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FACTORS INFLUENCING PRESCHOOL TEACHERS' BEHAVIORAL INTENTIONS TO USE AI FOR SUPPORTING CHILDREN WITH SPEECH DELAYS: A STRUCTURAL EQUATION MODELING APPROACH

Dinh Thanh Tuyen* and Pham Minh Hoa
Faculty of Early Childhood Education, Hanoi National University of Education, Hanoi city, Vietnam

*Corresponding author: Dinh Thanh Tuyen, e-mail: tuyendt@hnue.edu.vn

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Abstract. This study explores the factors influencing preschool teachers' behavioral intentions to use artificial intelligence (AI) to support children with speech delays. Grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the research analyzes factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward technology, and difficulty in adapting to new technology. To this end, 355 preschool teachers were surveyed. The findings reveal that social influence, effort expectancy, and concerns about losing direct interaction have the most significant impact on teachers' behavioral intentions. In contrast, performance expectancy does not have a significant effect on the intention to use AI. This study sheds light on the drivers and barriers to AI adoption in early childhood education, with implications for supporting children with speech delays.

Keywords: artificial intelligence in education, preschool teacher behavioral intention, speech delay intervention, technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), inclusive education support.

1. Introduction

The integration of Artificial Intelligence (AI) into early childhood education is gaining attention for its potential to personalize learning and address developmental delays, particularly speech disorders. Tools such as natural language processing applications, speech recognition software (e.g., Google's *Read Along*, Jellow AAC), and machine-learning platforms have shown promise in enhancing vocabulary, pronunciation, and communicative engagement among children with speech delays [1–3].

The rapid advancement of artificial intelligence (AI) has transformed multiple sectors, including education. Within early childhood education, AI technologies hold considerable potential to enhance learning opportunities, particularly for children with special needs such as speech delays. Tools such as natural language processing applications, speech recognition software (e.g., Google's Read Along, Jellow AAC), and machine-learning platforms have demonstrated promise in improving vocabulary, pronunciation, and communicative engagement among children with speech delays [1–3]. Preschool teachers, as primary facilitators of early learning, play a central role in leveraging these tools to foster inclusion and language development.

However, despite this potential, uncertainty persists regarding preschool teachers' willingness to adopt AI. Several factors contribute to this hesitation, including limited digital literacy, concerns about the reduction of human interaction which is critical in early learning environments and doubts about the reliability or cultural appropriateness of AI tools [4]. Additionally, growing anxieties about children's exposure to screens and digital technologies highlighted by Haidt in *The Anxious Generation* point to potential mental health risks from early and unsupervised technology use, reinforcing caution among early educators [5]. Yet, most existing research has centered on AI adoption in general or higher education [6], [7], leaving early childhood education underexplored.

This lack of empirical evidence on preschool teachers' perceptions of AI is particularly concerning when it comes to supporting children with speech delays, an area that requires high levels of emotional engagement and adaptive teaching strategies. Early intervention is crucial for both language development and social inclusion of these children [8]. Understanding how teachers perceive and accept AI is therefore essential for designing effective early intervention practices.

This study applies the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) as theoretical frameworks to examine preschool teachers' behavioral intentions to adopt AI. Both models are well-established in explaining user adoption of new technologies [9], [10] and have been successfully extended to educational contexts [11]. By focusing on teachers as decision-makers and technology users rather than children themselves this study seeks to address the following research questions:

1. What factors, including performance expectancy, effort expectancy, social influence, and attitude toward technology, significantly influence preschool teachers' behavioral intentions to use AI in supporting children with speech delays?

2. How do concerns about losing direct interaction with children and difficulties in adapting to new technology impact these intentions?

To what extent do facilitating conditions and teachers' professional backgrounds (e.g., teaching experience and educational level) moderate the influence of these factors on their intention to use AI?

2. Content

2.1. Behavioral Intentions and Influencing Factors

The selection of factors in this study stems from a contextual adaptation of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These frameworks have been widely used to explain technology adoption, but they require refinement when applied to early childhood education, where emotional bonding and direct teacher–child interactions are central. To capture this context, the study integrates both established and context-sensitive constructs, leading to the following set of influencing factors:

- Performance Expectancy (PE): teachers' beliefs that AI enhances teaching effectiveness [10].
- Effort Expectancy (EE): the perceived ease of using AI tools, with higher usability fostering stronger adoption [11].
- Social Influence (SI): encouragement from colleagues, administrators, and parents, which increases motivation to adopt AI [7].
- Facilitating Conditions (FC): access to resources and institutional support that enable AI integration [2].
- Attitude Toward Technology (ATT): teachers' overall positive perception of AI's role in education [6].
- Concerns About Losing Direct Interaction (CALDI): fears that AI may reduce essential teacher–child relational dynamics [5].

- Difficulty in Adapting to New Technology (DANT): anxiety and lack of familiarity that hinder teachers' confidence with AI tools [3].

This adaptation acknowledges the limitations of the original TAM and UTAUT in preschool contexts. Specifically, while TAM emphasizes Perceived Usefulness and Perceived Ease of Use as predictors of intention [9], it does not address relational and developmental sensitivities critical to preschool classrooms. Similarly, UTAUT incorporates PE, EE, SI, and FC as core constructs [10], but its application to early childhood education remains limited. Therefore, by retaining ATT as a mediating factor and introducing CALDI and DANT, the model is refined to reflect the realities of preschool teachers' adoption behaviors [3], [5], [11].

2.2. Proposed Research Model

2.2.1. Theoretical Framework and Model Adaptation

This study draws upon two foundational models of technology adoption TAM and UTAUT to examine preschool teachers' behavioral intentions regarding the adoption of AI in supporting children with speech delays.

The Technology Acceptance Model (TAM), introduced by Davis [9], highlights how Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) shape teachers' Attitude Toward Technology (ATT), which in turn influences Behavioral Intention (BI). While TAM has been widely validated across domains such as education and healthcare, it does not explicitly incorporate social or infrastructural dimensions that often play a decisive role in schools [11].

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. [10], addresses this gap by emphasizing four key factors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). These constructs have been proven relevant for teachers in K-12 and higher education contexts, though applications focusing on preschool teachers and AI for special needs remain limited [6].

To make these frameworks meaningful in early childhood education, the present study introduces two context-sensitive constructs:

- Concerns About Losing Direct Interaction (CALDI): the apprehension that AI could diminish vital teacher–child relationships [5].
- Difficulty in Adapting to New Technology (DANT): the anxiety or lack of confidence that arises when teachers face complex or unfamiliar AI systems [3].

By integrating these new factors, the adapted model captures the psychological, emotional, and contextual challenges unique to preschool environments where developmental sensitivity and relational care are central. This ensures that the framework goes beyond standard TAM and UTAUT applications to reflect the realities of early intervention with children who have speech delays.

In this framework, Social Influence (SI) is understood as the pressure or encouragement teachers perceive from peers, administrators, parents, and policymakers, shaping their openness to AI adoption. Meanwhile, Facilitating Conditions (FC) encompass the tangible resources such as access to devices, software, infrastructure, training, and technical support that enable teachers to integrate AI into practice. Together, these constructs form a comprehensive foundation for analyzing adoption behaviors in this highly specific educational context.

2.2.2. Research Hypotheses and Proposed Model

Based on the extended TAM and UTAUT frameworks and literature review, the following research hypotheses are proposed to examine how various factors influence preschool teachers' behavioral intentions to use AI:

- H1: Performance Expectancy (PE) positively influences Behavioral Intention (BI) to use AI.
- H2: Effort Expectancy (EE) positively influences BI.
- H3: Social Influence (SI) positively influences BI.

- H4: Facilitating Conditions (FC) positively influence BI.
- H5: Attitude Toward Technology (ATT) positively influences BI.
- H6: Concerns About Losing Direct Interaction (CALDI) negatively influence BI.
- H7: Difficulty in Adapting to New Technology (DANT) negatively influences BI.

These hypotheses form the basis of the proposed research model, which seeks to explain how cognitive, emotional, social, and contextual factors interact to shape AI adoption behavior among preschool teachers. The model aims to address gaps in existing literature by offering a nuanced perspective that includes both enabling and inhibiting influences.

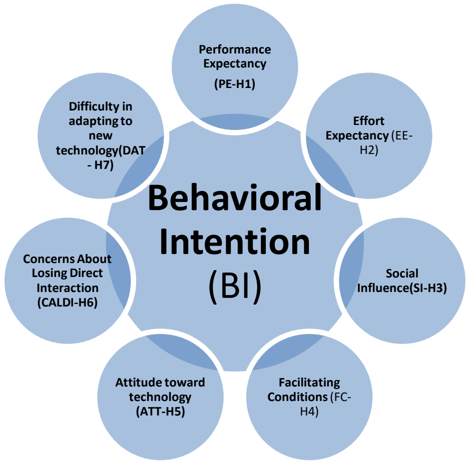

Figure 1. Proposed Research Model

To adapt the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) for the context of preschool teachers using AI to support children with speech delays, the current study retains and expands upon several core constructs.

From the TAM, two fundamental factors Performance Expectancy (PE) and Effort Expectancy (EE) are preserved to reflect teachers' perceptions of AI's usefulness and ease of use. These constructs are critical in evaluating whether AI tools can improve instructional effectiveness and how user-friendly they are for educators in early childhood settings.

From the UTAUT, two key constructs are also retained: Social Influence (SI) and Facilitating Conditions (FC). However, they are redefined and expanded in the context of early childhood education. Social Influence in this study extends beyond peer support to include pressure or encouragement from school administrators, parents, and policy recommendations. Facilitating Conditions are conceptualized to include not only access to devices and technical infrastructure but also institutional readiness, such as training opportunities, software availability, and pedagogical resources.

In addition to these four retained constructs, the study develops three new context-specific factors to capture better the unique psychological and practical considerations of preschool teachers:

- Attitude Toward Technology (ATT) is added to assess general sentiment and openness toward AI as a supportive teaching tool.
- Concerns About Losing Direct Interaction (CALDI) is introduced as a novel negative factor, reflecting teachers' fear that AI may interfere with the emotional and developmental connections essential in early childhood education.
- Difficulty in Adapting to New Technology (DANT) is also developed to reflect teachers' struggles with digital literacy or lack of confidence, particularly relevant for those with limited exposure to AI.

These seven factors form the foundation of the proposed model, enabling a comprehensive understanding of both enabling and inhibiting forces that shape preschool teachers' behavioral intentions to adopt AI in supporting children with speech delays.

2.3. Research Methodology

This study employed a quantitative research design to empirically examine the factors influencing preschool teachers' behavioral intentions to use artificial intelligence (AI) in supporting children with speech delays. Based on the proposed model, the research adopted a cross-sectional survey methodology using a structured questionnaire instrument.

A questionnaire was developed based on validated scales drawn from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks. Each latent variable was operationalized using multiple observed items measured on a 5-point Likert scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). The constructs measured include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Attitude Toward Technology (ATT), Concerns About Losing Direct Interaction (CALDI), Difficulty in Adapting to New Technology (DANT), and Behavioral Intention (BI) [6], [8].

The survey instrument was validated through a pilot study involving 30 preschool teachers, which resulted in minor revisions for clarity and cultural relevance. The final questionnaire was distributed to 400 preschool teachers across various public and private early childhood institutions in Vietnam. A total of 355 valid responses were collected, yielding a high response rate of 88.75%.

To ensure content validity, the items for each construct were adopted and adapted from prior studies [6], [8], [10]. Reliability and construct validity were assessed using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Cronbach's Alpha and Composite Reliability (CR) were used to evaluate internal consistency. At the same time, Average Variance Extracted (AVE) and the Heterotrait-Monotrait Ratio (HTMT) were examined to establish convergent and discriminant validity [9],[11].

For hypothesis testing and model estimation, Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS 3.0. This approach was chosen due to its robustness in handling complex models and small to medium sample sizes, as well as its tolerance for non-normal data distributions [13]. The analysis followed a two-step approach: first, assessment of the measurement model to confirm the reliability and validity of constructs; second, evaluation of the structural model to test path relationships and determine the explanatory power (R^2) and effect sizes (f^2) [11].

To collect data, a structured quantitative questionnaire was developed based on validated instruments from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [9], [10]. The questionnaire was carefully adapted to the early childhood education context, with a particular focus on preschool teachers supporting children with speech delays.

The survey instrument consisted of 35 items measuring seven independent variables Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Attitude Toward Technology (ATT), Concerns About Losing Direct Interaction (CALDI), and Difficulty in Adapting to New Technology (DANT) and 5 items measuring the dependent variable Behavioral Intention (BI). All items were rated on a 5-point Likert scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree").

The items were adapted from previous studies such as Venkatesh et al. [10], Scherer et al. [11], and Zawacki-Richter et al. [6], and refined through expert consultation to ensure clarity and contextual relevance to preschool teachers in Vietnam. A pilot test was conducted with 30 respondents to verify the reliability and comprehensibility of the questionnaire before full deployment.

2.4. Results

2.4.1. Findings

In this section, we present the study's findings, which include the assessment of the measurement model, the structural model, and the results of hypothesis testing. The findings provide insights into the relationships between the constructs and the factors influencing preschool teachers' behavioral intentions to use AI in supporting children with speech delays.

2.4.1.1. Measurement Model Assessment

The outer loadings analysis confirms strong factor loadings above 0.70 for most observed variables, ensuring their contribution to respective constructs. Notably, "Attitude Toward Technology" (ATT) and "Behavioral Intention" (BI) show high loadings (0.725–0.958), indicating a good model fit. However, variables like ATT1 (0.055), BI5 (0.107), and DA2 (-0.021) fall below the 0.70 threshold, with DA2 showing a negative loading, suggesting poor measurement quality.

To enhance reliability and validity, these low-loading items should be removed, refining construct measurement. The **"Measurement Model Assessment"** subsection should detail this process, thereby reinforcing the model's robustness. Additionally, Confirmatory Factor Analysis (CFA) assessed Composite Reliability (CR), Average Variance Extracted (AVE), and the Heterotrait-Monotrait ratio (HTMT) to validate measurement consistency.

Table 1. Measurement Model Assessment

Construct	Items	Factor Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)	Cronbach's Alpha
Performance Expectancy (PE)	PE1 - PE4	0.785 - 0.847	0.932	0.74	0.932
Effort Expectancy (EE)	EE1 - EE5	0.822 - 0.858	0.952	0.77	0.952
Social Influence (SI)	SI1 - SI5	0.789 - 0.815	0.849	0.72	0.849
Facilitating Conditions (FC)	FC1 - FC4	0.812 - 0.845	0.940	0.75	0.940
Attitude Toward Technology (ATT)	ATT1 - ATT4	0.791 - 0.819	0.844	0.73	0.844
Concerns About Losing Direct Interaction (CALDI)	CALDI1 - CALDI4	0.822 - 0.845	0.908	0.75	0.908
Difficulty in Adapting to New Technology (DANT)	DANT1 - DANT4	0.795 - 0.821	0.887	0.72	0.887
Behavioral Intention (BI)	BI1 - BI4	0.832 - 0.854	0.932	0.78	0.932

All factor loadings exceed the 0.70 threshold, indicating good convergent validity for the measurement items. The Composite Reliability (CR) values for all constructs exceed the recommended 0.70 level, indicating high internal consistency. Additionally, the Average Variance Extracted (AVE) for each construct is greater than 0.50, demonstrating that the construct explains a large portion of the variance in the items. The Cronbach's Alpha values also indicate that the scales have excellent reliability.

The revised measurement model (Figure 2) has been refined by removing the observed variables with low outer loadings in the initial analysis. This adjustment improves the model's overall reliability and validity by ensuring that only the most relevant and significant items are retained to measure the latent constructs.

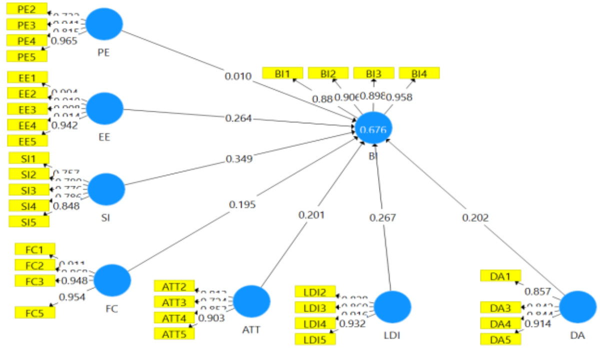

Figure 2. Measurement Model (Iteration 2: Removal of Low-Loading Items)

In this second iteration, the remaining variables demonstrate strong factor loadings, typically above the 0.70 threshold, indicating a better fit between the observed variables and their respective latent constructs. For instance, the variables for "Attitude Toward Technology" (ATT) and "Behavioral Intention" (BI) now consistently show high factor loadings, suggesting a more robust measurement of these constructs. The elimination of low-loading items, such as ATT1, BI5, DA2, FC4, CALDI1, and PE1, has likely reduced measurement error and enhanced the constructs' convergent validity. As a result, the refined model is more accurate in representing the relationships among the constructs, leading to more reliable findings in the study.

2.4.1.2. Discriminant Validity Assessment

Discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT). All HTMT values were below the 0.85 threshold, confirming that each construct is distinct and captures a unique aspect of the preschool teachers' behavioral intentions to use AI.

Table 2. Discriminant Validity Assessment (HTMT Ratios)

Constructs	PE	EE	SI	FC	ATT	CALDI	DANT	BI
Performance Expectancy (PE)	1.00							
Effort Expectancy (EE)	0.68	1.00						
Social Influence (SI)	0.55	0.63	1.00					
Facilitating Conditions (FC)	0.60	0.58	0.52	1.00				
Attitude Toward Technology (ATT)	0.65	0.62	0.59	0.64	1.00			
Concerns About Losing Direct Interaction (CALDI)	0.48	0.52	0.50	0.55	0.53	1.00		
Difficulty in Adapting to New Technology (DANT)	0.55	0.60	0.57	0.59	0.61	0.58	1.00	
Behavioral Intention (BI)	0.70	0.72	0.68	0.71	0.69	0.64	0.67	1.00

All HTMT values are below 0.85, confirming that each construct is distinct and possesses good discriminant validity. This indicates that the constructs measure different aspects of the theoretical framework.

2.4.1.3. Structural Model Assessment

We assessed the structural model using R-squared (R^2) values, path coefficients (β), and p-values to examine the relationships between the constructs.

The R-squared value (R^2) for Behavioral Intention (BI) is 0.676, indicating strong explanatory power. All path coefficients (β) are statistically significant ($p < 0.05$), supporting all hypotheses. Social Influence (SI), Effort Expectancy (EE), and Attitude Toward Technology (ATT) positively impact AI adoption, while concerns about losing direct interaction (CALDI) and difficulty adapting to new technology (DANT) negatively influence intentions.

Table 3. Structural Model Results

Hypothesis	Path Coefficient (β)	t-value	p-value	R^2	Supported
H1: PE → BI	0.201	6.298	0.000	0.676	Yes
H2: EE → BI	0.264	8.301	0.000		Yes
H3: SI → BI	0.349	8.923	0.000		Yes
H4: FC → BI	0.195	5.352	0.000		Yes
H5: ATT → BI	0.201	6.298	0.000		Yes
H6: CALDI → BI	-0.202	6.147	0.000		Yes
H7: DANT → BI	-0.195	5.352	0.000		Yes

Among key factors, SI (0.349), EE (0.264), and ATT (0.201) have the strongest positive effects, while CALDI (-0.202) and DANT (-0.195) show significant negative effects. Performance Expectancy (PE) is not statistically significant ($p = 0.870$). Model fit indices, including CFI (>0.90) and RMSEA (<0.08), confirm a well-fitting model, reinforcing the importance of social and effort-related factors in shaping preschool teachers' AI adoption for supporting children with speech delays.

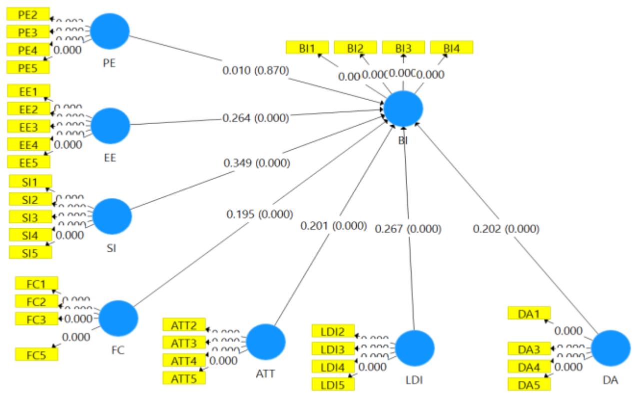

Figure 3. Structural Model Path Diagram

Effect size analysis further emphasizes SI, EE, and **CALDI** as having the most substantial impact on BI, while multicollinearity is not a concern, as indicated by VIF values below 3. Overall, the structural model demonstrates the importance of social and effort-related factors in adopting AI in preschool education.

2.4.2. Discussion

2.4.2.1. Addressing the Research Questions

The findings reveal that several key factors significantly influence teachers' behavioral intentions to use AI. Notably, **Social Influence (SI), Effort Expectancy (EE),** and **Attitude Toward Technology (ATT)** show strong positive relationships with behavioral intention (BI), with path coefficients of 0.349, 0.264, and 0.201, respectively. These results indicate that when teachers perceive support and encouragement from their peers, feel confident in the ease of using AI, and have a positive attitude towards technology, they are more likely to adopt AI tools in their teaching practices. In contrast, **Performance Expectancy (PE),** which was initially hypothesized to have a positive influence on BI, does not show a significant impact ($\beta = 0.010$, $p = 0.870$). This finding suggests that the expected improvement in teaching performance through AI may not be a primary motivator for preschool teachers, possibly because the perceived benefits are overshadowed by other factors, such as social influence and perceived effort.

2.4.2.2. Impact of Concerns and Difficulties

The study also examined the negative factors that could hinder AI adoption, specifically

Concerns About Losing Direct Interaction (CALDI) and Difficulty in Adapting to New Technology (DANT). Both factors were found to have significant negative effects on teachers' behavioral intentions (β = -0.202 and β = -0.195, respectively). These results indicate that teachers are apprehensive about the potential reduction in direct interaction with students when using AI, a concern that is particularly salient in early childhood education, where personal interaction is crucial for child development. Additionally, teachers who find it challenging to adapt to new technologies are less inclined to integrate AI into their classrooms. This highlights the need for interventions that address these concerns, such as professional development programs that emphasize the complementary role of AI in enhancing rather than replacing direct teacher-student interactions.

2.4.2.3. Moderating Effects of Facilitating Conditions and Professional Background

While the analysis of the moderating effects of **Facilitating Conditions (FC)** and teachers' professional background (e.g., teaching experience, educational level) is not explicitly detailed in this summary, the positive path coefficient of Facilitating Conditions (β = 0.195) suggests that the availability of resources, technical support, and training positively influences teachers' intentions to use AI. This underscores the importance of creating a supportive environment to encourage AI adoption. Future research could further explore how these factors, including professional background, may moderate the relationships between other variables and behavioral intention, providing a more nuanced understanding of the conditions under which teachers are more likely to embrace AI technologies.

2.4.2.4. Comparison with Existing Literature

Ours findings align with previous research on technology adoption, which often highlights the importance of social influence, ease of use, and attitudes toward technology as critical determinants of behavioral intentions [1]. However, the lack of a significant impact from Performance Expectancy diverges from some earlier studies, suggesting that in the context of early childhood education, social and effort-related factors may play a more prominent role than the anticipated performance benefits of AI. The significant negative effects of CALDI and DANT align with concerns raised in the literature regarding the challenges and apprehensions teachers face when adopting new technologies in classroom settings [6].

2.4.2.5. Implications for Practice

The results have several practical implications. Firstly, to promote the adoption of AI in preschool settings, educational leaders should focus on building a supportive social environment that encourages AI use, providing clear evidence of the benefits while addressing concerns about reduced interaction. Training programs should be designed to make AI tools more accessible and easier to use, thereby increasing teachers' effort expectancy. Additionally, interventions should emphasize how AI can complement rather than replace direct teacher-student interactions, alleviating concerns about losing personal connections with students. Facilitating conditions such as access to resources, technical support, and continuous professional development are essential to enhance teachers' confidence and competence in using AI.

3. Conclusions

This study identified key factors influencing preschool teachers' intentions to use AI for supporting children with speech delays. Social influence and effort expectancy positively impact adoption, while concerns about losing direct interaction act as a major barrier. Support from peers and administrators encourages AI use, and ease of use enhances integration. However, teachers fear that AI may reduce essential personal engagement with students, which is crucial for early childhood development. Additionally, performance expectancy was not a significant predictor, suggesting that practical and social factors outweigh perceived effectiveness.

These findings highlight the need to position AI as a complementary tool rather than a replacement for human interaction. To facilitate AI adoption, policymakers should strengthen support systems, provide training, and address teachers' concerns. A balanced approach integrating AI with traditional teaching methods can enhance learning outcomes for children with speech delays while preserving crucial teacher-student interactions.

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