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Determinants of artificial intelligence readiness and community-oriented competencies among pre-service teachers in community-engaged universities

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ABSTRACT

Artificial intelligence (AI) has become a key driver of educational transformation, particularly in teacher education, where pre-service teachers are expected to integrate technology with community-oriented teacher practices. This study examines the factors influencing AI readiness for teaching (AIRT) and community-oriented teaching competencies (COTC) among pre-service teachers in community-engaged universities. A quantitative research design using structural equation modeling (SEM)-based path analysis. Data were collected from 400 Rajabhat University pre-service teachers using a 35-item questionnaire. Mean composite scores were treated as observed variables in the SEM-based path model. The findings indicated that the model fit the empirical data well. The perceived usefulness of AI (PUAI) exhibited the strongest influence on AIRT, followed by community orientation (COO) and institutional support for AI and community engagement (ISCE). In turn, AIRT had the strongest influence on COTC, followed by ISCE and COO. Additionally, AIRT functioned as a significant mediating variable between PUAI, COO, ISCE and COTC. However, AI ethical awareness (AIEA) did not directly affect COTC, suggesting that ethical awareness alone is insufficient unless transformed through practicum, reflective practice, and community-based experience. The findings suggest that teacher education programs should integrate AI with community-based learning (CBL) and professional practice.

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1. INTRODUCTION

In the digital era, artificial intelligence (AI) is a transformative technology driving significant shifts in education systems globally. In particular, the advancement of generative AI supports personalized learning, provides immediate feedback, and broadens access to knowledge [1], [2]. These developments affect not only learners but also the role of teachers and teacher education in the 21st century. Therefore, teacher preparation programs must be restructured in terms of content, learning processes, and the essential competencies expected of pre-service teachers [3]. However, integrating AI into teacher education still faces several challenges, including AI readiness, self-efficacy, perceived usefulness, and ethical awareness [4], [5]. Despite the rapid growth of AI in education research, limited attention has been given to how AI readiness contributes to pre-service teachers' professional competencies in community-engaged contexts. Thus, AI

readiness should extend beyond technical proficiency to include broader professional competencies. This issue is becoming more urgent as pre-service teachers are expected to enter educational environments where AI-supported learning, data-informed decision-making, and digital instructional tools are integral to everyday practice. Without systemic preparation in teacher education programs, pre-service teachers may gain technical exposure to AI, but they may lack the knowledge and skills to employ it properly for meaningful learning, ethical decision-making, and community-responsive teaching.

Universities today go beyond teaching and research to encompass academic service and social development. This expanded mission is particularly evident in community-engaged universities, which integrate academic knowledge with community experiences through participatory learning and community-based learning (CBL). Such approaches are important for developing pre-service teachers' social competencies, public responsibility, and ability to apply knowledge in practical contexts. Consequently, pre-service teachers in such universities need to develop community-oriented competencies alongside AI readiness so that they can use technology critically and respond to community needs.

Rajabhat Universities represent a prominent example of community-engaged higher education institutions because of their explicit mission in teacher preparation, local school improvement, academic service, and community development. In this context, AI readiness goes beyond technological adoption; it reflects the extent to which pre-service teachers can use AI to understand learners, address local problems, and design instruction that responds to the needs of schools and communities. Therefore, examining AI readiness among pre-service teachers in Rajabhat Universities is essential for understanding how future teachers can integrate technology with social responsibility and community-responsive teaching.

Previous studies have largely focused on technology acceptance at the individual level or within general learning contexts, drawing on frameworks such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) [6], [7]. However, these studies have rarely integrated social and community dimensions, particularly for pre-service teachers whose professional roles require connecting learning with authentic school and community contexts. Existing AI readiness research has also primarily emphasized technological skills, whereas community-oriented teaching competencies (COTC) have rarely been examined in conjunction with AI readiness. Therefore, this study addresses theoretical, contextual, and methodological gaps by integrating technology acceptance, AI readiness, ethical awareness, and COTC into a single structural equation modeling (SEM)-based path model.

In this study, technological, psychological, and social factors are integrated into a SEM path model to explore two main ideas: AI readiness for teaching (AIRT) and COTC. Previous research has mainly focused on either technology acceptance or AI literacy; this study, however, connects AI readiness to the development of professional competencies within community-engaged teacher education. This integrated perspective demonstrates how AI readiness functions as a mediating mechanism translating the perceived usefulness, ethical awareness, community orientation (COO), and institutional support into community-responsive teaching competencies.

2. LITERATURE REVIEW

Research on AI in teacher education indicates that AI not only functions as a learning tool but also reshapes teachers' professional roles. Pre-service teachers therefore need technological knowledge, pedagogical judgment, ethical awareness, and the ability to design responsible AI use in authentic teaching contexts [1], [8], [9]. In the context of generative AI, teacher preparation should move beyond basic digital skills toward AI literacy, pedagogical judgment, and ethical responsibility [10], [11]. In community-engaged universities, teacher preparation must also emphasize collaboration with local communities and the co-creation of knowledge. Preparing pre-service teachers for this role requires both institutional support and students' commitment to community-oriented teaching [12]–[14]. Accordingly, this study conceptualizes AI readiness and COTC through three integrated dimensions: technological, psychological, and social-contextual factors. These dimensions provide the theoretical basis for the proposed structural model. While previous research has addressed AI literacy, technology acceptance, and teachers' digital competence, most of the literature has focused on technological readiness and individual-level adoption. Limited attention has been paid to the relationship between AI readiness and COTC, especially in teacher education programs that prepare graduates to collaborate with local schools and communities. Therefore, the present study addresses this gap by integrating technological, psychological, and socio-contextual factors into a single SEM path model to explain both AIRT and COTC.

2.1. Technological factors

Perceived usefulness of AI (PUAI) is a key technological factor influencing pre-service teachers' AIRT. Based on technology acceptance perspectives, individuals are more likely to accept and use

technology when they perceive it as useful for improving learning, work performance, and professional practice [15]. In teacher education, pre-service teachers who perceive AI as useful are more likely to recognize its potential for instructional design, learner support, assessment, instructional material development, learner data analysis, and community-based problem solving [16], [17]. Therefore, PUAI provides a theoretical basis for explaining how perceived technological value contributes to readiness for AI-integrated teaching.

AI self-efficacy for teaching (AIST) is another important technology-related factor supporting AI readiness. AIST refers to pre-service teachers' confidence in using AI appropriately for teaching-related tasks, including designing learning activities, developing instructional materials, conducting assessments, and supporting learners. Previous studies indicate that self-efficacy is closely associated with perceived usefulness, intention to use technology, and actual technology application in educational contexts [18], [19]. Therefore, pre-service teachers with higher AI self-efficacy are more likely to develop confidence and readiness to integrate AI into teaching practice.

In this study, AIRT is conceptualized as a multidimensional construct that extends beyond basic tool-use skills. It includes readiness to apply AI pedagogically, ethically, and contextually in authentic teaching situations. Accordingly, PUAI and AIST are considered important technological factors that contribute to pre-service teachers' readiness to use AI not only for instructional efficiency but also for meaningful learning design and community-responsive educational practice.

2.2. Psychological factors

AI ethical awareness (AIEA) is important in teacher education because AI use involves learner data privacy, algorithmic fairness, transparency, accountability, and academic integrity. In the context of AI-integrated education, teachers' AI self-efficacy extends beyond technical tool use ability. It includes AI pedagogy, AI assessment, AI ethics, and human-centered learning design [11]. Research indicates that self-efficacy is linked to both AI acceptance and actual implementation. It serves to develop teachers' confidence in implementation while lowering anxiety and uncertainty regarding AI [2], [4], [20]. AI self-efficacy is a significant predictor of AI readiness among pre-service teachers. Those who are confident in their ability to use AI for designing learning activities, conducting assessments, and supporting learners tend to exhibit greater openness to AI and readiness for its implementation [4].

AIEA is very important in teacher education since the use of AI in education raises critical ethical considerations, including learner data privacy, algorithmic fairness and bias, transparency, accountability, and academic integrity [8], [21], [22]. Teacher ethical awareness is a dynamic process shaped by social context, often developing after initial functional use of AI and then becoming recognition of potential risks [20]. These findings underscore that community-oriented teaching involves sensitive engagement with learner and community data, power dynamics, fairness, and social responsibility. It, therefore, requires a strong ethical foundation.

2.3. Social-contextual factors

Institutional support for AI and community engagement (ISCE) play a crucial role in community-engaged universities as developing AI readiness among pre-service teachers cannot solely rely on individual motivation. It requires supportive structures such as policies, guidelines, curriculum development, training, mentoring teachers, digital resources, and coordination with schools and communities [23], [24]. In higher education, perceived institutional support positively influences the perception of AI-supported learning. It also relates directly and indirectly to technology self-efficacy through perceived learning outcomes, serving as a mediating factor. When institutions provide resources, training, and guidelines, learners gain access to authentic practice, pedagogical demonstrations, and opportunities to develop practical readiness [2], [4]. In the context of community-engaged universities, institutional support goes beyond technical support. It includes establishing collaborative structures with schools, local communities, and local organizations to provide practice spaces where pre-service teachers can apply AI to address real-world problems, such as analyzing learner data, developing community-oriented materials, and designing area-based learning activities. Campus Compact [13] note that successful community-engaged institutions are typically characterized by clear institutional support systems that position community engagement is an institutional priority rather than an individual responsibility of instructor.

Furthermore, ISCE may directly relate to COTC because community-oriented work requires support systems, such as community coordination units, partner networks, and project management. These elements represent institutional-level mechanisms rather than individual capabilities [13]. Therefore, institutional support can create the structural conditions that enable pre-service teachers to engage meaningfully in community-connected teaching practices.

The COO represents collaborative partnerships between universities and communities to create and exchange knowledge and resources. To ensure that CBL benefits both learners and communities, this

orientation emphasizes collaboration, co-defining problems, shared goal setting, and shared responsibility for outcomes. When pre-service teachers develop strong COO, they are more likely to recognize the value of using pedagogical and technological resources to support both learner development and community improvement.

In this study, COTC are conceptualized as the outcome variable reflecting pre-service teachers' ability to design, implement, and evaluate community-connected learning activities through collaboration with schools and local communities. Within this framework, COO is expected to have a direct effect (DE) on COTC because it reflects pre-service teachers' attitudes, commitment, and willingness to connect teaching practices with community needs. Pre-service teachers with strong COO are more likely to value AI as a tool for supporting data-informed decision-making, communication, and authentic learning task design in community-based contexts.

Constructs, along with their operational definitions and supporting references, used in the hypothesized conceptual framework are provided in Table 1. These constructs encompass the technological, psychological, and socio-contextual dimensions within which this research was conducted. Table 1 provides the conceptual basis for formulating the research hypotheses.

Table 1. Variables and operational definitions

Variable	Definition	Reference
AIST	Pre-service teachers' confidence in their ability to use AI for instructional design, assessment, and learner support appropriately	[8]
PUAI	Perceived value of AI for improving teaching, learning, and community-based problem solving.	[6], [7], [15]
AIEA	Awareness of fairness, transparency, privacy, accountability, and the social impact of AI	[17], [23]
COO	Pre-service teachers' attitudes and commitment toward using learning and teaching to address community needs	[13]
ISCE	The perception of institutional policies, resources, infrastructure, and opportunities that support both AI use and community engagement	[13]
AIRT	Holistic readiness to integrate AI into teaching practices effectively, appropriately, and ethically	[8]
COTC	The ability to design, implement, and evaluate instructional activities that connect with community engagement based on collaboration	[13]

As shown in Table 1, the proposed constructs capture the multidimensional aspects of AI readiness and COTC. These constructs represent the technological, psychological, and socio-contextual dimensions of the hypothesized conceptual framework. Drawing from these operational definitions and the literature, the following hypotheses are presented: i) AIST has a DE on AIRT (H1); ii) PUAI has a DE on AIRT (H2); iii) AIEA has a DE on AIRT (H3); iv) COO has a DE on AIRT (H4); v) ISCE has a DE on AIRT (H5); vi) AIRT has a DE on COTC (H6); vii) AIEA has a DE on COTC (H7); viii) COO has a DE on COTC (H8); and ix) ISCE has a DE on COTC (H9).

3. METHOD

3.1. Research context

A quantitative research design using SEM-based path analysis was employed to examine factors influencing AIRT and COTC among pre-service teachers at community-engaged universities. The study was conducted in 38 Rajabhat Universities in Thailand, which have explicit missions in teacher preparation, local development, academic service, and CBL. This context was appropriate for the study because Rajabhat Universities are expected to prepare teachers who can integrate educational innovation with local school and community needs.

The application of SEM is justified by the complexity of the research model, which involves multiple variables with both direct and indirect relationships. Mean scores for each variable were used as observed composite variables to analyze causal relationships within the SEM framework. This approach enabled the evaluation of model fit between the theoretical model and empirical data and allowed an appropriate assessment of mediating variables.

3.2. Participants

The participants were pre-service teachers from Rajabhat Universities across Thailand, which are recognized as community-engaged universities. Purposive sampling was employed with specific selection criteria. Participants were required to be current pre-service teachers within the Rajabhat University system and to have at least one semester of experience using AI for educational purposes.

The study sample comprised pre-service teachers from Rajabhat Universities in four regions of Thailand: North, Central, Northeast, and South. Most participants were third- to fifth-year students who were

either undertaking their professional teaching practicum or had experience in coursework related to learning management in schools and communities. To comprehensively represent the teacher education context, the sample includes students from diverse academic majors.

During data collection, an online questionnaire was distributed to 425 pre-service teachers. Data cleaning was conducted by excluding respondents with incomplete answers to key items, missing values, outliers, or inconsistent responses. After excluding 25 cases, the final valid sample consisted of 400 participants. This sample size meets the minimum requirement for the number of model parameters, as Hair *et al.* [25] recommends a ratio of 10 cases per 1 estimated parameter. Furthermore, for SEM or path analysis involving multiple variables with both direct and indirect effects (IE), a sample size exceeding 300 participants is appropriate and sufficient for evaluating model fit, estimating path coefficients, and conducting statistical hypothesis testing, especially when composite scores of variables are used as observed variables. Although purposive sampling was appropriate for the study, the sample may not comprehensively represent all pre-service teachers in Thailand. There were regional and institutional differences among Rajabhat Universities that could have affected participants' access to AI tools and community-based practicum opportunities. Moreover, the use of an online questionnaire may have favored students with higher proficiency, which could result in higher self-reported AI readiness.

3.3. Instrument

Data were collected through an online questionnaire, consisting of 35 items on a 5-point Likert scale to assess factors influencing AIRT and COTC. The instrument was developed based on three integrated dimensions: technological, psychological, and social-contextual factors. It was further divided into seven factors: AIST, PUAI, AIEA, COO, ISCE, AIRT, and COTC. To ensure instrument quality, internal consistency was evaluated using a pilot sample. The results showed strong reliability, with Cronbach's alpha coefficients for the seven variables ranging from 0.82 to 0.90. Content validity was confirmed by three experts prior to piloting.

3.4. Data analysis

Because this study aimed to examine structural relationships among theoretically defined constructs, mean composite scores for each validated scale were computed and treated as observed variables in the SEM-based path analysis. Therefore, the analysis focused on testing the hypothesized structural paths rather than estimating a full latent measurement model. This approach was appropriate for examining theoretically specified relationships among reliable scale scores and for evaluating both direct and IE within the proposed model. However, the use of composite mean scores may not fully account for measurement error; therefore, the estimated path coefficients should be interpreted as relationships among observed composite variables rather than latent construct estimates. This limitation may affect the precision of the coefficients, although the reliability coefficients of all constructs were within acceptable ranges.

The initial conceptual model consisted of nine hypothetical relationships that were identified through literature review. No modification of the model by adding or removing any other pathways was done merely based on modification indices, but the conceptual model was used for hypothesis testing. In the final model, the pathway from AIEA to COTC was retained even though it was found to be nonsignificant because it was of theoretical significance in determining the impact of ethical awareness on COTC. This approach allows for clear reporting of both supported and unsupported hypotheses.

4. RESULTS

This section presents the results of the SEM-based path analysis examining the factors influencing AIRT and COTC among pre-service teachers in community-engaged universities. The analysis includes model fit evaluation, hypothesis testing, direct and IE, and the explanatory power of the endogenous variables.

4.1. Evaluation of the structural model

To assess the adequacy of the proposed structural model, several model fit indices were examined, including the relative Chi-square (χ^2/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker–Lewis index (TLI). Together, these indices provide complementary evidence regarding the adequacy of the proposed structural model. The results of the model fit evaluation are presented in Table 2.

From Table 2, the results demonstrated that the model fitted well with the empirical data. However, since the degree of freedom (df) of the model was extremely low, i.e., df=1, the use of goodness-of-fit measures was done with caution. This was because theoretical reasoning, instrument reliability, and consistency of the hypotheses were considered more important than fit indices.

Maximum likelihood estimation (MLE) was employed in this analysis because the data approximated a normal distribution. Skewness and kurtosis values of the observed variables were within acceptable ranges, and no multicollinearity issues were detected among the antecedent variables. To maintain theoretical integrity, model adjustments based on modification indices were not implemented without theoretical justification.

Table 2. Structural equation model fit indices

Model fit index	Value	Cut-point criteria	Interpretation
χ^2/df	0.740	<3.00	Good fit
RMSEA	0.000	<0.05	Good fit
CFI	1.000	>0.95	Good fit
TLI	1.001	>0.95	Good fit

4.2. Analysis of the structural model and hypothesis testing

After confirming the overall model fit, the structural model was examined to test the research hypotheses by analyzing the standardized path coefficients and statistical significance levels for each proposed relationship. The results indicated that most of the hypotheses were supported by the empirical data. Figure 1 presents the final structural model with standardized path coefficients among the antecedent variables, AIRT, and COTC.

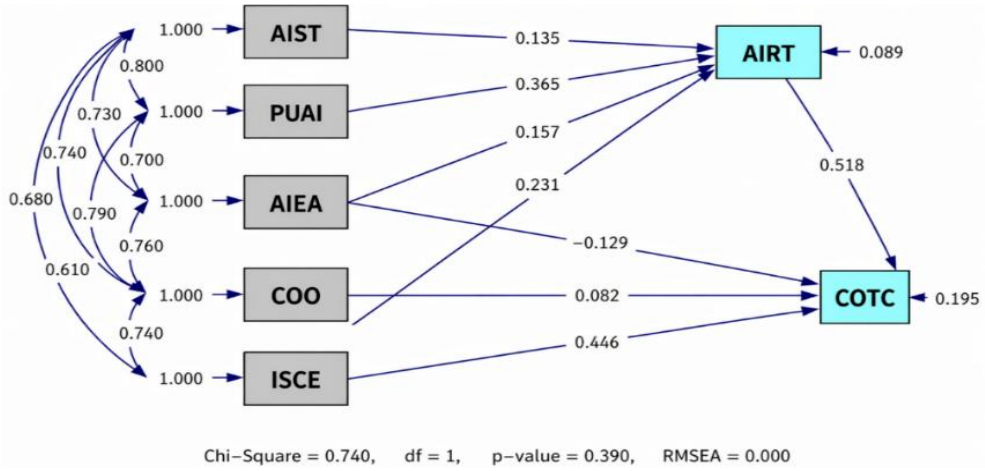


Figure 1. Structural model analysis

The path analysis demonstrated that all five antecedent variables: AIST, PUAI, AIEA, COO, and ISCE, had a statistically significant influence on AIRT. PUAI exhibited the strongest influence (β=0.365), followed by COO (β=0.231) and ISCE (β=0.180). These results suggest that the PUAI and community-oriented learning contexts play a significant role in developing AI readiness among pre-service teachers.

Regarding the factors influencing COTC, AIRT had the strongest influence (β=0.518), followed by ISCE (β=0.446) and COO (β=0.082). These results indicate that systemic support and AI readiness are important for the development of pre-service teachers' competencies. In contrast, AIEA did not demonstrate a statistically significant DE on COTC (β=-0.129). Although PUAI exhibited a negative DE on COTC (DE=-0.189), it showed a significant positive IE through AIRT (IE=0.189), resulting in a total effect (TE) of 0.000 and indicating competitive mediation (or inconsistent mediation). Thus, while the PUAI does not directly and positively influence COTC, such perceptions may be more effectively translated into these competencies when pre-service teachers possess AIRT. Table 3 provides a summary of the standardized path coefficients, their significance levels, and the conclusion reached for each hypothesis formulated.

4.3. Analysis of direct, indirect, and total effects

Since AIRT was hypothesized as a mediating variable, further analyses for the direct, indirect, and TEs were performed. The results of mediation are presented in Table 4. The mediation analysis revealed that AIRT served as a statistically significant mediating variable between multiple antecedent variables and

COTC. In particular, the path PUAI→AIRT→COTC exhibited the strongest IE (IE=0.189, 95% CI [0.112, 0.261]). While PUAI had a negative DE on COTC (DE=-0.189, p<0.05), its IE through AIRT was positive and significant. This resulted in a TE of 0.000 and indicated competitive mediation (or inconsistent mediation). That is, the PUAI alone is insufficient for the direct development of COTC without being systematically transformed into AIRT.

Table 3. Summary of DE in the structural equation model

Hypothesis	Path relationship	Path coefficient (β)	Statistical significance	Result
H1	AIST→AIRT	0.135	p<0.01	Supported
H2	PUAI→AIRT	0.365	p<0.001	Supported
H3	AIEA→AIRT	0.157	p<0.001	Supported
H4	COO→AIRT	0.231	p<0.001	Supported
H5	ISCE→AIRT	0.180	p<0.001	Supported
H6	AIRT→COTC	0.518	p<0.001	Supported
H7	AIEA→COTC	-0.129	p>0.05	Not supported
H8	COO→COTC	0.082	p<0.001	Supported
H9	ISCE→COTC	0.446	p<0.001	Supported

Table 4. Analysis of direct, indirect, and TEs

Antecedent variable	Outcome variable	DE	IE	TE	95% Boot CI
AIST	COTC	-	0.070**	0.070**	[0.031, 0.109]
PUAI	COTC	-0.189*	0.189**	0.000	[0.112, 0.261]
AIEA	COTC	-0.129	0.081**	-0.047	[0.014, 0.138]
COO	COTC	0.082	0.120**	0.201**	[0.066, 0.185]
ISCE	COTC	0.446**	0.093**	0.539**	[0.051, 0.142]

Note: *p<0.05, **p<0.01

The analysis also identified significant IE for the paths COO→AIRT→COTC (IE=0.120, 95% CI [0.066, 0.185]) and ISCE→AIRT→COTC (IE=0.093, 95% CI [0.051, 0.142]). Since the confidence intervals for these paths did not include zero, it is evident that AIRT serves as a statistically significant mediating variable. Despite having no significant DE, AIST indirectly influences COTC through AIRT (IE=0.070, 95% CI [0.031, 0.109]). Regarding AIEA, a negative but non-significant DE on COTC was observed (DE=-0.129, p>0.05). However, its IE through AIRT was positive and significant (IE=0.081, p<0.01), resulting in a slightly negative TE (TE=-0.047).

These findings indicate that the PUAI, COO, and institutional support do not independently influence COTC. Rather, AIRT functions as a key mechanism that transforms these antecedent factors into COTC. This is particularly significant in community-engaged universities, where pre-service teachers are required to develop both technological skills and the ability to apply knowledge for community development.

4.4. Explanatory power of dependent variables in the model

Along with the regression coefficients, the explanatory power of the model was evaluated in terms of R^2 values for the endogenous variables. Table 5 shows the variance of AIRT and COTC. The model explained 91.10% of the variance in AIRT, as indicated by an R^2 value of 0.911. This reflects a very high level of explanatory power. The result suggests that AIST, PUAI, AIEA, COO, and ISCE jointly provide a strong explanation of pre-service teachers' readiness to integrate AI into teaching.

Furthermore, the model explained 80.50% of the variance in COTC, as indicated by an R^2 value of 0.805. This result also indicates a high level of explanatory power. It shows that AIRT, together with psychological and socio-contextual factors, plays an important role in developing pre-service teachers' COTC.

The findings underscore that preparing pre-service teachers at community-engaged universities requires a dual focus on AI readiness and the ability to work collaboratively with communities. These two dimensions should not be developed in isolation. A key implication is that when pre-service teachers perceive AI not only as a technical tool but also as a practical resource for supporting learning, solving problems, and responding to real-life educational contexts, their readiness to use AI tends to increase significantly.

Table 5. Explanatory power of dependent variables in the model

Dependent variable	R^2	Interpretation
AIRT	0.911	Very high
COTC	0.805	High

Regarding COTC, AI readiness serves as a key foundation that enables pre-service teachers to design learning experiences that are responsive to community contexts. Pre-service teachers with higher AI readiness can apply technology more effectively to instructional design, problem analysis, learner support, and community-based educational development. However, AIEA alone did not significantly influence the development of COTC. Although pre-service teachers may recognize that AI should be used carefully, fairly, and ethically, such awareness may not translate into practical teaching competencies without opportunities to apply it in real school and community contexts.

5. DISCUSSION

It is observed from this study that AIRT is not merely driven by technological variables but emerges through the integration of technological, psychological, and socio-contextual factors within the context of community-engaged teacher education. This result supports the view that preparing future teachers for AI-integrated education requires more than basic digital skills or familiarity with AI tools. It also implies that it involves the ability to link the use of the technological tool with one's pedagogical reasoning, ethical responsibility, and responsiveness to the community's needs.

Regarding the technological dimension, PUAI was found to be the most significant predictor of AIRT. This result is in line with the technology acceptance paradigm, stating that individuals have higher probabilities to accept technology if they believe that it will improve their performance and enhance learning outcomes [2], [6], [7]. In the context of teacher education, pre-service teachers who view AI as useful for designing instruction, supporting learners, conducting assessments, and solving instructional problems are more likely to be ready to employ AI in their teaching practice. Similar results have been found in prior studies investigating AI literacy and technology acceptance [4], [10], [11], [17].

However, one significant implication of the findings is the identification of competitive mediation of PUAI. Whereas PUAI demonstrated a positive IE on COTC through AIRT, it exhibited a negative effect on COTC. In other words, the PUAI may lead pre-service teachers to primarily consider AI as a tool for enhancing efficiency in tasks, such as preparing materials, summarizing content, or supporting individual learning. However, this perception does not necessarily develop COTC. From a socio-technical perspective, AI attains educational significance only when its technical aspects are linked to ethical awareness and the social dimension of teaching [26]. Therefore, AIRT can be regarded as the mediation of PUAI into professional actions.

The psychological dimension showed the significance of AI self-efficacy and AIEA as the predictors of AIRT. In other words, internal self-confidence and ethical understanding regarding the use of AI are key factors influencing pre-service teachers' readiness to integrate AI into educational practices. When pre-service teachers feel confident in their ability to apply AI for designing learning tasks, assisting learners, and making instructional decisions, their readiness to use AI in teaching increases. This finding corresponds to the earlier studies suggesting that self-efficacy lowers anxiety and uncertainty about technology use and encourages AI adoption in education [4], [20].

Nevertheless, the relationship between AIEA and COTC is not significant. The non-significant direct connection between these two variables gives some theoretical insight into the gap between ethical awareness and professional competencies. Even though pre-service teachers have some knowledge about fair treatment, transparency, privacy, accountability, and social implications of AI, it does not necessarily mean that they can design and carry out CBL tasks. The absence of significance for the connection between AIEA and COTC could be explained by the assumption that ethical awareness helps pre-service teachers become more cautious and reflect on their decisions; however, they need to practice first to gain some skills. Ethical understanding becomes critical when it is applied during teaching practice. This can be supported by research that argues that AI ethics is supposed to be learned through practical experiences and reflective activities in the actual instruction contexts [27].

In this respect, AI ethics education for pre-service teachers should transcend mere knowledge transfer. Ethical awareness should shift towards ethical practice through teaching practicum, CBL, reflective supervision, and school-based decision making. As a result, AIRT can serve as a link between ethical awareness and professional competence. Pre-service teachers should be provided with practical experience in applying ethical principles in planning AI-driven instruction, analyzing learner needs, choosing appropriate technologies, and dealing with community challenges. Otherwise, ethical awareness may remain an academic exercise, failing to translate into practical teaching competence.

Within the socio-contextual dimension, COO and ISCE were identified as factors influencing AIRT and COTC. This result supports earlier studies emphasizing that pre-service teachers' competencies are influenced not only by individuals but also by institutional and community settings for practice. The COO promotes the relevance of addressing local needs in pedagogy, while institutional support provides necessary

structures, resources, policies, and partnerships for meaningful practice. The collaboration, shared responsibility, and institutional commitment are recognized as key pre-requisites for effective community-based education [28]–[30].

Given the high predictive power of ISCE for COTC, the findings further confirm that institutional support plays a crucial role in developing COTC among pre-service teachers. In the context of Rajabhat Universities, whose primary mission is local community development and teacher preparation for those communities, AI should be integrated into teacher education programs in connection with school partnerships, community-based practicum, and problem-solving tasks related to community needs. Thus, AI readiness should not be considered a separate form of digital literacy but an integral part of teaching practice. It should be incorporated into curricula, teacher education systems, practicum experiences, and community engagement activities. At the policy level, institutions should provide guidelines, resources, and professional development opportunities that support responsible AI use in community-responsive teaching.

5.1. Theoretical contribution

Theoretically, this study extends technology acceptance perspectives from the adoption of a specific technology to the development of professional competence in community-engaged teacher education. Traditional technology acceptance perspectives, such as TAM and UTAUT, mainly narrate technology adoption from individual perceptions, like perceived usefulness, self-efficacy, and facilitating conditions. However, the results of this study indicate that the use of AI in teacher education should not be seen as the mere acceptance of a technological tool. Instead, AI adoption should be understood as readiness for professional, ethical and community-responsive teaching practice.

Particularly, this study integrates technology acceptance perspectives with community-engaged learning and socio-technical perspectives. The COO and institutional support are considered not only as contextual background variables but also as socio-contextual mechanisms affecting AI readiness and COTC. This combination helps to understand AI adoption by showing that perceived usefulness and self-efficacy are insufficient without ethical awareness, institutional support, and authentic community-based practice.

Therefore, this study advances a competency-oriented view of AI readiness. In this view, AI readiness is not limited to tool acceptance, technical confidence, or willingness to use AI. Instead, it represents a process through which technological, psychological, and socio-contextual factors are transformed into professional teaching competence. This theoretical contribution broadens the understanding of AI adoption from an individual acceptance model toward an integrated model of teacher competence development in community-engaged universities.

5.2. Practical implications and limitations

From a practical perspective, the findings provide implications for teacher education programs, curriculum development, and institutional policy. Teacher education programs should incorporate AI literacy into CBL experiences, teaching practicum opportunities, and ethical reflection practices. Low-stakes approaches, including AI-supported lesson design tasks, micro-credentials for responsible AI use, reflective AI ethics portfolios, and community-based projects, can help pre-service teachers gradually develop competence without being overwhelmed. These strategies would enable universities to prepare future teachers who can use AI effectively, ethically, and responsively to the needs of learners, schools, and communities.

Some limitations of this study are noted. First, the data from the self-reported questionnaire can be influenced by social desirability bias, as the pre-service teachers may exaggerate their readiness for AI and/or teaching competence. Second, the online nature of the survey might have been an advantage to those participants who were technologically savvy. Third, the use of the mean composite score in SEM path analysis was useful in simplifying the model but did not address measurement error issues. Future research should use multiple methods, such as classroom observations, supervisor evaluations, teaching performance assessments, and in-depth interviews, to confirm whether there is a relationship between AI readiness and teaching performance.

6. CONCLUSION

AIRT and COTC among pre-service teachers depend on technological, psychological, and socio-contextual interactions, rather than technological factors alone. The three primary contributors to AI readiness are PUAI, COO, and institutional support. AI readiness serves as an intermediary between its antecedents and COTC. These findings extend the understanding of technology acceptance theory by demonstrating that the use of AI and the development of professional competencies in teacher education are inseparable from the professional context and social environment. Notably, the study found no direct relationship between AIEA and COTC. This suggests that while technical knowledge and ethical awareness are necessary, they are not sufficient for competency development. Practical application, reflection, and

decision-making in real-life contexts are also required. Consequently, teacher education programs should move beyond instructing students in the use of AI tools and instead provide opportunities to apply AI in authentic educational settings.

In terms of practice, AI should be incorporated into university programs through community engagement, school practicum, micro-certification, staff development, and university-school-community partnerships. Implementing AI through low-stakes approaches, such as AI-supported lesson design tasks, community-based projects, and reflective AI ethics portfolios, would help pre-service teachers gradually develop self-confidence without being overwhelmed. This is particularly applicable to the Rajabhat Universities and other community-engaged institutions, which aim to prepare future teachers who can integrate AI effectively, ethically, and responsively to community needs.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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R : **R**esources
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O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that supports the findings of this study are available from the corresponding author, [KM], upon reasonable request.

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