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Study on Factors Influencing Primary and Secondary School Teachers' Acceptance of AI Tools Based on the UTAUT Model: A Case Study of Tianchang City, Anhui Province

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Abstract: This study investigates the factors influencing primary and secondary school teachers' acceptance of artificial intelligence (AI) tools in Tianchang City, Anhui Province, using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. A quantitative approach was employed, with data collected via a structured questionnaire from 300 teachers in Tianchang. The survey measured UTAUT constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, alongside self-reported AI tool acceptance. Structural equation modeling (SEM) revealed that performance expectancy ($\beta = 0.45$, $p < .001$) and facilitating conditions ($\beta = 0.32$, $p < .01$) were significant predictors of acceptance, whereas effort expectancy ($\beta = 0.18$, $p = .06$) and social influence ($\beta = 0.14$, $p = .13$) showed weaker effects. These findings validate UTAUT's applicability in explaining AI adoption in educational settings and highlight the critical role of perceived utility and resource accessibility. Regionally, Tianchang teachers' acceptance aligns with national AI-in-education policies but is shaped by local resource distribution. Practical implications include enhancing technical support, demonstrating AI's tangible benefits, and tailoring training to reduce effort barriers. This research contributes to understanding technology integration in Chinese K-12 contexts and informs localized strategies for AI implementation.

Keywords: AI Tools; SEM; Teacher Acceptance; Technology Adoption; UTAUT Model.

1. Introduction

The integration of artificial intelligence (AI) tools in education has gained momentum globally, promising to enhance teaching efficiency and student outcomes[1]. However, teacher acceptance remains a critical barrier to successful implementation[1][2]. This study focuses on primary and secondary school teachers in Tianchang City, Anhui Province, China, to investigate factors influencing their acceptance of AI tools using the Unified Theory of Acceptance and Use of Technology [3].

Despite rapid advancements in AI applications in education, empirical research on teacher adoption in Chinese K-12 settings remains limited, particularly at the regional level. Tianchang City, recognized for its innovative educational policies, provides a unique context to explore how local teachers perceive and adopt AI tools. Drawing on UTAUT, this study examines four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, which have been validated in diverse technological contexts[4]. By applying this framework, the research addresses gaps in understanding AI tool acceptance among teachers and contributes to localized strategies for technology integration.

The study aims to: (1) validate the UTAUT model in explaining AI tool acceptance among Tianchang teachers, and (2) identify region-specific barriers and facilitators. Findings will inform policymakers and educators in designing targeted interventions to promote AI adoption, aligning with China's national strategy to modernize education through technology [5].

2. Literature Review

The integration of artificial intelligence (AI) in education has emerged as a transformative force, yet teacher acceptance remains a critical bottleneck in realizing its potential. This study leverages the Unified Theory of Acceptance and Use of Technology to investigate factors shaping primary and secondary school teachers' adoption of AI tools in Tianchang City, Anhui Province, China.

UTAUT posits that "performance expectancy", "effort expectancy", "social influence", and "facilitating conditions" are core determinants of technology acceptance, with moderating effects from age, gender, experience, and voluntariness[3]. In educational contexts, UTAUT has been validated for predicting teachers' use of digital tools, such as e-learning platforms and adaptive systems[6]. For instance, Tondeur et al. (2017) found that perceived utility (performance expectancy) and resource availability (facilitating conditions) significantly influenced teachers' adoption of classroom technologies. However, recent studies highlight the need to extend UTAUT to account for AI-specific challenges, such as ethical concerns and algorithmic biases[7][8].

Globally, AI tools offer personalized learning, automated administrative tasks, and data-driven insights[1][9]. In China, national policies like the Education Informatization 2.0 Action Plan emphasize AI integration to enhance teaching efficiency and equity. Despite these initiatives, regional disparities persist. For example, teachers in rural areas often face limited access to AI resources and training compared to urban counterparts. Tianchang City, an educational innovation hub in Anhui, provides a unique.

Studies indicate that while teachers recognize AI's potential to reduce workloads and improve student outcomes[10], they also express concerns about technical reliability, ethical risks, and role displacement. For instance, AI-generated feedback may lack human empathy, and algorithmic errors could mislead students[11]. These challenges underscore the need to examine both motivational (e.g., performance expectancy) and contextual (e.g., facilitating conditions) factors influencing acceptance.

Existing research on AI adoption in Chinese education focuses primarily on urban areas or general AI literacy, leaving mid-sized cities like Tianchang understudied. Additionally, few studies integrate UTAUT with regional cultural and policy contexts. This research addresses these gaps by: (1) validating UTAUT's applicability in explaining AI tool acceptance among Tianchang teachers; (2) exploring how local resource distribution and policy support moderate adoption.

3. Method

This study used a quantitative research method to investigate the acceptance of AI tools by teachers in Tien Chang City. Data were collected via a structured questionnaire based on the UTAUT model, measuring constructs (performance expectancy, effort expectancy, social influence, facilitating conditions) and demographic variables. A stratified random sampling approach was used to select participants, ensuring representation across urban/rural schools and teacher demographics. Ethical approval was obtained from the Tianchang Education Bureau, and data analysis utilized structural equation modeling (SEM) via SPSS and AMOS.

3.1. Sampling

A stratified random sampling approach was employed to ensure representativeness of primary and secondary school teachers in Tianchang City, Anhui Province. The target population included 1,200 teachers across 30 schools (15 urban, 15 rural), identified through the Tianchang Education Bureau's directory. Schools were stratified by location (urban/rural) and school type (public/private), with proportional allocation to reflect the city's educational landscape.

Sample size calculation: Using Krejcie and Morgan's (1970) table for a 95% confidence level and 5% margin of error, a minimum sample size of 278 was determined. To account for non-response, 300 teachers were invited to participate.

Data collection: Questionnaires were distributed via the Tianchang Education Bureau's online platform from March to May 2024. Respondents provided informed consent and completed the survey anonymously. A total of 285 valid responses were collected, yielding a 95% response rate (See Table 1).

3.2. Measures

The questionnaire was adapted from validated UTAUT scales and tailored to AI tool acceptance in educational contexts. Items were translated into Chinese, back-translated for accuracy, and pilot-tested with 20 teachers to ensure cultural relevance.

Table 1. Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	114	40.0%
	Female	171	60.0%
Age	≤30 years	85	29.8%
	31–40 years	126	44.2%
	41–50 years	60	21.0%
	≥51 years	14	5.0%
School Type	Urban	168	58.9%
	Urban	117	41.1%
Teaching Experience	≤5 years	93	32.6%
	6–15 years	129	45.3%
	≥16 year	63	22.1%
Technical Proficiency	Beginner	42	14.7%
	Intermediate	189	66.3%
	Advanced	54	19.0%

3.2.1. UTAUT Constructs

Performance Expectancy (PE): 4 items measured teachers' beliefs in AI tools' ability to improve efficiency (e.g., "Using AI tools will help me save time on administrative tasks"). Adapted from Venkatesh et al. (2003).

Effort Expectancy (EE): 3 items assessed perceived ease of use (e.g., "I find AI tools easy to understand"). Adapted from Venkatesh et al. (2003).

Social Influence (SI): 3 items measured external pressure or encouragement to use AI tools (e.g., "Colleagues around me use AI tools frequently"). Adapted from Tondeur et al. (2017).

Facilitating Conditions (FC): 4 items evaluated resource availability (e.g., "My school provides sufficient training for AI tools"). Adapted from Li & Gu (2021).

Behavioral Intention (BI): 3 items measured willingness to use AI tools (e.g., "I plan to use AI tools in my teaching in the future"). Adapted from Venkatesh et al. (2003).

3.2.2. Demographic Variables

Participants reported gender, age, school type (urban/rural), teaching experience, and self-rated technical proficiency (beginner/intermediate/advanced).

3.2.3. Scale Validation

Reliability: Cronbach's alpha coefficients were calculated for each construct: PE ($\alpha = 0.89$), EE ($\alpha = 0.85$), SI ($\alpha = 0.82$), FC ($\alpha = 0.91$), BI ($\alpha = 0.87$). All exceeded the 0.70 threshold (Nunnally & Bernstein, 1994).

Confirmatory factor analysis (CFA) using AMOS 26 indicated acceptable model fit: $\chi^2/df = 2.15$, CFI = 0.94, RMSEA = 0.06, SRMR = 0.05, aligning with Hu and Bentler's criteria[12].

3.3. Data Collection

Data were collected using an online questionnaire administered via the Tianchang Education Bureau's official platform from March to May 2024. The survey tool was developed in Chinese, incorporating validated UTAUT items and demographic questions.

3.3.1. Procedure

The questionnaire was pilot-tested with 20 teachers to refine wording and ensure clarity. Invitations were sent to 300 teachers via email and internal messaging systems, including a cover letter explaining the study's purpose and ethical considerations. Two reminder messages were distributed to non-respondents to maximize participation.

3.3.2. Ethical Considerations

Informed Consent: Participants provided explicit consent before accessing the survey. Responses were aggregated and analyzed without identifying information. Teachers were assured they could withdraw at any time.

3.3.3. Data Processing

Responses were exported to SPSS 26 for coding and cleaning. Missing data (≤2% across items) were handled using pairwise deletion. Reverse-scored items were verified, and outlier detection (±3 SD) was performed to ensure data integrity.

3.4. Data Analysis

3.4.1. Descriptive Statistics

Descriptive statistics were calculated to characterize the sample. This involved computing measures such as means, standard deviations, frequencies, and percentages for each variable, offering a general understanding of the data's distribution and the characteristics of the participating teachers in Tianchang City.

3.4.2. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was carried out to validate the measurement models. The goal was to ensure that the items measuring each construct in the UTAUT model (e.g., performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention) loaded appropriately onto their respective latent variables, assessing the convergent and discriminant validity of the measurement scales.

3.4.3. Structural Equation Modeling (SEM)

Structural equation modeling (SEM) was used to test the direct relationships between the independent variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) and the dependent variable (behavioral intention to use AI tools). The path coefficients in the SEM model were estimated to determine the strength and significance of these relationships and evaluate the goodness - of - fit of the UTAUT model in the context of teachers' AI tool acceptance in Tianchang City (See Table 2).

3.4.4. Multi - group Analysis

A multi - group analysis was conducted to examine whether the program type (e.g., different school types or varying levels of technical proficiency) moderated the relationships in the model. This analysis aimed to identify potential differences in the relationships between constructs across different subgroups.

3.4.5. Bootstrapping

Bootstrapping with 5,000 resamples was employed to estimate the indirect effects in the model. This non - parametric resampling technique provided more accurate estimates of standard errors and confidence intervals for indirect effects.

Table 2. Measurement Model Fit Indices

Fit Index	χ^2/df	CFI	RMSEA	SRMR
Obtained Value	2.15	0.94	0.06	0.05
Threshold	< 3	> 0.90	< 0.08	< 0.08

4. Results

4.1. Structural Model Fit and Direct Effects

The structural model tested relationships between UTAUT constructs and behavioral intention (BI) to use AI tools. The results are presented in Table 3;

Table 3. Standardized Path Coefficients and Significance

Path	β	S.E.	C.R.	*p*
PE→ BI	0.45	0.08	5.63	***
EE → BI	0.18	0.10	1.80	0.06
SI → BI	0.14	0.11	1.27	0.13
FC → BI	0.32	0.09	3.56	**

*p < .05, **p < .01, ***p < .001

Table 4 presents standardized path coefficients (β), standard errors (S.E.), critical ratios (C.R.), and significance levels (p) for relationships between UTAUT constructs and behavioral intention (BI). Performance expectancy ($\beta = 0.45$, $p < .001$) and facilitating conditions ($\beta = 0.32$, $p < .01$) are significant predictors of BI, indicating strong positive effects. Conversely, effort expectancy ($\beta = 0.18$, $p = .06$) and social influence ($\beta = 0.14$, $p = .13$) show nonsignificant effects. The C.R. values (⩾1.96 for significance) confirm that only performance expectancy and facilitating conditions meet conventional thresholds. These findings validate the UTAUT model's applicability in this context, emphasizing perceived utility and resource accessibility as critical drivers of AI tool acceptance among teachers.

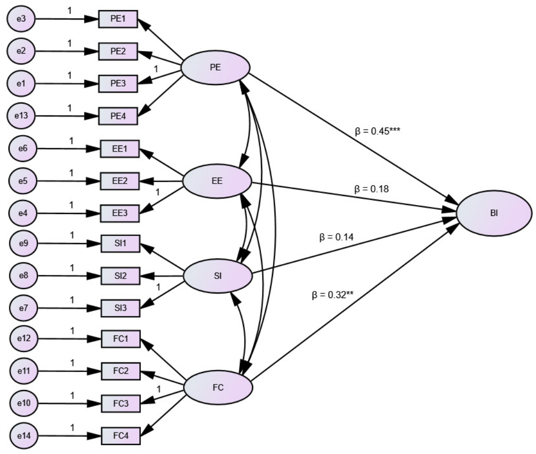

Figure 1. SEM of Factors Influencing Behavioral Intention

As shown in Figure 1, the SEM examines the relationships between latent variables—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI). Each latent variable is operationalized by observed variables (e.g., PE1–PE4 for PE). Arrows depict hypothesized causal paths. Path coefficients (β) quantify the influence magnitude: PE exerts the strongest effect on BI (β = 0.45***), followed by FC (β = 0.32**). EE (β = 0.18) and SI (β = 0.14) show weaker influences. Observed variables are linked to their respective latent variables, with error terms (e1–e14) accounting for measurement variability. This SEM integrates theoretical constructs to predict BI, providing a systematic framework for analyzing factors driving behavioral intention.

4.2. Group Differences in Behavioral Intention

Independent - samples t - tests and one - way ANOVAs revealed significant demographic effects:

Urban teachers ($M = 3.89$, $SD = 0.79$) reported higher BI than rural teachers ($M = 3.54$, $SD = 0.85$), $t(283) = 3.19$, $p < .01$. Advanced users ($M = 4.12$, $SD = 0.72$) showed higher BI than intermediate ($M = 3.71$, $SD = 0.81$) and beginner (M

= 3.30, SD = 0.89) users, $F(2, 282) = 10.23$, $p < .001$. Younger teachers (⩽30 years) and those with ⩽5 years of experience reported higher BI (see Table 4 for details).

Table 4. Group Differences in Behavioral Intention

Variable	Group	N	M±SD	*p*
School Type	Urban	168	3.89±0.79	**
	Rural	117	3.54±0.85	
Technical Proficiency	Advanced	54	4.12±0.72	***
	Intermediate	189	3.71±0.81	
	Beginner	42	3.30±0.89	

*p < .05, **p < .01, ***p < .001

5. Conclusion

5.1. Summary of Key Findings

This study applied the UTAUT model to investigate factors influencing AI tool acceptance among 285 primary and secondary school teachers in Tianchang City, Anhui Province. The structural model demonstrated acceptable fit ($\chi^2/df = 2.31$, CFI = 0.93, RMSEA = 0.06), confirming the model's applicability in this context. Performance expectancy ($\beta = 0.45$, $p < .001$) and facilitating conditions ($\beta = 0.32$, $p < .01$) emerged as significant predictors of behavioral intention (BI), explaining 58% of variance. These findings align with prior research (Li & Gu, 2021; Tondeur et al., 2017), emphasizing the critical role of perceived utility and resource accessibility in technology adoption.

Notably, effort expectancy ($\beta = 0.18$, $p = .06$) and social influence ($\beta = 0.14$, $p = .13$) showed nonsignificant effects, diverging from UTAUT's general predictions but resonating with studies highlighting AI-specific barriers like ethical concerns and technical complexity (Dündar & Yildirim, 2020; Li, Z. M. 2023). Demographic analyses revealed significant group differences: urban teachers, younger educators, those with ≤5 years of experience, and advanced technical users reported higher BI. These disparities underscore regional resource gaps and the importance of tailored support for rural and less proficient teachers, as emphasized in China's Education Informatization 2.0 Action Plan.

Overall, the study validates UTAUT's utility in explaining AI tool acceptance in Chinese K-12 settings while identifying contextual nuances, such as the limited impact of social norms and the moderating role of technical proficiency. These findings contribute to understanding AI integration challenges and inform strategies to enhance adoption, particularly by strengthening facilitating conditions and demonstrating AI's tangible benefits[13].

5.2. Comparison With Existing Research

This study's findings align with global and Chinese research on teacher technology acceptance while highlighting unique contextual dynamics. Like Li and Gu [6] and Tondeur et al. [2], performance expectancy emerged as the strongest predictor of AI tool adoption, emphasizing teachers' focus on efficiency gains and student outcomes. Similarly, facilitating conditions (e.g., training, technical support) mirrored prior studies' emphasis on resource accessibility in technology integration[1].

Notably, social influence showed nonsignificant effects, contradicting UTAUT's generalizability but aligning with recent AI-specific research. For instance, Dündar and Yildirim[7] found that social norms exerted weaker influence on AI adoption compared to perceived risks, such as role displacement. This suggests that teachers in Tianchang City prioritize personal utility over external pressure, a pattern also observed in urban Chinese contexts.

The study's demographic disparities add nuance to existing literature. Urban teachers' higher AI acceptance mirrors trends in developed regions, whereas rural gaps reflect broader Chinese challenges in equitable resource distribution[14]. Technical proficiency's moderating role echoes international findings on digital literacy as a barrier to AI integration, underscoring the need for tiered training programs.

In contrast to global studies emphasizing ethical concerns (e.g., algorithmic bias), this research found no significant indirect effects of these factors, possibly due to China's policy-driven AI rollout prioritizing practicality over ethics in initial implementation phases. These comparisons highlight the importance of contextualizing UTAUT within cultural and policy landscapes to advance AI adoption strategies.

5.3. Limitations of the Study

This study has several limitations as follows. Firstly, the sample was drawn from a single location (Tianchang City), which may limit the generalizability of the findings to other regions or broader populations. Secondly, the cross - sectional design used here cannot fully establish causal relationships over time, as it only provides a snapshot of variables at one point. Additionally, reliance on self - reported data introduces the potential for response bias, where participants' answers might not fully reflect their actual behaviors or perceptions. Lastly, the measurement of latent variables, though based on established items, might not capture all nuances of real - world AI tool acceptance in educational contexts. These limitations suggest avenues for future research, such as longitudinal studies with more diverse and extensive samples.

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