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RESEARCH ARTICLE

Understanding the Factors Influencing Higher Education Students' Intention to Adopt Artificial Intelligence-Based Robots

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ABSTRACT Although there has been some progress, the integration of artificial intelligence into higher education remains far from sufficient. The demand for teachers will persist for some time; however, with the introduction of AI-based robots into classrooms, the role of teachers has been reduced to a minimum. The purpose of the current study was to evaluate Chinese higher education students' intentions to adopt AI-based robots for educational purposes. Based on the Technology Acceptance Model (TAM) 3 model, the current study proposes 14 hypotheses to evaluate students' intention to adopt AI-based robots in education. The students' data were collected and analyzed using PLS-SEM. The study findings revealed that 12 hypotheses were accepted and two were rejected. The results indicate that students are willing to accept AI-based robots in their education. However, the findings revealed an insignificant influence of job relevance and robot anxiety on perceived usefulness and ease of use, respectively. The findings of this study will provide insight into university administrations regarding the significance of AI-based robots in education. Moreover, the findings will help robot developers, policymakers, and university administrators design and implement AI-based robots that fulfill contemporary education needs.

INDEX TERMS AI-based robot, education, TAM3, perceived usefulness, perceived ease of use, behavioral intention.

I. INTRODUCTION

The far-reaching impacts of technological revolution during the 20th century continue to shape contemporary society. The objective of Artificial Intelligence (AI) is to develop computational systems capable of acquiring knowledge from their surroundings and demonstrating intelligent and adaptable behaviors [1]. The advancement of technology has brought about fundamental shifts in communication methods, healthcare practices, and knowledge acquisition [2]. The education community has directed its attention towards developing AI-powered solutions, including Intelligent Learning Environments (ILEs), Intelligent Tutoring Systems (ITSs), and AI-based educational robots [3]. These systems aim to emulate the expertise of human one-to-one tutoring, offer personalized learning experiences that optimize the quality of learning for users [4], and strive to cater to students' social needs [5]. AI-based systems possess autonomy, adaptability, and interactivity as their defining features [6]. AI techniques can gather and assess learners' behavioral and psychological information and establish links with knowledge networks [7]. Instead of following a predetermined approach devised by experts, these techniques can adapt and modify personalized learning plans according to learners' interactions and feedback [3].

The future prospects of AI-driven educational systems rely not only on technological advancements but also on the willingness of users to accept them. Introducing AI

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in universities has the potential to produce lasting impacts on learners' attainment of knowledge and their ongoing personal growth throughout their lives [8]. Universities need to adjust to the new economy and potentially a different lifestyle while educating people to adapt to these changes. AI and robotics can revolutionize education, bringing significant changes to the learning process, the roles of teachers and researchers, and the overall functioning of universities as institutions [9]. Researchers have indicated that despite technological advancements, there has been no clear improvement in the current methods of education [2]. From this perspective, any educational method that integrates diverse technological resources should be connected to enhance learners' performance [5]. In recent times, students need to remain vigilant about the changes and accept the implementation of new resources to foster active and collaborative learning among student teachers. Over the decades, China's education network has undergone a remarkable expansion [3]. Therefore, there is an urgent need for profound transformation in the teaching-learning environment and administrative responsibilities within the higher education system in China. Contemporary educational settings require many factors to incorporate problem-based learning rooted in real-world complexities [2].

The AI robot industry is experiencing remarkable growth in the age of AI owing to the escalating demand for smartphones and growing utilization of messaging applications [10]. In the last few years, robot technology has been adopted by the food delivery, financial, e-commerce, and other industries [11], [12]. Using AI-based robot technology could bring substantial benefits to education, bringing it one of the industries assured of substantial growth [13]. Researchers have argued that the development of AI-based Chatbots for education offers various advantages. These intelligent systems can boost teaching and learning efficiency, improve productivity, enhance communication, and minimize ambiguity in interactions [2]. Utilizing AI-based technology as an interactive tool, a novel educational system demonstrates its ability to efficiently address urgent challenges in education [14]. Joen [15] argued that AI-powered chatbots in education enrich the student-learning journey. Yang et al. [16] indicated that the implementation of AI in the education sector enhanced human betterment policy, instruction, and research. Chatterjee and Bhattacharjee [17] conducted a study on the integration of AI into India's higher education. They found that the successful implementation of AI would greatly assist authorities in facilitating its adoption in the domain of higher education. Zhong and Xia [18] reviewed the literature on the integration of robotics in mathematics education. The findings of this study highlight the practical relevance and technical aspects of robotics in educational research.

In recent years, remarkable progress has been made in the field of education, particularly with regard to AI-based robots [19], [20]. In contrast to tablets and screens, studies have indicated that AI-based robots result in greater learning improvements [2], [20], and produce emotional expressions [21]. In the past, researchers have used AI-driven robots in the education of various subjects, such as mathematics [22], science [23], nutrition [24], and languages [25]. AI-based robots have various roles in education. They serve as both peers and companions during the learning process alongside students [26]. Additionally, they act as tutors, taking on the responsibility of instructing students [17]. Furthermore, AI-based robots have been employed in various teaching roles, including the frontal lecture mode [27], engaging in two-person dialogues [28], and one-on-one interactions [20]. The gradual integration of AI-based robots into educational systems [29] has led to significant advancements in technology. Over the past few years, there has been a growing emergence of various applications for social robots in higher education [30]. Rosenberg-Kima et al. [20] posited that AI-based robots have the potential to function as teaching assistants, providing assistance to students in small groups by addressing their basic inquiries.

Dai et al. [31] designed and validated a tool to evaluate students' preparedness to study AI. The researchers conducted a survey using a closed-ended questionnaire within a Beijing school district to evaluate students' intention to learn about AI. The findings of this study indicated that AI literacy does not predict AI readiness. Instead, students' level of confidence and their recognition of the significance of AI played a mediating role in determining AI readiness. Furthermore, the researchers found that neither decreasing AI anxiety nor enhancing AI knowledge affected students' AI readiness. Chai et al. [32] conducted a study on 131 primary students and examined the factors that influenced their behavioral intention (BI) to participate in AI learning. The findings of the study revealed that the learning goal of AI for the societal good is the most influential factor in determining students' BI. Chassignol et al. [33] stated that several levels of education have seen the integration of AI, such as learning, administration, and instruction. Researchers have extensively studied students' readiness to use AI for learning purposes. Timms [34] suggested that the implementation of college robots, which refer to working in tandem with teachers, is being utilized to instruct children in routine tasks, including pronunciation and spelling, while also adapting to each student's individual abilities. Recently, many researchers have studied the adoption of chatbots by students [35]. Ait-Mlouk and Jiang [36] argued that chatbot is a natural language processing technique used to interact with the user. In contrast, AI-based robots are physical machines capable of adapting to their surroundings and executing specific tasks [37]. The existing literature presents limited studies examining students' acceptance of AI-based robotics in the education sector. It is essential to understand the adoption of AI-based robots from the students' perspective. Therefore, this study addressed the following research questions:

1. What are the factors that influence Perceived Usefulness (PU) towards the acceptance of AI-based robots among students in education?
2. What are the factors that influence Perveived Easy of Use (PEOU) towards the acceptance of AI-based robots among students in education?
3. Do PU and PEOU influence the acceptance of AI-based robots among students in education?

This study aimed to evaluate students' acceptance of AI-based robots in higher education institutions in China. The current study used a modified technology acceptance model (TAM3). In the past, researchers utilized the theory of planned (TPB) [38], technology readiness index (TRI) [2], UTAUT [39], and UTAUT2 [40]. However, research posits that TAM offers a more comprehensive explanation of BI than UTAUT, TRI, and TPB [38], [41], [42]. Therefore, the current study will utilize the modified TAM3 to predict student acceptance of AI-based robots in education. TAM3 offers a comprehensive understanding of student acceptance of AI-based robots because it includes technology-related constructs that are appropriate for predicting the acceptance of novel technology. The results of the current study provide valuable insights regarding students' INT in adopting AI-based robots in education. Furthermore, the findings of this study will contribute to the development of AI-based robots and help university policy makers implement and use AI-based robots in the higher education sector.

II. LITERATURE REVIEW

A. THEORETICAL BACKGROUND: TECHNOLOGY ACCEPTANCE MODEL (TAM3)

TAM was originally presented by Davis [43] as a utilization of Ajzen's [44] theory of planned (TPB). The TAM has been employed to assess the impact of different factors on users' adoption of technology, focusing on two key constructs: perceived ease of use (PEOU) and perceived usefulness (PU). The characterization of these constructs depends on items that explain users' inclination to accept or reject new technology. Previous researchers have criticized the initial TAM for its ineffectiveness in engaging users and encouraging acceptance of new technologies [45], [46].

The original TAM model has been modified several times, leading to the development of TAM2 [47], and subsequently, TAM3 [46], [48]. TAM3 represents a comprehensive technology acceptance model wherein PEOU includes several antecedents: computer anxiety, computer self-efficacy, perceived enjoyment, computer playfulness, technology usability, and perception of external control. TAM3 incorporates PU and its determining factors. Additionally, it explores how result demonstrability (RES), subjective norm, image (IMG), job relevance (JR), and output quality (OPQ) affect PU [46]. This model incorporates additional relationships that examine how experience influences the connections between PEOU and PU, computer anxiety and PEOU, and PEOU and Behavioral Intention (BI).

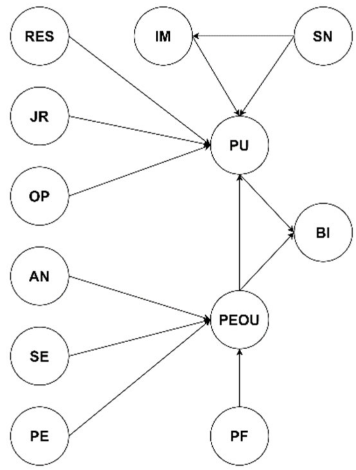

FIGURE 1. Theoretical model for evaluating students' behavioral intention to adopt AI-based robots (Note: BI = Behavioral intention; PEOU = Perceived ease of use; PU = Perceived usefulness; SN = Subjective norm; IMG = Image; RES = Results demonstrability; JR = Job relevance; OPQ = Output quality; ANX = Anxiety; SE = self = efficacy; PE = Perceived enjoyment; PF = Perceived playfulness.)

In the past, researchers have utilized TAM3 to examine workers' perceptions of social robots and their willingness to accept human-robot collaboration [46]. The primary concern in this case revolved around employees' fear of potential injuries caused by robots, the risk of job displacement due to automation, and the overall unease towards integrating robots into the workplace. Addressing these challenges requires a thorough examination of the implementation and acceptance of innovative social robots. Research on human-robot collaboration has primarily focused on industrial production systems, with limited exploration in social contexts within workplaces, such as workplace reception areas, cafeterias, and work environments [49]. Past studies on AI-based robots have predominantly utilized UTAUT [39] and extended TAM [2] to assess the acceptance of social robots within the context of healthcare and education [46]. However, UTAUT [50]. include constructs that may not be directly related to the educational context, such as effort expectancy and price value [2]. Therefore, the TAM3 model proved to be more appropriate than the UTAUT2 model for examining AI-based robots in an educational context as it includes output quality, results, demonstrability, self-efficacy, enjoyment, anxiety, and playfulness. TAM3 has been limited; therefore, researchers have called for its application of the TAM3 in several IT-based contexts to comprehensively understand the acceptance of technology [45], [48]. The current study used TAM3 to examine students' acceptance of AI-based robots in an educational context. Figure 1 shows the theoretical model used in this study.

B. HYPOTHESES DEVELOPMENT

PU refers to the extent to which a person believes that a specific technology can enhance task [51]. When considering AI-based technology, perceived usefulness refers to how

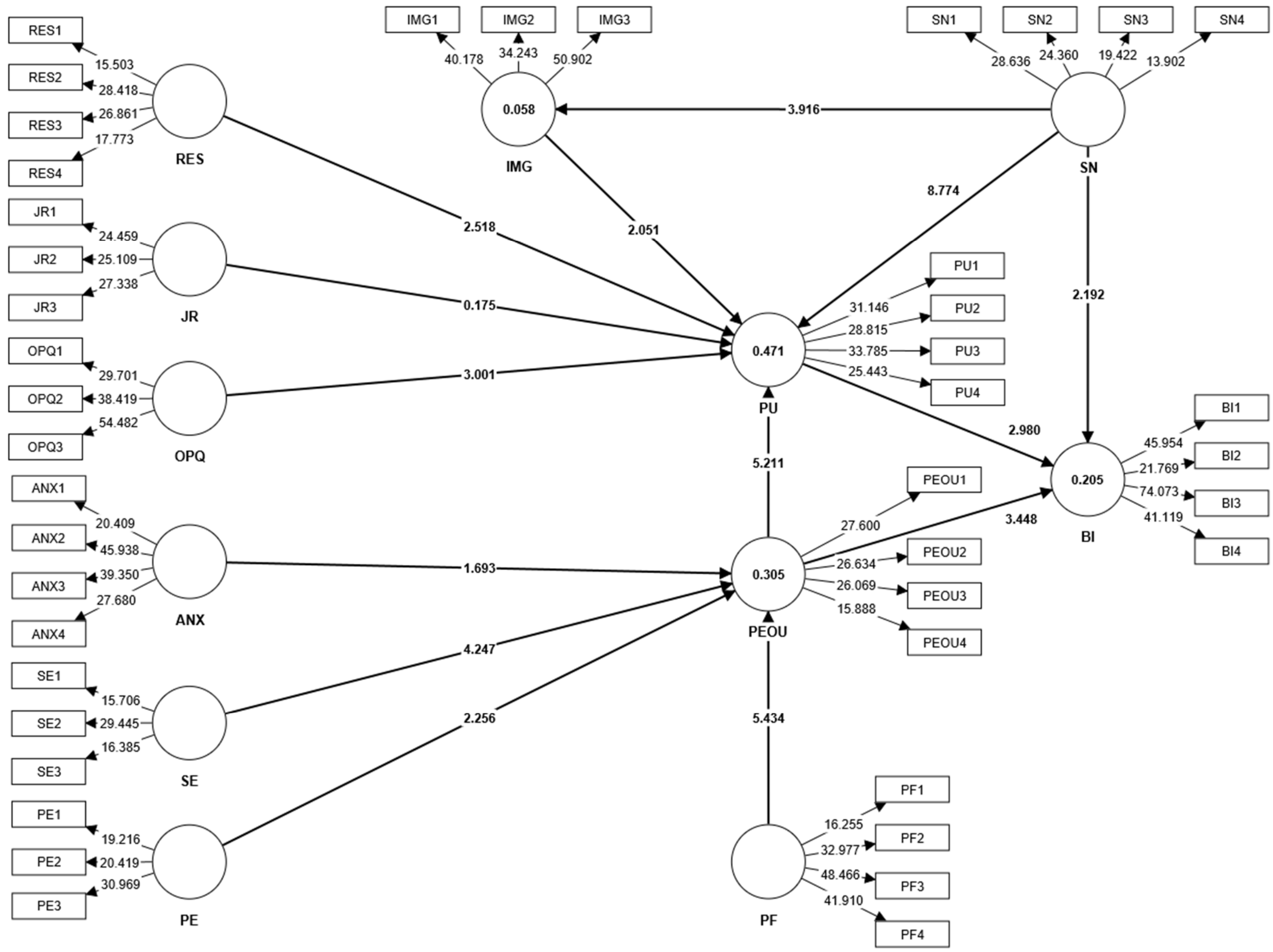

FIGURE 2. Structural model.

students perceive the potential of AI-based robots to offer a more efficient and productive alternative, ultimately enhancing their learning. PEOU refers to an individual's perception of how easily they can operate a specific technology [52]. Likewise, when considering AI-based technology, PEOU refers to the belief that utilizing AI-robots' robots for educational assistance is easy. When a person develops a belief in the PU and PEOU of a specific technology, coupled with its connection to their values, their inclination towards using it becomes more positive [53]. Researchers have revealed that PU and PEOU play crucial roles in predicting technology adoption in the education sector [54]. Recently, a study conducted by Almogren and Aljammaz [55] revealed the positive influence of PU and PEOU on BI to use mobile devices for educational purposes. Bailey et al. [56] found that PU and PEOU had a significant positive influence on students' learning through video conferencing technology. We assumed that the PU and PEOU of AI-based robots influence the adoption of AI-based education for learning purposes. Hence, we propose:

H_1: PU has a positive influence on students' BI to adopt AI-based robots.

H_2: PEOU has a positive influence on students' BI to adopt AI-based robots.

H_3: PEOU has a positive influence on PU of AI-based robots.

Subjective norms refer to people's opinions and attitudes toward their social circle, including friends, family members, and peers [57]. These perceptions can significantly impact a person's behavior and play a crucial role in shaping BI. Venkatesh et al. [39] discovered that there is a positive correlation between subjective norms and both perceived usefulness (PU) and BI [48]. Park et al. [58] found that Subjective Norm (SN) significantly influences PU and BI to use mobile devices for learning. Saari et al. [46] studied the adoption of social robots in the workplace. The authors found that subjective norms significantly influence the Image (IMG) of social robots, but they have an insignificant influence on the PU and BI to use social robots in the workplace. The inconsistent past results necessitated further exploration of the impact of subjective norms on the adoption of AI-based technology in other contexts. Therefore, we assume that subjective norms influence the IMG and affect PU and students' BI to use AI-based robots in education. Hence, the following hypothesis is proposed:

H_4: SN has a positive influence on IMG.

H_5: SN has a positive influence on PU.

H_6: SN has a positive influence on students' BI to adopt AI-based robots.

An IMG can be described as the extent to which the use of a system is perceived to enhance an individual's social status within their social network [59]. The rise of AI and its widespread integration into various aspects of human life create social pressure, particularly for universities to adopt AI-based education [60]. Previous research indicates that technology adoption can elevate a university's global reputation [61]. Chen et al. [26] revealed that AI student assistance chatbots have demonstrated good results in supporting students' learning. The integration of technology can also enhance students' learning outcomes [62]. Huang et al. [63] found that AI-enabled recommendations have a substantial impact on students' learning. Job relevance is people's perception of the extent to which the target technology is relevant or applicable to their job [48]. Kim et al. [64] found that the job relevance of information technology in auditing has a significant effect on the usefulness of information technology in auditing. Based on the findings of previous studies, it can be assumed that AI-based robots can improve university and learning IMG and have good demonstrability and quality outputs. Therefore, the following hypothesis was proposed:

H_7: The IMG of AI-based robots has a positive influence on PU.

H_8: RES of AI-based robots has a positive influence on PU.

H_9: OPQ of AI-based robots has a positive influence on PU.

H_{10}: JR of AI-based robots has a positive influence on PU.

One of the important features of the TAM3 model is the addition of PEOU antecedents [46], [48]. TAM 3 includes self-efficacy, anxiety, playfulness, perceived enjoyment, and job relevance as important antecedents of PEOU. The addition of these constructs will help broadly understand the application of novel technology. AI-based robots are emerging technologies that can assist students in enhancing their learning. The origin of self-efficacy can be traced back to Bandura's social cognitive theory [65]. It refers to the confidence an individual possesses in their ability to perform a particular task [66]. Researchers have revealed that robot self-efficacy significantly influences the PEOU of AI-based robots [46]. The fear of using AI-based robots is primarily influenced by individuals' state of mind regarding their willingness and ability to embrace the technology [67]. Anxiety is characterized as the level of unease an individual experiences when confronted with the prospect of using technology [48]. Recently, researchers indicated that robot anxiety negatively influences PEOU.

Furthermore, Venkatesh and Bala [48] argued that perceived enjoyment, playfulness, and job relevance are important factors that affect PEOU. Researchers posit that individual subjective experiences, irrespective of the outcomes, represent the perceived enjoyment of the technology [68], [69]. Playfulness refers to the level of cognitive spontaneity observed during interactions [70]. However, Saari et al. [46] revealed that robot playfulness had an insignificant effect on the adoption of AI-based social robots in the workplace. Based on the findings of previous studies, the following hypothesis was proposed:

H_{11}: Robot SE has a positive influence on PEOU.

H_{12}: Robot ANX has a negative influence on PEOU.

H_{13}: Robot PE has a positive influence on PEOU.

H_{14}: Robot PF has a positive influence on PEOU.

III. RESEARCH METHODOLOGY

A. RESERCH INSTRUMENT

This study employs a modified TAM3 to assess university students BI towards AI-based robots in education. The measurement scale utilized in this study was adopted from the literature (Table 1). The questionnaire was developed in English and Chinese and underwent minor modifications to match the study context. It was evaluated by education experts to ensure its appropriateness for the present study. Subsequently, a pilot study was conducted with 60 students to assess the appropriateness of the construct items. The results for all constructs, except IMG and JR, surpassed the threshold level of 0.70, indicating data reliability. Therefore, external experts reassessed these two constructs. They have suggested minor wording changes. Then, the questionnaire was presented to five students who had previously filled out the questionnaire to determine whether they understood the intended concepts. After confirming the scale's face and content validity, it was formally distributed to university students.

B. SAMPLE AND DATA COLLECTION

This research was undertaken at Chinese universities located in the northwest area of China, with a focus on the implementation of AI-based robots in education. The researchers distributed the questionnaire to the students in their study groups. Researchers have only sent the online website link wenjuan.com to students in the information technology and engineering fields because they have a greater understanding of AI-based robots than other department students. The sample size was determined according to the method described by Bentler and Chou [71]. They suggested five to ten responses per item for the construct. The total number of items was 43; therefore, the researchers decided to collect a maximum of 10 responses per item. A questionnaire was distributed to 650 full-time students. Out of 650, only 348 questionnaires were completed by the students, with a response rate of 53.53%. Table 2 presents the students' demographic profiles.

TABLE 1. Constructs' items and sources.

Constructs	Items	Sources
Perceived Ease of Use	PEOU1: The AI-based robots feature in education will be more accessible and attractive. PEOU2: Interacting with the AI-based robots does not require lot of mental effort. PEOU3: I find AI-based robots easy for learning purpose. PEOU4: The teaching environment will be more attractive with AI-based education robots.	[2]
Perceived Usefulness	PU1: Using AI-based robots improves my performance in education. PU2: Using AI-based robots enhance my effectiveness in understanding the concepts in education. PU3: I find AI-based robots to be useful in learning new concepts in education. PU4: I find AI-based robots' information accurate and helpful.	[2]
Subjective Norm	SN1: People who influence my behavior think that I should use AI-based robots in education. SN2: People who are important to me think that I should use AI-based robots in education. SN3: The teachers of the university have been helpful in the use of AI-based robots in education. SN4: In general, my university has supported the use of AI-based robots in education.	[48]
Image	IMG1: Students in my University who use the AI-based robot have more prestige than those who do not. IMG2: Students in my University who will use AI-based robot create good reputation. IMG3: Using the AI-based robot is a status symbol in my university.	[46]
Results demonstrability	RES1: I find it easy to share the results produced by the AI-based robot with others. RES2: I am confident that I can effectively convey to others the implications of using AI-based robots. RES3: The results of the AI-based robot are clear to me. RES4: I would find it easy to explain the potential advantages or disadvantages of the AI-based robot.	[48]
Output quality	OPQ1: The quality of the output I get using the AI-based robots is high. OPQ2: I rate the results from the AI-based robots to be excellent. OPQ3: I have no problem with the quality of the AI-based robot's output.	[48]
Job relevance	JR1: In my education, usage of my AI-based robot is important. JR2: It would be difficult to do my assignments without AI-based robot. JR3: Using AI-based robot is relevant to my education.	[48]
Robot self-efficacy	SEI1: I could complete the work using AI-based robot without any technical support. SE2: I could complete the work using AI-based robot If only I had access to the built-in facility for assistance. SE3: I could complete the work using AI-based robot If someone assist me using it for the first time.	[46]
Robot anxiety	ANX1: AI-based robot scares me. ANX2: Working with AI-based robot makes me nervous. ANX3: AI-based robot makes me uncomfortable. ANX4: AI-based robot makes me feel uneasy.	[48]
Perceived enjoyment	PE1: I find using the robot to be enjoyable. PE2: The actual process of using the robot is pleasant. PE3: I have fun using the robot.	[46]
Perceived playfulness	PF1: I would be spontaneous when I use AI-based robots. PF2: I would be creative when I use AI-based robots. PF3: I would feel playful when I use AI-based robots. PF4: I would feel original when I use AI-based robots.	[48]
Behavioral intention	BI1: I will use AI-based robots in education if it would be accessible. BI2: I would plan to use AI-based in education. BI3: In the future I would use AI-based. BI4: I would use AI-based robots because there is a positive environment of using AI-robots in our university.	[2], [46]

TABLE 2. Demographic profile.

		Frequency	Percentage
Gender	Male	216	62.07%
	Female	132	37.93%
Education	Bachelor	92	26.4%
	Master	208	59.8%
	PhD	48	13.8%
Field of specialization	Electrical	40	11.5%
	Mechanical	25	7.2%
	Software development & engineering	71	20.4%
	Computer Networks	80	23%
	Artificial intelligence	36	10.3%
	Information management	39	11.2%
	Others	57	16.4%

IV. RESULTS

In this study, the researchers used SPSS version 26 and Partial least squares structural equation modeling (PLS-SEM) version 4.0 for data analysis. SPSS was used to assess common method bias (CMB) and detect the presence of multivariate outliers. PLS-SEM was used to assess the measurement and structural models [72].

A. COMMON METHOD BIAS (CBM)

The CMB assists in assessing the presence of bias in respondents' responses. To achieve this, the researchers conducted the Harman single-factor test using SPSS 26. The results revealed that a single factor accounted for only 23.912% of the variance, which was significantly below the 50% threshold [72].

B. MEASUREMENT MODEL

Data reliability and validity were evaluated through Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) measures. Table 3 presents the CA values (threshold > 0.7) and factor loadings of 0.70 [73]. Table 3 displays CR values greater than 0.70 and AVE values greater than 0.50 [74]. Discriminant validity refers to the degree of differentiation between constructs in a proposed model. We assessed discriminant validity by employing the HTMT ratio of correlations [75]. The HTMT method confirmed discriminant validity as all HTMT values fell below the recommended threshold of <0.85. Discriminant validity results are presented in Table 4.

C. INNER MODEL PREDICTIVE POWER

The assessment of the fit for the inner model was conducted using two approaches: the coefficient of determination (R^2) and the model's predictive relevance, which is determined by the value of cross-validated redundancy (Q^2) [75], [76]. The R2 value reflects the extent to which exogenous constructs account for the variation observed in endogenous constructs. The results indicate that the (R^2) values pertaining to the endogenous constructs IMG, PEOU, PU, and BI were 5.8%, 30.5%, 47.1, and 20.5%, respectively. Subsequently, we evaluated the cross-validated redundancy (Q^2). A (Q^2) value greater than zero indicates the existence of a predictive significance within the model. The (Q^2) values for the IMG, PEOU, PU, and BI are 4.7%, 27.8%, 42.1%, and 24.4%, respectively, indicating moderate to high predictive relevance of the inner model.

D. STRUCTURAL MODEL

To evaluate the structural model, we adhered to the methods outlined in [77]. Our initial steps involved examining the path coefficients and significance of the relationships. A bootstrapping procedure comprising 5000 resampling of data was performed. The TAM 3 model contained 14 hypotheses. Except for two, all the proposed hypotheses were accepted. H1: PU has a positive and significant impact on BI; H2: PEOU has a positive and significant impact on BI; H3: PEOU has a positive and significant impact on PU; H4: SN has a positive and significant impact on IMG. H5: SN has a positive and significant impact on PU. H6: The positive and significant impact of SN on BI is accepted. H7: IMG has a positive and significant impact on PU. H8: RES has a positive and significant impact on PU. H9: OPQ has a positive and significant impact on PU. H10: JR has a positive and significant impact on PU and is rejected. H11: Robot SE has a positive and significant effect on PEOU. H12: Robot SE has a negative and significant impact on rejected PEOU. H13: Robot PE has a positive and significant effect on PEOU. H14: Robot PF has a positive and significant effect on PEOU.

V. DISCUSSION

The role of AI-based technology has been substantial in the education sector [2], [78]. In recent years, AI has consistently proven advantageous to both teachers and students, encompassing aspects such as robotic instruction and the development of automated systems for grading answer sheets [79]. With the growing prevalence of AI technologies in education, students can use AI-based robots to streamline time-consuming learning processes and enrich learning experiences [80]. The study findings revealed that students were inclined towards the adoption of AI-based robots in education. The positive and significant influence of PU and

TABLE 3. Reliability and convergent validity.

Constructs	items	Loadings	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
Robots Anxiety	ANX1	0.761	0.865	0.908	0.711
	ANX2	0.878			
	ANX3	0.886			
	ANX4	0.843			
Behavioral intention	BI1	0.874	0.898	0.929	0.767
	BI2	0.840			
	BI3	0.922			
	BI4	0.865			
Image	IMG1	0.904	0.876	0.924	0.801
	IMG2	0.895			
	IMG3	0.886			
Job Relevance	JR1	0.913	0.903	0.939	0.837
	JR2	0.910			
	JR3	0.922			
Output Quality	OPQ1	0.833	0.826	0.894	0.738
	OPQ2	0.857			
	OPQ3	0.887			
Perceived Enjoyment	PE1	0.807	0.751	0.856	0.665
	PE2	0.873			
	PE3	0.854			
Perceived Ease of Use	PEOU1	0.781	0.764	0.850	0.587
	PEOU2	0.813			
	PEOU3	0.836			
	PEOU4	0.768			
Perceived Playfulness	PF1	0.717	0.832	0.889	0.668
	PF2	0.821			
	PF3	0.878			
	PF4	0.845			
Perceived Usefulness	PU1	0.811	0.824	0.883	0.655
	PU2	0.821			
	PU3	0.836			
	PU4	0.768			
Results Demonstrability	RES1	0.759	0.794	0.865	0.616
	RES2	0.823			
	RES3	0.806			
	RES4	0.750			
Robot Self efficacy	SE1	0.752	0.705	0.835	0.628
	SE2	0.835			
	SE2	0.788			
Subjective Norm	SN1	0.804	0.747	0.839	0.567
	SN2	0.757			
	SN3	0.856			
	SN4	0.691			

TABLE 4. Discriminant validity heterotrait-monotrait ratio (HTMT) criterion.

Constructs	1	2	3	4	5	6	7	8	9	10	11	12
ANX												
BI	0.593											
IMG	0.668	0.581										
JR	0.209	0.299	0.096									
OPQ	0.186	0.329	0.164	0.098								
PE	0.185	0.425	0.218	0.278	0.367							
PEOU	0.361	0.417	0.243	0.332	0.434	0.417						
PF	0.470	0.573	0.255	0.657	0.212	0.414	0.585					
PU	0.378	0.451	0.362	0.188	0.420	0.415	0.566	0.260				
RES	0.397	0.501	0.475	0.188	0.209	0.423	0.294	0.235	0.427			
SE	0.375	0.445	0.471	0.228	0.364	0.526	0.533	0.382	0.545	0.334		
SN	0.334	0.414	0.297	0.169	0.375	0.290	0.417	0.219	0.745	0.382	0.470	

TABLE 5. Hypotheses testing.

Hypotheses	Path Coefficient (β)	T statistics (|O/STDEV|)	P values	Decision
H1: PU -> BI	0.203	2.980	0.003	Supported
H2: PEOU -> BI	0.203	3.448	0.001	Supported
H3: PEOU -> PU	0.229	5.211	0.000	Supported
H4: SN -> IMG	0.240	3.916	0.000	Supported
SH5: N -> PU	0.427	8.774	0.000	Supported
H6: SN -> BI	0.159	2.192	0.028	Supported
H7: IMG -> PU	0.102	2.051	0.040	Supported
H8: RES -> PU	0.108	2.518	0.012	Supported
H9: OPQ -> PU	0.116	3.001	0.003	Supported
H10: JR -> PU	0.007	0.175	0.861	Not supported
H11: SE -> PEOU	0.231	4.247	0.000	Supported
H12: ANX -> PEOU	0.085	1.693	0.091	Not supported
H13: PE -> PEOU	0.111	2.256	0.024	Supported
H14: PF -> PEOU	0.325	5.434	0.000	Supported

Note: Significant at ($p < 0.05$).

PEOU on students' BI to adopt AI-based robots is accepted. These results are consistent with the findings of Roy et al. [2], which indicated the positive impact of PU and PEOU on BI to adopt AI-based education. Furthermore, the findings are consistent with those of Chocarro et al. [81], who argued that the PU and PEOU of chatbots lead to their adoption in education. The positive and significant influence of PEOU on PU is consistent with the studies by Roy et al. [2] and Li et al. [82]. The authors found that the PEOU of AI-based technologies significantly influences their usefulness in the education sector.

Furthermore, the findings indicate the substantial role of SN in IMG, PU, and BI in the adoption of AI-based technology. These findings are consistent with previous studies that argued that SN has a significant impact on IMG [46]. PU, and BI [48], [58]. This shows that peers, friends, and family exert influence on the adoption of new technology, particularly enhancing learning experience. This study confirmed the positive influence of IMG on PU, which is consistent with the findings of Saari et al. [46]. The positive influence of IMG on PU indicates that students are willing to use AI-based robots in education because they perceive that using these technologies in education will improve their reputation. It was confirmed that the RES of AI-based robots positively influences PU; these findings are consistent with those of Chen et al. [26]. The results also indicate that OPQ has a positive influence on PU, which is consistent with the findings of Lee's et al. [62] study. This shows that the students considered that AI-based robots would produce high-quality results. However, the positive influence of the JR of AI-based robots on PU was insignificant, indicating that AI-based robots' jobs are not related to students' education. The insignificant impact of JR on PU could be students' higher tendency towards interactive learning processes with teachers, and they feel that AI-based robots are not fit for human-centric jobs that involve constant interaction.

The study findings confirmed the positive influence of AI-based robot SE on PEOU. The results indicate that students considered that they had the ability to operate and receive assistance from AI-based robots in education. These findings were consistent with those reported by Saari et al. [46]. However, the results indicate that the negative impact of the AI-based robot ANX on PEOU was insignificant, indicating that students have no fear of using AI-based robots in education. Furthermore, the findings confirm the positive and significant impact of PE and PF on PEOU. These findings show that students enjoy and perceive AI-based robots as playful and spontaneous. These results are consistent with those of previous studies [69], [70].

VI. IMPLICATIONS

A. THEORETICAL IMPLICATIONS

This study assessed Chinese university students' BI to adopt AI-based robots in the education sector. Past studies have ignored the TAM3 model and mostly assessed TAM, TAM2, UTUAT, modified UTUAT, TRI, and TPB. The study employed the TAM3 model, which included relevant constructs to assess students' adoption of AI-based robots in education. The study proposed 14 hypotheses from the TAM3 model, of which 12 hypotheses were accepted, confirming the significance of TAM3 in AI-based robot adoption for educational purposes. To the best of our knowledge, prior studies have not used TAM3 to assess students' intentions towards AI-based robots in education. Therefore, the findings of the current study will contribute to the AI literature in education. The findings confirmed that all constructs, except JR, had a positive and significant impact on PU, thus addressing research question one. The results indicate that SN, IMG, RES, and OPQ are crucial factors that affect AI-based robot PU in education. The findings also confirmed the positive and significant impact of robot SE, robot PE, and robot PF on PEOU AI-based robots in education, thus addressing research question two. Furthermore, the findings of the study validate the positive and significant impact of PEOU on PU, and the impact of PEOU and PU on BI to adopt AI-based robots in education, thus addressing research question three. These findings contribute to the TAM3 theory and AI-based robotics literature in education.

B. PRACTICAL IMPLICATIONS

The findings of the current research have many practical implications for higher education institutions, policymakers, and technology experts to effectively implement AI-based robots in education. The results indicate that university students have a high tendency to adopt AI-based robots for learning purposes. The results indicate that higher education institution students in (HEIs) are determined to enhance their skills and remain updated with the latest developments in Artificial Intelligence (AI) technologies. Therefore, it is imperative for universities to establish a knowledge management repository that documents all knowledge, encompassing insights on market demands, student requirements, and educational needs.

AI-based robots offer an exceptional learning tool for both students and teachers, presenting a deep learning experience for exploring subjects in a captivating manner. This presents a chance for students to explore and acquire new knowledge without the burden of being the sole focus in the classroom or facing criticism from peers when making mistakes. Robots create a safe and welcoming environment, allowing individuals to feel at ease, even if they face difficulty in understanding concepts. The results show that PEOU and PU of AI-based affect students' intention to adopt it. Therefore, educators should emphasize AI-related content and promote their application in education. Policymakers and educational institutions should design AI content for students and include it in the curriculum. By encouraging students to understand the application of AI to real-world students, they would be willing to opt for careers in science, technology, engineering, and math (STEM) [28].

Furthermore, it has been revealed that the AI-based robots IMG, OPQ, RES, and SN are crucial factors affecting the PU of AI-based robots in education. This shows that AI-based robots have acceptance in student circles and motivate them to use them for educational purposes. Furthermore, the results highlight the effectiveness of AI-based robots in generating the intended and quality outputs. Therefore, it is recommended that HEIs focus on further exploration of AI-based robot applications in education and align them with the university curriculum and users' needs. The technologies selected should align better with user requirements. Furthermore, the findings indicate that students' SE, PE, and PF are essential factors affecting the PEOU of AI-based robots. Therefore, it is suggested that the design of the AI-based robot is simple and user-friendly, providing a seamless experience during its utilization. Students must be informed about the capabilities of AI-based robots. To attain these objectives, it is crucial for authorities to assume responsibility in effectively conveying the fundamental requirements of users to developers. Thus, AI-based robot acceptance among students would increase significantly.

This study presents AI-based robot adoption that has the potential to revolutionize the educational sector in the coming years. The use of AI-based robots in the education sector will facilitate students and attract them for more experience. Through the utilization of AI-based robots, students have the opportunity to cultivate their analytical and logical abilities. The future includes AI and robots, making it imperative to embrace these cutting-edge technologies to revolutionize the conventional teaching environment. This advancement promises enhanced accuracy and effectiveness in student education.

VII. CONCLUSION AND LIMITATIONS

The objective of this research was to examine Chinese higher education students' acceptance of AI-based robots for educational purposes. This study conducted rigorous literature review and identified that TAM3 factors are relevant for assessing the acceptance of AI-based robots among higher education students in China. The researchers purposively collected data from engineering and information technology students studying at Chinese universities and assessed the effectiveness of the TAM3 model in the context of education. The findings of this study revealed that the TAM3 model is highly relevant for predicting students' acceptance of AI-based robots for educational purposes. Of the 14 proposed hypotheses, 12 were accepted. These findings will serve as a guideline for university administration and policymakers to actively pursue the implementation of AI-based robots in the education sector. This will not only increase teaching effectiveness, but also substantially contribute to the development of students' analytical skills.

Although the results indicate significant support for TAM3, there is a need to examine the gap between BI and the actual acceptance of AI-based robots in education. This study focused exclusively on engineering and information technology (IT) students within a university-level education system. However, to comprehensively understand its application, it is essential to broaden its scope to other departments and extend its reach to schools. This study was conducted in a developing country. Therefore, future researchers should extend their scope to developed countries for a broader understanding of AI-based robot acceptance in education.

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