Exploring Factors Influencing Preschool Teachers' Intention to Use AI Tools in Folktale-Based Instruction

Tran Thi Nhung [1], Vu Thi Thuy [1], Cao Thi Thu Hoai [1],
Nguyen Thi Thanh Huyen [2], Nguyen Thi Ut Sau [1]

[1] *Department of Early Childhood Education, Thai Nguyen University of Education, 20 Luong Ngoc Quyen street, Thai Nguyen, Vietnam*
[2] *Department of Educational Psychology, Thai Nguyen University of Education, 20 Luong Ngoc Quyen street, Thai Nguyen, Vietnam*

Abstract **– This study aims to explore the key factors influencing preschool teachers' intention to use Artificial Intelligence (AI) teaching aids in teaching folk literature. Drawing on foundational theoretical models such as the Technology Acceptance Model (TAM), Technological Pedagogical Content Knowledge for AI (AI-TPK), and Social Cognitive Theory (SCT), the study proposes a conceptual framework comprising ten hypotheses. A structured questionnaire was administered to 183 preschool teachers in the northern mountainous provinces of Vietnam. The collected data were analyzed using Generalized Structured Component Analysis (GSCA) with GSCA Pro 1.2 to examine both the measurement and structural models. The results revealed that teaching self-efficacy (TSE) was the strongest predictor of behavioral intention (BI), followed by perceived usefulness (PU). While AI-TPK had a significant positive influence on PEOU, its direct effects on TSE and BI were not statistically significant. Likewise, PEOU no longer had a direct effect on BI, but it played an important indirect role through PU and TSE.**

These findings suggest that confidence in teaching ability and perceptions of practical usefulness are more influential than interface simplicity alone in motivating teachers to adopt AI tools. The final model explains 71.9% of the variance in behavioral intention, indicating strong explanatory power. This study contributes both theoretically and practically to understanding AI acceptance in early childhood education, particularly in culturally rich, indigenous teaching contexts such as folk literature.

Keywords **– Artificial Intelligence (AI), preschool teachers, folktale education, Technology Acceptance Model (TAM), teaching self-efficacy.**

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Corresponding author: Vu Thi Thuy,
Department of Early Childhood Education, Thai Nguyen University of Education, 20 Luong Ngoc Quyen street, Thai Nguyen, Vietnam
Email: thuyvt.chir@tnue.edu.vn

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1. Introduction

In modern education, integrating folk literature into preschool education programs is considered a sustainable direction [1], [2]. Folk literature (in many forms such as fairy tales, legends, fables, nursery rhymes) is not only a valuable cultural treasure but also an effective tool to help young children form their personalities, develop language, and nurture their imagination [3], [1], [2]. Folk tales often reflect the lives, lifestyles, and customs of each region, so they are easy for children to understand, remember, and apply to real-life context. Furthermore, folk tales also contribute to fostering the ability to perceive literature, enhance memory, develop logical thinking and social emotions. As such, when bringing these works into the classroom, it is not only telling a story, but also sowing the seeds of ethical values, humanity, and national cultural identity [2].

Despite its many benefits, the integration of folklore into the curriculum for children is also facing many challenges. The first challenge is the lack of teaching materials suitable for the age and thinking of young children. Existing educational contents tend to be text-dominant, lengthy, and linguistically complex. As such, these are less effective for preschool instruction [1].

Furthermore, many teachers, especially in mountainous areas, not only face obstacles in communicating with (ethnic) students, but also have difficulty in transforming folk literature into creative, multimedia storytelling. Educational sessions based solely on old-style storytelling make it harder to attract and retain preschoolers' interest. In addition, the lack of storytelling tools such as pictures, videos, audio or projection equipment also significantly reduces the effectiveness of folk literature education activities in many remote kindergartens [4], [5].

To alleviate the aforementioned limitations, researchers proposed approaches to folk literature in preschool education. With the advancement of Artificial Intelligence (AI) in recent years, a prominent direction is the application of AI to support teachers in telling stories more vividly, while helping children to easily absorb and be interested in traditional content [6], [7], [8]. Some findings showed that the use of storytelling software with illustrations, vivid sounds, or the ability to automate reading voices has a positive impact on children's ability to concentrate, remember, and feel when exposed to folk tales [7], [9].

Although there is emerging interest, research on AI applications in this field is still fragmented and scarced [10], [11], [3], [2]. Prior studies are exploratory and mostly applied within a handful of school settings. There is a lack of scientific reports evaluating the specific analyses of factors affecting whether teachers are willing to accept and use technology in teaching folklore [12], [7], [13]. Preschool teachers in ethnic minority areas (technological divide) have not yet received much research attention. Therefore, the purpose of this study is to access the factors influencing the intention of preschool teachers to utilize AI technology in teaching folk literature, especially in schools in ethnic minority areas. Instead of just describing the current situation or introducing tools, the study aims to construct and evaluate a theoretical model. The unique in this study research is the combination of technological as well as psychological factors - the two aspects that play a pivotal role in facilitating innovation in education.

1.1. The Role of AI in Early Childhood Folktale Education

The utilization of AI has gained increasing attention in recent years in education, particularly in areas such as personalized learning, intelligent tutoring, and teacher assistance [14], [15]. In early childhood education, AI tools are gradually being explored for their capabilities to facilitate storytelling activities [16], especially with culturally significant content such as folk literature [17].

These emerging widgets include text-to-speech engines, AI-assisted visual generation, and content recommendation systems which are aligned with age-specific and cultural contexts [16], [18].

In early childhood education settings, storytelling plays an important role in developing young children's language, cognitive skills, and transmitting cultural values and social-emotional competencies [7]. However, teachers in ethnic minority areas often face challenges in accessing quality materials [6], Recent research findings have shown that AI-powered tools can enable teachers to animate culturally appropriate visual folktales, create spoken stories in local dialects, and personalize content to match classroom themes and children's interests [6], [7]. However, AI in early childhood education remains limited and under-evaluated. Another research gap is the lack of attention to factors that influence mountain teachers' readiness to adopt AI-based tools in their teaching activities. Previous studies considered either technological (e.g., usability, infrastructure) or psychological (e.g., confidence, perceived usefulness) variables separately, less focus on a unified perspective that synthesize them [7], [16].

Drawing on several widely used and evaluated theoretical frameworks such as the Technology Acceptance Model (TAM) [19], Technology Pedagogical Content Knowledge (TPACK) [20], and Social Cognitive Theory (SCT) [21], the current research pays special attention to four main dimension as AI-specific Technology Pedagogical Knowledge (AI-TPK), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Teaching Self-Efficacy (SE). Together, these factors form a new theoretical model that allows for examining how technological and psychological factors jointly influence teachers' willingness to integrate AI into their teaching practices. The following section presents each construct in detail and outlines the hypotheses derived from the proposed framework.

1.2. Theoretical Framework and Hypothesis Development

AI-specific Technological–Pedagogical Knowledge (AI-TPK) reflects teachers' ability to meaningfully integrate AI tools into their pedagogical practices, especially in designing and delivering folktale-based storytelling. Grounded in the TPACK framework [20], AI-TPK encompasses both technological skills and pedagogical understanding in selecting and applying tools like text-to-speech, animation, and digital folktale libraries. Within the present study, it is hypothesized that AI-TPK not only helps teachers perceive AI tools as easier to use (**H1**) [22], but also strengthens their confidence in applying these tools effectively (**H2**) [22].

Moreover, when teachers feel competent in using AI tools for storytelling, they are more likely to view such tools as beneficial to their instructional goals (**H5**) [23]. Ultimately, it is expected that teachers with higher AI-TPK will show greater intention to adopt AI-powered storytelling tools in their teaching practices (**H7**) [23].

Perceived Ease of Use (PEOU) refers to the extent to which teachers perceive AI tools as easy to learn and use. Grounded in the Technology Acceptance Model (TAM), PEOU reflects the effortlessness associated with using new technologies in the classroom. In this study, PEOU captures preschool teachers' perceptions of how intuitive and manageable AI-powered storytelling tools are. It is hypothesized that when teachers perceive AI tools as user-friendly, they are more confident in applying them during classroom activities (**H3**) [22]. Additionally, the perceived ease of use may positively shape how teachers assess the instructional value of the tools (**H6**) [23]. Ultimately, AI tools that require minimal effort to operate are more likely to be embraced and adopted by teachers (**H8**) [23].

Perceived Usefulness (PU) describes teachers' beliefs about the effectiveness of AI tools in improving their teaching outcomes. Grounded in the Technology Acceptance Model (TAM), PU reflects the degree to which teachers believe that using AI tools enhances their instructional effectiveness, lesson quality, and student engagement. In the context of this study, PU focuses on how AI storytelling tools help teachers prepare folktale-based content more efficiently and deliver it more engagingly.

It is hypothesized that when teachers perceive these tools as beneficial, their sense of teaching competence will also improve (**H4**) [22]. Moreover, the perceived instructional value of AI tools is expected to increase teachers' willingness to adopt and integrate them into classroom practice (**H10**) [23].

Teaching Self-Efficacy (TSE) refers to the level of confidence that elementary school teachers have in applying AI-enabled tools to their teaching activities. It is an important factor in Bandura's Social Cognitive Theory model [21], TSE plays an important role in linking technological awareness and behavioral intention. In the current study, TSE is understood as preschool teachers' belief in their ability to use AI tools to teach content in literature or folklore.

In this sense, higher levels of TSE will positively influence teachers' intention to adopt and implement AI-enabled storytelling tools in the classroom (**H9**) [24].

*Behavioral Intention (BI)*here is understood as whether teachers are willing to continue using AI-assisted tools in their teaching work or not. In other words, if they find it convenient, useful, and confident enough, then there is a high probability that they will use it in the long term [25]. In this research, BI is considered the main outcome variable and it is affected by many factors, from technology perception to personal beliefs, as mentioned in the aforementioned sections.

2. Methodology

To clarify the relationship between factors affecting preschool teachers' behavioral intentions in applying AI support tools to folk storytelling activities for preschool children, the study was designed with a quantitative approach.

The implementation steps include building a theoretical model, designing a survey instrument, collecting data, and analyzing data using modern techniques.

2.1. Research Design

In this study, a quantitative, cross-sectional design was employed, utilizing a structured questionnaire to assess the factors influencing preschool teachers' behavioral intentions in adopting AI-assisted tools in folktale-based instruction. The conceptual model includes five latent variables: AI-specific technological-pedagogical knowledge (AI-TPK), Perceived ease of use (PEOU), Perceived usefulness (PU), Teaching self-efficacy (TSE), and Behavioral intention (BI). From the five unobserved variables, 10 hypotheses were developed. To evaluate the relationships in the proposed model, Structural Equation Modeling (SEM) was applied [26], which is a widely used method in behavioral research to examine the causal pathways between latent variables. The proposed conceptual model was presented in Figure 1.

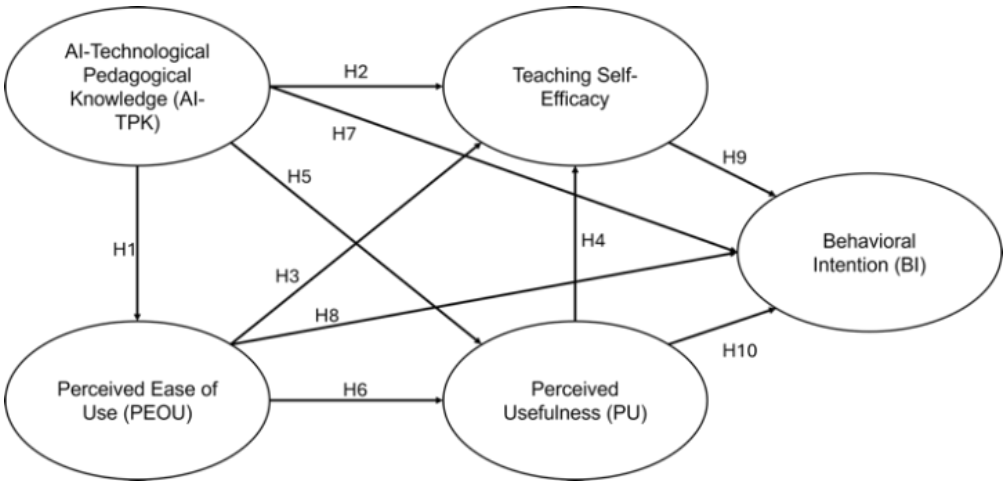

Figure 1. The proposed conceptual model examing factors influencing AI adoption

2.2. Instrument Development

The measurement items for each construct were adapted from previously validated instruments and revised to fit the context of preschool teachers in Vietnam. AI-TPK items were grounded in the TPACK framework, emphasizing teachers' ability to integrate AI tools such as text-to-speech engines and digital folktale libraries into instructional design. PEOU and PU were developed based on the Technology Acceptance Model (TAM) [19], capturing ease of learning and perceived instructional benefits of using AI for storytelling. Teaching Self-Efficacy items were derived from Bandura's theory of self-efficacy [21], reflecting confidence in applying AI tools despite potential challenges.

BI measured the extent to which teachers intended to use AI-powered storytelling tools consistently in the future.

All items were assessed using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The initial version of the questionnaire was written in English and then translated into Vietnamese through a back-translation process to ensure semantic equivalence and cultural appropriateness.

Table 1 presents the measurement items organized by construct, along with their sources.

Table 1. Constructs and measurement items

Construct	Item Code	Item Description	Source
AI-TPK	TPK1	I know how to integrate AI tools into folktale lesson plans.	[27]
	TPK2	I can choose suitable AI features (e.g., TTS, images) to support storytelling.	
	TPK3	I am able to design folktale-based activities with AI support.	
	TPK4	I know how to adapt folk content with the help of AI tools.	
	TPK5	I understand how AI can enhance storytelling pedagogy.	
PEOU	PEOU1	Learning to use AI storytelling tools is easy for me.	[28]
	PEOU2	My interaction with AI tools is clear and understandable.	
	PEOU3	I find it easy to use AI in teaching.	
	PEOU4	I can become skilled in using AI tools with minimal effort.	
	PEOU5	I can use AI storytelling tools without much assistance.	
PU	PU1	AI tools improve the quality of my storytelling lessons.	[28]
	PU2	Using AI tools helps me save time in lesson preparation.	
	PU3	AI tools help me engage students more effectively.	
TSE	SE1	I am confident in my ability to use AI storytelling tools.	[29]
	SE2	I can overcome difficulties when using AI in class.	
	SE3	I believe I can integrate AI into storytelling activities successfully.	
	SE4	I am comfortable experimenting with new AI tools.	
	SE5	I feel competent when applying AI in folktale teaching.	
BI	BI1	I intend to continue using AI tools in storytelling.	[25], [28]
	BI2	I will frequently use AI storytelling tools in future classes.	
	BI3	I plan to integrate AI into my regular teaching practice.	
	BI4	I am likely to recommend AI storytelling tools to peers.	
	BI5	If available, I will continue using AI tools in the future.	

2.3. Sampling and Data Collection

The target population of this study included preschool teachers working in mountainous districts of Thai Nguyen, Cao Bang, Bac Kan, Lang Son, Ha Giang province, where ethnic minority children account for a high proportion of school enrollments. A convenience sampling method was employed, and online questionnaires were distributed directly to teachers via social network channel such as Zalo or Facebook.

In total, 230 responses were collected, of which 183 valid samples were retained for analysis after screening for missing or invalid data. The sample included a diverse representation of gender, years of teaching experience, and school locations (Table 2). Respondents were informed about the study's purpose, and participation was voluntary and anonymous.

Table 2. Demographic profile of respondents (N = 183)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	145	88.5%
	Male	19	11.5%
Teaching Experience	Under 5 years	38	22.9%
	5–10 years	64	38.8%
	Over 10 years	63	38.3%
School Location	Urban	24	14.8%
	Semi-urban	49	30.1%
	Rural/mountainous	90	55.1%
Familiarity with AI Tools	Low	44	26.8%
	Moderate	79	48.1%
	High	41	25.1%

2.4. Data Analysis

The collected data were processed using Structural Equation Modeling (SEM), using GSCA software to support the analysis. The analysis process was carried out in two steps. In the first step, the research team assessed the reliability and validity of the measurement model through indicators such as composite reliability, average variance extracted (AVE), and factor loadings of each observed variable. The second step focused on the structural model, in which the hypothesized relationships between latent variables were tested through path coefficients.

To determine the statistical significance of these relationships, bootstrapping techniques with 1,000 subsamples were applied.

3. Results

Descriptive statistical analysis was conducted to assess the distribution characteristics of the observed variables in the model. The indicators considered included central tendency (mean value), skewness and kurtosis of the distribution. The results presented in Figure 2 show that the mean values of the variables ranged from 3.61 to 4.12. This reflects that the majority of participants tended to agree at a moderate to high level with the statements in each construct.

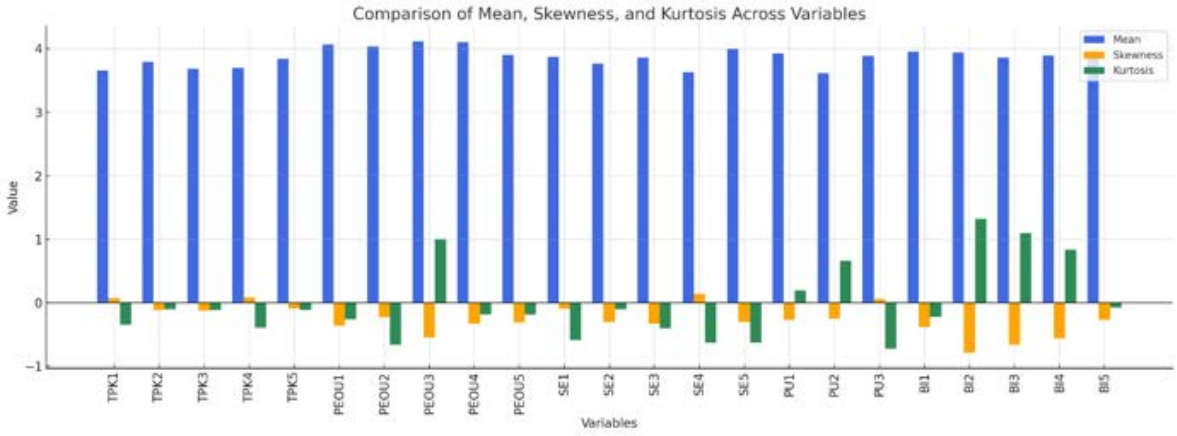

Figure 2. Descriptive distribution of the responses

The items in the Technological-Pedagogical Competency (TPK) construct [TPK1 →TPK5] had mean values between 3.68 and 3.84, implying that the majority of participants agreed with the statements related to the ability to integrate AI tools in storytelling activities. The skewness of these items was all approximately 0 (e.g., TPK1: –0.11; TPK3: 0.08), reflecting the relatively symmetrical distribution of the response data. In the same vein, the kurtosis [–.38 to –.09] was within acceptable limits and did not exhibit significant skewness. For the Perceived Ease of Use (PEOU) construct, items [PEOU1 - PEOU4] reported relatively high mean values [3.90 to 4.12]. Most items were slightly negatively skewed (e.g., PEOU3: –0.55) implying that participants tended to express higher levels of agreement with statements about PEOU. Yet of high PEOU3 (0.99), the kurtosis values were within the acceptable range. For the Teaching Effectiveness (SE) construct, the items [SE1-SE5] had mean values [3.89 - 4.00], indicating a high and stable level of consensus among participants. The data deviation ranged from –0.30 to –0.12. The kurtosis values [–0.62 to 0.20] showed no significant abnormalities in the shape of the distribution. In the Perceived Usefulness (PU) construct, the mean value of PU1 is slightly lower (3.61) than PU2 and PU3 [3.88 to 3.95] respectively. Although most teachers perceived the benefits of AI application, a small portion was still uncertain about the value of AI. With respect to distribution, PU2 had a slight positive skew (0.06), while PU3 has a slight negative skew (–0.38); both are within the acceptable range and do not show signs of significant distributional skewness. For the Behavioral Intention (BI) construct, questions BI1 to BI4 reflected a clear intention to continue using AI-powered tools. The mean values range from 3.84 to 3.94. The skewness is 0.78, indicating that many teachers were fully in agreement with actively applying AI in the future.

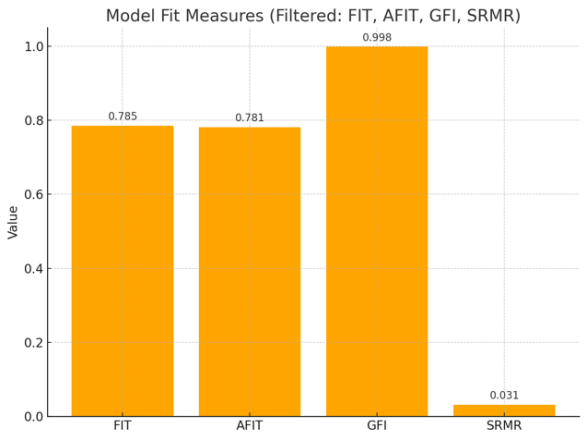

Figure 3. Model fit measures

The data from Figure 3 shows that the model has a relatively good fit. The FIT (0.785) and AFIT (0.781) indices both substantially exceed the commonly accepted threshold of 0.5, indicating that the model explains a considerable portion of the variance in the observed data. The GFI is exceptionally high at 0.998, far surpassing the 0.90 benchmark and demonstrating an excellent degree of model-data congruence. Additionally, the SRMR value of 0.031 is well below the 0.08 threshold, suggesting minimal discrepancy between the observed and predicted correlation matrices. Taken together, all fit indices not only meet but markedly exceed standard cut-off values, confirming that the proposed research model achieves an excellent level of empirical adequacy.

Table 3. Construct quality measures

	AI-TPK	**TSE**	**PEOU**	**PU**	**BI**
PVE	0.794	0.838	0.774	0.887	0.833
Alpha	0.936	0.952	0.927	0.937	0.95
Rho	0.951	0.963	0.945	0.959	0.961

The reliability and validity of the measurement model were evaluated using multiple established criteria, including Cronbach's Alpha (α), composite reliability (Rho), and average variance extracted (AVE or PVE), as summarized in Table 3. The results demonstrate that all latent constructs exceeded the recommended thresholds, indicating strong psychometric properties of the measurement model. Specifically, the Cronbach's Alpha values ranged from 0.927 to 0.952, all surpassing the conventional cutoff of 0.70 [30], thereby confirming high internal consistency. Among the constructs, TSE (α = 0.952) and BI (α = 0.950) showed the highest reliability, followed closely by PU (α = 0.937), AI-TPK (α = 0.936), and PEOU (α = 0.927). These results reflect a high degree of homogeneity among the items measuring each construct. Composite reliability (Rho), which accounts for the actual contribution of each indicator, further validated the internal consistency, with all constructs scoring between 0.945 and 0.963, again well above the 0.70 benchmark. TSE continued to show the highest composite reliability (ρ = 0.963), followed by BI (ρ = 0.961), PU (ρ = 0.959), AI-TPK (ρ = 0.951), and PEOU (ρ = 0.945). Regarding convergent validity, all constructs reported average variance extracted (AVE or PVE) values above the threshold of 0.50, indicating that a substantial proportion of variance in each construct's indicators is accounted for by the latent factor. The AVE values ranged from 0.774 (PEOU) to 0.887 (PU), confirming adequate convergence.

Together, these findings affirm the unidimensionality, internal consistency, and convergent validity of the latent constructs employed in the study, thus establishing a solid foundation for subsequent structural modeling.

Table 4. Loadings of each item in the construct

	Estimate	**SE**	**95%CI**	
AI-TPK				
TPK1	0.933	0.014	0.898	0.957
TPK2	0.956	0.007	0.942	0.968
TPK3	0.957	0.007	0.945	0.97
TPK4	0.96	0.006	0.949	0.974
TPK5	0.946	0.01	0.927	0.965
PEOU				
PEOU1	0.947	0.008	0.929	0.964
PEOU2	0.943	0.011	0.92	0.963
PEOU3	0.95	0.008	0.935	0.964
PEOU4	0.948	0.009	0.924	0.963
PEOU5	0.95	0.008	0.928	0.963
TSE				
SE1	0.953	0.008	0.938	0.969
SE2	0.959	0.009	0.94	0.974
SE3	0.964	0.007	0.947	0.977
SE4	0.957	0.008	0.941	0.971
SE5	0.959	0.008	0.941	0.971
PU				
PU1	0.976	0.004	0.966	0.985
PU2	0.97	0.007	0.958	0.984
PU3	0.965	0.009	0.945	0.979
BI				
BI1	0.955	0.009	0.935	0.971
BI2	0.956	0.008	0.941	0.97
BI3	0.97	0.005	0.961	0.98
BI4	0.954	0.009	0.937	0.97
BI5	0.944	0.009	0.925	0.961

To assess the reliability of each indicator, the loadings of all observed variables on their respective factors were examined. Depending on each study, the recommended loading values are at different thresholds, but in general, loading values of 0.6 or higher are considered statistically significant. As shown in Table 4, all items in this study achieved satisfactory loading levels. For the AI-TPK construct, the loadings ranged from 0.686 (TPK1) to 0.771 (TPK3), indicating a relatively uniform level of reliability across all five indicators. Although TPK1 has a value slightly lower than 0.70, it is still retained because it has theoretical significance and contributes positively to the overall reliability of the construct. For the PEOU factor, all five questions had high loadings [0.747 - 0.890]. A notable point for PEOU3 and PEOU4 is that the loadings exceeded 0.83, further reinforcing the strong internal consistency of this scale. Similarly, the questions in the Teaching Self-Efficacy (TSE) factor also showed very high reliability [0.796 - 0.874].

These values confirm that the TSE items well reflect teachers' feelings of confidence in using AI teaching aids in the context of folk tales. For the Perceived Usefulness (PU) construct, the loadings were all above 0.75, ranging from 0.762 (PU2) to 0.829 (PU3), indicating good reliability between the indicators. Finally, for the Behavioral Intention (BI) construct, all five items had loadings of 0.663 or higher. Although BI5 (0.663) and BI4 (0.702) showed slightly lower values compared to the remaining items, they were retained as their values remained within the acceptable range, particularly given that the overall reliability of this construct had been validated in previous analyses. The remaining three items – BI1 to BI3 – all had high factor loadings (ranging from 0.831 to 0.851), indicating that the BI scale has good reliability.

Table 5. Path coefficients

	Estimate	**SE**	**95%CI**	
H1: AI-TPK→PEOU	0.854	0.024	0.799	0.892
H2: AI-TPK→TSE	0.066	0.084	-0.097	0.198
H3: PEOU→TSE	0.359	0.112	0.171	0.587
H4: PU→TSE	0.513	0.085	0.355	0.725
H5: AI-TPK→PEOU	0.854	0.024	0.799	0.892
H6: PEOU→PU	0.847	0.078	0.709	1.01
H7: AI-TPK→BI	-0.015	0.064	-0.157	0.109
H8: PEOU→BI	-0.032	0.071	-0.148	0.111
H9: TSE→BI	0.719	0.086	0.553	0.875
H10: PU→BI	0.255	0.083	0.094	0.445

The path coefficients in the structural model were analyzed to assess the influence among the latent constructs. The empirical data from Table 5 show that most of the relationships are statistically significant, which reflects the reasonable links between the factors in the model. Notably, AI-related technological pedagogical knowledge (AI-TPK) maintains a profoundly significant and robust effect on perceived ease of use (PEOU) ($\beta = 0.854$, SE = 0.024, 95% CI: [0.799, 0.892]), reinforcing the theoretical postulate that when educators are equipped with domain-specific technological fluency, their cognitive load during system interaction is mitigated, thereby elevating intuitive usability perceptions. Nevertheless, diverging from previous empirical observations, the direct influence of AI-TPK on teachers' self-efficacy (TSE) is rendered statistically non-significant ($\beta = 0.066$, SE = 0.084, CI: [–0.097, 0.198]), suggesting a possible attenuation of its explanatory power or an indirect mediation via downstream cognitive appraisals such as PEOU or perceived usefulness (PU).

In contrast, both PEOU (β = 0.359, SE = 0.112, CI: [0.171, 0.587]) and PU (β = 0.513, SE = 0.085, CI: [0.355, 0.725]) exert statistically significant influences on TSE, indicating that subjective evaluations regarding the usability and instrumental value of AI tools are pivotal in fostering educators' pedagogical confidence and behavioral control beliefs. The exceptionally high path coefficient from PEOU to PU (β = 0.847, SE = 0.078, CI: [0.709, 1.01]) lends strong empirical support to the Technology Acceptance Model (TAM), wherein ease of use is posited as an antecedent to perceived utility. When examining behavioral intention to use AI (BI), the model identifies TSE as the most salient determinant (β = 0.719, SE = 0.086, CI: [0.553, 0.875]), corroborating theories of planned behavior which emphasize the criticality of perceived capability in enacting volitional technology adoption. PU also contributes meaningfully to BI (β = 0.255, SE = 0.083, CI: [0.094, 0.445]), albeit to a lesser degree. Conversely, both AI-TPK (β = –0.015, CI: [–0.157, 0.109]) and PEOU (β = –0.032, CI: [–0.148, 0.111]) fail to demonstrate significant direct effects on BI, implying that foundational knowledge and operational simplicity, while influential at earlier stages of cognitive appraisal, are insufficient alone to precipitate intentional adoption behaviors. This nuanced pattern of effects suggests a hierarchical mediation structure in which the transformation of technical familiarity and usability perceptions into action-oriented behavioral intentions is primarily mediated through heightened efficacy beliefs and instrumental value judgments.

4. Discussion

This section aims to analyze and interpret the research results in relation to the underlying theories, and to assess the suitability of the proposed model for the preschool education context. The findings are compared with previous research results to identify similarities or differences, thereby pointing out new theoretical contributions. In addition, this section also clarifies the potential practical applications of the model, especially in implementing AI tools to support the teaching of folk storytelling in preschools in ethnic minority areas - where there is a significant technology gap. Finally, limitations in methodology, sample size and research design are also analyzed to guide further studies to perfect the model or test it under other conditions.

4.1. Theoretical Implications

One of the most notable findings of this study is that the proposed model explains 71.9% of the variance in behavioral intention to use AI (BI), a substantial increase compared to the previous model.

This high explanatory power indicates that the integrated framework combining technological factors (AI-TPK, PEOU, PU) and psychological factors (TSE) remains theoretically sound and contextually appropriate for studying AI integration in early childhood education [24], [20]. The majority of hypothesized relationships were empirically supported, reaffirming the theoretical coherence of the proposed model.

Most prominently, teaching self-efficacy (TSE) continues to exert the strongest influence on behavioral intention (BI), with a markedly higher path coefficient of β = 0.719. This finding strengthens the position of self-efficacy as a pivotal motivational factor, in line with Bandura's social cognitive theory (2023), which identifies self-efficacy as central to volitional behavior. Recent empirical studies also highlight TSE as a critical determinant of technology adoption in education [29], [22]. Furthermore, perceived usefulness (PU) significantly predicts BI (β = 0.255), albeit to a lesser extent, indicating that when teachers perceive AI tools as pedagogically beneficial, their intention to use such tools increases accordingly.

Interestingly, perceived ease of use (PEOU) now plays a more foundational, indirect role. Although PEOU does not directly predict BI (β = –0.032, n.s.), it exerts strong influence on both PU (β = 0.847) and TSE (β = 0.359). This aligns with the Technology Acceptance Model (Davis, 1989), wherein PEOU acts as a key antecedent to both instrumental beliefs and psychological readiness. The strong path from PEOU to PU, in particular, suggests that usability significantly shapes teachers' evaluation of usefulness—echoing findings in early childhood education by [12] who found that tool simplicity is essential for both acceptance and confidence building.

Moreover, AI-TPK exhibits a very strong effect on PEOU (β = 0.854), confirming that familiarity with pedagogical and technological integration helps reduce cognitive friction during system interaction. However, its effect on TSE is no longer statistically significant (β = 0.066, CI includes 0), indicating a potential shift from a direct to an indirect pathway. This pattern supports recent studies suggesting that AI-TPACK constructs often influence behavioral outcomes via mediation through PEOU or PU. Most notably, AI-TPK no longer shows any significant direct effect on BI (β = –0.015), a result that suggests knowledge alone—detached from usability or experience—does not convert into behavioral intention. These findings reinforce calls for professional development programs to shift from solely delivering technological knowledge toward facilitating practical experience and self-efficacy enhancement [9].

In summary, this study advances the theoretical discourse in two critical ways: (1) It confirms the predictive salience of psychological factors—especially TSE—in driving AI adoption intentions, and (2) it delineates the indirect influence of AI-TPK, thereby reframing its role from a direct predictor to a structural enabler within the broader model. Future research should further investigate these mediated mechanisms and explore how experiential learning environments can bridge the gap between knowledge and intention in the context of AI integration in education.

4.2. Practical Implications

From a practical perspective, this study offers from a practical perspective, this study offers several key implications for effectively integrating AI technologies into folklore education within the context of early childhood education. First, the findings emphasize the pivotal role of teaching self-efficacy (TSE) in shaping teachers' willingness to adopt AI tools. This suggests that AI solutions should not merely aim for functional efficiency but must also be designed in ways that enhance teachers' confidence in delivering engaging and meaningful lessons. In folklore instruction—a domain deeply rooted in cultural nuance, emotional expression, and narrative delivery—confidence in tool use is indispensable. Therefore, AI platforms should provide pedagogically aligned, psychologically supportive features that facilitate lecture preparation, storytelling, content visualization, and formative assessment in intuitive ways suited to the cognitive and emotional development of young learners [31].

Second, although perceived ease of use (PEOU) no longer directly predicts behavioral intention, it significantly affects both perceived usefulness (PU) and self-efficacy (TSE), highlighting its continued indirect influence. This reinforces the idea that user-friendly interfaces and low learning curves remain essential in shaping downstream beliefs and motivational readiness. Tool developers should therefore prioritize accessibility and seamless interaction, particularly when designing AI platforms for use in subjects like folklore that demand rich multimedia content and adaptive instructional flows.

Third, the study newly identifies perceived usefulness (PU) as a statistically significant predictor of behavioral intention, underscoring the importance of clearly communicating the practical instructional benefits of AI tools. Developers and educational technology managers should explicitly showcase how AI can enhance folklore teaching—such as saving lesson planning time, offering a wide range of culturally authentic audio-visual folk materials, and scaffolding understanding for diverse learners.

This can be achieved through demo sessions, design-based research, or curated success stories from experienced teachers [32], which are often more persuasive than purely theoretical endorsements.

Finally, the data indicate that AI-TPK no longer has a significant direct effect on usage intention, suggesting that technological knowledge alone is insufficient for adoption. Thus, pre-service and in-service training programs should go beyond technical orientation and instead focus on applied integration strategies—such as AI-enhanced storytelling, folklore-based project work, and co-design activities where teachers collaboratively embed AI into lesson planning. These practices will not only increase familiarity but also nurture a sense of pedagogical ownership and professional confidence [33].

4.3. Limitations and Future Work

Although this study provides valuable findings, there are some limitations that need to be acknowledged. First, the data were collected through convenience sampling, mainly through social media platforms such as Zalo and Facebook. Although the sample size was sufficient to conduct structural model analysis, the geographic scope was mainly concentrated in some mountainous provinces in Northern Vietnam, so the results may not fully reflect the diversity of preschool teachers nationwide with different regional, ethnic, and teaching conditions. Future research should consider using random or stratified sampling to enhance the representativeness and generalizability of the results [14]. Second, the study used a cross-sectional design and relied entirely on teachers' self-reported intentions to use technology, rather than measuring actual classroom usage behavior. Therefore, the results only reflect subjective readiness and desire, and cannot accurately conclude that teachers have actually applied AI in their teaching practice. Future longitudinal studies will be needed to track trends in changing AI usage behavior over time [25]. Third, although the research model has integrated both technological factors (AI-TPK, PEOU, PU) and psychological factors (TSE), it has not considered contextual variables such as technology infrastructure, level of support from the school, or previous experience in using AI. These factors may help explain why perceived usefulness (PU) did not have a significant impact on intention to use AI in this study. Therefore, future models should be expanded to include contextual or organizational factors to provide a more comprehensive and in-depth view [32], [24]. Finally, the study focused on a specific teaching domain, folklore, which is deeply culturally and traditionally embedded. This may influence teachers' openness to AI tools, as narrative content is easily integrated with digital images and sounds.

Therefore, it is not yet certain whether these results can be applied to other subjects such as mathematics, science, or social-emotional education. Future comparative studies are needed to test the stability of the model across different subject and technology contexts [18], [8].

5. Conclusion

This study explored the factors influencing the intention to use AI-based teaching aids in teaching folk literature, based on the combination of components of the TAM model, the AI-TPK competency framework, and social cognitive theory (SCT). Based on data from 164 preschool teachers, the results showed that most of the hypothesized relationships were confirmed. In particular, teaching self-efficacy (TSE) emerged as the strongest predictor of behavioral intention (BI), emphasizing the critical role of psychological readiness in technology adoption. Additionally, perceived usefulness (PU) was found to have a significant direct effect on BI, indicating that practical value perceptions are key to teachers' decision to integrate AI into instruction. However, some relationships did not reach statistical significance. Specifically, perceived ease of use (PEOU) no longer had a direct influence on BI, and AI-TPK did not show a significant direct effect as initially hypothesized. These results suggest that while technical familiarity and interface simplicity remain important, their influence on behavioral intention may be indirect, mediated through perceived usefulness or self-efficacy. These findings need to be further tested through future studies, especially in real classroom contexts. Factors such as experience with AI, school support, or technology trust may play a mediating role. Therefore, future studies with longitudinal designs and larger sample sizes will help clarify the mechanisms that shape teachers' AI acceptance behavior.

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