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Assessing Gender Differences in Technological Readiness and AI Adoption Intentions among Pre-Service Teachers

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Abstract:

Background: Artificial Intelligence (AI) is increasingly transforming instructional processes across educational settings, creating a need to understand the factors associated with its adoption among future educators, particularly across gender groups.

Purpose: This study examined the relationships among technological readiness, attitude toward AI, and behavioural intention to adopt AI among pre-service teachers, and investigated whether gender moderates these relationships. Specifically, the study aimed to investigate the extent to which technological readiness is related to attitudes toward AI and behavioural intention to adopt AI, and whether these relationships vary between male and female pre-service teachers.

Method: A quantitative cross-sectional survey design was employed, and data were collected from 378 undergraduate pre-service teachers enrolled in teacher education programmes at public universities in southwestern Nigeria using a structured online questionnaire administered through Google Forms. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4, including multigroup analysis to examine gender differences.

Results: The findings indicate that technological readiness was not significantly associated with behavioural intention to adopt AI ($\beta = .092$, $t = 1.945$, $p = .052$), and no significant gender differences were found in this relationship ($t = 0.479$, $p = .630$). However, technological readiness showed a significant positive association with attitude toward AI ($\beta = .075$, $t = 2.330$, $p < .05$), with significant gender differences in the strength and direction of this relationship ($t = 3.991$, $p < .05$). The relationship was positive among female pre-service teachers but negative among male pre-service teachers.

Conclusion: These findings suggest the importance of strengthening technological confidence and promoting equitable AI integration initiatives within teacher education programmes. The study further highlights the need for teacher educators, informatics educators, and policymakers to create inclusive learning environments that support positive attitudes and engagement with AI technologies among future educators.

Keywords: *Artificial Intelligence, Attitude, Intention, Pre-service Teacher, Technological Readiness.*

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Introduction

Artificial Intelligence (AI) has emerged as a game-changing technology, transforming educational practices in the 21st century. Intelligent tutoring systems, adaptive learning systems and automated assessment tools are only some examples of how AI is shifting the approach to teaching and learning design, delivery, and experience in education settings (Holmes et al., 2022; Strielkowski et al., 2025). In the academic field, and teacher education in particular, AI is emerging as a driver of Education 5.0, whereby technology is leveraged to design more personalized, student-centered and innovation-based learning (Falebita et al., 2025; Shahidi Hamedani et al., 2024; Zawacki-Richter et al., 2019). However, the effective introduction of AI not only rests on the technological availability but on the desire, readiness, and behavioural intentions of the most significant stakeholders, specifically, the preservice teachers, who will become the new generation of teachers.

The consideration of gender is very critical in technology adoption. Previous studies have established that males and females differ in their technological confidence, their sense of usefulness and their attitude towards the adoption of new technologies (Cai et al., 2017; Scherer et al., 2019; Venkatesh & Morris, 2000). Given the increasing use of AI tools in teacher training, this gender difference can be examined to inform the development of more inclusive and effective adoption systems. Such constructs as the perceived usefulness (PU), the perceived ease of use (PEOU), the attitude towards technology, and the behavioural intention (BI) have always been highlighted in the studies of technology acceptance in education (Davis, 1989). Teo et al. (2015) demonstrates that perceptions of ease of use and usefulness among preservice teachers can be influential factors associated with adoption. Similarly, Scherer et al. (2019) demonstrated that the attitudes and perceptions toward a certain technology were significant predictors of its integration in the classroom. However, gender moderates these relationships in several ways. Male teachers have been found to be generally more exposed to attitudinal and affective factors, and female teachers are usually more concerned about the usefulness and career relevance of technology (Teo et al., 2015; Venkatesh & Morris, 2000). This implies that the use of AI might not follow a linear trend across genders, and thus, a gender-sensitive approach to teacher training is essential.

Although studies on educational technology adoption have reported gender differences in relation to learning management systems, online learning platforms, and digital technologies, less is known about whether these patterns apply to AI-specific contexts among preservice teachers. AI adoption differs from general technology adoption because AI systems often involve issues relating to automation, algorithmic decision-making, ethical concerns, trust, and career relevance. In the Nigerian teacher education context, empirical evidence remains scarce regarding how male and female preservice teachers perceive and respond to AI technologies, and whether gender alters the relationships among technological readiness, attitudes, and adoption intentions. Furthermore, within informatics education and digital pedagogy contexts, there is insufficient evidence regarding how future teachers' technological preparedness shapes their intentions to integrate AI tools into classroom practice. This represents an important knowledge gap because preservice teachers are expected to become future implementers of AI-driven instructional practices.

Technological readiness (TR), the level of readiness of people to adopt and use new technologies, is the other determinant in technology adoption (Parasuraman & Colby, 2015). Technological readiness refers to the degree to which individuals possess the confidence, competence, preparedness, and willingness required to engage with and effectively utilize emerging technologies within educational contexts (Falebita & Kok, 2024; Ghosh & Khatun, 2022). While technology readiness is frequently conceptualized as a specific construct within the Technology Readiness Index framework, this study adopts technological readiness as a broader educational construct reflecting preparedness for AI integration among pre-service teachers. In AI adoption contexts, technologically ready individuals are expected to perceive technologies as useful and manageable, develop positive attitudes toward their use, and demonstrate stronger intentions to adopt. However, technological readiness may not always yield positive outcomes, as individuals with higher technological competence may evaluate emerging technologies more critically, particularly when they fail to align with their expectations or perceived professional relevance. Consequently, technological readiness may exert both positive and negative influences on AI-related perceptions and intentions. Although TR is believed to have positive predictive value, emerging data show mixed results. For example, higher readiness sometimes correlates with more critical evaluations of new systems when tools do not meet advanced users' expectations (Tarhini et al., 2014). This is a complex issue that warrants more in-depth coverage, as the levels of readiness among preservice teachers seem to differ significantly. Still, although research on the topic has been growing, there is limited research specifically investigating the adoption of AI in teacher education. A majority of the earlier research has focused on educational technologies in general (learning management systems, e-learning platforms, or digital tools), and there has been less research that examines preservice teacher readiness and intentions to integrate AI (Scherer et al., 2019; Zawacki-Richter et al., 2019). Furthermore, there is little information on how these dynamics are moderated by gender in the context of AI.

This study is theoretically based on the Technology Acceptance Model (TAM) (Davis, 1989). TAM posits that attitudes towards technology are associated with perceived usefulness and perceived ease of use, which in turn affect behavioural intention and actual use. TAM has, over time, been expanded to contextual variables such as gender, technological preparedness, and career-related intentions (Falebita & Kok, 2024; Teo & Noyes, 2014; Venkatesh & Davis, 2000). This study uses TAM to investigate how preservice teachers' technological readiness, perceptions, and attitudes are associated with their behavioural and career-related intentions to adopt AI, and tests whether gender moderates this effect. This study proposes that technological readiness is associated with perceived usefulness, perceived ease of use, attitude toward AI, career intention, and behavioural intention to adopt AI, and that gender moderates these relationships. Based on TAM and prior literature, the model assumes that technological readiness predicts perceptions and attitudes, which in turn predict behavioural outcomes related to AI adoption. Several gaps emerge from the available literature. To start with, although TAM has been widely used in educational technology research, few researchers have used it to investigate preservice teachers' adoption of AI, even though AI is expected to significantly transform the education sector (Holmes et al., 2022). Secondly, technological readiness to adopt AI has not been investigated in depth, particularly its potential gender-based impacts. Third, despite research indicating that gender moderates technology adoption pathways more generally (Cai et al., 2017; Teo et al., 2015), empirical research on gender differences in AI adoption among preservice teachers remains scarce. It is important to address these gaps to provide evidence-based guidance for teacher education policies and practices. To address these gaps, this study is guided by the following research questions:

RQ1: What relationships exist among technological readiness, TAM constructs, career intention, and behavioural intention to adopt AI among preservice teachers?

RQ2: Do the relationships among technological readiness, TAM constructs, career intention, and behavioural intention differ between male and female preservice teachers?

This research contributes in several ways**.** In its conceptualization, it extends TAM by incorporating technological readiness and career intention while explicitly examining gender moderation within AI adoption contexts. Empirically, it presents evidence from Nigeria, a setting where AI implementation in teacher education remains immature yet is quickly gaining importance. Furthermore, the study contributes directly to informatics education by providing insights into AI literacy development, digital pedagogy, and technology integration within teacher education. Specifically, understanding gender-related differences in AI adoption can assist teacher educators and curriculum developers in designing AI-focused learning experiences, improving digital competencies among future teachers, and supporting effective integration of emerging technologies into educational practice. The study targets preservice teachers as a crucial group of stakeholders whose future behaviours will determine how AI is incorporated into the classroom. This study, therefore, investigates gender differences in technological readiness and AI adoption intentions among pre-service teachers using multigroup analysis.

Research Method

Research Design

This study adopts the cross-sectional research design, where data were collected from participants only once, thus enabling assessment of the relationship between variables without observation over a long period (Creswell & Creswell, 2017). The cross-sectional survey design was considered appropriate because the study sought to examine associations and path relationships among technological readiness, Technology Acceptance Model (TAM) constructs, career intention, and behavioural intention toward AI adoption at a specific point in time. The study does not seek to establish causal relationships; rather, it examines predictive associations among variables. Furthermore, the design was suitable for addressing the research questions because it enabled the collection of data from a relatively large sample of preservice teachers across multiple institutions, allowing the examination of relationships and gender differences in AI adoption patterns.

Sample and Sampling Techniques

The research was conducted among 378 undergraduates enrolled in teacher education programs at six public universities in southwestern Nigeria. Purposive sampling was employed to select the sample to ensure that preservice teachers in science, mathematics, and technology were represented. The six public universities were selected because they offer teacher education programmes with science-, mathematics-, and technology-related specializations and already integrate digital learning practices relevant to the study's objectives. Participants were therefore recruited from all six institutions rather than from a single university. Purposive sampling was considered appropriate because the study specifically targeted preservice teachers with educational experiences and disciplinary backgrounds relevant to AI use and technology integration. Participants were recruited through institutional communication channels and online student platforms, where the survey link, developed in Google Forms, was distributed. Inclusion criteria required that participants be enrolled as undergraduate preservice teachers in science, mathematics, and technology-related disciplines and be actively registered at the participating institutions during the data collection period. Students outside teacher education programmes and those from unrelated disciplines were excluded from participation. Prior to data collection, ethical approval was obtained from the relevant institutional authorities, and informed consent was obtained electronically from all participants. Participation was voluntary, and respondents were informed about confidentiality, anonymity, and their right to withdraw at any point during the study. The data were gathered using an online survey administered via Google Forms. Table 1 presents the demographic characteristics of the 378 preservice teachers who participated in the study. The sample comprised 150 males (39.7%) and 228 females (60.3%), indicating a higher representation of female preservice teachers. The majority of participants were aged between 20 and 26 years (78.6%), followed by those above 26 years (11.9%) and 15–19 years (9.5%), suggesting that most respondents were within the typical age range for university students pursuing undergraduate education degrees. Regarding academic level, participants were distributed across all levels, with the largest proportion in 200L (34.1%), followed by 400L (31.7%), 300L (27.8%), and 100L (6.3%). This distribution indicates a relatively balanced representation of students across different stages of their undergraduate programs, with slightly fewer first-year students. In terms of specialization, Biology students formed the largest group (28.6%), followed by Agricultural Science (19.0%), Chemistry (17.5%), Mathematics (15.9%), Educational Technology (12.7%), and Physics (6.3%).

Table 1: Participant Demographic Characteristics

Characteristics	Level	N	%
Gender	Male	150	39.7
	Female	228	60.3
Age	15 – 19years	36	9.5
	20 – 26years	297	78.6
	Above 26years	45	11.9
Level	100L	24	6.3
	200L	129	34.1
	300L	105	27.8
	400L	120	31.7
Specialization	Agricultural Science	72	19.0
	Biology	108	28.6
	Chemistry	66	17.5
	Educational Technology	48	12.7
	Mathematics	60	15.9
	Physics	24	6.3
	Total	**378**	100

Although the sample provided an adequate representation of preservice teachers across science, mathematics, and technology disciplines, caution should be exercised when generalizing the findings. The sample was restricted to public universities located in southwestern Nigeria and therefore may not fully represent preservice teachers from other regions, private institutions, educational systems, or other teacher education specializations. Consequently, the findings should be interpreted within the context of the study population. Regarding the multigroup analysis, although female participants (60.3%) outnumbered male participants (39.7%), both subgroup sizes exceeded the recommended thresholds for PLS-SEM multigroup analysis, providing sufficient statistical power for group comparisons. Previous studies suggest that PLS-MGA can yield stable results when subgroup sample sizes exceed the recommended minimum. Measurement invariance testing using the measurement invariance of composite models (MICOM) procedure was not conducted prior to the multigroup analysis due to methodological constraints and the exploratory nature of the group comparisons. Consequently, the multigroup results are interpreted as indicative rather than confirmatory, and caution is exercised in drawing conclusions about structural differences between groups, as these may be partially influenced by untested measurement invariance.

Instrumentation

A structured questionnaire adapted from validated scales was used to collect data based on the Technology Acceptance Model (TAM). It contained six constructs: Behavioural Intention, Attitude, Career Intention, Perceived Ease of Use, Perceived Usefulness, and Technological Readiness. A five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree, was used to measure the items. The questionnaire comprised items adapted from previously validated instruments, with each construct comprising 5 items. The items were adapted to specifically reflect perceptions of and intentions regarding AI use among preservice teachers. These measures have been shown to be reliable and sound in prior studies; they are adequate for examining the adoption of AI among preservice teachers (Adelana et al., 2024; Falebita & Kok, 2024). To ensure contextual suitability, the questionnaire items underwent adaptation, with wording modified to reflect AI applications in educational environments. Content validity was established through expert review by specialists in educational technology and teacher education who examined item clarity, relevance, and appropriateness. In addition, the instrument was piloted with a small group of preservice teachers prior to the main study to ensure clarity and comprehensibility of the items. Feedback obtained during the pilot phase resulted in minor wording adjustments before large-scale administration.

Data Analysis

The model we applied was the Partial Least Squares Structural Equation Modeling (PLS-SEM), which is an adequate model in treating complex models with latent constructs, especially when the data is not normally distributed, and the samples involved are relatively few (Hair et al., 2014). It was tested using the standard two-part technique of testing the measurement and structural model (Hair et al., 2017). Reliability in the measurement model was assessed using Cronbach's alpha and composite reliability, whereas convergent validity was assessed using the average variance extracted (AVE) and item loadings. Indicators were also validated using the Fornell-Larcker criterion in terms of the discriminant validity (Hair et al., 2019). Prior to model estimation, the dataset was screened for missing values and data completeness. Responses with substantial missing information were excluded, and the final dataset contained no significant missing values requiring imputation. Normality was assessed using skewness and kurtosis; however, PLS-SEM was selected because it does not require strict assumptions regarding data normality. All items were retained; items with factor loadings below 0.70 were considered for possible removal; however, these two items, which had factor loadings between 0.60 and 0.70, were retained when construct reliability and validity thresholds were met**.** It was then succeeded by testing the structural model to identify the kind of relationships that should be tested and the reliability of the path coefficients (Sarstedt et al., 2017). Structural model assessment involved examining path coefficients, t-values, p-values, effect sizes, and coefficient of determination (R^2). Significance testing was conducted using bootstrapping procedures with 5,000 resamples as recommended for PLS-SEM analyses. Multigroup analysis (MGA) was conducted using PLS-MGA and permutation testing to examine gender differences in structural relationships. However, measurement invariance for the composite model (MICOM) was not assessed. Hence, the gender-comparison findings should be regarded as exploratory and interpreted with caution, as the observed differences may reflect variation in measurement properties across groups rather than substantive gender differences.

Result and Discussion

Result

Measurement Model Assessment

Table 2 presents the reliability and validity assessment of the study constructs, including behavioural intention to use AI, preservice teachers' attitudes, career intentions, perceived ease of use, perceived usefulness, and technological readiness. Most outer loadings exceeded the recommended threshold of 0.70 (*also see Figure 1*), indicating that the items are good indicators of their respective constructs. Two items fell slightly below this threshold (PTI2 = 0.693, PTPU5 = 0.663), which is generally considered acceptable in social science research when the overall construct reliability and validity are satisfactory (Falebita & Kok, 2025; Henseler et al., 2015). Specifically, PTI2 (0.693) and PTPU5 (0.663) were retained because their loadings were close to the recommended threshold of 0.70 and their retention did not adversely affect construct reliability or convergent validity. The corresponding constructs demonstrated satisfactory composite reliability (PTI: CR = 0.887; PTPU: CR = 0.837) and average variance extracted values (PTI: AVE = 0.694; PTPU: AVE = 0.589), both exceeding the recommended thresholds of 0.70 and 0.50, respectively (Hair et al., 2020). Therefore, retaining these indicators was considered methodologically acceptable. All VIF values were below 5, indicating no multicollinearity among the items. Cronbach's alpha (CA) and composite reliability (CR) values ranged from 0.826 to 0.928, surpassing the recommended cutoff of 0.70, confirming high internal consistency. The average variance extracted (AVE) values ranged from 0.589 to 0.776, exceeding the 0.50 benchmark, which supports convergent validity (Hair et al., 2020). These results indicate that, despite slightly lower loadings, the constructs reliably and validly measure preservice teachers' attitudes, intentions, perceptions, and technological readiness toward AI use.

Table 2: *Reliability and Validity of Constructs*

Construct	Item	Outer Loading	VIF	CA	CR	AVE
Behavioural Intention Usage	BIU1	0.852	2.613	0.896	0.896	0.708
	BIU2	0.753	1.728			
	BIU3	0.898	4.089			
	BIU4	0.865	3.783			
	BIU5	0.833	2.519			
Pre-Service Teacher Attitude	PTA1	0.817	2.169	0.871	0.875	0.663
	PTA2	0.820	3.256			
	PTA3	0.881	3.244			
	PTA4	0.838	2.608			
	PTA5	0.705	1.685			

Pre-Service Teacher Intention	PTI1 PTI2 PTI3 PTI4 PTI5	0.825 0.693 0.874 0.840 0.832	2.120 1.591 2.717 2.568 2.207	0.873	0.887	0.694
Pre-Service Teacher Perceived Ease of Use	PTPEU1 PTPEU2 PTPEU3 PTPEU4 PTPEU5	0.727 0.842 0.825 0.817 0.765	1.752 2.505 2.033 2.511 1.807	0.855	0.864	0.634
Pre-Service Teacher Perceived Usefulness	PTPU1 PTPU2 PTPU3 PTPU4 PTPU5	0.803 0.810 0.725 0.824 0.663	2.208 3.317 3.352 2.772 2.138	0.826	0.837	0.589
Pre-Service Teacher Technological Readiness	PTTR1 PTTR2 PTTR3 PTTR4 PTTR5	0.852 0.938 0.847 0.906 0.857	3.180 4.957 2.526 3.534 2.601	0.928	0.947	0.776

Table 3 presents the discriminant validity analysis of the constructs using the Fornell-Larcker criterion. Under this criterion, constructs that exhibit sufficient discriminant validity show a square root of their average variance extracted (AVE) exceeding the correlations of the constructs with other constructs (Fornell & Larcker, 1981). In this analysis, all constructs, Behavioural Intention Usage (BIU = 0.841), Preservice Teacher Attitude (PTA = 0.814), Preservice Teacher Intention (PTI = 0.833), Preservice Teacher Perceived Ease of Use (PTPEU = 0.796), Preservice Teacher Perceived Usefulness (PTPU = 0.768), and Preservice Teacher Technological Readiness (PTTR = 0.881) show higher square root AVE values than their corresponding inter-construct correlations. This shows that each construct has greater variance among its indicators than among others, establishing satisfactory discriminant validity. Although the Heterotrait–Monotrait ratio (HTMT) has increasingly been recommended for discriminant validity assessment in PLS-SEM, the present study relied on the Fornell–Larcker criterion because the criterion adequately established discriminant validity across all constructs and remains an accepted approach when clear discriminant separation is observed (Fornell & Larcker, 1981; Hair et al., 2021a). Therefore, HTMT analysis was not considered necessary for additional confirmation. The negative correlations involving Preservice Teacher Technological Readiness (PTTR) warrant further clarification. These inverse relationships were carefully examined to rule out possible reverse coding or item coding errors, and no inconsistencies were identified during data screening and coding procedures. The observed negative relationships may suggest that respondents with higher technological readiness adopt a more critical or cautious perception regarding AI-related usefulness, attitudes, and behavioural intentions. This pattern may reflect increased awareness of the complexities, limitations, or potential challenges associated with AI integration among technologically prepared preservice teachers rather than indicating measurement problems.

Table 3: *Fornell–Larcker Criterion - Discriminant Validity Analysis*

Construct	BIU	PTA	PTI	PTPEU	PTPU	PTTR
BIU	**0.841**					
PTA	0.693	**0.814**				
PTI	0.729	0.807	**0.833**			
PTPEU	0.669	0.779	0.817	**0.796**		
PTPU	0.750	0.747	0.832	0.795	**0.768**	
PTTR	-0.274	-0.123	-0.226	-0.160	-0.286	**0.881**

Structural Model Assessment

Table 4a, 4b, 4c and 5 present the multigroup analysis of preservice teachers' behavioural intention to use artificial intelligence (BIU) by gender. The structural findings are presented in line with the study hypotheses and major research objectives to facilitate interpretation and highlight the most educationally meaningful findings. Regarding the predictors of behavioural intention toward AI use (BIU), attitude toward AI (PTA) and perceived usefulness (PTPU) emerged as the most important gender-differentiated predictors. Attitude toward AI (PTA) significantly predicts behavioural intention (BIU) among males ($\beta = 1.056$, $t = 3.594$, $p < 0.05$) but not females ($\beta = -0.066$, $t =$

0.503, $p > 0.05$), with a significant gender difference ($t = 3.522$, $p < 0.05$). From an educational perspective, this finding suggests that male preservice teachers may be more likely to translate favourable attitudes toward AI into concrete intentions to use AI tools for learning and teaching. Conversely, female preservice teachers may rely on additional factors beyond general attitudes, such as perceived usefulness, support systems, confidence, or contextual considerations, before developing behavioural intentions toward AI use. The relatively large path coefficient observed among males ($\beta = 1.056$) exceeds the conventional standardized range and may indicate suppression effects or scaling influences within the model. However, since multicollinearity diagnostics indicated acceptable VIF values (< 5), severe multicollinearity is unlikely. The coefficient should therefore be interpreted with caution, as its magnitude may reflect complex interactions among predictors rather than a direct inflation effect. Career intention (PTI) does not significantly predict BIU for either gender, but it significantly predicts attitude toward AI for females ($\beta = 0.956$, $t = 13.221$, $p < 0.05$) and not males ($\beta = 0.244$, $t = 0.978$, $p > 0.05$), with a significant gender difference ($t = 2.764$, $p < 0.05$). With respect to career-intention pathways, the findings suggest that female preservice teachers may more strongly integrate their future professional aspirations into their attitudes toward AI than male preservice teachers. This may indicate greater sensitivity among females toward the relevance of AI competencies in future teaching careers. Additionally, perceived ease of use (PTPEU) shows gender-specific effects. It predicts BIU negatively for males ($\beta = -0.423$, $t = 2.021$, $p < 0.05$) but not for females ($\beta = 0.155$, $t = 1.476$, $p > 0.05$), with a significant gender difference ($t = 2.491$, $p < 0.05$). PTPEU positively predicts attitude in the full sample ($\beta = 0.195$, $t = 2.206$, $p < 0.05$) and career intention for both genders, although these paths do not differ significantly by gender. PTPEU also strongly predicts perceived usefulness (PTPU) for both females ($\beta = 0.751$, $t = 18.353$, $p < 0.05$) and males ($\beta = 0.861$, $t = 13.326$, $p < 0.05$), highlighting its role in shaping perceived benefits rather than directly driving behavioural intention. Moreso, perceived usefulness (PTPU) positively predicts BIU among females ($\beta = 0.532$, $t = 3.704$, $p < 0.05$) but not males ($\beta = -0.177$, $t = 0.575$, $p > 0.05$), with a significant gender difference ($t = 2.108$, $p < 0.05$). This finding suggests that female preservice teachers may place greater emphasis on practical benefits and utility considerations before developing intentions to use AI technologies in educational contexts. PTPU significantly predicts career intention for both genders (females: $\beta = 0.476$, $t = 6.031$; males: $\beta = 0.311$, $t = 0.871$), whereas it does not significantly predict attitude for either gender, indicating that females' behavioural intentions respond more to perceived benefits, whereas career-related intentions are predicted across genders. In addition, technological readiness (PTTR) affects constructs differently by gender. It positively predicts attitude for females ($\beta = 0.148$, $t = 2.852$, $p < 0.05$) but negatively for males ($\beta = -0.289$, $t = 2.960$, $p < 0.05$), with a significant gender difference ($t = 3.991$, $p < 0.05$). PTTR negatively predicts perceived ease of use ($\beta = -0.160$, $t = 2.451$, $p < 0.05$) and perceived usefulness ($\beta = -0.162$, $t = 3.802$, $p < 0.05$), with the negative effect on usefulness stronger for females ($t = 2.355$, $p < 0.05$). PTTR does not significantly predict BIU or career intention for either gender, suggesting readiness shapes perceptions rather than immediate adoption intentions. The R^2 values indicate substantial explanatory power: BIU ($R^2 = 0.616$ complete sample; 0.708 females; 0.686 males), PTA ($R^2 = 0.772$ complete sample; 0.904 females; 0.681 males), PTI ($R^2 = 0.759$ complete sample; 0.822 females; 0.414 males), and PTPU ($R^2 = 0.658$ full sample; 0.671 females; 0.742 males). PTPEU shows minimal variance explained ($R^2 \approx 0.026$), consistent with its role as an antecedent.

Table 4a: Structural Path Analysis for the Complete Sample

Path	*β*	*t-value*	*P*	*f^2*	*Results*
PTA→BIU	0.221	1.447	0.148	0.029	NS
PTI→BIU	0.148	1.147	0.252	0.009	NS
PTI→PTA	0.699	9.876	0.000	0.517	S
PTPEU→BIU	0.040	0.444	0.657	0.001	NS
PTPEU→PTA	0.195	2.206	0.027	0.048	S
PTPEU→PTI	0.427	6.714	0.000	0.274	S
PTPEU→PTPU	0.769	19.451	0.000	1.686	S
PTPU→BIU	0.404	3.153	0.002	0.109	S
PTPU→PTA	0.032	0.372	0.710	0.001	NS
PTPU→PTI	0.488	6.700	0.000	0.338	S
PTTR→BIU	-0.092	1.945	0.052	0.019	NS
PTTR→PTA	0.075	2.330	0.020	0.022	S
PTTR→PTI	-0.018	0.460	0.645	0.001	NS
PTTR→PTPEU	-0.160	2.451	0.014	0.026	S
PTTR→PTPU	-0.162	3.802	0.000	0.075	S

Variable	*R^2*
BIU	0.616
PTA	0.772
PTI	0.759
PTPEU	0.026

PTPU	0.658

Table 4b: Structural Model Results for Female Preservice Teachers

Path	*B*	*t-value*	*P*	f^2	*Result*
PTA→BIU	-0.066	0.503	0.615	0.001	NS
PTI→BIU	0.244	1.134	0.257	0.013	NS
PTI→PTA	0.956	13.221	0.000	1.700	S
PTPEU→BIU	0.155	1.476	0.140	0.020	NS
PTPEU→PTA	-0.056	0.723	0.470	0.008	NS
PTPEU→PTI	0.484	7.054	0.000	0.479	S
PTPEU→PTPU	0.751	18.353	0.000	1.679	S
PTPU→BIU	0.532	3.704	0.000	0.221	S
PTPU→PTA	0.080	0.963	0.336	0.016	NS
PTPU→PTI	0.476	6.031	0.000	0.417	S
PTTR→BIU	-0.042	0.589	0.556	0.004	NS
PTTR→PTA	0.148	2.852	0.004	0.193	S
PTTR→PTI	0.001	0.011	0.991	0.000	NS
PTTR→PTPEU	-0.149	1.210	0.226	0.023	NS
PTTR→PTPU	-0.233	3.466	0.001	0.162	S

Variable	R^2
BIU	0.708
PTA	0.904
PTI	0.822
PTPEU	0.022
PTPU	0.671

Table 4c: Structural Model Results for Male Preservice Teachers

Path	*B*	*t-value*	*P*	f^2	*Result*
PTA→BIU	1.056	3.594	0.000	1.135	S
PTI→BIU	0.193	0.738	0.460	0.063	NS
PTI→PTA	0.244	0.978	0.328	0.110	NS
PTPEU→BIU	-0.423	2.021	0.043	0.131	S
PTPEU→PTA	0.280	1.397	0.162	0.060	NS
PTPEU→PTI	0.341	1.028	0.304	0.051	NS
PTPEU→PTPU	0.861	13.326	0.000	2.802	S
PTPU→BIU	-0.177	0.575	0.565	0.023	NS
PTPU→PTA	0.283	1.598	0.110	0.062	NS
PTPU→PTI	0.311	0.871	0.384	0.043	NS
PTTR→BIU	0.015	0.157	0.875	0.001	NS
PTTR→PTA	-0.289	2.960	0.003	0.252	S
PTTR→PTI	-0.067	0.523	0.601	0.008	NS
PTTR→PTPEU	-0.164	0.776	0.438	0.028	NS
PTTR→PTPU	-0.003	0.044	0.965	0.000	NS

Variable	R^2
BIU	0.686
PTA	0.681
PTI	0.414
PTPEU	0.027
PTPU	0.742

Table 5: Gender Differences in Structural Path Coefficients Among Preservice Teachers

Path	*t-value (|Male vs Female|)*	*p-value (Male vs Female)*	*Result*
PTA→BIU	3.522	0.001	S
PTI→BIU	0.152	0.880	NS
PTI→PTA	2.764	0.008	S
PTPEU→BIU	2.491	0.016	S
PTPEU→PTA	1.579	0.121	NS
PTPEU→PTI	0.425	0.673	NS
PTPEU→PTPU	1.450	0.153	NS

PTPU→BIU	2.108	0.040	S
PTPU→PTA	1.046	0.300	NS
PTPU→PTI	0.455	0.651	NS
PTTR→BIU	0.479	0.634	NS
PTTR→PTA	3.991	0.000	S
PTTR→PTI	0.475	0.637	NS
PTTR→PTPEU	0.061	0.952	NS
PTTR→PTPU	2.355	0.022	S

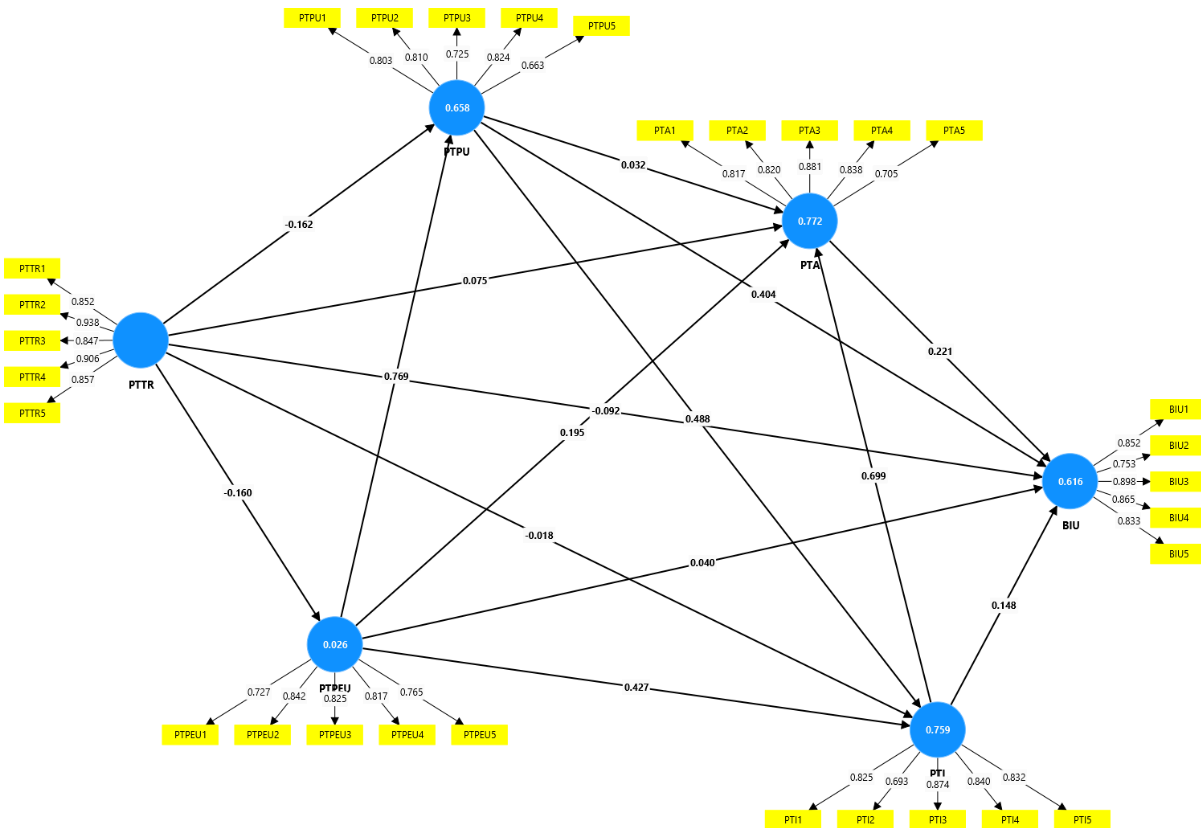

Figure 1: Paths among Preservice Teachers' Behavioural Intention, Attitude, Career Intention, Perceived Ease of Use, Perceived Usefulness, and Technological Readiness.

Discussion

This research paper explored gender differences in the technological readiness and intentions of preservice teachers to embrace artificial intelligence (AI) in education practices. Following the Technology Acceptance Model (TAM) (Davis, 1989), it is found that although the model's essential constructs tend to hold, the degree and nature of the relationships differ considerably across genders. These findings demonstrate the need to address gender as a moderator in AI adoption plans in teacher education. A central contribution of this study is the identification of distinct AI adoption pathways for male and female preservice teachers. While the overall TAM structure received partial support across both groups, the findings suggest that males and females rely on different psychological mechanisms when forming intentions to adopt AI in educational contexts. Specifically, male preservice teachers appear to follow a more attitude-driven pathway, whereas female preservice teachers appear to follow a utility-driven pathway in which behavioural intentions are shaped primarily by perceptions of AI’s practical and professional value. These findings suggest that gender is an important contextual factor in predicting how future teachers evaluate and respond to emerging AI technologies.

The study found that attitude was a significant predictor of behavioural intention among male preservice teachers, but not among female preservice teachers. The stronger role of attitude among males suggests that emotional and affective responses to AI technologies may be particularly influential in shaping their adoption decisions. Positive attitudes may reflect enthusiasm toward innovation, experimentation, and technological engagement, thereby increasing the likelihood of future AI use. In contrast, the absence of a significant attitude–intention relationship among females suggests that favourable perceptions alone may be insufficient to motivate adoption unless accompanied by clear evidence of instructional effectiveness and professional relevance. This is in line with the assumptions that TAM offers that positive attitudes lead to intentions to use technology (Davis, 1989; Teo et al., 2015). The fact that the same could not be said of females indicates that their adoption choices are determined by other factors, including perceived usefulness or career-related motivations. It has also been observed by previous researchers that females tend to use more instrumental appraisals in embracing educational technologies, whereas males are more inclined to affective dispositions (Campos & Scherer, 2024; Scherer et al., 2019; Venkatesh & Davis, 2000). This shows the necessity of gender-based interventions: strengthening attitudinal engagement for males, while focusing on practical value for females.

Career intention, however, did not have a direct impact on behavioural intention in either gender; it had a significant impact on females' attitude towards AI. That indicates that professional ambitions can predict female teachers' attitudes toward AI. It was similarly reported in a study that career objectives affected the understanding of females regarding the usefulness of technology in the teaching process (Teo et al., 2015). On the other hand, the weaker relationship observed among males suggests that career-related considerations may not strongly shape their attitudes toward AI adoption to the same extent as among females. The gender difference observed in the relationship between career intention and attitude further highlights the distinct motivational structures underlying AI adoption. For female preservice teachers, AI appears to be evaluated within a broader professional development framework. Their attitudes become more positive when AI is perceived as supporting future teaching effectiveness, employability, and professional growth. This finding suggests that female preservice teachers may adopt a more strategic and career-oriented approach toward educational technologies. By comparison, male preservice teachers may be influenced more by their immediate perceptions of AI than by long-term professional considerations. Therefore, teacher education programmes may need to place greater emphasis on demonstrating the career relevance and long-term professional value of AI, particularly for female preservice teachers, whose attitudes appear more closely linked to future professional aspirations.

More so, the research study revealed that perceived ease of use (PEOU) had complex, indirect effects. It failed to relate to behavioural intention among females and, surprisingly, showed a negative association with intention among males. This could indicate that male preservice teachers would equate too simple systems with limited capacity, which would decrease their chances of adoption (Tarhini et al., 2014). Also, it has no significant influence on attitudes towards the use of AI among both genders. Nonetheless, the PEOU had a positive influence on career intention and perceived usefulness, irrespective of gender, thus indicating its role indirectly in the adoption through these mediators (Teo & Noyes, 2014). An important observation emerging from these findings is that ease of use alone was insufficient to drive AI adoption intentions among either gender. This suggests that as AI technologies become increasingly prevalent, usability may be viewed as a basic expectation rather than a decisive factor in adoption. Preservice teachers may therefore place greater emphasis on what AI can accomplish pedagogically than on how easy it is to operate. Such a finding may indicate a shift in technology acceptance research, in which perceptions of value, relevance, and professional utility increasingly outweigh usability considerations in adoption decisions. This indicates that AI tools must be easy to use and advanced enough to meet functional expectations.

Also, the study revealed that perceived usefulness (PU) was a powerful predictor of behavioural intention among females, but not among males. Perhaps the most striking gender difference identified in this study concerns the role of perceived usefulness. While perceived usefulness emerged as the strongest determinant of behavioural intention among females, it did not significantly predict intention among males. This suggests that female preservice teachers may require stronger evidence that AI can enhance teaching effectiveness, improve instructional quality, and contribute to professional outcomes before committing to its adoption. Male preservice teachers, however, appear to base their adoption decisions less on instrumental benefits and more on their overall attitudes toward AI. These contrasting patterns indicate that female preservice teachers may adopt a more evidence-based, outcome-oriented evaluation process, whereas males may be more strongly inclined by affective dispositions toward the technology. This observation implies that females place greater weight on the instructional value of AI and professional advantages when deciding whether to use AI, in line with previous TAM extensions (Venkatesh & Davis, 2000). Also, preservice teachers' attitudes towards AI are not shaped by perceived usefulness, regardless of gender. Moreover, career intention among both genders was significantly predicted by PU, underscoring the need to emphasize the professional usefulness of AI in teacher education.

Additionally, the study indicates that technological readiness (TR) had gendered mixed effects. It had no direct influence on the behavioural intentions of both groups, but had a positive effect on female attitudes and a negative influence on male attitudes towards AI. It means that confidence in technology increases openness to AI in female teachers, which is probably due to a decrease in anxiety and an increase in self-efficacy (Teo et al., 2015). Higher technological readiness among males can lead to higher expectations, which, when not met, result in less favourable attitudes. TR also showed a negative association with PEOU and PU, particularly among females, which might indicate that more proficient users find AI systems less intuitive or even less useful due to not achieving the expectation of high-level functionality (Scherer et al., 2019). However, TR does not significantly predict career intention for either gender in AI usage. The findings regarding technological readiness further reinforce the existence of gender-specific adoption mechanisms. The positive relationship between technological readiness and female attitudes suggests that confidence in technology serves as an enabling condition, reducing uncertainty and encouraging openness to AI adoption. Conversely, the negative relationship observed among males may indicate a critical evaluation effect, whereby technologically competent individuals develop higher expectations regarding AI functionality and educational value. When these expectations are not fully met, attitudes may become less favourable. This interpretation helps explain why technological readiness does not uniformly translate into positive perceptions across gender groups. Collectively, these findings demonstrate that technological readiness influences AI adoption indirectly and differently for males and females, highlighting the need for more nuanced theoretical models that account for gender-specific pathways in educational AI acceptance.

Taken together, the findings suggest that male preservice teachers primarily adopt AI through an attitude-driven pathway, whereas female preservice teachers follow a usefulness- and career-oriented pathway. While positive attitudes are central to male adoption intentions, perceptions of professional value and instructional usefulness are more influential for females. Furthermore, technological readiness appears to increase females' openness to AI while encouraging more critical evaluations among males. These findings extend the Technology Acceptance Model by demonstrating that the determinants of AI adoption are not uniform across genders. Consequently, AI integration initiatives in teacher education should adopt gender-responsive strategies that simultaneously address affective engagement, perceived usefulness, professional relevance, and technological confidence to maximize future teachers' readiness for AI-enhanced educational practice.

Implications

The results point out that the use of AI by preservice teachers is a multidimensional and gender-sensitive phenomenon. For male preservice teachers, intrinsic factors such as attitudes are the major determinants of behavioural intention, whereas for females, instrumental factors such as perceived usefulness and career relevance are more dominant. Although perceived ease of use increases perceived usefulness and career intention in both genders, it does not have a strong direct impact on attitudes and behavioural intentions. Technological readiness, rather than uniformly contributing to adoption, is related to gender and expectations and influences attitudes and perceptions, with counterintuitive results in some cases. These findings highlight the importance of integrating gender-responsive AI literacy and digital pedagogy training within teacher education programmes, where preservice teachers develop both technical competence and the ability to apply AI tools meaningfully in teaching contexts. The dynamics point to the need for teacher education programs to adopt a subtler approach: they should make males more engaged and more challenged, and females more aware of AI's practical usefulness and professional value. Meanwhile, AI literacy and digital pedagogy modules should be deliberately structured to include scaffolded, hands-on AI tasks (e.g., prompt engineering, lesson planning with AI tools, and classroom simulation activities), ensuring that pre-service teachers engage with both the conceptual understanding and the practical application of AI in teaching. Furthermore, teacher educators should emphasize authentic technology integration activities that connect AI tools with classroom practices, including instructional design, assessment, and ethical decision-making. Such approaches can strengthen preservice teachers' readiness to adopt AI as a pedagogical resource rather than merely as a technological innovation. For male preservice teachers, inquiry-based and problem-solving AI tasks that challenge assumptions and promote deeper cognitive engagement should be emphasized, whereas for female preservice teachers, context-rich, career-oriented AI activities that explicitly demonstrate classroom relevance, instructional efficiency, and opportunities for professional advancement should be prioritized. Across both groups, teacher educators should integrate reflective practice sessions in which students critically evaluate AI outputs and discuss ethical and pedagogical implications in real classroom scenarios. Such a combined method may help create a situation in which all pre-service teachers, regardless of gender, are encouraged to embrace and effectively employ AI in their future classroom practice. Also, this study builds upon the TAM framework by introducing the subtle nature of gender in mediating the links among attitudes, perceived ease of use, perceived usefulness, technological readiness, career intention, and behavioural intention. It shows that the conventional predictors of technology adoption might operate differently for male and female preservice teachers and highlights the need for context-sensitive models in informatics education research that consider how AI literacy, digital competence, and learner characteristics shape technology adoption in educational practice.

Conclusion

The study's findings indicate that the interaction among attitudinal, perceptual, and readiness factors predicts preservice teachers' involvement in educational contexts involving artificial intelligence (AI), with notable gender-specific variations. The relationship between attitudes and behavioural intention in male preservice teachers was mainly shaped by attitudes, while career intention predicted attitudes towards AI in female teachers. Perceived ease of use and perceived usefulness significantly impacted AI adoption: both perceived usefulness and career intention positively affected gender, perceived usefulness positively predicted behavioural intention only in females, and perceived ease of use negatively affected behavioural intention in males. Technological readiness impacted attitudes toward AI differently for each gender- positively for females and negatively for males- and also affected perceived ease of use and perceived usefulness, especially in females. Overall, these results suggest that all these factors predict career-related intentions, with gender moderating the effects of attitude and technological readiness on behavioural intentions toward AI. This highlights the importance of incorporating gender sensitivity into AI literacy programs to ensure that both male and female preservice teachers are adequately prepared to utilize and implement AI technologies in teaching

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