AI in Higher Education: Does AI Fear Hinder Learning Outcomes?

Thanh Phong Cao, Thuy Huong Do, Quoc Thinh Duong and Thanh Hoang Nguyen

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1. Cao Thanh Phong
HumaniS lab
EM Strasbourg Business School, University of Strasbourg.
Vinh Long University of Technology Education.
Strasbourg, France
Email address:
thanh-phong.cao@em-strasbourg.eu

2. Do Thuy Huong
Faculty of Economics and Law
Vinh Long University of Technology Education.
Vinh Long City, Vietnam
Email address:
huongdt@vlute.edu.vn

3. Duong Quoc Thịnh
Faculty of Economics and Law
Vinh Long University of Technology Education.
Vinh Long City, Vietnam
Email address:
thinhdq@vlute.edu.vn

4. Nguyen Thanh Hoang
Ho Chi Minh City University of Social Sciences and Humanities, Vietnam
Email address:
ng.ngthoang@gmail.com

***Abstract* - This study delves into how AI fear impacts students' attitudes and learning outcomes in higher education. It finds that AI fear significantly influences student concerns regarding AI applications in learning environments, explaining around 50% of the factors affecting attitudes and outcomes. Perceived benefits, challenges, and familiarity with AI are identified as key factors influencing AI fear. In turn, AI fear negatively affects students' attitudes towards AI and their learning outcomes, while positive AI attitudes enhance learning outcomes. Understanding and addressing students' AI-related fears is crucial for higher education institutions to integrate AI and modern technologies into the curriculum, thereby enhancing educational experiences and outcomes in a conducive learning environment.**

Keywords: Technophobia, AI Fear, AI anxiety, Learning outcomes, Higher educational institutions.

I. INTRODUCTION

Traditional university learning platforms are ineffective compared to advancements in information and communication technology, which have significantly improved educational quality [1]. Higher education institutions face challenges with technology applications becoming crucial in development plans and educational reform initiatives [2]. Multimedia-sharing applications and social media platforms like Facebook, Twitter, and Skype, when effectively utilized, enable diverse access to ideas and presentations, promoting student-centered learning activities and overcoming geographical boundaries [3] [4].

The importance of Artificial Intelligence (AI) in education has surged significantly in recent years, creating high expectations and offering substantial innovation opportunities across the education sector [5]. Timms (2016) pointed out that AI has significant power and the potential to profoundly impact various fields of society, with education being particularly susceptible to AI influence [6]. Specifically, according to Chassignol et al. (2018), AI is increasingly integrated into educational activities, especially administrative tasks and teaching methods, directly impacting students' learning experiences [7]. Furthermore, online and web-based education has evolved from simple content delivery to incorporating intelligent systems that analyze teacher and learner behavior, personalizing the educational experience and enhancing learning efficiency [8]. Interest in AI in education has surged, with over 180 research papers published in 2019 alone [8]. Researchers are increasingly using advanced AI techniques like deep learning and data mining to address complex educational challenges and tailor teaching methods to individual student needs [1].

The prevalence of technology in contemporary society underscores the growing importance of studying "technophobia" and its impact on user psychology. As noted by Korukonda & Finn (2003), technophobia has remained a significant issue in industrial economies over the past two decades, with estimates indicating that nearly one-third of the population in industrialized countries may suffer from technophobia [9].

In psychology, fear is a fundamental emotion and an innate psychological state characteristic of humans [10]. Accordingly, fear is linked to the fight-or-flight response, which has supported our survival since the dawn of humanity. Therefore, as an emotion, fear tends to influence our behavior related to what threatens us. Specifically, behavioral and psychological science literature shows that under the pressure of fear, people will try to counteract the threat, or if unable to eliminate it, they will simply try to avoid it [11].

Researchers recognize technophobia, also referred to as computer anxiety, cyberphobia, or AI anxiety, as a common issue arising from the diversity of technology and AI [12]. This fear threatens user autonomy and satisfaction with AI systems, often influencing choices based on fear rather than logical reasoning [13]. AI, as defined by Chatterjee & Bhattacharjee (2020), encompasses computing systems capable of human-like processes, including adaptation, learning, synthesis, correction, and data utilization for complex tasks [14]. Portrayals of AI in science fiction movies have contributed to fears of highly intelligent AI making autonomous decisions, potentially leading to human extinction [15]. Technophobia is attributed to the pervasive integration of computer technology into everyday life [9], a phenomenon particularly relevant in education due to students' regular interaction with computers and digital media in modern learning environments.

There is a notable research gap in the advancement of pedagogical and psychological theories related to AI-driven educational technology. Zawacki-Richter et al. (2019) highlight the necessity for systematic reviews and encourage studies to delve into theoretical and empirical research on AI's implementation in education [16]. This exploration is crucial for understanding the mechanisms behind the dynamic development of AI and its impact on higher education. Despite the detailed insights provided by the multidimensional model of AI fear, there is still insufficient research on the factors contributing to various types of AI fear [15]. Previous studies reveal that individuals' perceptions of AI often stem from misconceptions and assumptions, primarily due to a general lack of understanding about algorithmic processes [15]. Thus, there is a clear need for deeper research into AI applications in higher education, particularly focusing on the analytical framework of AI fear, to address this significant theoretical gap.

II. LITERATURE REVIEW

A. *Artificial intelligence in higher educational institutions*

AI is a key driver of the Fourth Industrial Revolution, with organizations using it to overcome daily management challenges [17]. AI is integral to daily life, present in devices like smartphones with Siri, Google Assistant, and social network recommendation systems [8]. Raisch & Krakowski (2021, p.192) define AI as machines performing cognitive tasks traditionally linked to human intelligence, such as learning, interaction, and problem-solving [18].

Zhan et al. (2023) highlight the challenge of defining AI due to its evolving nature and varied industry interpretations [15]. Chassignol et al. (2018) offer a dual definition: academically, AI is a branch of computer science focused on tasks like learning, problem-solving, and pattern recognition; theoretically, it involves designing systems with human-like intelligence for tasks such as visual perception, speech recognition, decision-making, and language translation (p. 17) [7].

Furthermore, Popenici & Kerr (2017) describe AI in education as systems that simulate human processes like learning, adapting, and self-correcting, using data for complex tasks [19]. AI can also provide insights into learners' behavior, response times, and emotions [5]. Ahmad et al. (2020) categorize AI applications in education into areas such as intelligent tutoring systems (ITS), personalized learning, recommendation systems, student outcome analysis, emotion analysis, retention and dropout prediction, and classroom monitoring [20]. Holmes et al. (2023) similarly categorize AI applications into ITS, dialogue-based tutoring systems (DBTS), explorative learning environments (ELE), and automatic writing assessment (AWE) [5].

Diwan et al. (2023) suggest that AI enhances peer-to-peer learning, fosters collaborative knowledge sharing, and boosts engagement in educational activities, leading to improved learning outcomes and increased student motivation [21]. Integrating AI into learning objectives helps students acquire essential knowledge and skills for today's technological landscape [22]. AI tools like Turnitin and Pearson's Write-to-Learn also promote academic honesty and integrity [23]. However, there are concerns about AI facilitating dishonest behavior through platforms like paper mills [24].

An analysis by Chen, Chen, & Lin (2020) shows that AI has been implemented in various aspects of higher educational institutions, including automating administrative tasks, developing curricula, teaching methods, and the learning process of students. For example, Rus et al. (2013) suggest that Intelligent Tutoring Systems (ITS), such as CIRCSIM_Tutor and Why2-Atlas in modern online learning environments, perform diverse functions, including grading, providing feedback, and detecting plagiarism in student assignments [25]. Additionally, AI plays a crucial role in curriculum development and content creation, as well as instruction, leveraging technologies such as virtual reality, web platforms, robots, video conferencing, audio-visual files, and 3D technology to enhance the learning experience for students [26] [4] . This application of AI has led to increased efficiency and productivity for teachers, as well as more personalized and enriching educational experiences for students.

Similarly, Reisoğlu et al. (2017) highlight another aspect of AI through the use of virtual and 3D technology [27]. Virtual reality offers significant opportunities for experiential learning and integrated simulation-based instruction [6], enriching the learning process. Additionally, Kahraman, Sagiroglu, & Colak (2010) discuss the development and application of Adaptive and Intelligent Web-Based Educational Systems (AIWBES), integrating AI principles and technologies into web-based learning platforms, thus enhancing the learner's experience beyond the traditional "just-put-it-on-the-Web" approach [28].

B. *Technophobia and AI fear*

In academic literature, "technophobia" is often used interchangeably with "computer anxiety," and many studies assess individuals' discomfort and stress toward computers [29]. Korukonda (2005) notes a lack of consensus on the definitions and distinctions between computer anxiety, computer phobia, and technophobia. Despite frequent mentions in research titles, related concepts like computer anxiety, phobia, stress, or cyberphobia are often discussed instead [9]. This confusion indicates an inconsistency in terminology within the literature [30].

Technophobia, also known as computerphobia, is characterized by an irrational fear or anxiety about the impact of advanced technology [31]. It manifests through various indicators, including anxiety about current or future interactions with computer-related technologies, negative attitudes towards these technologies and their societal impact, and specific negative thoughts during or when contemplating interactions with technology [32]. Technophobia is conceptualized when anxiety and negative attitudes converge. It is important to distinguish between anxiety, such as computer anxiety, and negative attitudes, which relate to beliefs and feelings about technology rather than emotional reactions when using it [33]. Negative attitudes do not necessarily affect actual behaviors related to advanced technology [34]. Anxiety is defined as a heightened cognitive state due to perceived threats or unresolved fears, with trait anxiety being a stable personality characteristic and state anxiety being a temporary situational response [10]. Technology anxiety, including computer anxiety and internet anxiety, is a fluctuating state that can change depending on circumstances [35].

Technophobia, a global phenomenon, transcends geographical boundaries and is surveyed across various countries alongside technology (Rosen & Weil, 1995) [32]. Technophobia is closely linked to technological advancements, and new technologies continuously generate specific instances of this fear [8]. Khasawneh's (2018) research demonstrates that technophobia operates independently of computer anxiety, highlighting distinct underlying factors and emphasizing its unique significance among other technology-related anxieties. According to Khasawneh (2018), technophobia is an irrational fear or anxiety when faced with new technology that disrupts usual tasks. This fear can lead to avoidance or cause distress and anxiety [12].

Research on technophobia spans various theoretical perspectives, including cognitive spontaneity, social cognitive theory, the technology acceptance model, the theory of planned behavior, the theory of reasoned action, and the diffusion of innovations [30]. These approaches, classified into individual, structural, and interpersonal analysis levels, mainly focus on individual factors like fear, skill level, computer experience, self-confidence, and cognitive style, while also examining structural and process-related factors to understand technophobia's nature and causes [30].

Mishra & Pandey (2023) [36] suggest that a psychological model for assessing technophobia should include factors such as computer anxiety, cognitive approach, locus of control, and self-efficacy, expanding on the Technology Acceptance Model and the Theory of Reasoned Action [37]. They argue that behavioral intention, influenced by perceived usefulness and ease of use of technology, along with self-confidence, experience, and anxiety, is crucial for predicting technology acceptance and use.

Johnson & Verdicchio (2017) argue that AI anxiety stems from a perceived lack of control over AI [38]. Research shows that fear of AI predicts behavior, with personal beliefs about AI, such as anxiety, shaping behavioral intentions according to the Theory of Reasoned Action (TRA) [33]. Yu, Xu, & Ashton (2023) add that the relevance and alignment of innovation with an individual's experiences, values, and needs significantly impact technology adoption, with higher compatibility increasing acceptance[17].

III. HYPOTHESIS FRAMEWORK

The perceived benefits of AI, such as increased efficiency and enhanced problem-solving, significantly shape individuals' attitudes and reduce their fears. Studies using the Technology Acceptance Model indicate that perceived ease of use and usefulness positively influence attitudes toward AI [39]. These factors are crucial in predicting students' [40] and teachers' [41] attitudes and intentions to use AI.

The study by Schepman & Rodway (2020) emphasizes that awareness of AI's potential to streamline processes and facilitate innovation can mitigate anxiety and fear [42]. In higher education, integrating AI-driven tools like adaptive learning systems and administrative automation has demonstrated tangible benefits, with students and faculty experiencing practical improvements in educational experiences and operational efficiency, leading to lower levels of fear [16]. Thus, we hypothesize:

H1: Perceived benefits of AI negatively affect AI Fear.

Despite initial fear stemming from challenges like ethical concerns and potential job displacement associated with AI, a deeper understanding of these issues typically helps alleviate such fears as individuals perceive them as manageable and believe in the development of solutions to address them. According to Cao et al. (2020) [43], a comprehensive understanding of both the benefits and challenges of AI promotes a balanced perspective, reducing irrational fears. In the context of higher education, students and educators who engage in critical discussions about the ethical implications and potential limitations of AI are better equipped to overcome these challenges. This critical engagement helps demystify AI and reduces fear by fostering informed perspectives and proactive problem-solving [44]. Therefore, the following hypothesis is proposed:

H2: Perceived challenges of AI negatively affect AI Fear.

Increased familiarity with AI reduces fear by improving understanding and comfort with the technology, with studies indicating that exposure through education and practical experience diminishes initial anxieties and enhances acceptance [26]. In practice, integrating AI-related curricula and practical applications into coursework helps students develop a comprehensive understanding of AI. This familiarity, gained through direct interaction with AI tools and systems, mitigates fear by fostering a sense of competence and control [16]. Hence, we hypothesize:

H3: Familiarity with AI negatively affects AI Fear.

The importance of AI Attitudes has grown, with increasing interest in understanding the beliefs and factors influencing them [45]. Neudert et al. (2020) discovered widespread AI risk concerns across 142 countries, while Zhang & Dafoe (2019) reported that 41% of 2,000 surveyed American adults supported AI development, with 22% opposing it [44]. Kaya et al. (2024) noted that knowledge levels influence attitudes: more internet use and higher education correlate with positive AI attitudes. Despite documented predictors, attitudes toward AI in different cultural contexts need further exploration [45].

Research shows a correlation between anxiety/fear and the acceptance of new technology [46], with high anxiety levels often leading to decreased technology use [47]. Researchers have explored AI fear and AI attitudes using diverse methods [48]. Kaya et al. (2024) found that AI anxiety significantly affects attitudes toward AI, with AI learning and configuration anxieties being key predictors of attitudes [45]. Almaiah et al. (2022) argue that AI-related anxieties in educational settings negatively impact students' perceptions [49]. Fear of AI, stemming from a lack of understanding, can lead to apprehension and resistance to AI integration in learning experiences. Thus, the following hypothesis is proposed:

H4: AI Fear negatively affects AI Attitudes.

When students feel anxious and fearful about AI, it can lead to reduced engagement, decreased motivation, and hindered learning processes [49]. For example, students who fear AI might avoid courses or activities related to AI, thereby missing out on important learning opportunities and skill development [42]. Additionally, fear can cause cognitive overload, making students too preoccupied with their anxiety to effectively process and understand new information, resulting in poorer learning outcomes [50]. In a study by Zawacki-Richter et al. (2019), it was found that students who perceived AI as a threat had lower academic performance compared to those who viewed AI more positively [16]. Thus, we hypothesize:

H5: AI Fear negatively affects Learning Outcomes.

Positive attitudes toward AI in higher education are crucial for enhancing learning outcomes, as students who view AI favorably are more inclined to engage with AI-driven tools, thereby enriching the learning experience. Positive AI attitudes promote active learning environments, where AI is seen as valuable for personalizing learning, providing instant feedback, and aiding complex problem-solving [44]. Additionally, Wang, Liu, & Tu (2021) found that positive AI attitudes facilitate smoother adoption of AI in classrooms, improving student performance and satisfaction [51]. Thus, the following hypothesis is proposed:

H6: AI Attitudes positively affect Learning Outcomes.

Based on the hypotheses mentioned above, we propose the following research model:

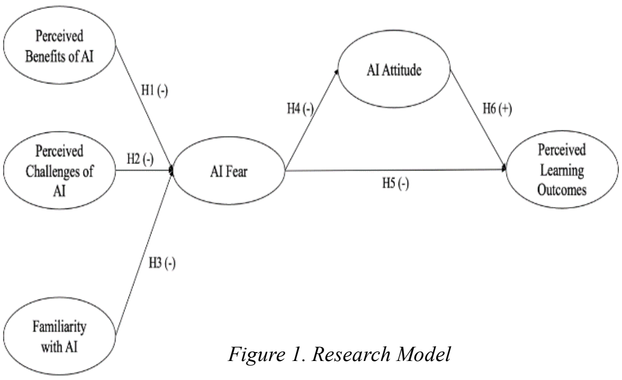

Figure 1. Research Model

IV. METHODOLOGY

In this research, we used a quantitative approach, conducting surveys via Google Forms. Data was collected from December 2023 to April 2024, targeting university students in major Vietnamese cities. Sample size determination in structural equation modeling (SEM) depends on factors like variable distribution, model complexity, and estimation methods. A large sample is needed to ensure reliable estimates and adequate statistical power [52]. We gathered responses through online platforms and personal networks, resulting in 519 valid responses after excluding incomplete ones, which were then analyzed.

After an extensive literature review, the researchers conducted an item-generation process based on a theoretical framework, including translation, review, discussion, and finalization. Initially, the English scale items were translated into Vietnamese, followed by a meticulous review and discussion by two bilingual English researchers to ensure translation accuracy and quality.

- *Perceived benefits of AI*: A 7-point Likert scale consisting of 19 items, including 5 factors: Ease to Use [56] [57] , Social Influence [53], Reciprocal Benefit [54], Recognition [55], and Usefulness [56] [57].
- *Perceived* challenges *of AI*: Denisova et al.'s (2020) 7-point Likert scale consists of 26 items, including 4 factors: Cognitive Challenge, Emotional Challenge, Performative Challenge, and Decision-Making Challenge [58].
- *Familiarity with AI*: Applying Chi et al.'s (2021) 7-point Likert scale, consisting of 5 items [59].
- *AI Fear*: A scale comprising 18 items, utilizing a 7-point Likert scale, adapted from Wang & Wang's (2022) [33].
- *AI Attitude*: Grassini's (2023) scale, utilizing a 7-point Likert scale, consisting of 5 items [60].
- *Learning Outcomes*: Applying Hytti et al.'s (2010) scale measuring perceptions of learning outcomes, utilizing a 7-point Likert scale, consisting of 9 items [61].

In this study, we will perform statistical analysis employing descriptive statistics with Smart-PLS (v.3.2.9). We utilized SEM through the partial least squares approach via the analysis software to assess the gathered data and examine the research hypotheses.

V. RESULTS

A. Demographic characteristics of participants

The dataset comprises responses from 519 participants, predominantly female (62%) and mostly in their fourth year of school (41%). Economics majors accounted for the majority (54%), followed by social sciences (11%) and information technology & AI (10%) majors (Table 1).

TABLE I. PARTICIPANT DESCRIPTIVE STATISTICS (N = 519)

Category	Frequency	Percentage
Gender		
Male	195	38%
Female	324	62%
Year		
1st	35	7%
2nd	127	24%
3rd	145	28%
4th	212	41%
Major		
Biotechnology	7	1%
Urban architecture	11	2%
Law	21	4%
Finance - Banking	43	8%
Engineering and Technology	45	9%
Information Technology and AI	54	10%
Social Sciences	59	11%
Economics	279	54%

B. Multigroup Structural Analysis by Gender

We will conduct a Multigroup Analysis (MGA) using the Smart-PLS software to examine whether there are differences in the effects of factors on Learning outcomes among different groups based on Gender. The results indicate no difference between male and female students as the p-value is greater than 0.05.

C. Structural Equation Model

a) Outer Loadings

Hair et al. (2019) suggest that an outer loading coefficient of 0.708 or higher indicates high quality, with the latent variable accounting for at least 50% of its variance. Indicators with coefficients between 0.4 and 0.7 should only be removed if they improve overall reliability. Hence, all observed variables in our study meet these criteria, requiring no removal [62].

b) Measurement Reliability and Convergence

Many researchers prefer Composite Reliability (CR) over Cronbach's Alpha for its precision, targeting CR values of 0.6 or higher in exploratory research and 0.7 in confirmatory studies [63]. Hair et al. (2019) also recommend a 0.7 threshold. Convergence is measured using Average Variance Extracted (AVE), with values above 0.5 indicating that the latent variable explains at least 50% of the variance in each observed variable [62]. Our analysis showed AVE values of 0.470 and 0.479 for Perceived benefits and Perceived challenges of AI, respectively, both confirming convergent validity (see Table 2).

TABLE II. MEASUREMENT RELIABILITY AND CONVERGENCE

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Perceived benefits of AI	0,913	**0,915**	**0,925**	**0,470**
Perceived challenges of AI	0,945	**0,947**	**0,950**	**0,479**
Familiaity with AI	0,875	0,877	0,909	0,666
AI Fear	0,965	0,965	0,968	0,654
Learning outcomes	0,929	0,929	0,940	0,637
AI Attitude	0,901	0,901	0,926	0,716

c) *Discriminant*

Discriminant validity evaluates the distinctiveness of a structure within the model. Traditionally, this is assessed using the square root of the Average Variance Extracted (AVE) index, but Henseler, Ringle, & Sarstedt (2015) introduced the Heterotrait-Monotrait ratio (HTMT), which offers a more precise evaluation [63]. They recommend a threshold below 0.85, which aligns with SMART-PLS assessments. The model's results confirm discriminant validity (see Table 3).

TABLE III. DISCRIMINANT

	Perceived benefits of AI	Perceived challenges of AI	Familiaity of AI	AI Fear	Learning outcomes	AI Attitude
Perceived benefits of AI	0,686					
Perceived challenges of AI	0,836	0,692				
Familiaity with AI	0,624	0,632	0,816			
AI Fear	-0,702	-0,747	-0,578	0,809		
Learning outcomes	0,689	0,723	0,542	-0,572	0,798	
AI Attitude	0,778	0,764	0,577	-0,689	0,677	0,846

Model Fit

Smart-PLS (v.3.2.9) software was used to run SEM with PLS-SEM and Bootstrapping capabilities. The results are depicted in Figure 2 below.

When evaluating the SEM model, we pay attention to the following: (1) VIF coefficients to assess multicollinearity, (2) Effect coefficients and significance of path coefficients, (3) R-squared coefficients, and (4) F-squared coefficients

VIF - Multicollinearity

As indicated by Hair et al. (2019), when the VIF reaches a value of 3 or higher, it suggests the presence of multicollinearity in the model [62]. With the VIF values of all variables in the model not exceeding 3, no variables need to be removed.

Evaluating Impact Relationships - Path Coefficients

We assess impact relationships using Bootstrap analysis, focusing on two columns: (1) Standardized impact coefficient and (2) P values compared to a threshold of 0.05. All p-values are < 0.05, indicating acceptance of all hypotheses. Specifically, Perceived benefits, Perceived challenges, and Familiarity with AI negatively impact AI Fear. Additionally, AI Fear negatively influences AI Attitudes and Learning Outcomes, while AI Attitudes positively affect Learning Outcomes (see Table 4).

TABLE IV. PATH COEFFICIENTS AND HYPOTHESIS TESTING

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis
Perceived benefits of AI → AI Fear	-0,213	-0,216	0,075	2,844	0,005	**H1: Accepted**
Perceived challenges of AI → AI Fear	-0,479	-0,476	0,079	6,049	0,000	**H2: Accepted**
Familiarity with AI → AI Fear	-0,142	-0,143	0,054	2,629	0,009	**H3: Accepted**
AI Fear → AI Attitudes	-0,689	-0,686	0,032	21,262	0,000	**H4: Accepted**
AI Fear → Learning Outcomes	-0,202	-0,199	0,070	2,881	0,004	**H5: Accepted**
AI Attitudes → Learning Outcomes	0,538	0,542	0,063	8,493	0,000	**H6: Accepted**

The degree of explanation of the independent variable for the dependent (R squared)

The coefficient of determination (adjusted) reflects the impact of independent variables on Learning Outcomes, ranging from 0 to 1. With R-square = 0.479 (adjusted R-square = 0.477), about 48% of the variation in Learning Outcomes is explained by the observed variables.

The value of the effect size f-square

Effect size indicators like f-square and standardized regression coefficients reveal the impact levels of independent variables on the dependent variable, with f-square providing thresholds for strength assessment. Results show small effects on Perceived benefits and Familiarity, a strong effect of Perceived challenges on AI Fear, a large impact of AI Fear on AI Attitudes, a small effect on Learning Outcomes, and an average effect of AI Attitudes on Learning Outcomes (see Table 5).

TABLE V. F-SQUARE

	f-square
Perceived benefits of AI → AI Fear	0,032
Perceived challenges of AI → AI Fear	**0,157**
Familiarity of AI → AI Fear	0,028
AI Fear → AI Attitudes	**0,904**
AI Fear → Learning Outcomes	0,041
AI Attitudes → Learning Outcomes	**0,292**

VI. DISCUSSION

Initially, a multigroup analysis based on gender shows no significant difference in AI Fear's impact on Learning Outcomes between male and female students, aligning with Khasawneh (2023) [64]. However, research often finds females exhibit higher technology fear [65], linked to perceptions of gender roles in male-dominated fields, which hinders their technology proficiency [17]. Higher internet usage and education levels correlate with positive AI attitudes, with males and younger individuals generally more favorable [45]. Further research is needed, particularly in diverse cultural contexts.

Studies suggest that perceptions of Benefits, Challenges, and Familiarity have a detrimental effect on AI Fear, aligning with previous research [42] [16] [44] [26] [41]. These findings are significant because, although many individuals may not regularly encounter machines or robots, they are likely to interact with AI in the future (e.g., Siri or Google Home). Exploring models and theories on human-AI relationships can enhance these associations and overall performance [66]. Research shows that increased familiarity with AI correlates with reduced AI Fear.

Zhang et al. (2023) suggest that AI fear often arises from a lack of awareness or insufficient foundational knowledge about AI technology, especially among students who may have limited exposure to AI-based educational products [41]. These individuals tend to focus more on the tangible benefits of AI in education and prioritize user-friendliness due to potential barriers in navigating complex AI systems without technical expertise. However, as students become more familiar with AI in education, their perceptions and attitudes towards it may evolve. Therefore, effective implementation of AI-based educational products requires training programs that provide adequate exposure and education for both students and educators, enabling them to understand the technology better and make informed decisions regarding its use in the classroom. An intuitive, user-friendly AI tool minimizes students' learning and product management time, enabling greater focus on learning and decreasing anxiety about AI applications [67]. Incorporating features like gamification enhances motivation and engagement, while chatbots offer personalized student interactions, ultimately reducing teachers' workload and providing tailored support.

Furthermore, engagement with AI technology is just one aspect of the learning process, as highlighted by Diwan et al. (2023) [21]. Utilizing AI in real-world courses can enhance practical skills and interactions among students, thereby supporting final performance outcomes. Almaiah et al. (2022) discovered that cooperative learning environments significantly reduce social anxiety, computer anxiety, and AI fear in online learning by fostering a collaborative atmosphere where learners share information and support each other [49]. Educational programs should promote open learning environments that encourage student interaction and collaboration, ultimately boosting motivation, and confidence, and improving learning outcomes.

Moreover, the results show that AI Fear strongly influences AI Attitude, consistent with previous studies [45] [49]. Kaya et al. (2024) found that personality traits, AI anxiety, and demographics significantly influence attitudes toward AI [45]. Their research highlights that positive AI attitudes correlate with improved student learning outcomes.

Research demonstrates that the "novelty effect" is a phenomenon that can occur in studies related to new or improved technologies, such as dialogue systems, where initial excitement and curiosity generated by the technology can lead to increased student engagement and performance [68]. Educational programs should encourage positive attitudes toward AI to enhance learning outcomes. However, Lubis et al. (2019) caution against the novelty effect of AI dialogue systems in language practice, which could impede long-term collaboration. To mitigate this effect in studies involving new technology, learners must receive adequate training and support [69].

Higher education institutions must establish learning goals for students and staff to develop skills and adapt to new AI technologies, such as those implemented at Athabasca University in Canada [70]. These initiatives promote learner autonomy, duty of care, transparency, and other principles, facilitating the conscientious use of Generative AI in classrooms [70]. Implementing these actions in higher education institutions can enhance educational capabilities and meet market demands. Moreover, AI dialogue systems aid in information retrieval, feedback, and guidance for students [26] [5] , allowing teachers to focus on critical thinking skills. Consistent use of AI dialogue systems helps identify students needing support and offers personalized guidance. These systems also incorporate students' interests, provide hands-on activities, and offer multimedia-rich resources for effective learning [26].

VII. CONCLUSION

The study investigated AI's effect on university education, particularly students' AI fear, and its impact on learning outcomes. Findings revealed significant effects, with AI fear explaining approximately 50% of the factors, indicating student apprehension regarding AI applications in learning settings. This fear notably influences students' attitudes toward AI, subsequently affecting learning outcomes. Addressing AI fear is crucial for improving learning outcomes, underscoring the necessity for higher education institutions to acknowledge this concern when integrating AI and modern technologies into education.

The study acknowledges limitations that warrant attention in future research. It focused solely on university students, potentially limiting the study's scope and applicability. Future studies should strive for demographic diversity, considering variables like income, education level, age, personality traits, profession, and cultural backgrounds. Employing methods such as big data analysis or behavioral experiments can deepen insights into technology and AI fear. Additionally, investigating how personality traits influence perceptions of AI adaptation can offer a valuable understanding of individual reactions to AI fear.

Additionally, this study relied on self-reported online surveys, potentially introducing methodological biases that hindered a direct examination of students' perceptions of fear and attitudes toward AI. To address this issue, future research could employ alternative research designs, such as experimental approaches, to enhance interaction experiences and gain deeper insights into the research topics. Moreover, considering that Vietnamese people exhibit a moderate level of uncertainty avoidance [71], future studies should expand models to incorporate specific cultural characteristics. This refinement would enhance the theoretical framework and increase the realism of experimental studies [72].

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