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Fostering critical AI competency: a structural equation model of pre-service teachers' trust and actual AI use in higher education

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ABSTRACT

In recent years, education has experienced rapid change due to the rise of artificial intelligence (AI). This study analyzed how twelve interconnected factors, based on technology acceptance and trust theories, influence trust in AI for learning (TL) and actual AI use (AU) among pre-service teachers in Thailand. Using a quantitative design, with data collected from 260 pre-service teachers through purposive sampling based on prior AI experience. A 60-item, 5-point Likert-scale questionnaire, validated through pilot testing and internal consistency analysis (α=0.82–0.91). Data was analyzed using structural equation modeling (SEM) with maximum likelihood estimation. The model showed very good fit (χ^2/df=1.601, root mean square error of approximation (RMSEA)=0.049) and explained 90.80% of behavioral intention (BI) and 71.20% of AU. Results indicated that cognitive load regulation (CLR) was the strongest predictor of TL (β=0.786, $p<0.001$), while responsible AI awareness (RAA) also showed positive effect. In contrast, AI self-efficacy (ASE) in a negative way (β=-0.159, p=0.009). The primary predictor of AU was BI (β=0.884, $p<0.001$). These findings highlight the importance of AI education systems, which will reduce teachers' cognitive load and contribute to an improved ethical AI literacy in teacher training institutions.

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1. INTRODUCTION

The pace of the world reform has accelerated under pressure exerted by developments in digital technology. The emergence of generative artificial intelligence (GenAI) such as large language models (LLMs) has hastened this change. These technologies have deeply changed the teaching and learning environments, which allows entering the "post-AI era," in which AI has become an indispensable part of education as well as people's lives not just an auxiliary tool [1]. Artificial intelligence also has considerable potential to remove the burden of repetitive instruction and enable teachers to deal more effectively with learners. It also encourages more personalized and broader approaches to enhance the quality, equity, and sustainability of education [2].

Integrating AI into education faces some challenges that need to be explored. Among the key challenges are privacy and security risks for student data collection and use, ethical considerations regarding algorithmic decision-making and the possibility of exacerbating existing biases [3], [4]. Ethical and ethical plus public concerns mostly relate to transparency plus accountability, especially when AI models are developed by private companies, which barely makes it feasible for verification of training processes and taking logical steps to ensure that misuse as well as lies cannot occur [5]. Computational bias arising from non-neutral training data, such as gender, ethnicity or socioeconomic status, can moreover exacerbate existing disparities [6]. We find that being stored and reused for additional training (where an echo wakes it up), prompts can also pose substantial threats to both academic integrity and participant privacy. Tackling the challenges demands an understanding of the drivers behind trust in AI and its adoption. Several theoretical approaches provide perspective on attitudes and intentions related to technology adoption or acceptance.

Despite growing research on AI in education, a critical research gap remains. Most existing studies focus on teachers' intention to use AI or on perceived usefulness (PU), with limited attention has been paid to how trust in AI is developed, calibrated, and translated into actual use, particularly among pre-service teachers who will shape future classrooms practices. Furthermore, there is a lack of empirical evidence explaining how cognitive, ethical and self-efficacy related jointly influence the trust in AI in the post-AI era. This gap is particularly critical, as trust in AI plays a decisive role in whether teachers adopt AI in school. Although understanding these mechanisms is essential for teacher educators, teacher education programs currently lack a well-researched foundation for fostering the AI competencies required for such informed adoption. To address this gap, the present study develops and empirically test an integrated model linking cognitive load regulation (CLR), responsible AI awareness (RAA), and behavioral capability with trust in AI and actual AI use (AU). This goes beyond descriptive adoption studies by providing a causal account of how trust is developed, tuned and enacted into practice.

As such, the term "AI competency" for educators extends beyond basic AI literacy, while AI literacy refers to understanding and explaining how AI technology's function, AI competency reflects a higher level of confidence and capability to apply AI effectively and ethically in real-world educational contexts [7]–[9]. Assessing this confidence is a key sign of the readiness of teachers in today's educational sphere, where AI has gained access to daily life as well as learning. In line with this, the present study investigates the causal influences of 12 combined constructs, originated from technology acceptance models (TAMs) and trust theory (TT), on trust in AI for learning (TL) and AU among Thai public school's preservice teachers.

The theoretical and practical implications of this study are significant. In theoretical terms, our study contributes to the literature on education and demonstrates that AI trust is rooted in a process of critical judgment based on cognitive beliefs and ethical sensibility rather than simply in positive attitudes. In practical terms, these findings provide a policy basis for colleges and open universities to structure teacher education training programs, improve the AI literacy and competency levels of teachers, and propose principles for morally integrating AI within digital learning systems. Therefore, this study aims to answer the following three research questions:

i) What are the factors that affect pre-service teachers for TL?
ii) What are the contributions of trust in AI to behavioral intention (BI) and real use of AI?
iii) Whether AI self-efficacy (ASE) has a positive or negative effect on trust in AI suggesting the possibility of a self-efficacy paradox?

2. LITERATURE REVIEW

The improvement of AI, particularly generative-based AI models, has largely affected the educational field [10]. Factors influencing the acceptance and use of AI for learning by pre-service teachers are shaped by multiple interrelated factors. The theoretical framework of this study integrates several well-established models. These include the TAM, which emphasizes PU and perceived ease of use (PEOU); the unified theory of acceptance and use of technology (UTAUT), which incorporates social influence (SI) and facilitating conditions (FC); and extensions from technology TT that address AI-specific dimensions in the post AI-era, including AI literacy (AIL), RAA, and CLR. Table 1 summarizes 12 key constructions derived from these theoretical foundations and empirically tested using the structural equation modeling (SEM) approach in this study. The literature review of key determinants that underpin the proposed research framework and explain pre-service teachers' TL in the post-AI era, encompassing multiple interrelated dimensions.

Table 1. Constructs and theoretical foundations

Item	Categories	Theoretical foundation	Theoretical foundation
1	AIL	AI literacy	AI literacy is a reflection of the knowledge, understanding, and capability to use AI appropriately.
2	ASE	Self-efficacy/perceived behavioral control	Perceived-confidence-based on the TPB-SE in performing the behavior of using AI effectively.
3	PEOU	TAM/UTAUT	The perception that the AI is easy to use, non- complex, and requires minimal effort.
4	PU	TAM/UTAUT	The belief that AI enhances learning performance.
5	RAA	Responsible AI/technology TT	Awareness of ethical principles, transparency, fairness, and data protection in AI use.
6	CLR	Cognitive load theory/AI usability	The extent to which AI reduces cognitive burden and supports efficient learning without confusion.
7	INC	Diffusion of innovation theory	Inclination to try new technologies and perceived compatibility of AI with one's learning style.
8	SI	UTAUT/TPB	Peer, instructor, and community support influence attitudes and AI usage.
9	FC	UTAUT	The availability of infrastructure, resources, and technical support for AI use.
10	TL	Technology TT	Degree of trust in the reliability, transparency, and controllability of AI outcomes.
11	BI	TAM/UTAUT/TPB	Use of AI for learning by pre- service teachers in the future.
12	AU	UTAUT/extended TAM	Actual use of AI in daily-life, such as frequency, duration, or types of AI-support tasks.

2.1. Cognitive load regulation and responsible AI awareness

This study highlights two factors that are hypothesized to directly influence TL: CLR and RAA. CLR reflects the extent to which AI system design minimizes unnecessary cognitive effort, enabling users to concentrate on higher-level learning tasks. When AI tools effectively support subtasks and offer clear, intuitive interfaces, they can significantly reduce cognitive load, thereby promoting greater trust in the technology [11]. This includes when learners perceive that smart technology supports meaningful learning and aligns with fair assessment practices, the level of confidence in and continued use of the technology will increase [12], [13]. At the same time, RAA emphasizes the importance of ethical aspects, such as fairness, transparency, and data privacy, as essential bases for trust in AI. Trust is more likely to develop when users see that AI systems are used in a fair, transparent, and responsible way, especially in educational settings where data sensitivity and academic integrity are critical [14].

2.2. The AI self-efficacy paradox

In most TAMs, ASE would be generally expected to have positive influence towards trust [15]. For GenAI, this relation is theoretically challenging according to this work. As suggested in the study by Hazzan-Bishara *et al.* [16], pre-service teachers with higher levels of ASE might have a deeper understanding of AI limitations, such as hallucinations, errors and more general risks related to AI outputs. This higher level of awareness could encourage more in-depth review (scrutiny) of the AI output and help to avoid overuse (overreliance) on AI system [16], [17]. This type of behavior is indicative of trust calibration, where we consciously calibrate our trust to a level, we deem proper or cautious. Quite the contrary, increased levels of ASE can ironically cause lower automatic trust in AI. Therefore, the current study hypothesizes that there may be a negative association between ASE and TL.

2.3. The path to actual AI use

The provided model also investigates the way toward real AI applications. TL is postulated to be a core psychological factor in understanding BI [2], [11]. In contrast, BI is anticipated to be the strongest determinant of AU consistent with UTAUT. Furthermore, in the same stride, contextual and environmental factors, INC, SI, and FC are reported to directly influence BI. Innovativeness and compatibility (INC) is one of the important internal enablers to openness to innovation, and predisposition of organizational members for experimentation with new technologies [18], [19]. In conclusion, the review indicates that pre-service teachers' TL is a multi-dimensional construct depending on self-knowledge and skills, psychological preparedness, perceived technical factors, social and organization influence as well as ethical and trust dimensions. These understandings underpin a strong theoretical basis on which to build the framework for this research and for advancing the SEM to investigate pre-service teachers' readiness and trust in AI adoption in higher education.

3. METHOD

3.1. Research context

The study was conducted at government-funded public universities in Thailand that offer teacher education program across a wide range of disciplines. These programs include early childhood education, special education (for both special and general education teachers), English, foreign languages, mathematics, science, social studies, physical education, art, educational technology, and related fields. Within these programs, pre-service teachers are trained under an outcome-based education (OBE) framework, in which digital technologies are intentionally integrated as a systematic component of teacher preparation. This approach, pre-service teachers with the knowledge, skills and professional competencies required prior to entering the teaching profession as licensed teachers. Through this technology-enhanced instructional approach, pre-service teachers are provided with opportunities to engage with AI tools in completing coursework, designing learning activities, and preparing lessons. Such tools include Canva, Claude AI, Grammarly, ChatGPT [20], Perplexity, NotebookLM, and Gemini. These AI applications are used to support learning in foundational courses, professional subject areas, and teaching practicum preparation.

Crucially, pre-service teachers in Thai public universities are educated within a standardized teacher education programmed regulated by the Teacher's Council of Thailand. This approach guarantees that all institutions, if not equal, are at least close to being exposed equally to educational opportunities and technologies like AI tools. These factors enhance the reliability, consistency and context validity of the findings to capture what is happening in teacher preparation in Thailand.

3.2. Participants

The sample of pre-service teachers in this study consisted of preservice teachers studying at government universities in Thailand. A purposive sampling method was used with inclusion criteria. Eligible applicants are those who were prospective pre-service teachers in a public university and had access for at least one semester to apply AI in educational purposes within the last academic term. These criteria were designed to ensure that the data generated was specifically relevant to the research aims and produced analytically rich results.

The pre-service teachers who participated (N=283) completed an online survey. Subsequently data clean-up processes were conducted, and screening of incomplete responses, missing values, outliers and internally inconsistent responses was performed. The study sample consisted of 260 valid cases, after excluding 23 responses. This sample size satisfied the minimum for SEM, according to suggested guidelines proposed by Hair *et al.* [21], should be applied when there are at least 10 cases per estimated parameter.

3.3. Instrument

Data were collected using an online questionnaire comprising of 60 items measured on a 5-point Likert scale. The scale was developed to measure pre-service teachers' trust in and use of AI for learning. The questionnaire was designed based on a synthesized theoretical framework, which integrated the technology TT and TAM, as well with its extended version UTAUT, AI literacy of users and ethical handling of AI in educational settings. The questionnaire included 12 constructions: AIL, ASE, PEOU, PU, SI, FC, RAA, INC, CLR, TL, BI and AU. Internal consistency reliability was tested via a pilot study and Cronbach's alpha coefficients for all 12 (sub)constructs ranged from 0.82 to 0.91, indicating good reliability.

3.4. Data analysis

Statistical hypotheses test data were analyzed utilizing complex statistical procedures, based on to the one hand the proposed concept framework and its variables was tested relationships. We used SEM–because it is a powerful means to estimate the fit of the theoretical model to the data and provides simultaneous analysis of multiple direct and indirect effects among latent variables.

4. RESULTS

4.1. Model fit statistics

A particularly good fit was obtained for the SEM provided. Results of the fit indices for the full model, the overall model fit indices showed that the model fitted well according to the suggested thresholds in statistical literature, as summarized in Table 2. The key statistics including relative chi-square ($\chi^2/df=1.601$) was less than the recommended threshold of 2.0 indicating a high adequacy of model fit. Moreover, the value of root mean square error of approximation (RMSEA)=0.049 came into the close fit, validating that recommended model demonstrated an excellent fit to the observed data.

4.2. Predictive power

The exogenous and mediator variables in the model accounted for a large percentage of the variance in the endogenous variables together.

- The predictor variables accounted for 82.10% of the variation in TL.
- The independent variables accounted for 90.80% of BI variance.
- The predictor variables explained the variance in AU with 71.20%.

The very high prediction of the model, especially higher R² [BI (90.80%)], confirms that the 12 dimensions framework used in this study is robust, comprehensive, and fits well into our conceptual representation.

Table 2. Goodness-of-fit indices for the SEM

Fit index	Value	Recommended cut-off	Model fit classification
Chi-square	22.415	-	-
Degrees of freedom (df)	14	-	-
p-value	0.071	p>0.05	Acceptable
Relative chi-square	1.601	≤2.0	Excellent
Goodness of fit index (GFI)	0.986	≥0.90	Excellent
Adjusted goodness of fit index (AGFI)	0.921	≥0.80	Excellent
RMSEA	0.049	≤0.05	Excellent
Root mean square residual (RMR)	0.008	≤0.08	Excellent

4.3. Analysis of causal effects (path coefficients)

The study used path analysis to examine causal relationships in the proposed model of real AI use and viability for empirical data. The aim of this study was to explore the roles of variables as they were proposed. The framework, as shown in Figure 1, comprises nine exogenous variables that influence the model: AIL, ASE, PEOU, PU, RAA, CLR, INC, SI, and FC. Two endogenous mediating variables were included: TL and BI. The final endogenous dependent variable was AU.

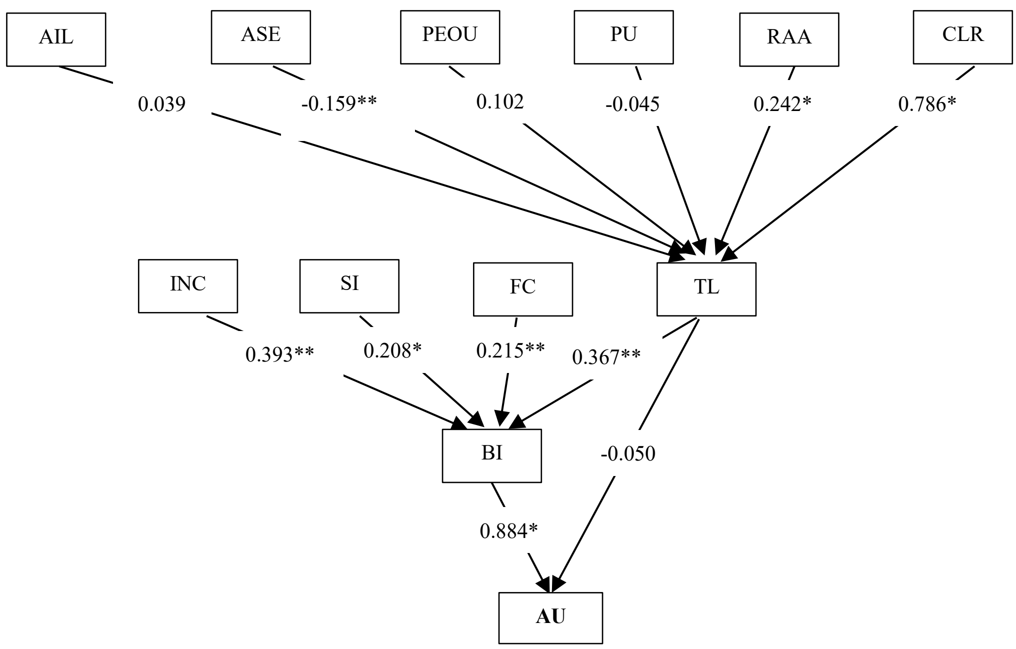

Figure 1. The SEM of AU among pre-service teachers, with standardized path coefficients (β) indicated for each relationship

The SEM results support that TL is influenced by CLR and RAA, rather than by technology skills or prior usage experience alone. Furthermore, BI emerged as significant determinant leading to AU. Furthermore, the finding highlights the prominent role of social and contextual factors. Especially, individual INC, along SI and FC, exerted direct and significant effects on AU among pre-service teachers in post-AI Era context, as summarized in Table 3.

4.3.1. Effects on trust in AI for learning

CLR produced the strongest positive direct effect on TL, as indicated by a high standardized coefficient (β=0.786, p<0.001). RAA also had a significant positive effect on TL (β=0.242, p<0.001). ASE had a significant negative direct on TL (β=−0.159, p=0.009), revealing a complex relationship. Traditional TAM/UTAUT-related variables, such as AIL, PEOU, and PU did not have significant direct effects on TL.

Table 3. Summary of direct effects in the SEM

Path	Relationship	Coefficient (β)	SE	p	Finding
BI→AU	Positive	0.884	0.109	<0.001	Supported
INC→BI	Positive	0.393	0.048	<0.001	Supported
TL→BI	Positive	0.367	0.049	<0.001	Supported
CLR→TL	Positive	0.786	0.120	<0.001	Supported (strongest)
RAA→TL	Positive	0.242	0.058	<0.001	Supported
FC→BI	Positive	0.215	0.045	<0.001	Supported
SI→BI	Positive	0.208	0.041	<0.001	Supported
ASE→TL	Negative	-0.159	0.092	0.009	Supported (paradoxical)
TL→AU	Not significant	-0.050	0.083	0.548	Not Significant

4.3.2. Effects on behavioral intention to use AI

There were four key determinants played a crucial role in BI:
- INC ($\beta=0.393$, $p<0.001$), showed the most direct relationship with BI.
- TL ($\beta=0.367$, $p<0.001$).
- FC ($\beta=0.215$, $p<0.001$).
- SI ($\beta=0.208$, $p<0.001$).

Moreover, CLR and RAA exerted significant, positive, indirect effects on BI, fully mediated by TL.

4.3.3. Effects on actual AI use

BI was identified as the primary direct predictor of AU, with the most significant standardized coefficient in the model ($\beta=0.884$; $p<0.001$). TL did not show a significant direct effect on AU ($\beta=-0.050$, $p=0.548$). However, TL had a significant positive total effect on AU ($\beta\_total=0.275$, $p<0.01$); this was mainly mediated BI. INC, FC, SI, CLR and RAA also exerted significant positive total effects on AU, all of which were mediated by TL and BI.

5. DISCUSSION

In the post-AI Era, to investigate the determiners of both TL and AU among pre-service teachers, a SEM was created. The model showed a strong alignment with the data well and had high explanatory power for BI and AU. The results offer important theoretical and practical insights and future research avenues. This section discusses the findings across three main areas: i) theoretical contributions to trust and AI acceptance in teacher education; ii) practical recommendations for higher education institutions and open universities; and iii) future research directions considering the complex role of ASE.

5.1. Theoretical contributions to trust and AI acceptance in teacher education

The results show that, among pre-service teachers, traditional factors such as PEOU and usefulness are no longer the only drivers of AI acceptance. Now, it is cognitive fluency—that is the capacity of AI to lower mental friction and in turn drive a more effective use of the brain-but also ethics such as ethical and transparent adoption of AI play now an important role. So, trust in AI has more do with perceptions of lower cognitive load and responsible AI, than it does just pure technical benefits. This is consistent with Choi *et al.* [22] who posits that the ethical standard of teachers and their transparency are determinants for AI acceptance in education. It is also in line with Ho *et al.* [6], which indicates that prospective educators have become more sensitive to ethical concerns, including violations of privacy and bias. Consequently, preservice teachers are likely to trust AI only if they perceive that it is being used in a fair, transparent and responsible manner prioritizing learners' welfare [14]. This trend reflects a paradigm shift in TAMs for contemporary AI where ethical-and trust-related considerations, previously marginal to acceptance washes, are now central. The present findings complement prior work that has emphasized the importance of ethics and trust in AI adoption [7], [8], [11], [17], [23] by showing that CLR acts as a more basic psychological mechanism for shaping trust when new users first encounter the technology consistent with previous studies [5], [24]. The results suggest that trust is not simply an attitudinal response but a calibrated appraisal between users' cognitive and moral judgments about AI systems.

A remarkable and theoretically interesting finding is the negative association between ASE and TL. Where prevalent theories suggest that greater self-efficacy should lead to increased trust and more positive attitudes, this study shows that among pre-service teachers an increase in confidence about managing AI relates to less trust. To explain this puzzling finding, we can turn to the trust calibration framework. Individuals with more knowledge about AI are generally more aware of, and sensitive to, the limitations and vulnerability associated with it [25], [26]. For instance, they may understand that LLMs like ChatGPT can generate hallucinations or make mistakes. Such understanding would facilitate vigilant trust and skepticism, preventing blind reliance on AI which may lead to liability risks (over-reliance) for extreme use [27]. Hence, the contrasting relationship between ASE and trust does not imply dysfunctional distrust but signifies emerging critical AI competence [5]. The findings extend existing knowledge by showing that not all relationships between self-efficacy and trust are linear or positive. Instead, its existence is contextual and user- driven, as is informed by their knowledge and critical capacities in line with trust calibration principles that emphasize the relevance of trust situating. The ASE paradox also resonates with Hur [28], that good users are often more skeptical towards AI systems. This study extends this literature by theoretically situating ASE in a structural model that integrates cognitive, ethical and behavioral paths of trust, providing a more complete theoretical understanding for how trust is calibrated in teacher education.

In the research on the relationship between TL and AU it has been found that: trust does not enhance directly AI usage. Instead, trust affects BI, which in turn impacts actual use. Thus, BI mediates between TL and AU, which means that trust is at the bottom of intention, while other constructions are required for actual use. In such a model, users who put faith in AI might not adopt it instantly. Trust, however, indirectly affects usage by fostering BI as a precursor to adoption. This understanding suggests the necessity to distinguish between trust's direct and indirect effects, as they may be relevant based on context and type of user. This mediating path aligns with previous SEM works in education technology [12], [26], but a new contribution of the present research is to consider trust not as parallel predictor but as precursor to intention clarifying theoretical models of AI acceptance. Overall, this study contributes to three theoretical aspects: i) reconceptualizing AI trust as a calibrated construct that is formed by cognitive and ethical judgments; ii) in the context of TAM, incorporating ASE paradox for understanding technology acceptance mechanism; and iii) disentangling differences between trust and actual use while BI serves as mediator in teacher education.

5.2. Practical implications for higher education institutions

The findings offer important practical implements for teacher education programs and distance learning /lifelong education open universities. A more general point is that the preparation of teachers by their courses should focus more on developing critical AI competence rather than simple AI literacy or regular tool use [29]. In this study, pre-service teachers prefer AI systems that reduce cognitive load and foster deeper learning, which also suggests the necessity of a complete curriculum reform. Therefore, choosing and designing AI-powered tools should consider the functionalities that relieve users of repetitive or cognitively heavy duties such as AI-based summarization, assistance to assessment or information processing to keep a desired impact on learners' satisfaction and beliefs towards AI [30]. Teacher education programs need to shift from basic AI literacy to critical AI competence, from technical skills only to reflective use, ethical reasoning and trust calibration. In the meantime, educational institutes should integrate AI ethics education into teacher training programs one after another [11]. Embedding responsible AI principles (fairness, transparency, accountability and learner protection) within teaching can support learners to develop their ethical reasoning for use of AI in teaching and learning. While these efforts build both trust in AI as seen by the positive effect of RAA on TL, they also begin to establish future teachers who will have opportunities for practicing ethical AI.

In addition to curricular development, institutional context and systemic support matter. Previous studies show that SI and FC are major factors contributing to preservice teachers' intention to use AI [17]. Support from fellow students, mentors, college members, and available technological resources as well drive people to adopt AI. Colleges and open universities should develop learning communities and networks for sharing experiences that support best practices, innovative AI integration. AI system cognitive ergonomics should reduce extraneous cognitive load and enhance higher-level thinking, as opposed to simply automating tasks. The administrative and technical authorities need to promptly ensure the availability of sound infrastructure, support services such as high-speed internet access, secured AI software environment and timely supported help desk. Investments made in these areas help to reduce access barriers and increase the confidence that users can use AI effectively and productively when they are ready for it. Together, these acts can engender an ecosystem in which trust, competence and responsible use are allowed to coevolve to support a sustainable AI adoption in open and distance education.

5.3. Future research directions arising from the ASE paradox

The ASE paradox, which describes the counterintuitive negative relationship between ASE and TL, opens several promising avenues for future research. Although this study sees such tendency for positive development, it brings up numerous questions about the circumstances and reasons aside from critical AI skills creating the mutual influence. First, longitudinal research should examine whether the ASE paradox remains stable as teachers transition from pre-service to in-service roles. Tracking changes in ASE, trust, and AI acceptance over time, such as before and after teaching practicum experiences or across the full teacher education through graduation. Such research could help to determine whether the impact is a fading characteristic of initial training or a persistent feature in professional practice. Second, cross-AI tool and between-educational setting comparisons are essential to examine the generalizability of the ASE paradox. Furthermore, studies need to investigate whether the ASE paradox holds across AI and EdTech environments. For instance, in cases where AI systems are reliable, it would be interesting to check if high ASE is still associated with less trust than low ASE. In low-quality AI conditions, though, with high error rates, the amount of distrust in their system might be even higher for high-ASE users. These issues are difficult to handle except with well-designed experiments that can find causal effects. Third, mixed method studies are necessary to investigate how teachers understand trust, risk and AI dependence in actual classroom practice. Another promising direction would be to research trust calibration in enhanced AI educational settings. Applying qualitative or mixed methods research, may provide us with richer stories on how pre-service teachers at several levels of ASE reasoning understand trust, risk and dependency to AI for several teaching contexts. Methodologically, the complexity of the ASE paradox might also be revealed using techniques such as in-depth interviews, think-aloud protocols, or behavioral observations to understand the underlying decision-making processes.

Among other things, future research should develop and evaluate training interventions addressing trust calibration and responsible use of AI in teacher education. Future research could also work towards designing and testing training programs or interventions that encourage appropriate trust calibration in using AI. These might teach users to critically go about assessing AI's usefulness and limitations. Beyond their theoretical relevance, these tools also have practical potential for teacher training, to promote an ethical and pedagogically appropriate attitude of future teachers to AI.

6. CONCLUSION

The present study givens a full structural model to account for trust in AI and actual usage of AI by pre-service teachers at the time when all or most industries have been penetrated by AI–post-AI era. The findings reveal that minimizing cognitive load and addressing ethical challenges of AI are critical building blocks for trust, which takes precedence over rudimentary technical capacity or cursory utilitarian perception. Further, intention to use AI is shaped not only by individual factors such as innovation, but also social or institutional contexts that are critical in the translation of intentions into action. Contributing to the existing research on AI trust and adoption in teacher education, this study highlights the new dimensions related to technology acceptance which have become important for today's classroom involving AI. The results are also of value to schools interested in kits for achieving a successful and ethical AI deployment. Finally, the finding of the ASE paradox in the context of AI as an opposite relationship between ASE and trust is a promising avenue for future research. More fully comprehending this paradox can support the development of practices that enable purposeful, responsible and safe learning environments in schools.

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C : **C**onceptualization
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Va : **Va**lidation
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

INFORMED CONSENT

Informed consent has been obtained from all individuals included in this study.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author, [KM], upon reasonable request.

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