efficacy and learning anxiety may affect the experiences and the degree of satisfaction that a student has with a particular learning process.

Students' Learning Satisfaction

Learning satisfaction describes students' perceptions about how well their education and learning needs were fulfilled by their educational experiences. It is one of the most important indicators of educational quality in online learning. One aspect of satisfaction is the evaluation of the course organization, the quality and range of instructional support, the ease of interaction with and the accessibility of the technologies, and the perceived effectiveness of learning processes. In online learning augmented by AI, additional satisfaction indicators may include whether AI technologies and tools contribute to the convenience and efficiency of learning processes, the personalization of learning, and the engagement and responsiveness of students' learning needs. Examples of AI technologies may include systems that have the ability to automatically capture learners' feedback, generate personalized recommendations and explanations, and increase adaptivity of the learning processes, all of which may enhance overall learning satisfaction (Topala & Tomozii, 2014).

Close connection exists among learning satisfaction, technology, and studying competencies. In several studies, it was shown that learning satisfaction in online learning is positively related to computer self-efficacy, perceived ease of use and perceived usefulness of online learning systems, and learning engagement and study processes. Therefore, satisfaction is the result of a combination of competencies, perceptions, feelings, and experiences in the learning process (Aldhahi et al., 2022).

Learning anxiety negatively impacts technology acceptance and learning satisfaction, as anxiety increases perceived technological difficulty and decreases willingness to engage with learning systems

Digital learning technologies may seem needlessly convoluted to students who have concerns about or are simply uncertain towards their use. Such students may perceive a lack of ease of use and may ultimately not adopt the technology. On the other hand, lower anxiety, digital self-efficacy and technology acceptance positively impact the learning experience. For this reason, studying user satisfaction can help in evaluating the effectiveness of AI-based online learning. The application of these concepts also helps explain the disparate responses of students to AI-based learning environments.

Research Objectives

- To examine the relationship between Artificial Intelligence-supported online learning, digital self-efficacy, learning anxiety, technology acceptance, and students' learning satisfaction.
- To determine the effects of digital self-efficacy and learning anxiety on students' technology acceptance in Artificial Intelligence-supported online learning environments.
- To assess the effects of digital self-efficacy, learning anxiety, and technology acceptance on students' learning satisfaction.

Problem Statement

Artificial Intelligence (AI) is an increasingly important element of online education at all levels, but most related studies have been limited to the engagement and satisfaction of students in online courses that use AI support. Anxiety about learning, digital self-efficacy, acceptance of technology used in learning, and satisfaction with learning are important elements of online learning that have received less attention, especially in relation to AI. Some studies have focused on a few related factors in the context of AI. For example, the study by Chen et al. (2024) is focused on assessing AI self-efficacy and anxiety, but it also considered AI's role in facilitating second language learning. The study continues to focus on satisfaction and AI chatbot anxiety, but it is a part of the first systematic review that includes the psychology of students and AI learning. Based on the above, a major gap in the literature that is important to address is how digital self-efficacy and learning anxiety may impact the acceptance of technology and the satisfaction of students using AI during online learning.

Significance of the Study

This study describes the combination of digital self-efficacy, learning anxiety and technology acceptance on students' satisfaction when learning in AI supported online learning environments. This study is valuable to universities and colleges because it is one of the few studies that includes some of the psychological aspects concerning students and AI based learning. It may help academics realize the risks students may be feeling surrounding the use of AI. It may help universities better assist students, open new AI based learning programs, and maybe modify the current technological structures of the university surround the new AI. It may appease the students' anxiety concerning the new AI technology. This study would help developers of AI based educational programs to make AI programs and supports easier for students to use. This study is important to academia because the field of educational AI is still young. It may help people understand the C.A.S.E (Cognitive, Affective, Social, Emotional) factors in educational and psychological AI based systems.

Literature Review

Artificial Intelligence-Supported Online Learning

New methods of online learning using AI make it possible to offer specific services. Learning systems can now be designed to provide automatic feedback, conduct conversations with learners, and predict learner needs based on data. Such systems can help learners at just the right time as they learn by adapting their instruction accordingly. AI-based systems can help facilitate processes such as motivating students to learn, sustaining their interest in a given task, and helping them feel confident about their ability to complete tasks (Design and Assessment of AI-Based Learning Tools in Higher Education, 2025).

AI dynamically responds to student input, which requires learners to re-examine the purpose of online education and their role within this new online learning ecosystem. Students must be able to engage with, evaluate, and interpret outputs of AI within the context of their learning tasks while planning effective prompts to the system. Using AI requires managing the cognitive and

emotional impacts of new technologies. The use of AI can be amplified by a strong sense of self efficacy, while the presence of anxiety can be a significant barrier (Tang et al., 2023).

When using AI, students must join tools designed to adapt to various users' needs. Without this customization, advanced AI tools can remain unused. New studies report that adaptive systems built by combining personalization, real-time feedback, and adaptive and intelligent interaction raise engagement and satisfaction, but may challenge the acceptance of systems built on an unstable foundation of reliability and privacy concerns and excessive reliance on AI (Artificial Intelligence in Online Education, 2026). For this reason, tying together digital self-efficacy, learning anxiety, the acceptance of technology, and satisfaction of learning increases the scope of insights into the AI-enhanced online education of the students (Tonbuloglu, 2023).

Digital Self-Efficacy

Digital self-efficacy is a student's belief about their ability to use digital technologies to accomplish tasks and resolve issues while learning. Based on Bandura's social cognitive theory, self-efficacy is the belief in one's ability to execute the actions necessary to accomplish a task. Digital self-efficacy pertains to online learning and encompasses confidence in completing online courses and maintaining contact and engagement with instructors and course participants using the respective technologies. According to the literature, the self-efficacy related to online learning is multidimensional and encompasses much more than basic computer skills and includes students' confidence in the online learning activities and social interactions (Shen et al., 2013).

Digital self-efficacy is important in AI-supported learning, as an increasing number of students are encountered with technologies that are generally more complex than everyday digital tools. Students may need to hold a dialogue with AI, assess AI-generated output, make use of intelligent tutoring in an integrated manner, and integrate automated feedback to aid their learning. Self-efficacy is seen as a key motivator in the context of education supported by AI, with a strong body of research showing positive impacts of learning activities integrated with AI on students' confidence. Students with a stronger self-efficacy are more likely to consider new technologies as a potential challenge, while students who have less self-confidence may avoid using complex technology (Design and Assessment of AI-Based Learning Tools in Higher Education, 2025).

In some learning environments, students' digital self-efficacy and technology acceptance may be quite disassociated. Barz et al. (2024) had similar results to the previously stated studies, and reported that in the context of university students, digital self-efficacy does not affect technology acceptance, indicating multiple influencing factors may exist. AI self-efficacy correlates positively with attitude and use of AI technologies while online learning self-efficacy correlates with learning satisfaction (Rohde et al., 2025). Therefore, digital self-efficacy in AI integrated online learning would help understand AI-integrated online learning's implications on student anxiety, acceptance of technology, and satisfaction with AI integrated learning (Paredes-Aguirre et al., 2024).

Learning Anxiety

Learning anxiety is the term used to describe specific worries or uneasiness affecting students while learning. While learning in person, students may worry about their academic performance. In online education, students may worry about a lack of in-person interaction with the teacher and about learning hurdles caused by challenges with technology. AI may help reduce some of the challenges, however, AI poses its own challenges and may increase anxiety. Students may worry about the integrity of information, the ethics of increased reliance on technology, and they may even worry about privacy. Learning anxiety may be especially important in the context of AI-supported education.

The use of AI in the classroom presents both opportunities and challenges which differ from traditional learning. Some intelligent systems can help reduce anxiety and assist students with learning through real time support and feedback. However, students may worry about the use of these systems. They may worry the systems will become too complex and too reliant on AI, and if they can be trusted with their privacy. It has been found that AI interventions have both positive and negative effects on anxiety and are context specific Wang et al. (2024). The use of AI in learning demonstrated negative anxiety and engagement with the technology, however, this was only true among students who had low self-efficacy (Eysenck, 1979).

Despite the anxiety induced by learning new technologies, anxiety also affects students' Intentions to use these technologies and their overall satisfaction with the process of learning. Anxiety can occupy a lot of a student's mental energy and make the student feel like a technology is beyond their capabilities and make it harder to get the student to even attempt working with the technology. Stronger digital self-efficacy may help students perceive both difficulty and threat as less significant when confronting a technology challenge. They as a result are more likely to successfully cope with complex and uncertain technology

in their education. For this reason, learning anxiety helps to create a rational basis for distinguishing among students regarding their satisfaction and acceptance of technology in AI-assisted online learning environments (Chen et al., 2025).

Technology Acceptance

Technology acceptance deals with the extent to which users accept a given technology. The Technology Acceptance Model (TAM), developed by (Davis, 1989), describes the adoption of technology in terms of how users perceive technology in terms of usefulness and how easy the users believe it is to use the technology. In the case of online education, ease of use means the technology is intuitive and easy to manage, whereas for usefulness, learners need to believe that the use of technology will improve their learning. These perceptions are important in AI-assisted learning, as students need to decide if there are educational benefits to the use of AI tools that require minimum effort.

The relevance of TAM within the context of educational technology is supported by many recent studies. Barz et al. (2024) found that the components of TAM are relevant and are also influenced by learners' self-regulated learning and technology affinity and by their attitudes towards e-Learning, which in turn are positively influenced by the use of AI and negatively by the presence of AI anxiety. In addition, a recent meta-analysis found that the factors of technology acceptance in AI-based educational technology depend on individual belief, attitude, and the intention to use (Choung et al., 2023). Technology acceptance therefore bridges students' psychological characteristics and the learning experience. Students with high digital self-efficacy will experience AI technology as useful and easy, and AI anxious students will experience the technology as difficult and threatening.

Favorable attitudes and engagement towards AI-enhanced learning arise when students believe AI is useful, understandable and easy to use. These attitudes are likely to vary in different learning contexts and in different students, making this area in particular ripe for more empirical work. It is possible that digital self-efficacy and learning anxiety can influence students' acceptance of technology in AI-inclusive online learning contexts (Liang et al., 2026).

Students' Learning Satisfaction

Satisfaction with learning refers to students' perception of the fulfillment of their academic needs through their overall evaluation of their learning experiences. In online learning, several factors affect satisfaction, such as course organization, instruction, interaction, feedback, perceived learning, and available support. Effective online learning is not solely about providing access to technology; it means providing learning experiences that students perceive as useful and manageable.

Learning satisfaction is associated with digital self-efficacy. Students' confidence in inhabiting online learning environments affects their navigation. It was reported that the online learning self-efficacy significantly predicted learning satisfaction. In other words, students who can handle online learning are more likely to appreciate their experiences. Technology that supports learning also has an effect. Educational technology that is perceived to be useful and easy to use results in students forming positive experiences. In AI-supported learning, immediate feedback, as well as personalized support and learning that is adapted to the individual, is perceived as useful and leads to higher satisfaction. Adaptive support in learning is enhanced through intelligent interaction (Design and Assessment of AI-Based Learning Tools in Higher Education, 2025).

The use of AI in education is expected to lead to greater satisfaction and positive experiences as a result of personalization, immediate feedback, and intelligent interaction that supports learning, as well as adaptive learning (Design and Assessment of AI-Based Learning Tools in Higher Education, 2026). However, the extent to which learning is improved and the satisfaction of users is increased by the use of AI systems is constrained by issues of reliability, privacy and the degree to which such systems are used (Artificial Intelligence in Online Education, 2026). Therefore, the effects of AI on learning are dependent upon students' psychological readiness.

Users that possess a high degree of digital self-efficacy and acceptance of technology are more likely to have a positive outlook toward learning with AI. Issues with technology, a lack of perceived usefulness, and anxiety are all likely to lead to a low degree of satisfaction with learning. For this reason, satisfaction with learning provides an important metric by which the effectiveness of AI-based online learning can be assessed (Almulla, 2024).

Research Gap

Although recent research has increasingly examined Artificial Intelligence in higher education, an important empirical gap remains regarding the integrated relationship among digital self-efficacy, learning anxiety, technology acceptance, and students' learning satisfaction within AI-supported online learning. Previous studies have generally examined these constructs separately

or within specific contexts, with focusing on AI self-efficacy, anxiety, attitude, and actual AI use in AI-assisted language learning, while (Falebita & Kok, 2025) showed that self-efficacy does not consistently predict all dimensions of technology acceptance. Similarly, Cao et al. (2026) examined AI anxiety and adoption intention, while Gholamian Varnamkhasti et al. (2026) highlighted the fragmented nature of research connecting AI anxiety, self-efficacy, technology acceptance, and student engagement. Therefore, limited evidence exists on how digital self-efficacy and learning anxiety influence technology acceptance and how these factors subsequently contribute to students' learning satisfaction in AI-supported online learning environments. Addressing this gap can extend existing technology-acceptance research beyond adoption intention and provide a more comprehensive understanding of the psychological and technological conditions that shape students' satisfaction with AI-supported online learning.

Hypotheses

- **H1:** There is a significant relationship between digital self-efficacy, learning anxiety, technology acceptance, and students' learning satisfaction in AI-supported online learning.
- **H2:** Digital self-efficacy, learning anxiety, and technology acceptance significantly predict students' learning satisfaction in AI-supported online learning.
- **H3:** Digital self-efficacy and learning anxiety significantly predict students' technology acceptance in AI-supported online learning.
- **H4:** There is a significant difference in students' digital self-efficacy, learning anxiety, technology acceptance, and learning satisfaction between the two demographic groups.
- **H5:** There are significant differences in digital self-efficacy, learning anxiety, technology acceptance, and learning satisfaction across different demographic groups.

Methodology

Research Design

The current study used a quantitative approach with a cross-sectional research design to understand Digital Self-Efficacy, Learning Anxiety, Technology Acceptance, and AI-integrated online learning students' satisfaction. A structured survey with Likert-scale questions was used to collect data from university students who had experience with AI-integrated online learning. The quantitative approach was appropriate to measure the study variables and understand their relationship and predictor variables with the help of statistics.

Population

The population of this study consisted of university students enrolled in higher education institutions in Pakistan who had experience with Learning Management Systems (LMS) and AI-supported educational technologies. To ensure geographical and institutional diversity, the study included students from five universities representing the provinces of Punjab, Sindh, and Khyber Pakhtunkhwa (KPK). The selected universities included Bahauddin Zakariya University, Multan (Punjab); University of the Punjab, Lahore (Punjab); University of Karachi, Karachi (Sindh); University of Sindh, Jamshoro (Sindh); and University of Peshawar, Peshawar (KPK). The population comprised students from diverse academic disciplines and educational backgrounds who had prior exposure to online learning environments, Learning Management Systems, and AI-integrated educational tools. This population was considered appropriate for examining students' experiences and responses toward the integration of artificial intelligence and digital technologies within Pakistani higher education.

Sampling Technique

A non-probability convenience sampling technique was employed to recruit participants. The sampling technique was adequate as the focus of the study was to collect responses from university students who could be reached via online communication and who satisfied the study's inclusion criteria. The survey was sent to students at higher education institutions through academic WhatsApp groups/online pages, student unions' social media pages, and direct online communication. Participation was voluntary, and respondents were informed about the academic nature of the study prior to filling out the survey.

Sample Size

The final sample consisted of 343 respondents. Data collection was completed and 343 valid responses were collected and were ready for statistical analysis. The respondents covered students of different demographic and academic backgrounds from the selected regions of Pakistan.

Data Collection

Data were collected through a self-administered structured questionnaire from university students in Pakistan. The questionnaire assessed AI-supported learning, digital self-efficacy, learning anxiety, technology acceptance, learning satisfaction, and demographic characteristics. All constructs were measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaire was reviewed for clarity and relevance before being converted into Google Forms. It was then electronically distributed to eligible students from selected Pakistani universities. Participants completed the questionnaire independently, and the responses were collected electronically for subsequent data cleaning, coding, and statistical analysis.

Data Analysis

The responses were downloaded from Google Forms and imported to IBM SPSS Statistics after they were organized and checked for duplicates and missing values in Microsoft Excel. The data were analyzed only after an assessment for the consistency of logic and coding. Descriptive analyses (frequencies, percentages, means, standard deviations, etc.) were performed to characterize the participants and the major study elements. The internal consistency of the scales was assessed using Cronbach's alpha. Pearson product-moment correlation was used to determine the relationships among the digital self-efficacy, learning anxiety, technology acceptance and learning satisfaction.

Three multiple linear regressions were performed to predict technology acceptance and learning satisfaction based on digital self-efficacy and learning anxiety. Independent two-sample tests were performed to determine if there were differences in demographic groups, whereas one-way ANOVA was used to analyze demographic groups containing three or more individuals. Also, Tukey's HSD post-hoc tests were administered to determine specific demographic differences. The significance level was set to $p < .05$.

Table 1: Demographic Characteristics of Respondents (N = 343)

Demographic Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	187	54.5
	Female	156	45.5
Age	18–22 years	128	37.3
	23–27 years	121	35.3
	28–32 years	61	17.8
	33 years and above	33	9.6
Academic Level	Undergraduate	207	60.3
	Master's	91	26.5
	M.Phil./MS	32	9.3
	PhD	13	3.8
Province	Punjab	118	43.6
	KPK	100	25.0
	Sindh	125	31.4
Academic Discipline	Social Sciences	82	23.9
	Business/Management	71	20.7
	Computer Science/IT	65	19.0
	Education	59	17.2
	Natural Sciences	38	11.1

Demographic Variable	Category	Frequency (f)	Percentage (%)
Online Learning Experience	Other	28	8.2
	Less than 1 year	54	15.7
	1-2 years	117	34.1
	3-4 years	109	31.8
	More than 4 years	63	18.4
Frequency of AI Use for Learning	Rarely	48	14.0
	Sometimes	102	29.7
	Often	127	37.0
	Very often	66	19.2
Total		343	100.0

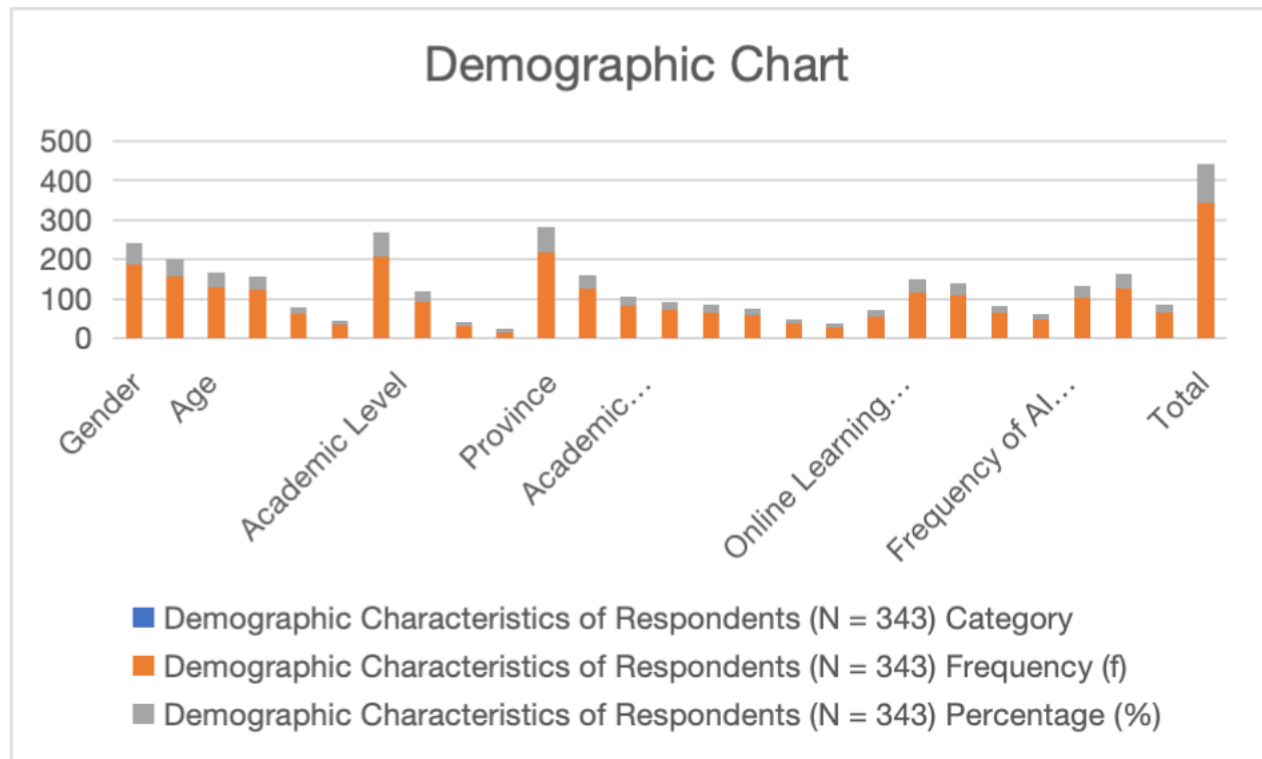


Fig.1: Demographic characteristics of Respondents (N=343)

The demographic data shows respondents were a diverse population for our study, with males comprising 54.5% of respondents and females comprising 45.5%. Most respondents were between the ages of 18 and 27 and were students at the undergraduate level, with 60.3% of respondents falling in this category. The majority of respondents were from Punjab (63.6%), with Sindh containing 36.4% of the second highest population. Students from various fields and academic backgrounds, of the Social Sciences, Business/Management, Computer Science/IT, Education, and Natural Sciences, were represented. The majority of respondents had at least one year of experience with online learning. A considerable number of respondents reported that they use AI tools for learning at a frequent or very frequent basis, resulting in a high exposure to online learning, specifically tools that

utilize AI for educational activities. This further strengthens the sample for research on digital self-efficacy, learning anxiety, technology acceptance, and learning satisfaction.

Table 2: Reliability Analysis of Study Variables

Variables	No. of Items	Cronbach's Alpha (α)	Mean	Std. Deviation
AI-Supported Online Learning	8	0.891	3.74	0.71
Digital Self-Efficacy	7	0.876	3.81	0.68
Learning Anxiety	6	0.842	3.21	0.79
Technology Acceptance	12	0.914	3.86	0.65
Learning Satisfaction	6	0.887	3.78	0.70
Overall Scale	39	0.938	3.68	0.71

Regarding Reliability analysis, it was reported that Cronbach's alpha coefficients ranged from 0.842 to 0.914, which indicates good to excellent internal consistency. Constructs of the sample survey scales yielded mean scores at a level of 3.21 to 3.86, which indicates that the level of the constructs was very high, with a low variation (0.65 to 0.79) of the respondents' scores. It was determined that the questionnaire would be sufficiently consistent and reliable for further analysis.

Table 3: Pearson Correlation Analysis of Study Variables

Variables	1	2	3	4
1. AI-Supported Online Learning	1			
2. Digital Self-Efficacy	.641**	1		
3. Learning Anxiety	-.428**	-.462**	1	
4. Technology Acceptance	.673**	.594**	-.417**	1
5. Learning Satisfaction	.681**	.619**	-.451**	.726**

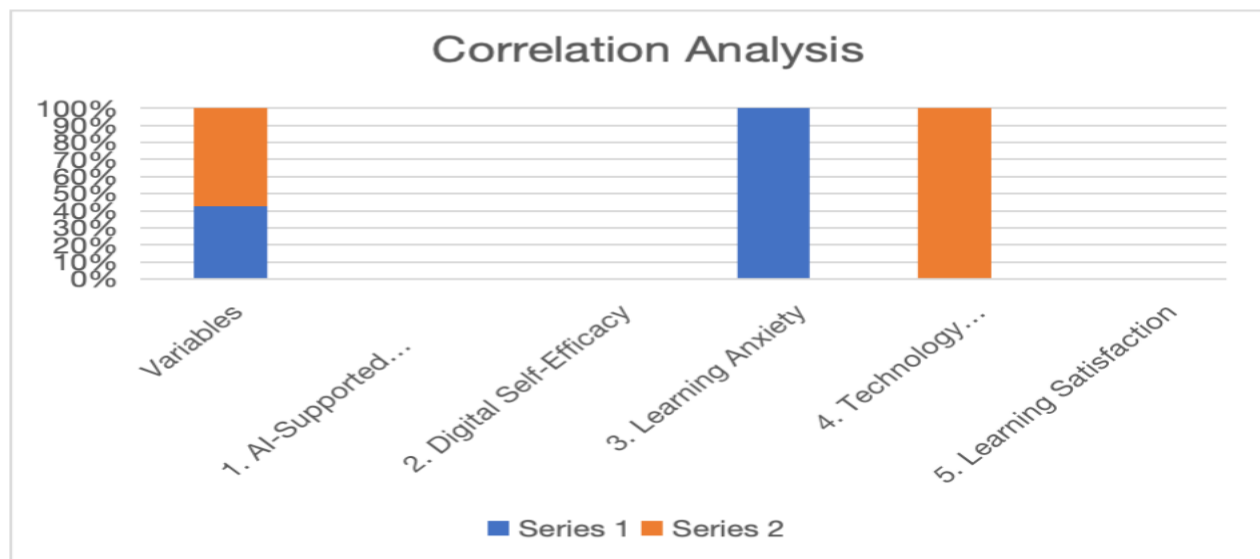


Fig.2: Pearson correlation Analysis of study variables

Pearson correlation analysis showed that the major study variables had significant relationships. There were positive correlations of AI-based online learning with digital self-efficacy ($r = .641$, $p < .01$), technology acceptance ($r = .673$, $p < .01$) and learning satisfaction ($r = .681$, $p < .01$) and there was a negative correlation with learning anxiety ($r = -.428$, $p < .01$). Self-digital efficacy had a positive correlation with technology acceptance ($r = .594$, $p < .01$), and learning satisfaction ($r = .619$, $p < .01$), and negative correlation with learning anxiety ($r = -.417$, $p < .01$). The strongest correlation was found between technology acceptance and learning satisfaction ($r = .726$, $p < .01$), which means that digital self-efficacy and technology acceptance had a positive correlation with learning satisfaction, and learning anxiety had a positive correlation with technology acceptance and learning satisfaction.

Table 4: Multiple Linear Regression Analysis Predicting Technology Acceptance

Predictor Variable	B	SE	β	t	p
Constant	1.214	0.214	—	5.673	<.001
Digital Self-Efficacy	0.487	0.058	.472	8.397	<.001
Learning Anxiety	-0.263	0.051	-.291	-5.157	<.001

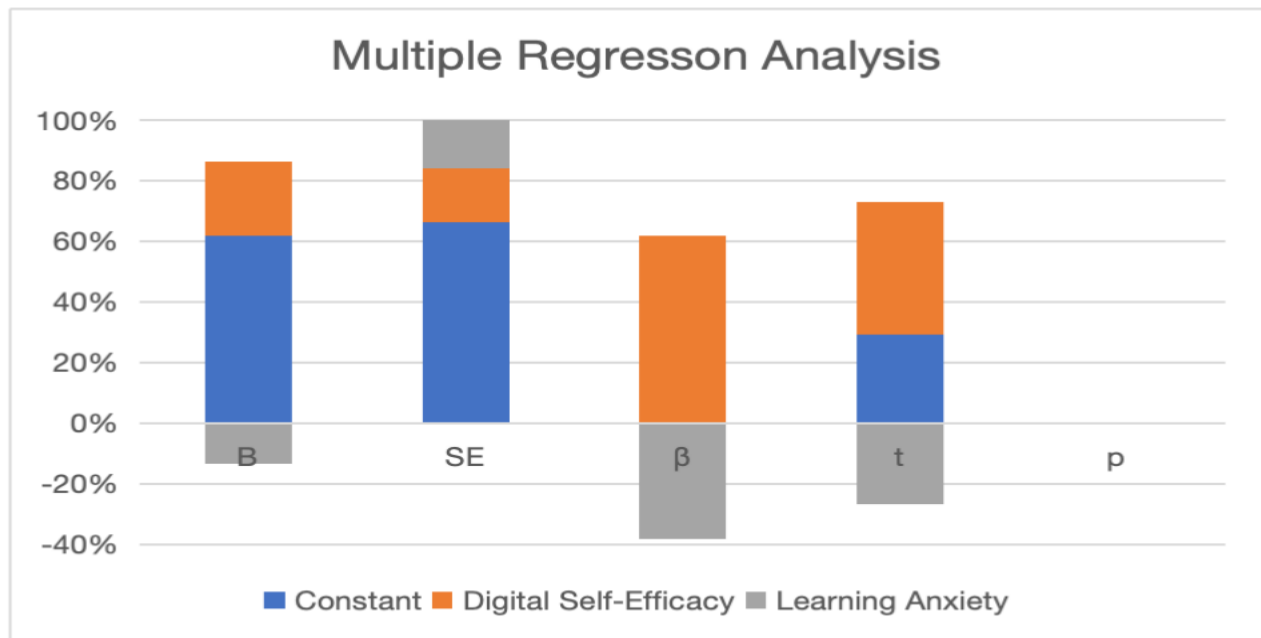


Fig.3: Multiple Linear Regression Analysis

Multiple regression analysis determined an association between the acceptance of technological integration and digital self-efficacy and learning anxiety. Digital self-efficacy was positively associated with the acceptance of technological integration ($\beta = .472$, $p < .001$) indicating the role of a higher level of digital self-efficacy in a more significant acceptance of technology integrated into AI-based online learning. Learning anxiety was negatively associated with the acceptance of technological integration ($\beta = -.291$, $p < .001$) indicating the higher the learning anxiety, the lower the acceptance of technological integration. The overall regression model was significant, $F(2, 340) = 109.62$, $p < .001$, with a 39.2% explanation of the integration of technological acceptance ($R^2 = .392$), and therefore, the relationships postulated in H2 were confirmed.

Table 5: Independent-Samples t-Test for Gender Differences

Variable	Gender	N	Mean	SD	t	df	p
Digital Self-Efficacy	Male	187	3.88	0.66	2.114	341	.035
	Female	156	3.73	0.70			
Learning Anxiety	Male	187	3.12	0.77	-2.236	341	.026
	Female	156	3.32	0.80			
Technology Acceptance	Male	187	3.94	0.62	2.476	341	.014
	Female	156	3.77	0.68			
Learning Satisfaction	Male	187	3.86	0.67	2.301	341	.022

An independent samples t-test showed statistically significant gender differences for all four of the study variables. Male respondents showed higher digital self-efficacy ($M = 3.88$, $SD = 0.66$) than female respondents ($M = 3.73$, $SD = 0.70$), $t(341) = 2.114$, $p = .035$. In contrast, female respondents ($M = 3.32$, $SD = 0.80$) showed higher learning anxiety than male respondents ($M = 3.12$, $SD = 0.77$), $t(341) = -2.236$, $p = .026$. Male respondents also showed greater acceptance of technology ($t(341) = 2.476$, $p = .014$) and learning satisfaction ($t(341) = 2.301$, $p = .022$). In summary, the integration of technology was significantly affected by gender for digital self-efficacy, learning anxiety, acceptance of technology, and satisfaction of learning.

Table 6: One-Way ANOVA of Study Variables by Academic Level

Variable	Academic Level	N	Mean	SD	F	p
Digital Self-Efficacy	Undergraduate	207	3.74	0.68	4.327	.005
	Master's	91	3.89	0.62		
	M.Phil./MS	32	4.02	0.61		
	PhD	13	4.18	0.55		
Learning Anxiety	Undergraduate	207	3.29	0.79	3.681	.012
	Master's	91	3.17	0.76		
	M.Phil./MS	32	3.05	0.71		
	PhD	13	2.82	0.68		
Technology Acceptance	Undergraduate	207	3.77	0.67	5.214	.002
	Master's	91	3.92	0.59		
	M.Phil./MS	32	4.06	0.57		
	PhD	13	4.21	0.51		
Learning Satisfaction	Undergraduate	207	3.69	0.72	4.756	.003
	Master's	91	3.84	0.65		
	M.Phil./MS	32	3.98	0.60		
	PhD	13	4.15	0.53		

Note. $N = 343$; significance level = $p < .05$.

Table 7: Tukey HSD Post-Hoc Analysis

Variable	Group Comparison	Mean Difference	p
Digital Self-Efficacy	Undergraduate vs. M.Phil./MS	-0.28	.021
	Undergraduate vs. PhD	-0.44	.018
Learning Anxiety	Undergraduate vs. PhD	0.47	.031

Variable	Group Comparison	Mean Difference	p
Technology Acceptance	Undergraduate vs. M.Phil./MS	-0.29	.016
	Undergraduate vs. PhD	-0.44	.009
Learning Satisfaction	Undergraduate vs. M.Phil./MS	-0.29	.028
	Undergraduate vs. PhD	-0.46	.014

One-way ANOVA showed statistically significant results for all measures relating to digital self-efficacy, learning anxiety, technological adoption, and satisfaction of learning. Statistically significant results were found in digital self-efficacy ($F = 4.327$, $p = .005$), learning anxiety ($F = 3.681$, $p = .012$), technology acceptance ($F = 5.214$, $p = .002$), and satisfaction of learning ($F = 4.756$, $p = .003$). According to the Tukey HSD post-hoc test, students at the UG level differed statistically from students at the M.Phil./MS and PhD levels in the measures of digital self-efficacy, technology acceptance, and learning satisfaction, with the former being the most anxious about learning at the PhD level. Generally, results of the study supported the association between academic level and the major study measures.

Table 8: One-Way ANOVA of Study Variables by Online-Learning Experience

Variable	Online-Learning Experience	N	Mean	SD	F	p
Digital Self-Efficacy	Less than 1 year	54	3.51	0.72	6.184	<.001
	1-2 years	117	3.72	0.67		
	3-4 years	109	3.91	0.62		
	More than 4 years	63	4.05	0.58		
Learning Anxiety	Less than 1 year	54	3.52	0.81	5.027	.002
	1-2 years	117	3.35	0.77		
	3-4 years	109	3.12	0.75		
	More than 4 years	63	2.94	0.70		
Technology Acceptance	Less than 1 year	54	3.51	0.71	7.416	<.001
	1-2 years	117	3.74	0.66		
	3-4 years	109	3.95	0.61		
	More than 4 years	63	4.12	0.55		
Learning Satisfaction	Less than 1 year	54	3.48	0.76	6.892	<.001
	1-2 years	117	3.69	0.71		
	3-4 years	109	3.88	0.65		
	More than 4 years	63	4.04	0.59		

Note. $N = 343$; $p < .05$ was considered statistically significant.

Table 9: Tukey HSD Post-Hoc Analysis

Variable	Group Comparison	Mean Difference	p
Digital Self-Efficacy	Less than 1 year vs. 3-4 years	-0.40	.006
	Less than 1 year vs. More than 4 years	-0.54	<.001
	1-2 years vs. More than 4 years	-0.33	.018
Learning Anxiety	Less than 1 year vs. 3-4 years	0.40	.009

Variable	Group Comparison	Mean Difference	p
Technology Acceptance	Less than 1 year vs. More than 4 years	0.58	.002
	Less than 1 year vs. 3-4 years	-0.44	.003
	Less than 1 year vs. More than 4 years	-0.61	<.001
Learning Satisfaction	1-2 years vs. More than 4 years	-0.38	.011
	Less than 1 year vs. 3-4 years	-0.40	.005
	Less than 1 year vs. More than 4 years	-0.56	<.001
	1-2 years vs. More than 4 years	-0.35	.021

The results of the one-way ANOVA determination on the major study measures supported the association of online learning experience to digital self-efficacy, anxiety of learning, acceptance of technology, and satisfaction of learning. There were statistically significant results on digital self-efficacy ($F = 6.184$, $p < .001$), learning anxiety ($F = 5.027$, $p = .002$), acceptance of technology ($F = 7.416$, $p < .001$), and satisfaction of learning ($F = 6.892$, $p < .001$). Students who had four or more years of online learning experience had the highest levels of digital self-efficacy and acceptance of technology and lowest levels of learning anxiety, while the rest of the measures were the opposite. The results of the Tukey post HSD test indicated that the most significant differences were found between students with less online learning experience and those with three or more years of experience, thus indicating that the students who had a greater online learning experience were more digitally effectively self-efficient, adopted technology more, and had the highest satisfaction of learning, while having the least anxiety of learning.

Discussion

The current study showed that AI-based online learning demonstrated a positive relationship with digital self-efficacy and technology acceptance, and a negative relationship with learning anxiety. Digital self-efficacy and technology acceptance also showed a positive relationship with learning satisfaction. As expected, learning anxiety and technology acceptance, as well as learning satisfaction, showed a negative relationship. In particular, the results of our study show the relationship between AI-supported technology and online learning with positive self-confidence, emotional readiness, and a willingness to accept new technologies. Our results support the view of Ye and Zhou (2025), who state that in education supported by AI, self-efficacy and psychological factors, as well as the acceptance of technology, assume particular importance.

The positive relationship of digital self-efficacy and technology acceptance shows that if students have a stronger digital self-efficacy and confidence in the use of digital and AI tools, they will perceive these tools as useful and manageable. A negative relationship was found of learning anxiety on technology acceptance and learning satisfaction. This shows that learning anxiety is a barrier to using technology with a positive attitude to learn. Similar results to ours were found in Naidoo (2023), in AI self-efficacy and an attitude of accepting and using AI technology. Overall, the technology acceptance was the most important factor in predicting learning satisfaction. This showed that students' perceived easiness and usefulness of the technology in the learning process is the predominant factor in their satisfaction with learning (Katalinic et al., 2026).

This finding corroborates Technology Acceptance Model and Xue et al. (2026) studies which show strong relationships among TAM constructs of AI in educational technologies. Similarly, suggest that the positive effects of integrating AI technologies to educational processes will depend on how the technology is designed. Therefore, the availability of AI will not ensure satisfaction without design and pedagogical integration. tracts of the digital space, and will reduce learning anxiety.

According to demographic findings, there were differences in regards to gender, level of academics, and experience with online learning. Among the online students, men had a higher level of Digital Self-Efficacy and technology acceptance, and women had a higher level of anxiety and lower level of satisfaction in the learning process. People at a higher academic level had a lower level of anxiety and a higher level of satisfaction in the learning process and technology acceptance, and a higher level of Digital Self-Efficacy. Likewise, people who had a higher level of experience with online learning had a higher technology acceptance level and a higher level of Digital Self-Efficacy and satisfaction, and a lower level of anxiety. The findings support the hypothesis that online learning, as well as online teaching, can help reduce anxiety in the learning process and increase satisfaction; however, because of their educational and technological backgrounds, the levels of anxiety and confidence differ (Oubibi, 2025).

The findings support a complex and multidimensional perspective to AI in online learning, where the technological, psychological, and experiential dimensions interact. From a theoretical perspective, this study extends the Technology Acceptance Model by including Digital Self-Efficacy and Learning Anxiety in a framework on technology integration. From a practical perspective, universities need to offer AI and digital literacy training, technical assistance, and digital citizenship training for responsible use of AI. AI helps learners, but learners also need person-to-person contact. Colleges need to develop positive spaces for student learning that incorporate responsible and useful AI technologies, along with designing courses to match the tech, student confidence, and emotional maturity. AI does its job best when it acts as a guide. There should be a balance between technology and facial contact. The result should be an edge in learning. Schools are most responsible for developing technology to support learning the most (Feng, 2025).

Conclusion

The findings of this study showed that using AI in online learning improved students' digital self-efficacy and learning satisfaction. It also helped reduce anxiety and increased students' acceptance of learning technologies. Higher self-efficacy and satisfaction were linked to an increased acceptance of learning technology. Learning anxiety was related to a lower acceptance of technology and satisfaction. Digital self-efficacy was found to lead to an increased acceptance of learning technology, and the anxiety of self-efficacy was found to have a negative impact on the acceptance of learning technology. Acceptance was also positively related to satisfaction of the learning technology. The integration of AI and technology in online learning builds confidence and acceptance of students towards online learning.

This study found AI-integrated technology built psychological confidence and self-efficacy in students in the educational use of technology. The building of digital self-efficacy, technology acceptance, and the reduction of learning anxiety was found to improve students' online learning experiences. AI technologies, when integrated in education, should be built in a certain way to accommodate confidence and acceptance of differing students based on their gender and level of education and their experience with online learning. Academic-related technologies build confidence by offering digital and AI literacy, training, technical program support and safe AI responsibility in digital learning integration.

Future Implications

Future research should examine how AI-based online learning affects students' digital self-efficacy, anxiety, and satisfaction with learning and technology over time. These studies may also incorporate added layers (mediators) and boundaries (moderators) to the data, such as, trust in AI, perceived risk, and prior AI experience, as well as AI literacy and digital competence. Most would agree that studies performed in other areas of Pakistan and within a greater variety of centrally-administered institutions of learning would contribute to the understanding of the factors influencing digital self-efficacy. It would also contribute to a greater understanding of how these factors impact the satisfaction of learners. Further, the comparison of different AI technologies, including intelligent tutoring systems, adaptive learning technologies, and AI-based learning assessment systems, would provide a greater understanding of the cognitive and psychological effects of technologies used in online learning on the learners' satisfaction, perception, and acceptance of these technologies. It may also provide greater insights into the boundaries and layers that would make a distinction between responsible, inclusive, and student-centered technology integrated into higher learning.

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