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AN ENHANCED INNOVATION RESISTANCE THEORY TO MEASURE THE BARRIERS OF AI-BASED CHATBOTS USAGE AMONG TEACHER TRAINEES

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ABSTRACT

In recent years, Information and Communication Technology (ICT) has experienced tremendous progress (especially the advancement of AI-based Chatbots), profoundly affecting the global economic structure, social transformation, business innovation, education models, soft skills acquisition, human lifestyles, and so on. The main objective of this study is to develop and validate an enhanced Innovation Resistance Theory (IRT) model to measure the barriers of AI-based Chatbots usage among teacher trainees. This study mainly uses the quantitative research method and PLS-SEM for data analysis. This study finds that Value Barrier (VB), Risk Barrier (RB), Image Barrier (IB), Information Quality Barrier (IQB), and Job Relevance Barrier (JRB) have a significant and direct influence on teacher trainees' resistance to AI-based Chatbots (RTAC). However, the effects of Usage Barrier (UB) and Tradition Barrier (TB) on teacher trainees' RTAC are less significant. VB plays a mediating role in the relationship between Technology Anxiety (TA) and RTAC. RB mediates the relationship between the Electronic Word-of-Mouth Barrier (E-WOMB) and RTAC. JRB can also play a mediating role. This study not only proposes a new theoretical model, which is based on the traditional IRT model and combines new constructs (e.g., IQB and E-WOMB) and new paths (e.g., the mediating role of JRB), but also contributes to the cultivation of future technological talents and the spread and development of AI-based Chatbots in the future.

Keywords: *AI, AI-based Chatbots, Information and Communication Technology (ICT), Barrier, Education.*

1. INTRODUCTION

In recent decades, Information and Communication Technology (ICT) has become one of the most inventive technological domains and a crucial facilitator of innovation across different industries (1). ICT has experienced tremendous progress, profoundly affecting the global economic structure, social transformation, business innovation, education models, soft skills acquisition, and human lifestyles (1–4). Subjects associated with ICT have experienced some of the most accelerated growth in patent publications; their proportion of total patent publications increased greatly (Figure 1) (1). In 2020, the seven largest investors in research and development (R&D) were all ICT companies: Alphabet, Amazon, Apple, Huawei, Meta, Microsoft, and Samsung (1). Therefore, ICT has gained a significant share and occupies a non-negligible position in the global landscape, and it is likely to continue to have a vital influence on future economic dynamics, societal evolution, technological upgrading, educational situation, and others.

As an important component of ICT, Artificial Intelligence (AI) incorporates multiple technologies such as Natural Language Processing (NLP), Machine Learning (ML), Deep Learning (DL), and has extremely strong perception, learning, inferencing, and problem-solving capabilities (4–6).

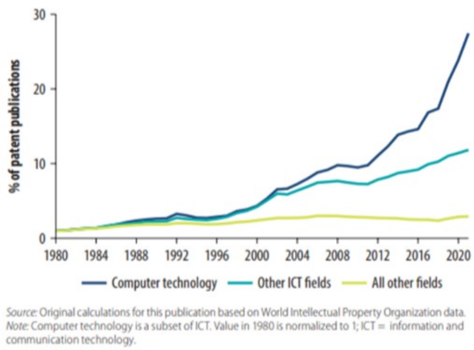

Figure 1: Global ICT-related Patent Publications from 1980-2020

AI has outperformed human performance on various criteria, such as picture classification, visual reasoning, and English comprehension (Figure 2) (7). According to the International Monetary Fund's staff forecasts, nearly 40 % of global employment is affected by AI, and about 60 % of jobs in developed economies are likely to be affected by AI (8). As a result, a number of technologies embedded in AI have not only demonstrated the ability to outperform humans in several aspects but also have the potential to have a widespread and profound impact on both the economy and the job market worldwide.

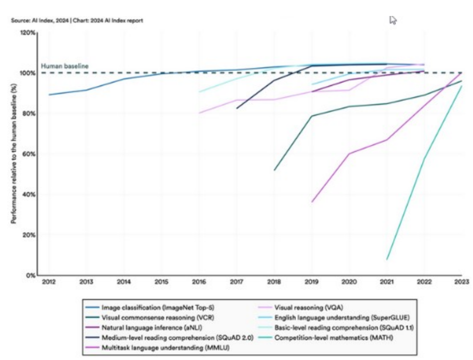

Figure 2: Select Al Index Technical Performance Benchmarks VS. Human Performance

With the iteration of AI technology, especially the flourishing of AI-based Chatbots represented by ChatGPT and Sora, the capability boundaries, visual scope, NLP capabilities, DL capabilities, simulation capabilities, and so on of AI technologies have been greatly improved. AI-based Chatbots are software programs that can communicate with users verbally or through text (6,9). Currently, many AI-based Chatbots have emerged globally, including but not limited to: ChatGPT, Google Bard, New Bing, Kimi, Ernie Bot, and Tongyi Qianwen. AI-based Chatbots perform well in programming, continuous dialogue, writing, text analysis, logical deduction, memory consolidation, and others. Numerous industries are also gradually being affected to varying degrees by AI-based Chatbots, for example: computing (10–12), smart driving (13,14), unmanned aerial vehicles (UAVs) (15–17), video production (18,19), data science (20,21), healthcare (22,23), education (10,24). In the field of education, despite the huge possibilities of AI-based Chatbots for lesson planning (25–27), teaching efficiency (28,29), content improvement (30,31), educational assessments (27), personalized instruction (32), stimulating motivation (33), and numerous other benefits, it is still being resisted by lots of teacher trainees. The integration between AI-based Chatbots and education is still very insufficient, and many teacher trainees are resistant (e.g., postponing, delaying, or rejecting) to AI-based Chatbots (34–40).

However, previous studies mainly focused on the relationship between AI-based Chatbots and other populations (5,20,30,40–42), while the study targeting the specific group of teacher trainees are still very limited. Simultaneously, a number of prior researchers have attempted to utilize Technology Acceptance Model (TAM) (43,44), Unified Theory of Acceptance and Use of Technology (UTAUT) (45,46), Diffusion of Innovation (DOI) theory (47) in the field of information systems (IS) to explore different factors influencing users' technology acceptance, while neglecting the function of Innovation Resistance Theory (IRT) in teacher trainees' AI-based Chatbots resistance behaviors. Regrettably, TAM, UTAUT, DOI, and other theoretical models are primarily applicable to the analysis of technology acceptance behaviors, and it is difficult to capture the psychological barriers, physical barriers, negative behavior characteristics, and other factors of users in terms of technology resistance behaviors. Since this study mainly focuses on the technology resistance behaviors of teacher trainees, these theoretical models are not suitable for this study. IRT provides a comprehensive framework to analyze why users are resistant to adopting new products or technologies, and explains in-depth the resistance behaviors of consumers when they are confronted with new technologies or products (48–52), so it is suitable to be used as the basic theoretical framework for this study. Additionally, historical research on IRT has primarily focused on its five foundational variables (Usage Barrier (UB), Value Barrier (VB), Risk Barrier (RB), Tradition Barrier (TB) and Image Barrier (IB)) (53–58), but ignoring empirical

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examinations of Information Quality Barrier (IQB) and Job Relevance Barrier (JRB).

Noticeably, with the development of information technology (IT), the quality of information generated by AI-based Chatbots is becoming more and more important. With respect to teacher trainees, if the content generated by AI-based Chatbots has serious IQB (e.g., fraudulent information, misleading teaching guidelines, or non-verified statistics), it is quite likely to lead teacher trainees to resist AI-based Chatbots. Unfortunately, a lot of previous studies have paid attention to the relationship between information quality and the adoption of other technologies (45,59,60), while neglecting to deeply analyze the association between IQB and the resistance behaviors of AI-based Chatbots, particularly among the peculiar group of teacher trainees.

Besides, the JRB signifies teacher trainees' perception of barriers referring to the degree to which the AI-based Chatbots are applicable to his or her job. If teacher trainees perceived that AI-based Chatbots are irrelevant to their present job and future work contents, they may lack enough motivation to accept these innovative technologies. Nevertheless, past studies have largely focused on the positive impact of job relevance on acceptance behaviors (29,61–63), while ignoring the influence of JRB among teacher trainees.

Previous work has also noted the significant effect of Technology Anxiety (TA) on adoption behaviors or resistance behaviors (64–69), but very few studies have explored the indirect effects of TA on resistance to AI-based Chatbots (RTAC) behaviors via VB and JRB. The role of Electronic Word-of-Mouth Barrier (E-WOMB) in consumer decision-making behaviors should also not be ignored (65,70–72), while the relationship between E-WOMB and RTAC has not been fully explored, especially when RB, JRB are used as mediating variables.

Therefore, the main objective of this study is to develop and validate an enhanced IRT model to measure the barriers of AI-based Chatbots usage among teacher trainees. Within this enhanced IRT model, this study also empirically examines the relationship between IQB, JRB, and teacher trainees' RTAC. Teacher trainees are both users and future promoters of AI-based Chatbots techniques. The persistence of barriers may result in technological lags, economic losses, and weakened competitive advantages. Although innovation has been one of the focuses of scholars, however, previous researchers have devoted more attention to the logical relationship between AI-based Chatbots and positive attributes and less attention to the logical relationship between AI-based Chatbots and negative attributes (73,74). One of core concerns of this study focuses on the barriers of AI-based Chatbots usage among teacher trainees, and its choice is also based on the considerations: (1) Theoretical gap: the existing theoretical models for measuring teacher trainees' RTAC are still very rare; (2) Realistic demand: studying this topic will not only contribute to the spread of AI-based Chatbots among teacher trainees, but also contribute to the cultivation of future technological talents and the spread and development of AI-based Chatbots in the future society; (3) Method innovation: the test of the negative factors and new scale in this paper can capture the essence of barriers more accurately and make up for the limitations of traditional methods. This study not only helps to extend the theoretical boundaries, suitable scope, and applicable groups of the IRT model, but also provides referenceable data and practical guidance for overcoming the barriers in the process of AI-based Chatbots diffusion.

2. LITERATURE REVIEW

2.1 Information and Communication Technology (ICT)

In recent decades, the significant advancement of ICT has resulted in many economic and non-economic transformations, social revolutions, lifestyle modifications, and education changes across the world (3,4,32,75). ICT applications include but are not limited to NLP, internet of Things (IoT), virtual reality (VR), augmented reality (AR), mixed reality (MR), automatic speech recognition (ASR), online learning platforms, intelligent tutoring systems, metaverse, AI-based Chatbots (1,32,76,77). From 2005 to 2019, the global ICT services exports virtually increased fourfold, which was mostly due to IT services, and the proportion of ICT services in overall services exports increased consistently from 7% to 11% (see Figure 3) (1). In 2022, IT services, the fundamental component of ICT services exports, increased by 43% relative to 2019 (1). According to the Trade in Value-Added (TiVA) data set, the value-added development rate of IT services is around double that of the global economy, outperforming all other industries during the previous two decades (1). Nonetheless, a series of difficulties and challenges have arisen, such as ethical issues (32), regional imbalance issues (1,4), and outdated infrastructure

(75). Therefore, reviewing the great opportunities and myriad challenges that have arisen during the evolution of ICT also provides a valuable reference for the continuation of this study.

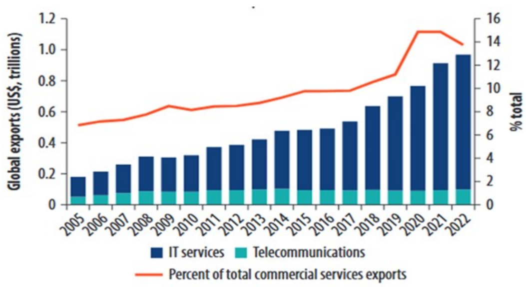

Figure 3: The Global ICT Services Exports

2.2 Artificial Intelligence

As one of the crucial branches of ICT, the role of AI in enhancing international competitiveness, allocating resources, knowledge management, digital transformation, and improving decision-making efficiency cannot be underestimated, and it has become one of the core driving forces of the fourth industrial revolution (78–82). According to Statista data, the market size of AI is projected to exhibit a compound annual growth rate (CAGR 2025-2030) of 27.67%, culminating in a market volume of US$826.73 billion by 2030 (83). Simultaneously, the AI market's impact on GDP might reach 50% to 70% by 2030 (Figure 4) (83). PwC's Global Artificial Intelligence Study indicates that global GDP may increase by as much as 14% by 2030 due to AI, representing an additional $15.7 trillion, hence being the most significant commercial potential in the current rapidly evolving economy (84). Numerous countries have also paid high attention to the evolution of AI and have taken a series of measures in many aspects such as financial investment, policy preference, talent cultivation, and technological upgradation, for example: the United States, Canada, United Kingdom, Australia, Singapore, China (4,85–88).

In terms of industries, AI has also had a widespread and profound impact on different industries, including healthcare, finance, industrial robotics, knowledge management, marketing, journalism, movies, short videos, art, unmanned vehicles, UAVs, education, and so on. For example, in the healthcare industry, AI is playing a role in empowering medical professionals to diagnose patients with a wide range of diseases, reshaping healthcare business models, innovating system performance, improving the patient experience, and others (89–91). In the financial domain, AI has tremendous potential in stock price prediction, asset allocation, investment consulting, risk control, algorithmic transactions, fraud detection, credit scoring, and other directions (92–95). In the educational sector, AI presents both a lot of opportunities, such as: a smart tutoring system (96), supplementary teaching and learning resources(97,98), programming self-efficacy (99), tailoring the learning experience (100), and human-computer interaction (101); and various challenges, such as: inappropriate utilization of AI technologies (98), misinformation (101), algorithmic biases (24), ethical issues (96,102), or privacy concerns (24). As a result, the current growing tendency of AI is hard to stop, and how to make full use of the advantages brought by AI to raise international competitiveness, optimize the economic and social structure, and promote the development of different industries while circumventing the incidental negative effects and so on are all problems worthy of further in-depth study.

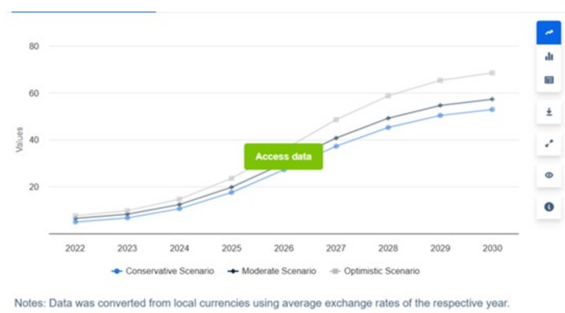

Figure 4: The Impact of the Artificial Intelligence Market on GDP

2.3 Artificial Intelligence-Based Chatbots and Teacher Trainees

In recent years, AI-based Chatbots, which are supported by large-scale language models, for instance ChatGPT, Bard, Grok, New Bing, Kimi, Ernie Bot, Tongyi Qianwen, DeepSeek, have significantly improved the ability of AI in various dimensions, such as language understanding, information generation, human-computer interaction, and content analysis (6,98,103,104). AI-based Chatbots fully leverage NLP, ML, DL, Deep Neural Network (DNN), Sentiment Analysis (SA), Context-Awareness, Conversation Management, and other technologies to enable computers to engage in human-like verbal interactions that lead to conversations, question answering, and task completion (9,10,33,98,103). According to Deloitte forecasts, with the rapid growth in demand for generative artificial intelligence (GAI) training and inferencing, global data center electricity use might double to about 1,065 TWh by 2030 (Figure 5) (105).

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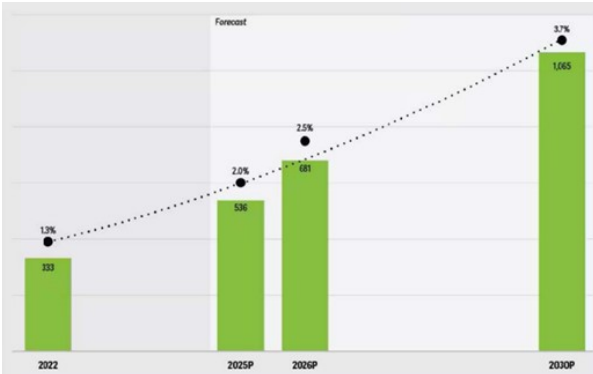

Figure 5: Global Data Center Electricity Use Expected (Note: P represents the predicted value)

GAI has the potential to contribute approximately $4.4 trillion annually to the world's economy, transforming industries and worldwide commerce (106). AI-based Chatbots have begun to influence a variety of different industries, including but not limited to e-commerce, customer service, short video making, healthcare, and education. For instance, in the domain of customer service, AI-based Chatbots are playing a role in enhancing customer engagement (107), improving customer satisfaction (108), smart searching (109), and maintaining brand reputation (110). In the field of education, AI-based Chatbots are becoming an important tool to support teaching and learning. AI-based Chatbots offer a number of benefits for teaching and instruction in different aspects, like teaching methods (29,31,111), teaching resources (31,101,111), individualized feedback (27,30,112), customized tutoring (31,32,76,111), students' self-paced learning (24,32,99), classroom management techniques (5,61,63,102,111), and many others.

Despite AI-based Chatbots having so many advantages and benefits, however, many teacher trainees still show different levels of resistance (e.g. rejection, postponement, procrastination, or even a tendency of opposition) to AI-based Chatbots (34,36,39,112–114). Some teacher trainees' resistance to AI-based Chatbots may derive from technological incompatibility, perceived value barriers, risk worries, traditional perceptions, or unfavourable images (34,39,43,50,99,111–113,115–117). Notably, teacher trainees, as future educators, are both important consumers and influential promoters of AI-based Chatbots, while their negative attitudes or resistance behaviours towards AI-based Chatbots will directly affect the valid promotion and application of AI-based Chatbots in future education. However, so far, there is still a lack of suitable and valid theoretical models to measure the relationship between the main barriers and teacher trainees' resistance to AI-based Chatbots.

2.4 Innovation Resistance Theory

Previous studies have attempted to study AI-based Chatbots with different theoretical models, such as TAM (118–120), UTAUT 1 or 2 (121,122), Diffusion Theory of Innovation (123), Theory of Social Support (124), Protection Motivation Theory (PMT) (125), Elaboration Likelihood Model (ELM) (126), Expectation-Confirmation Model (ECM) (122), Use and Gratification Model (127), Status Quo Bias (SQB) Theory (128), and so forth, but they have mainly focused on testing the acceptance willingness or adoption behaviours of different groups of people, and have neglected to measure the resistance behaviours of teacher trainees to AI-based Chatbots from the negative perspective.

In exploring the phenomenon of teacher trainees resisting AI-based Chatbots, choosing the appropriate theoretical framework is critical. Although models of technology acceptance categories commonly employed in past research have delivered essential theoretical support for understanding technology adoption behaviour, these models primarily concentrate on users' positive acceptance paths to technology, emphasizing positive drivers such as perceived usefulness, ease of use or hedonic motivation, while these theories are inadequate for explaining why teacher trainees resist emerging technologies.

In contrast, Innovation Resistance Theory (IRT) (Ram & Sheth, 1989) provides a more comprehensive perspective for understanding technological resistance behaviours by systematically analysing the Usage Barrier (UB), Value Barrier (VB), Risk Barrier (RB), Tradition Barrier (TB) and Image Barrier (IB) that users encounter in accepting innovative technologies. Inside the classical constructs of the IRT model, the UB primarily refers to the incompatibility between innovative products and consumers' existing workflows, practices, or habits (50,129). Prior investigations in information systems have shown that the correlation between UB and the acceptance of different merchandise has garnered significant scholarly focus (130–135). VB is mostly associated with a weaker performance-to-price value, particularly in comparison to alternatives (50,136). In the past, the role of VB has also been tested in different scenarios, which include MOOC (134), eco-friendly cosmetics (135), hotel booking apps (132), mobile payment (137), and so on. Ram and Sheth (1989) posited that consumers were likely to postpone or reject the adoption of new commodities after recognizing the relative RBs, which contained economic risk, social risk, physical risk, and functional risk. The correlation between RB and the acceptance or resistance to innovation has been acknowledged as significant by numerous prior surveys (51,54,64,130,137–139). For example, teacher trainees may be resistant to AI-based Chatbots because of worries about the potential RB, including ethical risks, privacy leakage, misinformation dissemination, and more. Some teacher trainees may prefer to follow the traditional mode (one of RB) of teaching because it is more familiar and comfortable for them, whereas AI-based Chatbots are unable to offer timely communication or emotional support during the teaching process, leading to some teacher trainees' RTAC.

Ram and Sheth (1989) thought that TB for personal customers might arise when their behaviours deviate from social norms or familial values. There was a number of published literature explaining the effects of TB (53,133–135,137,139–141). IB is mainly related to the customer's unfavourable image of a product, which may stem from any unfavourable association, such as the category to which the product belongs, the industry to which the product belongs, or the country in which the product is manufactured (50). The impact of IB has attracted heightened attention from several researchers (134–137,142). Synchronously, the IRT has been validated and applied to a number of areas of research, for example: mobile payments (52,143), service robots (SRs) (144), metaverse (145), facial recognition payment (146), driver assistance systems (147), smart hotels (74,148), non-fungible tokens (NFTs) (56,149), green IT (150), shopping platforms (151), over-the-top services (OTTs) (152), autonomous delivery vehicles (ADVs) (153), online-learning (154), healthcare (155), fitness apps (156), online dating apps (ODAs) (157), algorithm aversion (158), online-to-offline (O2O) platforms (159), virtual streamers (160), electric vehicle (161,162), travel applications (163,164), and so on. Therefore, the IRT is a suitable foundational model for this study, which not only contributes to deepening the understanding of the phenomenon of teacher trainees' RTAC at the theoretical level and identifying some of the major barriers behind this phenomenon, but also helps to propose valuable references for the direction of technological research and development of AI-based Chatbots and their applications at the practical level.

However, with the shifting economic situation, social restructuring, and technological advances, especially the rapid changes in generative AI such as ChatGPT, the limitations of the traditional IRT model have been gradually exposed, for example: insufficient consideration of the quality of the information generated, and insufficient comprehensiveness in capturing the technical features. Prior researchers have experimented with adding some variables such as mobile innovativeness (165), embarrassment (146), inertia (159), expertise barriers (166), technology vulnerability barriers (152), surveillance (143), information overload (167), or moderating variables such as attitude (157), gender (153), environmental concern (168) and discoverability (159) to increase the explanatory power of the model or to increase the applicability of the scenarios, however, empirical validation of the relationship between the IQB, JRB, and RTAC is still very inadequate, particularly among teacher trainees.

What's more, the progression of AI-based Chatbots technologies, coupled with modifications in economic and social situations, has rendered the constraints of conventional IRT influencing factors increasingly conspicuous (134,137,169,170), whereas the factors that include Information Quality Barrier (IQB) and Job Relevance Barrier (JRB) may become significant constructs that impact teacher trainees' resistance behaviours. For instance, in the education background, if AI-based Chatbots are unable to generate accurate, valid, latest, or personalized teaching information, it is likely to lead directly to teacher trainees' resistance to AI-based Chatbots. Unfortunately, most previous studies have paid attention to the association between information quality and the adoption of other technologies (59,119), while having neglected in-depth analysis of the connection between IQB and the resistance behaviours of AI-based Chatbots, particularly among teacher trainees. Besides, if teacher trainees perceive JRB, which means that AI-based Chatbots have little relevance to their present tasks and future jobs, hence lack a strong incentive to apply to these innovative techniques. Nevertheless, past research mainly focused on the positive effect of job relevance on adopter behaviours (29,61–63,171), while few empirical studies have measured the relationship between JRB and resistance to AI-based Chatbots.

In this study, Technology Anxiety (TA) mainly relates to the degree of anxiety and emotional reactions that are caused by using AI-based Chatbots or considering the possibility of new technology utilization (68,69,172–177). Cham et al. (2022) found that TA was one of the key psychological barriers affecting mobile payment services. The relationship between anxiety and other factors affecting technology adoption (67). In the case of T-Express, there are some researchers noticed the influence of TA on VB (65). In spite of many researchers have pointed out the important role of TA in consumer technology acceptance or resistance behaviours (64–69), little research has systematically explored the indirect effects of TA on resistance to AI-based Chatbots through VB and JRB, and this study will fill this gap.

Electronic Word-of-Mouth Barrier (E-WOMB) is primarily associated with the perception of negative comments made by potential, actual, or former netizens about AI-based Chatbots, which are made available to numerous individuals or institutions through the internet (178–180). E-WOMB also played an important role in people's decision-making behaviours (65,70–72), but the connection between E-WOMB and resistance to AI-based Chatbots among teacher trainees has not been thoroughly studied, especially when RB and JRB are treated as mediating variables. As teacher trainees will be pivotal in the future of education, their perceptions of AI-based Chatbots may significantly influence the future implementation of such technology in educational settings.

All in all, as ICT's global influence increases and AI technologies advance rapidly, they are becoming more penetrative and powerful in the education space. In the past, the related studies on theoretical models for measuring teacher trainees' RTAC were still very limited, while this study proposes a new theoretical model that is based on the traditional IRT and combines new constructs and new paths. In recent years, with the emergence of AI-based Chatbots such as ChatGPT, related research has once again become one of the hot directions. However, there is still a paucity of research examining teacher trainees' resistance to AI-based Chatbots behaviours from the innovation resistance theory, so there is a need to develop a model and conduct an empirical study.

3. CONCEPTUAL MODEL

Based on the analysis of the aforementioned literature review and the core framework of IRT, this study proposes a conceptual model for teacher trainees' RTAC. Inheriting the five barrier dimensions in the Innovation Resistance Theory - UB, VB, RB, TB, IB- this model further combines the situational characteristics of the field of educational AI-based Chatbots with the uniqueness of the teacher trainee population, so as to construct a theoretical model that is more in line with practical application contexts. This new conceptual model introduces two new independent variables (IQB and JRB) and attempts to test the indirect effects of TA and E-WOMB on RTAC (Figure 6).

Unlike the previous TAM and UTAUT models that focus on positive acceptance behaviors, the current conceptual model in this study emphasizes the complex psychological dynamics and behaviors of teacher trainees when facing new technologies from the perspective of "resistance," providing a new research path for the theory and practice of the application of AI-based Chatbots in the field of information technologies.

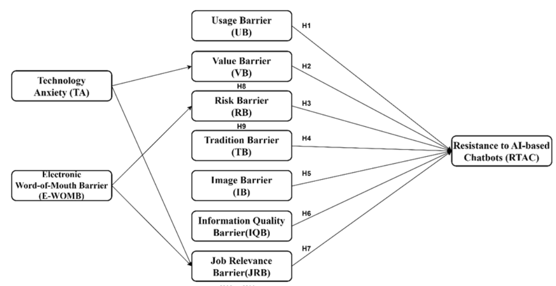

Figure 6: Overview of Conceptual Model and Research Hypotheses

4. HYPOTHESES

The hypothesis is a statement, or a set of statements presented as a provisional causal explanation for an observable phenomenon, and it is critically significant in the scientific process (181–183). In the present study, to identify the main barriers of teacher trainees' RTAC, the following hypotheses are proposed (Figure 6).

4.1 Main Hypotheses

4.1.1 Usage Barrier

Based on Ram and Sheth's (1989) opinions, one of the important reasons for customers' resistance to innovative products was the incompatibility between the new and traditional things. Some researchers argued that UB had a non-significant impact on algorithm aversion (158). Nonetheless, a majority of studies discovered that UB had an impact on the acceptance or rejection (52,56,153,157). For instance, Siddiqui et al. proved that UB had a remarkable negative impact on the acceptance of online dating apps (ODAs) (157). For teacher trainees, if they perceived that AI-based Chatbots were incompatible with their current

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habits, working style, or lifestyle, they might not want to utilize them again in the future. Therefore, the present examination proposes the subsequent hypothesis:

H1: Usage Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.1.2 Value Barrier

One study found that VB was not statistically significant evidence contributing to small merchants' hesitance toward O2O platforms (159). But a lot of previous studies have proved the relationship between VB and users' behaviors in various contexts, for instance: green IT (150), over-the-top services (OTTs) (152), autonomous delivery vehicles (ADVs) (153), smart hotels (148), AI algorithms (158), NFTs (56), mobile social commerce (142). According to these findings, it is probable that VB will similarly influence users' behaviors in the realm of AI-based Chatbots, either positively or negatively. The present study posits that VB is likely a significant factor influencing teacher trainees' RTAC, hence proposing the following hypothesis:

H2: Value Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.1.3 Risk Barrier

In the past decade, the majority of research in IS has concentrated on the impact of RB on the acceptance of innovation (51,56,138,150,157). Conversely, Ma and Lee (2019) contended that RB was inconsequential to the utilization of MOOCs in a developing nation. Regrettably, these studies have primarily examined the correlation between RB and the adoption of commodities. Only a limited number of studies have investigated resistance to innovation from the perspective of RB, such as by Cham et al. (2022), Leong et al. (2020), Uddin et al., (2024). The prior inconsistencies and disputes about content and outcomes have prompted the present research to assert that an additional comprehensive examination of the relationship between RB and RTAC is urgently required. Thus, this study proposes the subsequent hypothesis:

H3: Risk Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.1.4 Tradition Barrier

In the background of psychological resistance, Ram and Sheth (1989) also illustrated that entrenched traditions significantly impact individual behaviors. A considerable number of scholars have already looked into the correlation between TB and technology acceptance or use intention in various dimensions: digital payment systems (139), eco-friendly cosmetics (135), ODAs (157), green IT (150), virtual streamers (160), e-learning (154). Nevertheless, such studies have predominantly been approached from the perspective of TB and customers' acceptance behaviors. Empirical research carried out by Uddin et al. (2024) that measured the WhatsApp payment system (WPS) revealed the relationship between TB and resistance to innovation. Consequently, based on the preceding considerations, this study posits that teacher trainees' RTAC may be influenced by TB, and presents the following hypothesis:

H4: Tradition Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.1.5 Image Barrier

Ram and Sheth (1989) thought that innovations acquired a distinct character from their birth, and the IB emerged out of stereotyped concepts and made innovations difficult. Numerous studies have focused on the correlation between IB and usage intention or adoption across many domains: mobile payments service (137), O2O platforms (Chawla et al., 2024), stereotype for MOOCs (134), green IT (150), and so on. Only very few researchers (e.g., 151) studied IB from a resistance viewing angle. In light of the preceding arguments concerning IB, the following hypothesis is proposed in this study:

H5: Image Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.1.6 Information Quality Barrier

Based on Eom's (184) findings, the utilization of e-learning management systems (e-LMS) did not exhibit a positive relationship with information quality. Nevertheless, a lot of prior surveys have demonstrated the relevance between information quality and the adoption of innovations in dissimilar domains, such as big data analytics (BDA) (185), blockchain (186), and cash on delivery (COD) payment system in Shopee (187). What's more, Michel-Villarreal et al. (98) elucidated that the deficiency in accuracy and dependability of the information produced by the GenAI system would lead to issues. For teacher trainees, if the information quality created by AI-based Chatbots was low mass and produced IQB, it might cause teacher trainees' resistance and the failure of innovative technologies. The preceding information and arguments led to this study to propose the hypothesis:

H6 : Information Quality Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.1.7 Job Relevance Barrier

Job relevance is an influential element of TAM2 for assessing intention to use or use behaviors (63,188). The majority of previous studies examined the positive correlation between job relevance and the acceptance of innovative products in miscellaneous subjects, for example, LMS (61,63) and AI-based conversational agents (42). Nevertheless, a great deal of prior research has concentrated on job relevance rather than JRB, particularly with the implementation of AI-based Chatbots. On the opposite side, if teacher trainees perceived that the results generated by AI-based Chatbots were irrelevant to their present work or future job (e.g., incorrect teaching information, incompatible pedagogical styles, or misleading instructional guidelines), they may reject the utilization of AI-based Chatbots. Consolidating the above-mentioned deliberations and arguments, the subsequent hypothesis is formally propounded:

H7 : Job Relevance Barrier has a significant influence on Resistance to AI-based Chatbots among teacher trainees.

4.2 Mediating Hypotheses

4.2.1 The Mediating Effect of Value Barrier between Technology Anxiety and Resistance to AI-based Chatbots

Previous studies have realized the negative impact of TA on perceived VB in different situations (65). For example, TA had an impact on the perceived value of an individual's use of the mobile ticketing application T-express, thereby reducing the willingness to adopt (65). There are also several studies that have found that TA directly or indirectly contributes to people's acceptance of technology (189,190). Whereas VB is closely related to the final behavioral decision of the users (56,150,154,191). Dogra et al. (192) argued that pricing value is the most important component and essential for visitors' intention to acquire online travel products. For teacher trainees, if they feel VB due to TA, they are likely to resist AI-based Chatbots. VB may play a mediating role between TA and teacher trainees' RTAC, which means that teacher trainees with higher technology anxiety are more likely to develop value skepticism towards AI-based Chatbots, which enhances their tendency to resist. Synthesizing the above deliberations, the next hypothesis is formulated for this study:

H8 : Value Barrier mediates the relationship between Technology Anxiety and Resistance to AI-based Chatbots among teacher trainees.

4.2.2 The Mediating Effect of Risk Barrier between Electronic Word-of-Mouth Barrier and Resistance to AI-based Chatbots

Web-based technologies have provided multiple chances for E-WOM transmission (193). Ashtiani and Iranmanesh (194) found that positive word of mouth (P-WOM) had a positive influence on the acceptance of electronic banking, whereas negatively influenced the perceived risk of electronic banking services. In another empirical investigation, Tang and Chen (195) revealed that negative E-WOM had a positive effect on the seller's resistance to the digital device recycling platform (DDRP). And for users, RB could have a strong implication on their decision to adopt or resist an innovation (52,64,133,137,138). For teacher trainees, electronic word-of-mouth barrier (E-WOMB) (e.g., generating misleading information, erroneous theoretical underpinnings, or various unfavorable comments) may exacerbate their perceived RB of AI-based Chatbots, which in turn may enhance their resistance behaviors. Considering the preceding discussions, the following hypothesis is subsequently proposed:

H9 : Risk Barrier mediates the relationship between Electronic Word-of-Mouth Barrier and Resistance to AI-based Chatbots among teacher trainees.

4.2.3 The Mediating Effect of Job Relevance Barrier between Technology Anxiety and Resistance to AI-based Chatbots

TA encompassed fears of total incapacity to acquire new technologies, inadequate mastery of new technologies, inability to apply learned skills, and job displacement by younger (196). TA may increase users' worries about JRB. Some research suggested that different forms of anxiety (e.g., Learning Anxiety, AI Configuration Anxiety, and Job Replacement Anxiety) may influence practitioners' attitudes and psychological responses to AI (197). For teacher trainees, those individuals with higher levels of TA are more likely to perceive AI-based Chatbots as potentially of insufficient practical functionalities in their current professional training and future teaching job, and to develop a perception of JRB that enhances their tendency to resist AI-based Chatbots. After considering the above factors and preceding discussions, this study

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proposes the following hypothesis of mediating effects:

H10： Job Relevance Barrier mediates the relationship between Technology Anxiety and Resistance to AI-based Chatbots among teacher trainees.

4.2.4 The Mediating Effect of Job Relevance Barrier between Electronic Word-of-Mouth Barrier and Resistance to AI-based Chatbots

Contingent upon the different types of worker electronic word of mouth (weWOM) (e.g., positive, neutral, and negative) on the internet, individuals produce varying behavioral intentions concerning distinct recruitment factors (198). For the adoption of social networking sites (SNSs), the E-WOM has a significant impact (199). Even for prospective students, E-WOM in social media also significantly influenced their university selection process (200). Regarding teacher trainees, E-WOMB may make them perceive that AI-based Chatbots have multiple JRBs in terms of lesson planning, instructional material preparation, educational skill enhancement, and others, thereby enhancing their resistance behaviors. Therefore, on the basis of the above-mentioned discussions on E-WOMB, JRB, and AI-based Chatbots, the following hypothesis is formulated in this study:

H11： Job Relevance Barrier mediates the relationship between Electronic Word-of-Mouth Barrier and Resistance to AI-based Chatbots among teacher trainees.

5. RESEARCH METHODOLOGY

After comparing the advantages and disadvantages of quantitative and qualitative research methods (201–204) and the features of the IRT model, the quantitative research method was selected for this study because it was more suitable for the research objectives and research characterizations of this study. All the Likert scales employed in this study were adapted from previous scales (e.g. 64,133,136,137,167,184,188,205,206) and were adjusted to fit the target population and specific characteristics of this study. Drawing on previous sampling methods and sampling experiences (207–211), and the lack of a complete list of teacher trainees and various limitations, this study mainly utilized convenience sampling and the snowball sampling method. Over the past years, the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique has been extensively applied in a number of studies (56,150,212,213). Hair et al. (2017) found that the IS domain showed a higher degree of maturity in employing PLS-SEM to address model complexity and formative measures. Consequently, in accordance with past research experience and the personalized nature of this study, PLS-SEM is the appropriate data analysis strategy for this study. The reliability test and validity test of this study presented good status and met the requirements for further research. Cronbach's Alpha (α) is adopted to test the reliability and internal consistency of the scales in the current study, which has been widely referred to in numerous research (214–216). Considering the aforementioned discussions about Alpha's values (215,217), this study intends to select 0.7 ($\alpha \geqslant 0.7$) as a standard for evaluating good reliability. Based on previous researchers' suggestions for the pilot study (218–220) and the unique characteristics of this study, 40 questionnaires were used for the pilot study and the examination of Alpha's values. The reliability test results (Table 1) indicate that the distribution of α values is between 0.770 and 0.942, signaling a good degree of reliability.

Table 1. Overview of Reliability Analysis

	UB	VB	RB	TB	IB	IQB	JRB	TA	E-WOMB	RTAC
α	0.900	0.807	0.818	0.805	0.851	0.902	0.917	0.942	0.853	0.770

6. DATA ANALYSIS

This study's data analysis techniques mostly reference works of significant scholars in the realm of data analytics (e.g., 211, 212,221–225). After the implementation of data collection pertaining to AI-based Chatbots impacting factors, the present study predominantly employs IBM SPSS Statistics and Smart PLS 4 for data analysis, which is briefly described in the next steps. In this study, 570 questionnaires were returned, out of which 9 were deleted due to missing data or other reasons, and 561 questionnaires remained. At the stage of checking for suspicious response patterns, this study drew on the experience of data analysis professionals (e.g. 222,224), resulting in the deletion of 42 questionnaires with the same answers or suspicious answers and the retention of 517 questionnaires. The detection of outliers is mainly done by univariate and multivariate detection methods (222,224,226,227). In the univariate testing phase, this study utilized "box plot" checking and discriminant Z-scores (between -3.29 and +3.29), resulting in the deletion of 27 questionnaires with outliers and the preservation of 490 questionnaires. In the procedure of multivariate outlier detection, this study primarily deployed

Mahalanobis Distance and chi-square (X^2) ($p < 0.001$) distribution testing method, causing 87 questionnaires to be deleted and leaving 403 questionnaires for further analysis. Among the 403 questionnaires, there were 127 males and 276 females. Most respondents were between the ages of 18 - 20 (216 respondents, 53.6%), followed by those between the ages of 21 - 23 (104 respondents, 25.8%), with the other age groups making up a fairly small percentage. The highest number of people occupying a medium level of knowledge about AI-based Chatbots totaled 290 respondents (72.0%), followed by the number of people who knew very little, 92 (22.8%), and the smallest number of people who knew a lot, only 21 people (5.2%). J. F. Hair et al. (222) believed that in order to understand the distribution of the data, Skewness and Kurtosis should be examined. When the data shows a normal distribution, the values of Skewness and Kurtosis lie between -2 and +2 (222,228). After testing, the Skewness values are between -0.386 and 0.154, and the Kurtosis values are between -0.511 and 0.174, which conforms to the normality data distribution pattern. This study's PLS-SEM is primarily conducted from two perspectives: the evaluation of the measurement model and the evaluation of the structural model, which has been mentioned in some research (212,222,226,229). The subsequent sections will comprehensively describe the information regarding the evaluation methodologies, metrics, and results obtained from these two models.

6.1 Assessment of Measurement Model

Taking into account previous experiences in the assessment of measurement model, this study assesses the measurement model from four aspects (Internal Consistency Reliability, Indicator Reliability, Convergent Validity, and Discriminant Validity), so that to confirm the validity and reliability of the measurement model and to get ready for the subsequent phase of hypothesis examination and structural model evaluation. Indicator Reliability often signifies that the associated indicators share significant commonalities, and it is typically advised that the standardized outer loadings should be equal to or exceed 0.708 (222,226). However, indicators with lower outer loadings are occasionally retained because of their significance to content validity (222). Several items with outer loadings below 0.708 were removed from this study, including: UB1, RB5, IQB2, RTAC1, and RTAC2. Despite the individual indicator RB1 being a minor lower than 0.708, it is satisfied in the field of CR and Average Variance Extracted (AVE), so the item is kept for subsequent examination. Composite Reliability (CR) (pc) was considered to evaluate internal consistency reliability (222,226), and this study chose 0.7 as the threshold value. As can be seen in Table 2, the CR values in the current study are between 0.737 and 0.849, which meets the demand of internal consistency reliability. Convergent Validity can be assessed by measuring the value of AVE (AVE⩾0.5) (222,226), and all the AVE values in this study were above 0.5, which meets the requirement of convergent validity. There are multiple techniques for assessing discriminant validity, for example: Fornell-Larcker criterion, cross-loadings, and Heterotrait-Monotrait Ratio (HTMT) (212,222,223,226,230). Table 3 illustrates that all construct values exceed the squared associations of other constructs, hence confirming the fulfillment of discriminant validity standards.

Table 2. The Outer Loadings, CR, and AVE

Constructs	Indicators	Outer loadings	CR	AVE
UB	UB2	0.749	0.802	0.598
	UB3	0.791		
	UB4	0.716		
	UB5	0.832		
VB	VB1	0.731	0.764	0.581
	VB2	0.732		
	VB3	0.802		
	VB4	0.780		
RB	RB1	0.699	0.78	0.606
	RB2	0.842		
	RB3	0.825		
	RB4	0.737		
TB	TB1	0.743	0.742	0.563
	TB2	0.775		
	TB3	0.745		
	TB4	0.739		
IB	IB1	0.739	0.774	0.592
	IB2	0.808		
	IB3	0.785		
	IB4	0.744		
IQB	IQB1	0.750	0.849	0.621
	IQB3	0.791		
	IQB4	0.804		
	IQB5	0.799		
	IQB6	0.795		
JRB	JRB1	0.759	0.849	0.622
	JRB2	0.79		
	JRB3	0.806		
	JRB4	0.806		
	JRB5	0.780		
TA	TA1	0.772	0.841	0.607
	TA2	0.779		

Table 3. Analysis of the Fornell-Larcker Criterion

	EWOMB	IB	IQB	JRB	RB	RTAC	TA	TB	UB	VB
EWOMB	0.746									
IB	0.605	0.769								
IQB	0.65	0.747	0.788							
JRB	0.622	0.674	0.657	0.788						
RB	0.488	0.411	0.539	0.372	0.778					
RTAC	0.482	0.604	0.592	0.689	0.288	0.809				
TA	0.673	0.677	0.663	0.774	0.423	0.671	0.779			
TB	0.531	0.673	0.648	0.638	0.448	0.53	0.634	0.751		
UB	0.418	0.531	0.512	0.465	0.378	0.436	0.518	0.481	0.773	
VB	0.472	0.545	0.592	0.564	0.52	0.535	0.603	0.549	0.657	0.762

6.2 Assessment of Structural Model

After examining the validity and reliability of the measurement model, the next step is to evaluate the structural model, which primarily assesses collinearity issues, significance, relevance, and so forth (212,222,226). J. F. Hair et al. (222) highlighted that the Variance Inflation Factor (VIF) values for the predictor constructs ought to be under 5, and preferably below 3, to guarantee that collinearity did not substantially affect the estimations of the structural model. The results indicate that all VIF values (Minimum: 1.299, Maximum: 1.983) in the present study are below 5, signifying the absence of collinearity concerns. The accepted metrics for the path coefficients varied from -1 to +1, with values nearing +1 signifying strong positive associations (212,222,226). If a coefficient was notably established by its standard error, calculated through the "t" value generated from bootstrapping (226). Typically, a few critical t values (e.g., 1.65, 1.96, 2.57) exist for two-tailed tests, contingent upon the study objectives and disciplines (222,226), while the current research chooses 1.65 as a critical t value. Researchers typically reported "p" values (5% probability of error) in lieu of t values, indicating the likelihood of erroneously denying the null hypothesis (222,226), and the present study also selects 0.05 (equal to 5%) as a critical p-value. Table 4 and Figure 7 depict the evaluation outcomes of the structural model in this study. Usually, one of the important techniques to evaluate the structural model is the coefficient of determination (R^2) (0.25, 0.50, and 0.75), which is measured as the squared correlation between the real and predicted values of a specific endogenous construct (212,222,226). As shown in Table 5, R^2 is 0.539, which represents that the structural model's explanatory power in this study is moderate level.

Table 4. Assessment of Hypotheses in the Structural Model of the IRT

Hypotheses	Relationships	β	T	P	Results
H1	UB -> RTAC	0.005	0.102	0.919	Unsupported
H2	VB -> RTAC	0.174	2.879	0.004	Supported
H3	RB -> RTAC	-0.108	2.366	0.018	Supported
H4	TB -> RTAC	0.02	0.342	0.732	Unsupported
H5	IB -> RTAC	0.143	2.185	0.029	Supported
H6	IQB -> RTAC	0.148	2.346	0.019	Supported
H7	JRB -> RTAC	0.423	6.96	0.000	Supported
H8	TA -> VB -> RTAC	0.105	2.762	0.006	Supported
H9	EWOMB -> RB -> RTAC	-0.053	2.276	0.023	Supported
H10	TA -> JRB -> RTAC	0.275	6.273	0.000	Supported
H11	EWOMB -> JRB -> RTAC	0.078	3.426	0.001	Supported

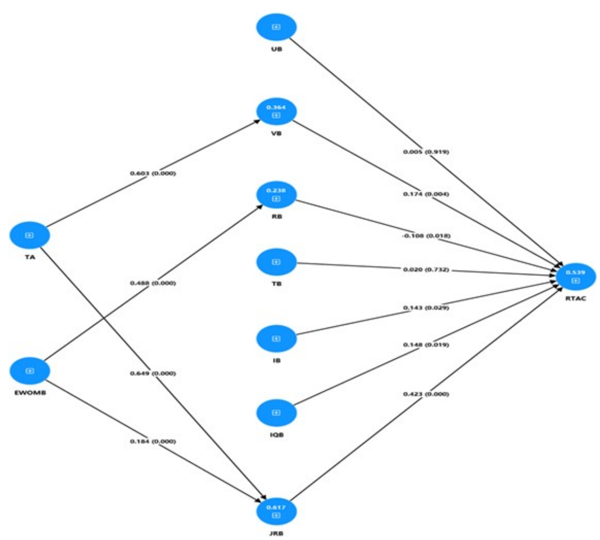

Figure 7: The Evaluation Outcomes of the Structural Model

Table 5. The Calculation of R^2 Values

Constructs	R^2	the level of R^2
RTAC	0.539	Moderate

7. DISCUSSIONS

Within the hypotheses proposed in this study, the majority of hypotheses have garnered substantial support, but others have failed to meet the significance threshold. Afterward, this study analyzes each proposed hypothesis and performs

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the relevant examination. The statistical results do not corroborate H1, indicating that the direct impact of UB on RTAC is not statistically important. This phenomenon might stem from the advanced nature of AI-based Chatbots technologies and the simplicity of the interactive discussion interface, making initiation relatively effortless. According to the research results, the significant effect of H2 is entirely verified, which is not only consistent with the core hypothesis of IRT but also sheds further light on the unique mechanisms through which VB works in the context of educational technology uptake. Compared with prior correlated literature (e.g.133,134,136,156,167,191,231), this new finding expands the applicable boundaries, suitable groups, and core points of VB in the rapidly evolving AI era. This result enhances the theoretical framework in IS and practically offers a concrete reference for AI-based Chatbots promotion tactics, such as mitigating the substantial influence of VB on RTAC by augmenting the cost-effectiveness of AI technology to elevate users' adoption. Besides, Hypothesis 3 is also supported by statistical data, demonstrating that RB has a significant effect on teacher trainees' RTAC. This new discovery not only corroborates the outcomes of Cham et al. (2022), Leong et al. (2020), and Uddin et al. (2024) but also further implies the resonance of RB roles (i.e., data privacy concerns and fraudulent information) across different groups.

Hypothesis 4 is not supported; this result differs from the findings of some existing studies, such as Leong et al. (2020), M. Talwar et al. (2024), Rabaai et al. (2024), and Uddin et al. (2024). The possible reasons are: (i) with the universalization of AI technologies and the acceleration of education informatization, teacher trainees' awareness of AI technologies has increased, which may weaken the influence of traditional concepts on their willingness to use them; (ii) teacher trainees belong to a group of young people who have received higher education, and they may be more open-minded towards emerging techniques, which may reduce the constraints imposed by conventional perceptions on their behavioral decision-making. Hypothesis 5 of this study receives support, indicating that IB significantly affects teacher trainees' RTAC. Future research could further explore how to lower IB to AI-based Chatbots through reshaping technology branding, improving the external image of the enterprise, optimizing the human-computer interaction experience, improving content quality, and so on.

Hypothesis 6 of this study is supported, suggesting that IQB significantly influences teacher trainees' RTAC. For teacher trainees, if AI-based Chatbots fail to provide accurate, up-to-date, efficient, and professional information that matches their teaching needs (e.g., incorrectly generated information, out-of-date pedagogical content, and irregularities in citations), it may negatively influence their own training and teaching practice. Synchronously, the data supports H7 and demonstrates a significant relationship between JRB and RTAC. Such significance illustrates that JRB (e.g., low relevance of generated information to job requirements; ignorance of individualized needs of teacher trainees; incoherence of goals) can significantly influence teacher trainees' RTAC.

H8 receives statistical support suggesting that VB plays a significant mediating role in the relationship between TA and teacher trainees' RTAC. When teacher trainees feel TA over the complexity, acquisition costs, or potential uncertainties of AI-based Chatbots, they may further appraise the value of this technology, particularly whether it is effective in enhancing pedagogical efficiency, assisting with work, alleviating the burden of lesson planning, or other material benefits. H9 is confirmed, signifying that RB mediates significantly in the relationship between E-WOMB and teacher trainees' RTAC. This finding further reveals that E-WOMB (e.g., negative online reviews) can easily lead teacher trainees to higher RB for AI-based Chatbots, which in turn can lead to resistance behaviors. Hypothesis 10 gains support, signaling that JRB plays a significant mediating role in the relationship between TA and teacher trainees' RTAC. The TA that teacher trainees feel when using AI-based Chatbots may trigger stronger JRBs (e.g., perceptions of limited functions of the technology in education and difficulty in fitting their own teaching needs), which will further reinforce their resistance behaviors. The results of this study indicate that Hypothesis 11 holds true and that JRB plays a significant mediating role in the connection between E-WOMB and teacher trainees' RTAC. Teacher trainees, while being approached about the E-WOMB of AI-based Chatbots, will further assess whether the technology is able to meet their pedagogical needs, and if they perceive the technology to have JRBs (e.g., difficulty in integrating it into their daily pedagogical practices), this will further contribute to the emergence of a stronger tendency to resist AI-based Chatbots.

AI-based Chatbots not only involve the current world's cutting-edge techniques, but will also have a far-reaching influence on numerous aspects of the future of humanity. As the backbone of the instructional group in the future, teacher trainees' technological skills, capabilities to use AI-based Chatbots, and educational ideas are closely linked to long-term growth and prospective competitiveness. Theoretically, compared with the previous literature (e.g., 42, 61,63), this study is one of the earliest documents that put forward the mediating role of JRB between E-WOMB and RTAC, and solved the limitations that JRB had not been fully discussed before. At the application level, existing studies (e.g., 132, 135, 137) focus on other aspects, while this paper extends the research scope to new fields and new groups, thereby revealing the complex psychological and behavioral mechanisms of teacher trainees in the face of AI-based Chatbots. Through the perspective of Innovation Resistance Theory, this study deeply explores the resistance behaviors of teacher trainees to AI-based Chatbots, which opens a new theoretical path for research in the domain of IS and provides practical insights. This study reveals that teacher trainees' resistance to AI-based Chatbots is not only caused by traditional barriers (such as VB and IB), but also driven by new barriers (such as IQB and JRB). Such a study not only deepens the understanding of IRT, but also injects new vitality into the research of technology adoption and resistance in the realm of IS through an interdisciplinary perspective.

8. CONCLUSIONS AND LIMITATIONS

On the basis of the Innovation Resistance Theory, the current study develops and validates an enhanced theoretical model that offers a comprehensive analysis of the impact of various barrier elements on resistance behaviors toward AI-based Chatbots. This study aligns technological evolution trends, incorporates recent academic advancements, and adapts to the demands of AI-based Chatbots iteration by introducing new independent variables (e.g., IQB, JRB, E-WOMB) and employing a quantitative analysis technique and PLS-SEM to empirically evaluate behavioral data from groups of teacher trainees. This study finds that VB, RB, IB, IQB, and JRB have a significant and direct influence on teacher trainees' RTAC. However, the effects of UB and TB on teacher trainees' RTAC are less significant. VB plays a significant mediating role in the relationship between TA and teacher trainees' RTAC. RB mediates significantly in the relationship between E-WOMB and teacher trainees' RTAC. JRB plays a significant mediating role in the relationship between TA and teacher trainees' RTAC. JRB plays a significant mediating role in the relationship between E-WOMB and teacher trainees' RTAC. The principal contributions of this study are reflected in the following aspects: (i) Expanding the application scenarios of Innovation Resistance Theory by introducing it into the field of AI-based Chatbots acceptance and resistance; (ii) Adding the study population (teacher trainees) to which the AI-based Chatbots and IRT models apply; (iii) Deepening the understanding of educational technology resistance behaviors among teacher trainees; (iv) The findings of the present study offer significant insights into the advancement and enhancement of AI technology, the exploration of barriers factors of personal behaviors, and the establishment of a supportive social framework.

Although this study makes important contributions to both IS theory and AI-based Chatbots practice, it still has some limitations. For example, this study utilizes a cross-sectional data collection strategy, which elucidates the associations among different factors, but it is difficult to fully capture the temporal dynamics of teacher trainees' psychology and behaviors, which may constrain the long-term implications of the research conclusions. Although this study synthesizes several variables from IS, education science, marketing science, behavioral science, and others, it cannot encompass all factors that may affect technological resistance behaviors, for example, external environmental differences, emotional fluctuations, social influence, herd effects, or asymmetric information. Future research could further investigate the heterogeneity of technology resistance behaviors under different groups and cultural backgrounds, so as to promote both theoretical and practical breakthroughs in AI-based Chatbots.

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