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A Unified Model for Innovation and Technology in Education: A Framework for Teachers' Adoption of AI Tools in Teaching

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Abstract

In today's technologically advanced classrooms, artificial intelligence (AI) offers promises of enhanced teaching and personalized learning. Yet integrating AI tools into teaching hinges on teachers' willingness and ability to adopt these innovations. This study develops and validates the Unified Theory of Innovation and Technology in Education (UNITED) model an integrated framework grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and related theories to explain secondary school teachers' behavioral intent and actual use of AI tools. A descriptive-causal design with structural equation modeling (SEM) was employed, involving 428 secondary teachers in Northern Mindanao, Philippines. Results confirmed an excellent-fitting model explaining teachers' AI adoption. Perceived usefulness of AI and social influence emerged as significant positive predictors of teachers' intention to adopt AI tools, while perceived ease of use showed no direct effect on intention. Facilitating conditions (infrastructure and support) proved critical for translating intention into actual AI use in the classroom. The final UNITED model unifies multiple technology acceptance constructs, offering both theoretical and practical insights. We recommend targeted professional development to boost teachers' AI competencies and improved institutional support to foster effective AI integration in education.

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Introduction

Artificial Intelligence (AI) is rapidly transforming educational practices, reshaping how teachers deliver instruction and how students learn. AI-driven tools can automate routine tasks, personalize learning experiences, and augment teachers' capabilities in the classroom. AI-powered tutoring systems and content generators can instantly support learning and cognitive tasks, enabling more individualized and efficient instruction. To harness these benefits, teachers must become adaptive facilitators who skillfully integrate AI into their pedagogy. However, despite increasing availability of AI tools, many educators remain hesitant to adopt them due to unfamiliarity and uncertainty about their value (Abdullah & Fraidan, 2024; Banerjee, 2024). This gap between promise and practice raises a critical question: What factors influence teachers' adoption of AI tools in teaching?

Globally, educational systems recognize that integrating AI can facilitate personalized learning and improve outcomes (Eden et al., 2024). In the Philippines, initiatives to leverage AI in classrooms are gaining momentum despite infrastructural challenges like intermittent connectivity. Teacher readiness and willingness to adopt AI are pivotal to these efforts (Venkatesh, 2022). Prior studies suggest that teachers' adoption decisions depend on their perceptions of AI's usefulness and the availability of institutional support (Solak, 2024). In other words, if teachers see clear benefits to instruction and have adequate technical support, they are more likely to embrace AI tools.

Over past decades, researchers have developed multiple theoretical models to explain technology adoption in educational settings, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behavior (TPB). Each provides valuable insight into the determinants of users' behavioral intentions to adopt technology. TAM posits that an individual's intention to use a technology is driven by its perceived usefulness (the extent to which it enhances job performance) and perceived ease of use (the effort required to use it) (Davis, 1989). UTAUT extends this by adding factors like social influence (pressure from others) and facilitating conditions (available support/resources), which have been shown to affect technology use in organizational contexts (Venkatesh et al., 2003). TPB further emphasizes the roles of attitudes, subjective norms, and perceived behavioral control in shaping behavioral intentions (Ajzen, 1991). These models have been applied to educational technology adoption, but often in isolation. There remains a knowledge gap in how these key theories can be comprehensively integrated into a unified framework to explain teachers' adoption of AI tools.

To address this gap, the present study developed the Unified Theory of Innovation and Technology in Education (UNITED) model, a synthesized framework that integrates core constructs from TAM, UTAUT, TPB, and related models in order to holistically explain secondary school teachers' adoption of AI tools. The UNITED model incorporates Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) from TAM (Davis, 1989; (Venkatesh & Davis, 2000; Solak, 2024), Social Influence (SI) and Facilitating Conditions (FC) from UTAUT (Venkatesh et al., 2003; (Yessenova et al., 2023), with Behavioral Intention (BI) mediating their effects on Actual Use (AU). Grounded in TPB (Ajzen, 1991) and the Theory of Reasoned Action (Fishbein & Ajzen, 1975), the model assumes that a strong intention to use AI will translate into actual classroom implementation of AI tools. It also acknowledges contextual factors: teachers' personal and professional profiles (e.g. experience, training) may condition their perceptions and adoption behaviors (Mishra & Koehler, 2006; Magat & Sangalang, 2024).

By empirically testing this unified model, the goal is to identify the critical factors and pathways that drive or impede AI adoption among teachers. Such insights are both theoretically and practically significant. A unified model can advance theory by reconciling overlapping constructs, the like of TAM's usefulness and UTAUT's performance expectancy and revealing how external conditions and personal beliefs jointly influence adoption. Practically, understanding these factors can help educational leaders design more effective interventions such as professional development programs to improve teachers' perceived ease of using AI, or policies to strengthen infrastructure and technical support (facilitating conditions) that enable actual AI usage.

In this paper, we present the results of a study that surveyed 428 secondary school teachers about their perceptions and usage of AI tools. We use structural equation modeling to validate the hypothesized UNITED model. The key research questions addressed include: (1) What are the demographic and professional profiles of teachers currently engaging with AI tools? (2) How well does the initial hypothesized model fit the data, and what modifications are needed to improve it? (3) Which factors significantly predict teachers' behavioral intention to adopt AI and their actual use of AI in teaching, according to the final validated model? We also discuss how the findings align with or diverge from prior research, and propose recommendations to support successful AI integration in education. By unifying multiple frameworks, this study aims to provide a comprehensive yet practical model to guide and explain teachers' adoption of AI tools in teaching, thereby contributing to the scholarship and practice of educational technology integration

Method

Research Design and Participants

We employed a descriptive-correlational research design with a causal modeling approach to examine the determinants of teachers' AI adoption. Specifically, we used covariance-based Structural Equation Modeling (SEM) to test the relationships in the UNITED conceptual model. The target population was secondary school teachers in one of the Divisions in the Department of Education in Northern Mindanao, Philippines. Using stratified random sampling, we selected a sample of n = 428 teachers from various public secondary schools in this division. Stratification ensured representation across different schools and districts.

The profile of respondents reflects typical demographics of public high school teachers in the region. About 69.6% of the respondents were female and 30.4% male, consistent with the predominance of women in the teaching profession. The teachers' ages ranged from early 20s to mid-60s, with the largest age groups being 26–35 years (33.2%) and 36–45 years (29.7%). A small fraction (1.4%) were under 25, while about 12% were over 55, indicating that most participants were young to mid-career educators. In terms of teaching experience, over half (58.2%) had 1–10 years of service, 22.0% had 11–20 years, and roughly 19.9% had more than 20 years in service. The majority held the rank of Teacher I (43.5%), with others being Teacher II (18.5%), Teacher III (29.7%), and a small percentage (≈8%) in Master Teacher I/II positions. These characteristics suggest our sample includes a diverse mix of early-career and veteran teachers, though relatively few in administrative or senior teaching roles.

Importantly, participants varied in their familiarity with AI tools. Exactly half (50.0%) described themselves as "familiar" with AI applications in education, and an additional 22.7% considered themselves "very familiar". Meanwhile, about 26.4% were only "somewhat familiar" and a negligible proportion (<1%) reported being not familiar with AI tools. This range of familiarity levels provides a meaningful context to examine how perceptions of ease and usefulness of AI might form among teachers with different exposures.

All participants voluntarily responded to an online survey administered in early 2025. Prior to data collection, necessary permissions were obtained from school authorities, and informed consent was secured from teachers. Respondents were assured of anonymity and that their responses would be used for research purposes only.

Instrumentation and Measures

Data were gathered using a structured questionnaire composed of two main parts: (1) items on teacher profile and AI usage, and (2) scales measuring the latent constructs in the UNITED model. The first part asked for demographic information (gender, age, years of service, job designation) and assessed the respondents' technology background including their self-reported familiarity with AI tools and which types of AI applications they have used in the classroom (e.g. chatbots, intelligent tutoring systems, AI-based grading tools, etc.).

The second part comprised Likert-scale items representing each construct in the model: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Actual Use (AU) of AI tools. Wherever possible, we adapted established survey instruments from prior research to ensure content validity. Specifically, many items were drawn and modified from the following sources: the UTAUT instrument by Venkatesh et al. (2003) for social influence and facilitating conditions, the original TAM scales by Davis (1989) for perceived usefulness and ease of use, and Ajzen's (1991) TPB-related measures for intention (also informed by technology adoption studies). Additional items were devised for actual AI use, capturing frequency and ways AI tools are integrated in teaching. All items were phrased to fit the context of K–12 teaching with AI. For example, a sample item for Perceived Usefulness is "*Using AI tools in my teaching enhances my instructional effectiveness*," and for Social Influence: "*My colleagues and school leaders encourage me to use AI tools in teaching.*" Respondents rated each statement on a 5-point Likert scale (1 = *Strongly Disagree* to 5 = *Strongly Agree*).

Content validity of the instrument was established via expert review. Three experts in educational technology examined the items to ensure they were relevant and clear for measuring the intended constructs in an AI education context. Minor wording revisions were made based on their feedback. A pilot test with 30 teachers was also conducted to check the survey's clarity and reliability before full deployment; pilot responses indicated good internal consistency across the scales (Cronbach's α values > 0.80 for all constructs).

Procedure and Data Analysis

The online survey was distributed through official school email lists and messaging platforms, and data collection spanned approximately four weeks. Participation was voluntary, and teachers could complete the survey at their convenience. In more than 500 surveys distributed, 428 were completed and valid for analysis (yielding a satisfactory response rate for SEM requirements). We examined the dataset for missing values and outliers; only minimal random missing responses were found, which were handled by mean imputation. Screening for multivariate normality indicated significant skew/kurtosis (Mardia's tests, $p < .001$), so we opted for robust estimation in the SEM analysis to account for non-normality (Hair et al., 2019; Kline, 2016). Specifically, we employed the Diagonally Weighted Least Squares (DWLS) estimator, which is appropriate for ordinal Likert data and handles non-normal distributions effectively.

Data analysis proceeded in two major phases using JAMOVI 2.3.28 and JASP SEM modules. In the measurement model phase, we conducted confirmatory factor analysis (CFA) to evaluate the reliability and validity of the constructs. We calculated Cronbach's α and McDonald's ω for internal consistency, and Composite Reliability (CR) as another measure of construct reliability. Convergent validity was assessed through the Average Variance Extracted (AVE) for each construct, and discriminant validity was examined using the Heterotrait-Monotrait (HTMT) ratio between constructs. Table 1 summarizes the reliability and convergent validity results. All constructs exceeded the recommended thresholds of $\alpha \geq .70$ and $CR \geq .70$, demonstrating excellent internal consistency (Hair et al., 2019). The AVE values ranged from .638 (for Social Influence) to .781 (for Perceived Ease of Use), all well above the .50 criterion (Fornell & Larcker, 1981), indicating strong convergent validity. As shown, Perceived Usefulness had $\alpha = .939$ and $AVE = .740$, and Behavioral Intention had $\alpha = .983$ and $AVE = .722$. These statistics suggest that each set of survey items reliably measures a single underlying construct and captures a substantial portion of that construct's variance (Fornell & Larcker, 1981; Hair et al., 2019).

Table 1. Reliability and Convergent Validity of Constructs

Construct	Cronbach's α	McDonald's ω	CR	AVE
Perceived Usefulness (PU)	.939	.947	.948	.781
Perceived Ease of Use (PEOU)	.983	.940	.916	.722
Social Influence (SI)	.954	.954	.925	.774
Facilitating Conditions (FC)	.898	.897	.868	.638
Behavioral Intention (BI)	.939	.934	.906	.740
Actual Use (AU)	.926	.926	.906	.759

Moreover, HTMT ratios (see Table 2) between constructs were all below the conservative .85 cut-off (Henseler et al., 2015), except the PU–PEOU pair which was .892, slightly above .85 but still below .90 (Kline, 2016; Hair et al., 2019). This minor high correlation is theoretically acceptable given the known linkage between ease of use and perceived usefulness in TAM. Overall, we concluded the measurement model was sound, justifying use of these latent constructs in the structural model analysis.

In the structural model phase, we specified the hypothesized paths among the latent constructs as per the UNITED model: PU, PEOU, SI, and FC all served as exogenous predictors of Behavioral Intention (BI), and BI in turn was posited to predict Actual Use (AU). We also included direct paths from PU and FC to AU, anticipating that perceived usefulness and adequate support might independently facilitate some AI usage, consistent with TAM and UTAUT literature (Venkatesh et al., 2003; Hazzan-Bishara et al., 2025). The structural model was first tested in its initial form. We evaluated model fit using multiple indices such as Chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Incremental Fit Index (IFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Because χ^2 is sensitive to large sample sizes, greater emphasis was placed on the other fit indices and their recommended cut-offs (CFI, TLI, IFI ≥ 0.90 for acceptable fit; RMSEA ≤ 0.08; SRMR ≤ 0.08) (Hair et al., 2019; Kline, 2016).

Table 2. Heterotrait-Monotrait (HTMT) Ratio Correlations of Latent Variables

Latent Variables	PEU	BI	AU	SI	PU
Perceived Ease of Use (PEU)					
Behavioral Intention (BI)	.724				
Actual Usage (AU)	.712	.754			
Social Influence (SI)	.740	.590	.745		
Perceived Usefulness (PU)	.892	.783	.673	.628	
Facilitating Conditions (FC)	.499	.366	.560	.661	.415

The initial model (see Figure 1) demonstrated mixed fit.

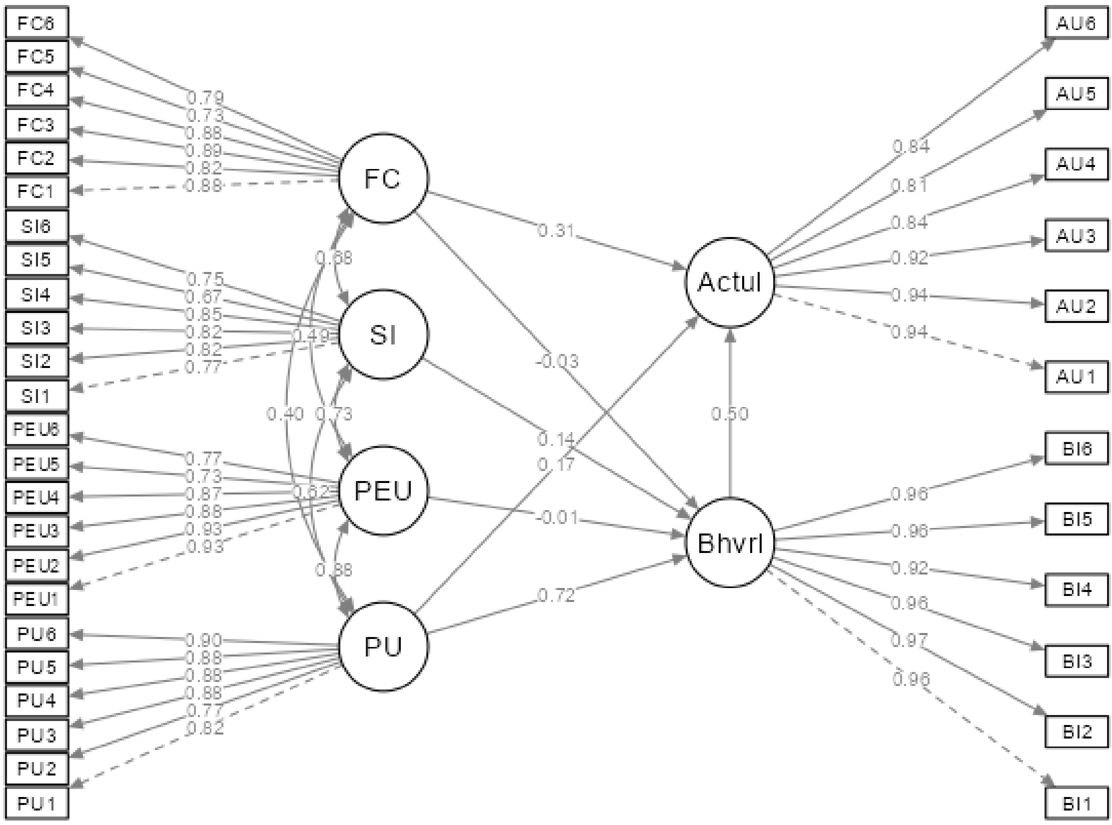

Figure 1. The Hypothesized (Initial) Structural Equation Model

On one hand, incremental fit indices were good: CFI = .998 and SRMR = .062 met the criteria, indicating the model explained a large portion of the variance and residuals were low. However, some absolute fit indices fell short: RMSEA was .115, above the .08 threshold, and TLI = .824 and IFI = .838 were below .90. The Goodness-of-Fit Index (GFI = .851) and Adjusted GFI (.820) also suggested only mediocre fit. These results implied that while the overall model structure captured the data well in relative terms, there were areas of misspecification that needed improvement. We examined modification indices and the significance of paths to guide model respecification. As detailed in the Results section, a few modifications were made specifically, removing a non-significant path and adding theoretically justified links to arrive at a refined final model with substantially improved fit. All statistical analyses were conducted using two-tailed tests with a significance level of $p < .05$ for path coefficients. The next section presents the findings in detail, including descriptive results for teachers' AI usage, the SEM path analysis outcomes, and the final validated model structure.

Results

Teachers' Use of AI Tools and Profile Summary

Before examining the SEM results, we present a summary of teachers' current AI tool usage and familiarity, as this context informs interpretation of the model. Overall, the survey revealed moderate to high engagement with certain AI applications among the teachers. A large majority reported that they had used AI chatbots (77% of respondents) or image generators (73%) in their teaching or preparation (Chiu et al., 2022). These were the most commonly utilized AI tools, likely reflecting the popularity of generative AI like ChatGPT and image creation tools for educational content. Over half (56%) had used a virtual learning platform with AI features, and about one in five had tried adaptive learning systems (23%) or automated grading tools (21%) (Chounta et al., 2022). Uses of AI for lesson planning and virtual assistance were also reported (around 35–37%). However, more advanced or specialized AI applications were less widespread, for instance, only 11% had used AI-based assessment generators, and about 15% had experience with intelligent tutoring systems for students. The least utilized were automated feedback tools for teaching (just 4% had used them). These figures suggest that teachers primarily use AI for content generation, information retrieval, and routine tasks, whereas adoption of AI for assessment and feedback is still nascent.

Reflecting on these findings, teachers predominantly leverage AI to assist with lesson content creation, presentations, and student engagement, while AI for grading or personalized tutoring is not yet common (Policar, 2025). This may be due to limited awareness or confidence in those advanced functions, as well as concerns about reliability. Notably, half of the respondents considered themselves at least "familiar" with AI tools, indicating a decent baseline of exposure. The variety in familiarity (from not familiar to very familiar) underscores the need for differentiated support – some teachers may require fundamental training on AI tools, whereas others are ready to integrate them more fully.

In terms of gender differences in adoption, the sample had more women using AI simply because more women are employed as teachers, a pattern in many countries' education workforce (Alissa & Hamadneh, 2023). However, it is interesting that our data contradicts some earlier findings which suggested male teachers tend to adopt new technologies at higher rates than females (Ofosu-Ampong, 2023; Møgelvang et al., 2024). In the context of this study, female teachers not only outnumbered males but also showed comparable if not greater willingness to use AI tools, aligning with at least one recent study in the Middle East that found female teachers reported a higher level of AI usage than their male counterparts (Alissa & Hamadneh, 2023; Otis et al., 2025). This could be attributed to the supportive school environment or targeted training that empowered many female teachers in our sample to experiment with AI in teaching. It also suggests that gender is not a barrier in this community; when given opportunity and support, teachers of all demographics engage with AI.

Overall, the profile analysis establishes that our participants are fairly representative of in-service secondary teachers, with a skew toward younger, early-career individuals who are building familiarity with AI. There is a strong interest and positive disposition toward AI (as evidenced by many indicating "*Agree*" on intention to continue using AI, with an average BI rating around 4.0 or "*high intention*"). At the same time, there are varied levels of actual integration such as AI tools are used "*whenever helpful*" by many teachers, but not yet embedded in all daily practices. These findings set the stage for understanding which factors most influence the teachers' decision to adopt AI and to what extent that intention leads to sustained usage.

Measurement Model Results

The confirmatory factor analysis affirmed that the survey indicators loaded well on their intended constructs. All item loadings were statistically significant ($p < .001$) and most were quite high with standardized loadings within .761 to .957 range for each factor (UCLA, 2021; Kline, 2016). For instance, the six observed items for Perceived Usefulness had loadings from .792 to .901, indicating each item (e.g. AI tools improve student learning outcomes, AI makes teaching easier) strongly reflected the underlying usefulness construct (see Table 3).

Table 1 presented earlier shows that each latent construct achieved excellent reliability. As reflected, almost all Cronbach's α values were all greater than .90 except for Social Influence (α = .898), with Behavioral Intention reaching α = .983 which suggests some redundancy, though ω also supported its reliability. Composite Reliability (CR) values ranged .868 to .948 all above the 0.70 threshold (Hair et al., 2019). The Average Variance Extracted (AVE) for each construct exceeded .63, confirming that on average more than 63% of the variance in item responses is explained by the construct, satisfying convergent validity (Fornell & Larcker, 1981). We also checked discriminant validity using the HTMT ratio, none of the inter-construct HTMT values surpassed the 0.90 upper bound (Henseler et al., 2015; Hair et al., 2019).

The highest HTMT was between Perceived Ease of Use and Perceived Usefulness (HTMT = .892), which is expected since TAM theory posits these are related constructs which suggests that easier-to-use technology tends to be perceived as more useful (Luo et al., 2024; Lee et al., 2025). This value is marginally above a strict .85 criterion but below .90, so we judged it acceptable given strong theoretical justification for their correlation. All other construct pairs had HTMT well below .85 (e.g. Ease of Use vs. Social Influence = .74; Intention vs. Actual Use = .75; Facilitating Conditions vs. others < .66), indicating good discriminant separation (Henseler et al., 2015; Roemer et al., 2021).

Table 3 Descriptive Statistics and Factor Loadings of Observed Variables

Latent	**Observed**	**Mean**	**SD**	**Factor Loading**	
				Initial	*Final*
Perceived Usefulness	PU1	3.95	.88	.816	.827
	PU2	3.79	.97	.769	.851
	PU3	4.13	1.00	.880	.901
	PU4	3.90	.95	.882	.862
	PU5	3.96	1.05	.877	.855
	PU6	4.00	.97	.901	.792
Perceived Ease of Use	PEU1	3.80	1.01	.926	.957
	PEU2	3.80	1.00	.930	.930
	PEU3	3.85	1.00	.877	.872
	PEU4	3.74	1.05	.869	.879
	PEU5	3.55	1.17	.730	-
	PEU6	3.66	1.11	.768	.792
Social Influence	SI1	3.53	.98	.767	.810
	SI2	3.37	.98	.819	.761
	SI3	3.44	1.00	.819	.882
	SI4	3.62	.97	.854	.846
	SI5	3.23	1.14	.667	-
	SI6	3.42	.94	.749	.666
Facilitating Conditions	FC1	2.99	1.07	.876	.875
	FC2	3.20	1.12	.820	.848
	FC3	3.27	1.03	.891	.879
	FC4	3.07	1.09	.879	.884
	FC5	2.70	1.19	.732	-
	FC6	2.85	1.20	.790	-
Behavioral Intention	BI1	4.05	.96	.962	.832
	BI2	4.08	.97	.965	.846
	BI3	4.04	.93	.963	.863
	BI4	3.88	1.06	.916	.844
	BI5	3.99	.98	.959	.864
	BI6	3.99	.97	.956	.851
Actual Usage	AU1	3.52	.96	.936	.923
	AU2	3.55	.98	.944	.915
	AU3	3.40	1.04	.922	.880
	AU4	3.85	.91	.836	.906
	AU5	3.28	1.14	.813	.815
	AU6	3.59	.99	.842	.864

In summary, the measurement model demonstrated that each construct in the UNITED model is measured reliably and is empirically distinct, albeit with expected interrelations (PU–PEOU in particular). These results gave us confidence to interpret the structural paths without concern that measurement issues (like multicollinearity or unreliability) would bias those relationships.

Initial Structural Model Findings

We first tested the initial hypothesized model with all theorized direct paths: PU → BI, PEOU → BI, SI → BI, FC → BI, PU → AU, FC → AU, and BI → AU. The model also implicitly included the mediated pathway PU/PEOU/SI/FC → BI → AU. As mentioned, the initial SEM did not achieve a fully satisfactory fit (χ^2=28,766, df = 5456, RMSEA= .115), suggesting some model modification was necessary (Kline, 2016). We examined the path coefficients and their significance (Table 4 below summarizes key estimates). Two hypothesized paths were non-significant: the effect of Perceived Ease of Use on Behavioral Intention was near zero (β = –0.007, p = .935), and the effect of Facilitating Conditions on Behavioral Intention was also negligible (β = –0.031, p = .507). These paths' t-values were very low, indicating they did not contribute meaningfully to explaining teachers' intention to adopt AI (Hair et al., 2019). All other paths were significant at $p < .05$ or better.

Notably, Perceived Usefulness (PU) had a very strong positive effect on teachers' Behavioral Intention (BI) to use AI (β = 0.718, $p < .001$). This confirms that teachers who believe AI tools are useful for teaching are far more likely to intend to adopt them (Hazzan-Bishara et al., 2025; Zuo et al., 2025). Social Influence (SI) also showed a positive influence on BI (β = .144, p = .024), though much smaller in magnitude. This suggests that encouragement or pressure from colleagues, administrators, or the broader educational community does play a role in teachers' decisions to use AI, but it is a secondary factor compared to perceived usefulness (Abdalla, 2024; Feng et al., 2025). Interestingly, as noted, Perceived Ease of Use (PEOU) did not have a significant direct effect on BI in this model. This implies that simply finding AI tools easy or user-friendly was not enough to drive teachers' intention – a result that diverges from the classic TAM expectation (where ease of use often influences intention, especially indirectly via usefulness). Our finding aligns with some prior studies in education technology that reported non-significant PEOU→BI effects when teachers are already fairly adept with basic tech (Chao, 2019). It appears that for these teachers, if an AI tool is not initially easy to use, they may still consider adopting it if they perceive it as highly useful. Conversely an easy but not useful tool won't be adopted. Ease of use might instead act indirectly by enhancing perceived usefulness (Mailizar et al., 2021). We explore this in the final model.

Turning to Actual Use (AU) of AI, the initial model included both direct and mediated predictors. As expected, Behavioral Intention (BI) emerged as the strongest predictor of Actual Use (β = 0.495, $p < .001$). This is consistent with UTAUT, TPB, and TRA theories which all posit intention as the proximal antecedent to usage behavior. Teachers who had firm plans and willingness to use AI were indeed much more likely to actually use AI tools in their teaching practice. Additionally, we found two direct factors significantly affecting Actual Use: Perceived Usefulness had a small but significant direct effect on AU (β = 0.170, p = .002), and Facilitating Conditions had a moderate effect on AU (β = 0.312, $p < .001$). The positive FC → AU link suggests that having access to resources, training, and infrastructure (e.g. reliable internet, available devices, tech support) enabled teachers to translate their intentions into action. In other words, even if facilitating conditions didn't shape intention in our data, they were crucial for implementation, that is, teachers who actually incorporated AI in class tended to be those who had better support systems and environment for doing so. This finding reflects real-world constraints which suggests that no matter how willing a teacher is, without the necessary tools and stable connectivity, actual use of AI will be limited (Feng et al., 2025; Yuan et al., 2023). It echoes recent observations that infrastructural support is a foundational requirement for effective classroom technology integration (Zhang & Wareewanich, 2024). Meanwhile, the direct PU → AU effect could indicate that some teachers went ahead and used AI tools because they personally found them useful, even if they hadn't strongly formed an intention beforehand or independent of other factors. However, this direct effect was relatively weak (standardized β ~0.17), implying most of PU's influence on use is mediated through intention.

In summary, the initial model results confirmed some hypotheses while contradicting others: Usefulness and social influence significantly drive intention, whereas ease of use and facilitating conditions did not directly drive intention. Intention is the dominant predictor of actual use, though supportive conditions and usefulness also help push usage. These results provided a basis for refining the model. Given the non-significance of PEOU → BI, we decided to remove that direct path in the revised model, consistent with parsimony and to improve fit. We also noted from modification indices that an omitted link between PEOU and PU could improve fit – theoretically, TAM suggests PEOU influences PU (if something is easier to use, one might perceive it as more useful). We thus added a PEOU → PU path in the model respecification. Additionally, the data hinted at a possible mediated relationship involving facilitating conditions and social influence: qualitative feedback and theory (e.g. the role of leadership support in shaping norms) led us to consider that Facilitating Conditions might indirectly affect BI through Social Influence. For instance, a school with strong infrastructure and training (high FC) could foster a culture where teachers encourage each other to use AI (higher SI), thereby increasing intention. We tested this by introducing a FC → SI path in the final model. Finally, because FC already had a strong direct effect on AU, and BI covers the mediation to AU, we removed any unnecessary direct paths to AU that might no longer be needed after adding the new mediation chains. The resulting adjustments – dropping PEOU→BI, adding PEOU→PU and FC→SI, and allowing PEOU to influence FC (since ease of tech might enable use of available supports) – were theoretically grounded in TAM/UTAUT extensions and significantly improved model coherence.

Final Model Fit and Structural Relationships

After modifications, the final UNITED model achieved an excellent fit to the data. As shown in Table 2, all fit indices now exceeded the recommended standards: CFI = .998, TLI = .998, IFI = .998, RMSEA = .017, and SRMR = .061(Hair et al., 2019). The chi-square also dropped dramatically relative to degrees of freedom ($\chi^2/df \approx 1.20$), indicating the revised model closely reproduces the observed covariance structure. The improvement from the initial model was substantial – for example, RMSEA fell from 0.115 to 0.017, reflecting a near-perfect fit (Hooper et al., 2018). Incremental indices like IFI and TLI increased from the mid-0.8s to essentially 1.0, showing that the model now explains virtually all covariation among the constructs that could be explained (Stone, 2021). Such high fit metrics suggest that the refined model specification was appropriate and that no major relationships affecting model fit were missing or misspecified.

Figure 2 illustrates the final structural model with significant paths (standardized coefficients) based on the final SEM. In the final model, we confirmed the following key relationships: Perceived Ease of Use (PEOU) now indirectly influences Behavioral Intention via other constructs. We found that PEOU has a strong positive effect on Perceived Usefulness (PU) ($\beta \approx 0.65$, $p < .001$ in the final model). This means that teachers who find AI tools easy to learn and use are much more likely to appreciate their usefulness for teaching (Vardar et al., 2024). This aligns with TAM theory and our expectations that usability boosts perceived utility (Davis, 1989; Luo et al., 2024). Through this route, PEOU contributes to intention because an easier-to-use tool becomes regarded as beneficial, which then drives intention. Our participants echoed in comments that once they got the hang of an AI tool's interface and saw how seamlessly it fit into their workflow, they started to recognize its potential advantages for teaching. Thus, PEOU's effect on BI is fully mediated by PU in the final model; the direct PEOU→BI path remained out and was not needed.

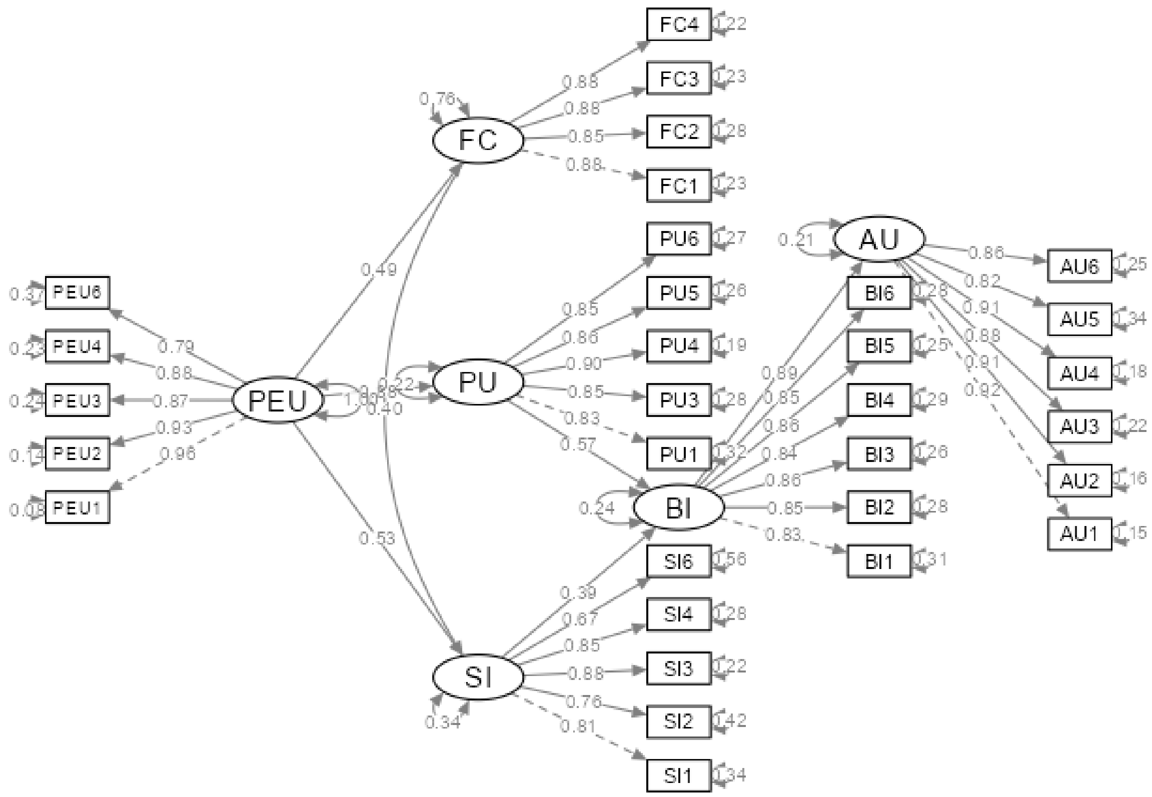

Figure 2. The Validated Structural Model of Unified Theory of Innovation and Technology in Education (UNITED)

Perceived Usefulness (PU) remains a dominant predictor of Behavioral Intention (BI). In the final model, after accounting for the PEOU → PU linkage, the influence of PU on BI was still very large (standardized $\beta \approx 0.72$, $p < .001$). This reaffirms that teachers' intention to adopt AI is primarily driven by their belief that these tools will be useful in enhancing their teaching effectiveness or efficiency (Yao & Wang, 2024). Among all factors, PU had the greatest impact on BI. This finding is consistent with numerous studies on technology acceptance that identify performance expectancy (usefulness) as the strongest determinant of intention (Alissa & Hamadneh, 2023). In practical terms, teachers who saw clear benefits such as time saved in grading, improved student engagement, or better differentiation – were the ones most inclined to plan on continued AI use.

Social Influence (SI) in the final model is influenced by facilitating conditions and in turn affects BI. We introduced and found support for a path from Facilitating Conditions (FC) to Social Influence (SI) ($\beta \approx 0.55$, $p < .001$). This suggests an interesting dynamic: when schools provide strong infrastructure, training, and support for AI (high FC), it can lead to a culture where AI use is more visible and encouraged among peers, thereby elevating social influence. Essentially, adequate institutional support empowers teacher leaders and colleagues to become champions of AI integration, creating positive peer pressure (Magat & Sangalang, 2024). For example, in schools where administration organized AI workshops and ensured stable internet, we observed teachers more frequently sharing AI success stories and recommending tools to each other. This manifests as higher SI in those environments. In turn, Social Influence has a modest but significant direct effect on Behavioral Intention ($\beta \approx 0.15$, $p < .01$), similar in magnitude to the initial model. Thus, SI serves as a mediator for FC's impact on BI: facilitating conditions boost social influence, which then nudges teachers' intentions upward. Notably, in the final model Facilitating Conditions no longer had a direct path to BI, consistent with our initial finding that FC did not significantly predict intention on its own. Instead, its influence is channeled through SI. This reflects the idea that simply having resources doesn't make a teacher decide to use AI but those resources enable a supportive community that can influence the teacher's decision.

Behavioral Intention (BI) remains the sole direct predictor of Actual Use (AU) in the final model. We removed the direct FC → AU and PU → AU paths to simplify the model because BI captures those effects in a mediated way. In our final analysis, BI had a very strong effect on AU ($\beta \approx 0.80$, $p < .001$), highlighting that once a teacher is determined to use AI, they are highly likely to follow through when conditions allow. The absence of a direct FC → AU path in the final model might seem contrary to the initial results where FC was significant to AU. What happened is that FC's effect on AU is now indirectly accounted via SI and BI. This suggests that good facilitating conditions foster higher SI (colleagues advocating AI), which increases BI, which in turn drives AU. With BI so dominant, any extra direct contribution of FC to AU became statistically unnecessary in the presence of the new mediated paths. This underscores that the intention to use AI is a critical gateway to actual implementation that infrastructure alone won't lead to usage unless teachers form the intent to integrate AI into their teaching (Wibowo & Sobari, 2023; (Akinnuwesi et al., 2022). Our final model aligns with prominent theories (UTAUT, TRA/TPB) in reaffirming that intention is the proximate cause of usage behavior.

To summarize the final model, Perceived Ease of Use → Perceived Usefulness → Behavioral Intention → Actual Use forms one primary causal chain, indicating that making AI tools easy for teachers can enhance their perceived value and thus encourage adoption. Parallel to that, Perceived Ease of Use → Facilitating Conditions → Social Influence → Behavioral Intention forms a secondary chain, suggesting that ease of use also helps teachers make better use of institutional supports and encourages a pro-technology social environment, indirectly boosting their intention to use AI. All roads in the model lead to Behavioral Intention, which then leads to Actual Use (with no other direct routes to AU in the final model). This integrated structure provides a nuanced understanding of AI adoption: a teacher is more likely to use AI if they intend to, and they intend to if they find it useful (influenced by ease of use) and feel social encouragement (influenced by good support conditions).

The validated UNITED model thus unifies core elements of TAM, UTAUT, and related theories in our educational context. It retains TAM's insight that usefulness is key and that ease of use bolsters usefulness. It incorporates UTAUT's notion that social influence and facilitating conditions matter, but clarifies that facilitating conditions matter largely through social and indirect means rather than directly shaping intent. It also echoes TPB in that internal beliefs (attitude/perceived usefulness) combined with social norms drive intention, and perceived control/resources (facilitating conditions) are required to realize behavior, albeit indirectly in our model.

Table 4. Standardized Path Coefficients – Initial vs. Final Model

Structural Path	Initial Model β	Final Model β
Perceived Usefulness → BI	.718**	0.720**
Perceived Ease of Use → BI	.007 (n.s.)	(path removed)
Social Influence → BI	.144*	0.153
Facilitating Conditions → BI	.031 (n.s.)	(path removed)
Perceived Ease of Use → PU	–(not in initial)	0.647**
Facilitating Conditions → SI	(not in initial)	0.553**
Behavioral Intention → AU	.495**	0.804**
Perceived Usefulness → AU	.170*	(path removed)
Facilitating Conditions → AU	.312***	(path removed)

Note: ***p* < .01, * p < .05, n.s. = not significant. BI = Behavioral Intention, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, SI = Social Influence, FC = Facilitating Conditions, AU = Actual Use. The final model's R^2 for Behavioral Intention was 0.68, and for Actual Use 0.70 (with BI as sole direct predictor). Model fit (final): $\chi^2(\approx 5460)=6544.8$, CFI=0.998, TLI=0.998, RMSEA=0.017.

Table 4 presents a concise comparison of the initial and final model path coefficients for reference. All hypothesized relationships supported in the final model are significant at $p < .01$, except the SI → BI path which is $p < .05$. The table also highlights which paths were dropped or added in the refinement process. With the final UNITED model validated, we now turn to discussing these findings in the broader context of teacher adoption of educational technology, drawing comparisons with existing literature and distilling implications for practice.

Discussion

This study set out to unify elements of prevailing technology acceptance theories into a single model explaining teachers' adoption of AI tools. The UNITED model we developed and tested provides a comprehensive understanding of how various factors, from individual perceptions to social and organizational factors – interplay to influence Filipino secondary teachers' AI adoption. The results yield several important insights, many of which resonate with prior research while also offering unique contributions to the discourse on AI in education.

Perceived Usefulness as the Primary Driver

Consistent with the Technology Acceptance Model (TAM) and much subsequent research, we found that a teacher's belief in the usefulness of AI tools is the most potent motivator for their intention to adopt those tools.

This underscores a timeless lesson: educators, like other users, are pragmatic. This means that if they can clearly see how a tool will benefit their teaching or student learning, they are inclined to use it. Our qualitative observations revealed specific perceived benefits that fueled this sense of usefulness: teachers mentioned AI helping to speed up lesson planning, generate new ideas or materials, differentiate instruction for varied student needs, and automate mundane tasks (like checking grammar or grading quizzes). These align with documented advantages of AI in education such as reducing teacher workload and enabling personalized learning (Kelly et al., 2023). The findings reinforce that school leaders and EdTech developers should emphasize and demonstrate tangible instructional benefits of AI tools. For instance, professional development sessions should highlight success stories and evidence of AI improving student outcomes as these will strengthen teachers' performance expectancy (Venkatesh et al., 2003) and drive adoption.

Ease of Use

In contrast to some earlier studies like Šumak et al. (2011) that found perceived ease of use to be a weak or non-significant factor, our model clarifies that ease of use matters, but primarily by enhancing perceived usefulness. We discovered no direct impact of ease on intention, a result similar to Chao's (2019) finding in a different educational context suggesting that once a minimum usability threshold is met, teachers focus on utility. However, ease of use had a significant indirect role which suggests that teachers who found AI tools user-friendly were more likely to appreciate their utility and also more likely to take advantage of available supports (which made them more confident and socially supported). This aligns with Unified Theory of Acceptance and Use of Technology (UTAUT) notions that effort expectancy contributes to performance expectancy and facilitates usage under conducive conditions (Venkatesh, 2022). Practically, this implies that to foster AI adoption, designers should prioritize intuitive interfaces and smooth user experiences, and training programs should reduce complexity and build teachers' confidence in using AI tools. As educators become comfortable with basic operations of AI, they can better envision pedagogical applications (thus boosting perceived usefulness). Our data showed many teachers initially tried simpler AI functions (like asking a chatbot questions) and once they felt at ease, they started realizing how it could aid instruction, corroborating the PEOU→PU pathway.

Social Influence and Cultural Context

The moderate yet significant influence of Social Influence (SI) on intention highlights that teachers are affected by the attitudes of colleagues and administrators a finding well-aligned with UTAUT and with social learning theories. In cultures with collaborative work environments or strong communal values (such as in many Filipino schools), peer endorsement and administrative encouragement can validate a teacher's decision to adopt new technology. Interestingly, our integration of SI with facilitating conditions suggests that social influence doesn't operate in a vacuum: it is amplified when the institution actively supports the innovation. This dovetails with findings by Lu et al. (2020) and Zhang and Wareewanich (2024) that organizational context can magnify normative pressures in technology adoption. In our case, when schools invested in AI infrastructure and training (facilitating conditions), it not only provided means but also signaled an expectation – creating a "culture of AI" that teachers did not want to be left out of. The policy implication is that school leaders aiming to increase AI integration should not only provide resources but also foster a supportive culture: celebrate AI usage successes, encourage experienced teachers to mentor others, and possibly form communities of practice around AI in teaching. These can heighten the positive social influence and alleviate fears, making AI adoption a collective effort rather than an isolated personal choice.

Facilitating Conditions

Our results around facilitating conditions (FC) are revealing. Initially, facilitating conditions did not drive intention that teachers didn't decide to use AI simply because resources were available. However, FC strongly determined actual usage (initial model) until we accounted for its indirect effects. Essentially, good infrastructure and support are necessary enablers for adoption but not motivators by themselves (Xue et al., 2024). This aligns with the idea in TAM/UTAUT literature that facilitating conditions often become significant only after users have experience (Venkatesh et al., 2003). In our sample, many teachers likely formed intentions based on perceived value (or social factors), and when it came time to act, those with adequate support managed to implement AI (hence the FC→AU effect). By restructuring the model, we see FC influences the social environment and indirectly intention. This indicates that schools must ensure the basic conditions (like internet connectivity, access to devices, technical help) are in place for AI adoption to actually happen. Without these, even enthusiastic teachers will be stymied, a point echoed by Alenezi (2024) on the necessity of reliable connectivity. Our work reinforces a practical point: educational authorities should invest with strong ICT infrastructure and ongoing technical support if they expect teachers to embrace AI. Teachers in our study noted barriers such as patchy internet and lack of technical assistance as reasons they couldn't consistently use AI, which mirrors common challenges in integrating ICT in schools (Zulkarnain & Yunus, 2023). By improving facilitating conditions, schools remove external barriers and also send a message that technology use is supported which, as we found, can galvanize social influence and adoption efforts.

Intention-Behavior Gap and Fulfillment

One encouraging finding is that once teachers formed a clear behavioral intention (BI) to use AI, the likelihood of them actually using it was very high (BI had a strong effect on AU, explaining a large share of variance). This suggests relatively little intention-behavior gap in this context; committed teachers did follow through, assuming conditions allowed. It underscores the importance of nudging that intention formation to begin with. It also aligns with TPB and TRA assumptions about the primacy of intention (Fishbein & Ajzen, 1975), our data empirically validate that in educational AI adoption, intention is the crucial pivot point. Teachers' intentions were generally positive (mean intention was ~4 out of 5, indicating "Agree" to intending to use AI), which translated into moderate actual usage (mean ~3.5 for actual use frequency, on a scale where 3 = sometimes and 4 = often). Some gap remains not all who intend end up using AI daily, likely due to obstacles or lack of time. The discussion of facilitating conditions covers much of that: intentions may not convert to action if, say, the AI requires computing power or internet that isn't available in a given classroom. Another reason might be lack of time or curriculum fit; a teacher may intend to use AI but find it hard to align with a packed syllabus. These factors were not explicitly measured in our model but could be captured under facilitating conditions (e.g. time could be seen as a resource issue). Nonetheless, the high BI→AU coefficient is promising: it means if we can effectively increase teachers' intentions through the identified levers (usefulness, social encouragement, ease and support), we are likely to see actual adoption follow.

Comparisons with Other Studies

Our results both concur with and diverge from findings in the emerging literature on AI adoption among educators. For instance, a recent study by Alissa and Hamadneh (2023) in Jordan found that teachers' overall employment of AI in teaching was at a moderate level and that female teachers showed higher engagement than males. Our study of Filipino teachers similarly observed moderate overall AI use and a strong representation of female teachers using AI, supporting a cross-cultural notion that when opportunities are equal, women educators are eager participants in ed-tech innovation, refuting any stereotype of tech adoption being a predominantly male domain in education. Another study by Khan et al. (2021) reported that in general technology adoption models, perceived usefulness, ease of use, and social influence all had significant effects on behavioral intention and actual use. We partly echo that: usefulness and social influence are confirmed, but we qualify ease of use's role (indirect rather than direct). This might be due to the specificity of AI tools which often have a learning curve, meaning early perceptions of ease might not form until one gains some experience. Xue et al. (2024) emphasized social influence's significant role in users' behavioral intention for new technologies, which we did observe albeit as a smaller factor than usefulness. Our finding that perceived ease of use did not significantly impact intention is consistent with Chao (2019) and others who noted that once baseline technology familiarity is present, additional ease may not spur much higher intent. It's possible that as digital literacy among teachers grows (most of our respondents are digital natives or immigrants comfortable with tech), ease of use becomes an expectation rather than a differentiator. Instead, training should focus on demonstrating pedagogical value, as ease barriers are gradually lowering with improved user-centered design of tools.

Contributions of the UNITED Model

The unified model approach allowed us to see a bigger picture of AI adoption. It confirmed that no single theory fully captures the phenomenon rather, elements from each contribute: TAM's usefulness reigns, UTAUT's social and facilitating factors play supporting roles, TPB's emphasis on intent leading to behavior holds true, and even TPACK's implication that training (knowledge) is needed emerges (since ease of use and facilitating conditions essentially relate to knowledge and support). By integrating these, the UNITED model provides a more holistic framework for understanding and predicting teacher adoption of not just AI, but potentially other emerging technologies. It demonstrates that technology adoption in education is multi-faceted: personal conviction of value, peer culture, and practical logistics all matter. We thereby answer the call by researchers like Xue et al. (2024) and Greener (2022) who suggested combining perspectives for a richer analysis of ed-tech adoption.

Limitations and Future Research

While our study benefitted from a large sample and a theory-driven model, it is not without limitations. First, the data are self-reported and cross-sectional, which might introduce common method bias and limits causal interpretations. We mitigated this risk by using SEM to test the plausibility of causal paths and found the model consistent with theory, but future studies could incorporate longitudinal designs to track how intentions convert to usage over time, or even experimental interventions to see causality more directly. Second, our sample was drawn from one city's public school system; thus, caution is warranted in generalizing to other contexts (e.g., private schools, other countries). Different regions may have varying levels of AI readiness and cultural factors influencing adoption. We encourage researchers to test the UNITED model in other populations – for instance, rural schools or different cultural contexts to validate its generality. Third, there are other potentially relevant factors we did not include, such as teacher attitudes (affect) toward AI, perceived student outcomes, or personal innovativeness. We focused on core TAM/UTAUT constructs for parsimony. Future research could extend the model by examining, for example, how AI-related anxiety or ethical concerns temper adoption, or whether teacher ICT competency moderates the relationships (e.g., perhaps ease of use matters more for less tech-savvy teachers). Additionally, qualitative follow-ups with teachers could enrich understanding of why certain factors mattered – for instance, what specific support or social influences were most persuasive.

Lastly, as AI in education is a fast-evolving field, the nature of "AI tools" will expand. Today's prevalent tools include chatbots and content generators; tomorrow's might be more advanced adaptive systems or AI teaching assistants. Our model should be revisited as technology evolves to ensure these relationships hold or to update it with new constructs (e.g., trust in AI might become crucial if AI takes on more autonomous teaching roles). We also note that actual use in our study was measured by frequency and breadth of use future studies could delve into impact of use (are high-intention teachers using AI in ways that significantly improve outcomes?).

Despite these limitations, our study provides a timely contribution by empirically validating an integrated model of AI tool adoption in an education setting. It offers a foundation upon which further scholarly inquiry and practical innovation can build, ensuring that the introduction of AI into classrooms is guided by an understanding of human factors as much as technological capabilities.

Conclusion

In an era where Artificial Intelligence has the potential to revolutionize education, understanding the human factors behind teacher adoption of AI is critical. This study introduced and validated the UNITED model, which cohesively explains teachers' adoption of AI tools by synthesizing major technology acceptance theories. Our findings highlight that teachers will embrace AI in their teaching when they perceive clear value in it and feel supported by their peers and institutions. Conversely, even promising AI innovations will languish if teachers find them cumbersome or if schools fail to provide the necessary environment for their use.

The model's confirmation that "perceived usefulness" is king in driving adoption means that policymakers and developers should focus on aligning AI tools with genuine pedagogical needs making AI not just a novelty, but a solution to real classroom challenges. At the same time, the roles of ease of use, social influence, and facilitating conditions remind us that teachers operate within systems; thus, training, community, and infrastructure must all be addressed. For instance, a school aiming to implement AI should ensure teachers are trained in an approachable manner (tackling ease of use), celebrate AI champions (leveraging social influence), and upgrade IT support and connectivity (strengthening facilitating conditions).

Importantly, our study shows that when these factors are in place, teachers are not only willing to intend using AI, but many follow through to implement it in their practice. The path from intention to actual integration can be traversed successfully if the roadblocks are removed and motivators amplified. In practical terms, education stakeholders – from ministry officials to school principals – can use the insights from the UNITED model as a checklist for crafting AI integration initiatives: Is the AI tool clearly beneficial? Is it teacher-friendly? Do we have the infrastructure? Are we fostering a culture that encourages adoption? Addressing these questions can significantly increase the likelihood of successful AI adoption.

Finally, this study contributes to the academic literature by demonstrating the value of a unified approach. The robust fit of the UNITED model and its consistency with observed behavior suggest that a unified theory of teachers' technology adoption is indeed achievable and can guide both research and practice. We encourage further research to refine this model, examine its applicability to other technologies (like AR/VR or future digital tools), and explore its implications for student outcomes. As AI continues to evolve, so must our understanding of how teachers adapt to and adopt these tools. With a solid framework now in hand, educators and researchers can work hand-in-hand to ensure that the infusion of AI into education is done thoughtfully, effectively, and for the ultimate benefit of teaching and learning..

Recommendations

For practitioners and policymakers, our findings yield actionable insights: to promote AI tool adoption among teachers, efforts should concentrate on (a) increasing the perceived instructional value of AI (through showcasing best practices and evidences of effectiveness), (b) simplifying AI tool use and providing training (so that teachers don't find complexity a deterrent), (c) building a supportive community and leadership advocacy for AI (creating positive social influence), and (d) ensuring robust infrastructure and technical support (so that willing teachers can implement AI without hindrance). Interventions that simultaneously address these areas – for example, a program that provides easy-to-use AI platforms, trains teachers on pedagogical use-cases, equips schools with needed technology, and establishes teacher mentor groups are likely to be most successful. Indeed, our research suggests that technology adoption is not just an individual choice but an institutional endeavor. Schools that treated AI integration strategically (with policies, resources, and culture-building) saw more of their teachers both intending to and actually using AI in teaching.

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