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Pre-Service Science Teachers Trust in Artificial Intelligence-Based Educational Technologies: A Gender-Based Analysis

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Abstract

Trust in artificial intelligence (AI)-based educational technologies involves more than favourable perceptions, as pedagogical benefits may coexist with concerns about reliability and varying willingness to collaborate with AI. This study examined three dimensions of AI-related trust and gender differences among Malaysian pre-service science teachers. A quantitative cross-sectional survey involving 116 participants from several Institutes of Teacher Education employed an adapted questionnaire measuring perceived benefits, reasons for distrust, and willingness to work alongside AI. The findings revealed relatively high perceived benefits and willingness, alongside substantial distrust-related concerns. Although no significant gender differences were found in perceived benefits or distrust, a significant difference emerged in willingness, with male participants reporting higher scores than female participants. These findings highlight the importance of examining AI-related trust through distinct dimensions rather than relying exclusively on an overall trust score. The study contributes empirical evidence on multidimensional trust in AI-based educational technologies and emphasises the importance of integrating critical AI literacy, ethical awareness, and responsible human–AI collaboration into science teacher education programmes to promote informed trust and equitable opportunities for AI engagement.

Keywords: Artificial Intelligence (AI), teacher trust, Technology Acceptance Model (TAM), Gender

Introduction

Artificial intelligence (AI), particularly generative AI (GenAI), is reshaping lesson preparation, feedback, assessment and the presentation of complex scientific concepts. In science education, AI-supported representations and inquiry resources may enrich learning, but scientifically inaccurate or fabricated content can also reinforce misconceptions. Its educational value therefore depends on teachers' capacity to evaluate scientific accuracy and pedagogical appropriateness, rather than on technological functionality alone (Kasneci et al., 2023). Proposed applications in primary science include adaptive scaffolding, multimodal explanations and personalised support, although their educational effectiveness requires empirical evaluation (Tiong, Chongo, & Lapawi, 2025).

This tension creates a professional preparation challenge for pre-service science teachers, who will be expected to make defensible instructional decisions about AI-generated material. Responsible use requires more than familiarity with digital tools: prospective teachers must decide whether to adopt, modify, verify or reject AI outputs. UNESCO's AI Competency Framework for Teachers foregrounds human-centred values, ethical responsibilities and pedagogical judgement in such decisions (Miao & Cukurova, 2024). In this setting, trust matters because both uncritical acceptance and blanket rejection of AI recommendations may undermine informed instructional practice.

A specific empirical gap concerns how such trust-related evaluations are represented among Malaysian pre-service science teachers. Perceived educational benefits, reasons for distrust and willingness to work alongside AI need not move together; treating them as a single undifferentiated attitude could obscure meaningful patterns, including differences between gender groups. Moreover, international findings cannot simply be assumed to apply to Malaysian Institutes of Teacher Education (Institut Pendidikan Guru, IPG), where professional preparation and opportunities to engage with AI may differ. Examining these reported orientations separately can therefore contribute context-sensitive evidence without assuming that gender itself explains the responses or that the three orientations have already been validated as a single measurement structure.

Accordingly, this study describes Malaysian pre-service science teachers' reported perceived benefits of AI, reasons for distrust and willingness to work alongside AI, and examines gender-group differences in these domains. The study is descriptive and comparative: it does not measure actual AI reliance or establish causal relationships. It addresses the following research questions:

i) What is the level of trust in AI-based educational technologies among Malaysian pre-service science teachers?
ii) Are there significant gender differences in trust toward AI-based educational technologies?

Literature Review and Theoretical Framework

Trust in AI-based educational technology concerns expectations of dependable performance when users must act under uncertainty. Lee and See's (2004) Trust in Automation framework emphasises appropriate reliance rather than maximum trust, whereby reliance on automated systems should be aligned with their demonstrated capabilities and limitations. For prospective science teachers, this entails maintaining accountability for the scientific claims and learning activities they select, even when AI assists their preparation. This framework provides the study's primary conceptual orientation, while the distinction between reported trust-related perceptions and observed reliance remains essential because reliance behaviour was not measured.

The Technology Acceptance Model (TAM) proposes perceived usefulness and perceived ease of use as antecedents of technology acceptance (Davis, 1989). It offers a secondary perspective on perceived value, but the present questionnaire did not directly operationalise these TAM constructs or test adoption pathways. A related professional perspective is AI literacy, which involves understanding and critically evaluating AI systems (Long & Magerko, 2020). Recent research synthesising AI in pre-service teacher education points to a growing

emphasis on AI competencies (Wang, Zhang, Han, & Wei, 2026), while reviews of teachers' AI-literacy measures highlight variation in construct definitions and reliance on self-report measures (Zainal, Mohd Matore, & Maat, 2026). These perspectives contextualise professional readiness; neither AI literacy nor demonstrated AI competence was directly assessed in this study.

The measurement literature provides a further reason to avoid reducing trust to an unexamined composite. Nazaretsky, Cukurova, and Alexandron (2022) developed a teacher trust instrument with eight exploratory factors. For the present study, 24 retained items were organised into three reporting domains: perceived benefits (six items), reasons for distrust (nine items) and willingness to work alongside AI (nine items). This organisation is an adaptation for descriptive comparison, not evidence of a newly validated three-factor or higher-order reflective model. High internal consistency within a domain does not, on its own, establish factorial or discriminant validity or justify an aggregate trust score. The domains are consequently interpreted as related but non-interchangeable observed orientations.

Studies of prospective teachers illuminate why these orientations require careful distinction. Drawing on the Theory of Planned Behavior, Ramnarain, Ogegbo, Penn, Ojetunde, and Mdlalose (2025) examined pre-service science teachers' intentions to integrate GenAI into inquiry-based teaching, demonstrating the relevance of intended pedagogical use. Gamlem, McGrane, et al. (2026) documented both opportunities and concerns in Norwegian pre-service teachers' experiences, whereas Gamlem, Johnston, Moltudal, McGrane, and Hopfenbeck (2026) compared perspectives of pre-service teachers and teacher educators, drawing attention to professional context. In an investigation involving 20 pre-service science teachers, H. Hu, Yu, and Xu (2026) examined how participants judged AI-generated scientific explanations, including the evidentiary standards and verification strategies they used. These studies address different outcomes but collectively suggest that enthusiasm for AI should not be read as either an absence of reservations or proof of appropriate reliance.

Broader educational and institutional perspectives further qualify interpretations of trust. A review by Lelescu, Sava, Grosseck, and Malita (2025) identified individual, institutional and socio-ethical influences on educators' trust in GenAI, implying that stated attitudes cannot be explained solely as personal preferences. In STEM education, Lapawi, Osman, and Husnin (2026) discussed GenAI in relation to computational thinking skills and learner dispositions. Such work helps establish the wider pedagogical significance of AI, but evidence about student learning or disposition is not direct evidence of pre-service teachers' trust. These distinctions are important when positioning teacher trust as a specific focus within a rapidly expanding AI education literature.

The Malaysian evidence base offers relevant, although non-equivalent, points of comparison. In a survey of 112 pre-service science teachers, Chongo and Ruzaimi (2026) reported high readiness to integrate AI into science teaching and no statistically significant gender difference in readiness. Readiness, however, is not synonymous with trust or willingness to collaborate with AI. In a qualitative case study involving four teacher trainees, Er and Chongo (2025) described perceived advantages of personalisation and conceptual visualisation together with concerns about training and unequal access. These findings locate the present

investigation within Malaysian teacher preparation while leaving the three trust-related response domains to be examined concurrently in its own sample.

Gender comparisons require equal conceptual caution. Research on technology acceptance has considered group-specific patterns (Marquez Garcia, Gallego Gomez, Tapia Lopez, & Schlosser, 2024), including investigations of gender in educational technology contexts (Sudrajat, Suherman, & Yusuf, 2024), but such findings should not be transferred uncritically to AI trust in science teacher education. Similar aggregate scores can conceal different domain-level responses; conversely, a non-significant difference does not establish equivalence. In this cross-sectional convenience sample, gender serves only as a grouping variable. Any observed contrast may be associated with unmeasured exposure, training or access, and cannot establish an inherent gender-based explanation.

Taken together, the theoretical and empirical literature supports a framework in which perceived benefits, reasons for distrust and willingness to work alongside AI are examined separately, with gender used for group comparisons. Appropriate reliance supplies the primary theoretical rationale, TAM and teacher AI-literacy perspectives provide complementary context, and the adapted trust questionnaire supplies the observed reporting domains. The framework neither tests causal pathways nor claims factorial validation or actual adoption behaviour. Figure 1 presents this conceptual organisation.

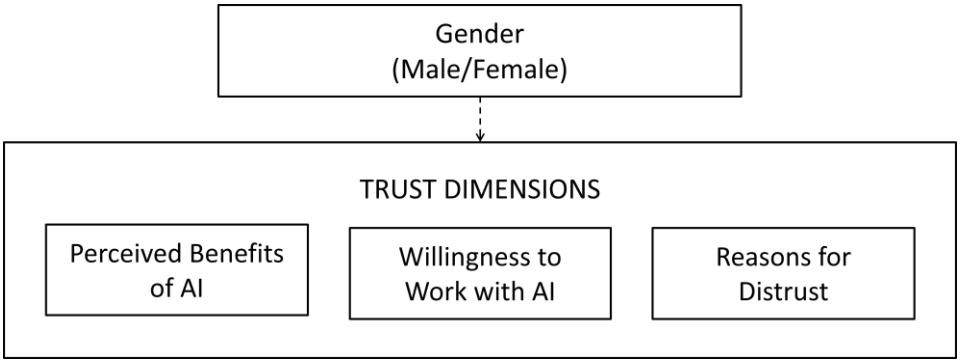


Figure 1 Conceptual Framework of the Study
Note. The framework presents three analytically distinct domains of AI-related trust adapted from Nazaretsky et al. (2022).

Methodology

Research Design

This study employed a quantitative cross-sectional survey design to examine pre-service science teachers' trust in AI-based educational technologies. This design enables the collection of data at a single point in time to describe participants' perceptions and examine differences between groups (Creswell & Creswell, 2018).

Participants

The participants consisted of pre-service science teachers enrolled in Institutes of Teacher Education (IPG) campuses in Malaysia. A convenience sampling method was employed, with participants recruited through online distribution. A total of 116 valid responses were obtained from pre-service science teachers across multiple IPG campuses in Malaysia.

Instruments

Data were collected using a 24-item questionnaire adapted from Nazaretsky et al. (2022) to measure teachers' trust in AI-based educational technologies. One item (Q3) from the original 25-item instrument was excluded as it was deemed less relevant to the local context. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The original instrument has been previously validated in educational contexts. Content validity was established through expert review during the original instrument development, ensuring that the items adequately represented the construct of teacher trust in AI. Construct validity was supported by the factor structure identified in the original study (Nazaretsky et al., 2022). However, the validity evidence for the original instrument does not necessarily establish the structural validity of the adapted three-domain version used in the present study.

Prior to the main data collection, a pilot test was conducted with a small group of pre-service teachers to assess clarity, readability, and contextual relevance. The instrument was found to be clear and appropriate based on participant feedback, with no major issues reported. This procedure supported the face validity of the adapted instrument. For the purpose of this study, the 24 items were organised into three broader reporting domains: perceived benefits of AI (6 items), reasons for distrust (9 items), and willingness to work alongside AI (9 items). For the distrust domain, higher scores indicate stronger agreement with reasons for not trusting AI-based educational technologies (i.e., greater distrust). Although the original factor analysis revealed a more detailed multi-factor structure, this three-part grouping reflects the way the instrument was administered. In this study, trust is operationalised as a multidimensional evaluative construct based on perceived benefits, distrust, and willingness to work alongside AI.

Data Collection

Data were collected using an online survey administered via Google Forms. The survey link was distributed through communication platforms such as WhatsApp to reach pre-service science teachers across multiple IPG campuses. Participation was voluntary, and informed consent was obtained prior to data collection.

Data Analysis

The collected data were analysed using IBM SPSS Statistics software. The data analysis procedures were guided by the study's two research questions. First, reliability analysis was conducted using Cronbach's alpha to assess the internal consistency of the instrument. A Cronbach's alpha value of 0.70 or higher was considered acceptable (Field, 2018).

For Research Question 1: "What is the level of trust in AI-based educational technologies among Malaysian pre-service science teachers?", descriptive statistics, specifically the mean and standard deviation, were used to evaluate the three trust-related dimensions. Responses to the Likert-scale items, which ranged from 1 (strongly disagree) to 5 (strongly agree), were analysed to obtain mean scores for each of the three dimensions: perceived benefits, reasons for distrust, and willingness to work alongside AI. The mean scores were interpreted separately to provide a more detailed understanding of pre-service science teachers' evaluations of AI-based educational technologies.

For Research Question 2, an independent-samples t-test was conducted to examine whether there were significant gender differences in overall trust toward AI-based educational technologies. Descriptive statistics were also used to compare group means across the three trust dimensions. Additional dimension-level inferential comparisons were calculated from the reported group summary statistics and interpreted cautiously because these estimates were not independently verified using the original participant-level dataset.

Research ethics

Ethical considerations were taken into account during the data collection process. Participation in the study was voluntary, and informed consent was obtained from all participants before they completed the online questionnaire. Participants were informed about the purpose of the study and their participation in the research. The collected data were used for research purposes, and the findings were reported in an aggregated form to describe participants' perceptions without identifying individual respondents.

Results and Discussion

This section presents the findings and discussion of the study, including respondent profile, reliability analysis, descriptive statistics, and gender differences in trust toward AI-based educational technologies. All statistical analyses were conducted at a significance level of $p < .05$. A total of 116 respondents participated in this study. Among them, 80 (69.0%) were female and 36 (31.0%) were male. The gender distribution of the respondents is illustrated in Figure 2.

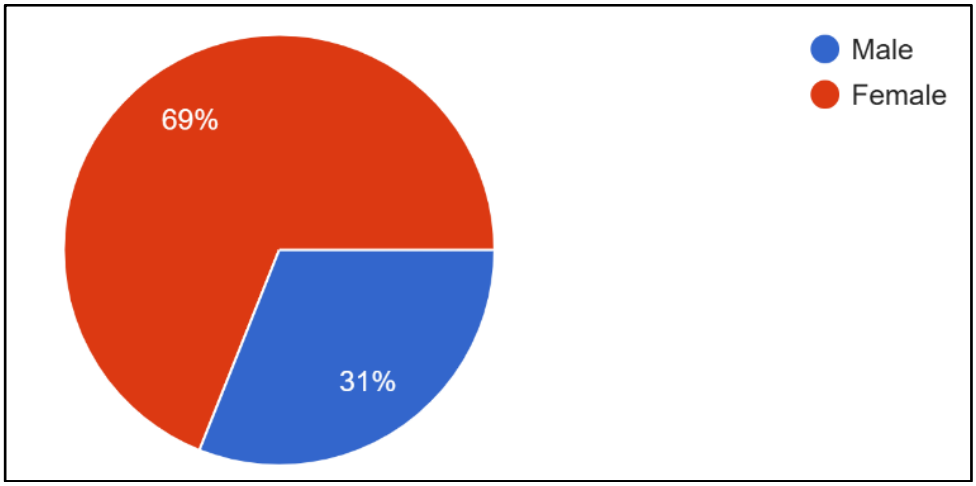


Figure 2 Gender Distribution of Participants

The respondents were drawn from multiple Institutes of Teacher Education (IPG), with the majority from IPG Kampus Pulau Pinang, followed by IPG Kampus Kent, IPG Kampus Ipoh, and other campuses. In terms of specialization, most respondents were Science majors, while a smaller proportion were Science minors. The internal consistency of the measurement scales was assessed using Cronbach's alpha. As shown in Table 1, all constructs demonstrated high reliability, with values exceeding the recommended threshold of 0.70.

Table 1
Reliability Statistics

Construct	Cronbach's α	Std. Error	95% CI Lower	95% CI Upper
Benefits	0.861	0.027	0.809	0.913
Distrust	0.864	0.027	0.810	0.917
Willingness	0.908	0.017	0.874	0.942

The results indicate that all constructs possess strong internal consistency, suggesting that the instrument is reliable for measuring perceptions of AI in education.

Level of Trust in AI-Based Educational Technologies
Descriptive statistics were computed to examine the level of trust toward AI in education across the three dimensions: perceived benefits, distrust, and willingness. The descriptive statistics for these three dimensions are presented in Table 2.

Table 2
Descriptive Statistics of Trust Dimensions

Variable	Mean	Standard Deviation
Benefits	4.386	0.578
Distrust	3.637	0.720
Willingness	4.125	0.603

Overall, respondents reported relatively high levels of perceived benefits (M = 4.386, SD = 0.578) and willingness to work alongside AI (M = 4.125, SD = 0.603), alongside a substantial level of distrust-related concerns (M = 3.637, SD = 0.720). These findings indicate that pre-service science teachers generally recognise the educational potential of AI and express willingness to engage with AI-based technologies while maintaining reservations about their reliability, transparency, and potential risks. Notably, higher scores on the distrust dimension represent stronger agreement with concerns about AI rather than greater trust. The simultaneous presence of favourable perceptions and distrust-related concerns suggests that evaluations of AI-based educational technologies are multidimensional rather than simply positive or negative. This interpretation is consistent with Nazaretsky et al. (2022), who emphasised the importance of understanding teachers' trust and concerns when integrating AI into educational practices.

Recent evidence provides a useful empirical comparison. Fuchs and Lenzgeiger (2026), in a survey of 295 primary school teachers, identified distinct engagement profiles characterised by different combinations of perceived risk, trust and professional development needs. Although their sample involved practising teachers and different measures, the coexistence of positive evaluations and distrust-related concerns in the present sample similarly cautions against interpreting AI engagement as a uniformly favourable or unfavourable attitude. Importantly, the present descriptive data cannot establish individual-level profiles or correlations among the three domains.

From a theoretical perspective, this pattern is compatible with the concept of appropriate reliance proposed by Lee and See (2004), which emphasises that effective interaction with

automated systems requires users to recognise both their capabilities and limitations. Similarly, the Technology Acceptance Model (TAM) highlights perceived usefulness as an important consideration in technology acceptance (Davis, 1989). Although the relatively high perceived benefits and willingness scores are consistent with the broader propositions of TAM, the present study did not directly examine relationships among perceived usefulness, distrust, and willingness. Therefore, these descriptive findings should not be interpreted as evidence that perceived benefits exert a stronger influence on willingness than distrust or that concerns have no effect on AI engagement.

The findings are particularly relevant to science teacher education, where AI-generated scientific explanations, instructional materials, and learning activities require careful evaluation to ensure scientific accuracy and pedagogical appropriateness. Kasneci et al. (2023) highlighted concerns regarding factual inaccuracies, algorithmic bias, and the need for human oversight when integrating large language models into education. Similarly, Miao and Cukurova (2024), through UNESCO's AI Competency Framework for Teachers, emphasised human-centred approaches, ethical responsibility, and critical judgement in educational AI applications. Accordingly, the coexistence of positive perceptions and concerns may provide a useful basis for designing teacher preparation activities that promote informed AI engagement rather than unquestioning technological acceptance. This interpretation is further supported by H. Hu et al. (2026), who found that pre-service science teachers applied context-sensitive evidence standards and verification strategies when assessing AI-generated explanations. Their qualitative findings clarify why expressed willingness should be accompanied by explicit procedures for checking scientific claims; however, the present questionnaire measured reported orientations rather than actual verification practices.

The relatively high willingness to work alongside AI, despite the presence of distrust-related concerns, may also reflect the distinctive professional preparation context of pre-service teachers. Unlike practising teachers, pre-service teachers are still developing their pedagogical knowledge and professional judgement through coursework and teaching practice. However, the present study did not examine prior AI experience, professional responsibility, or actual classroom behaviour; therefore, explanations based on participants' developmental stage or exposure to AI limitations remain theoretical possibilities rather than empirically established findings. Future research could compare pre-service and in-service science teachers to investigate whether teaching experience, AI literacy, and professional responsibilities are associated with differences in their evaluations of AI-based educational technologies. Evidence from pre-service teacher education also distinguishes intention from implementation. Arthur et al. (2026) examined determinants of intended and actual GenAI use as instructional media in Ghana, highlighting the relevance of trust and enabling conditions to adoption-related outcomes. This provides a comparative rationale for investigating willingness separately, without suggesting that the current respondents' willingness scores demonstrate actual classroom adoption.

It is also important to recognise that the descriptive mean scores do not establish causal or predictive relationships among the three dimensions. Furthermore, classifications such as high or moderate should be interpreted cautiously because empirically validated cut-off values for the adapted instrument were not established. Nevertheless, the findings provide useful descriptive evidence that favourable perceptions, willingness to collaborate with AI,

and concerns about its limitations can coexist among pre-service science teachers. Overall, the study highlights the importance of integrating critical AI literacy, ethical awareness, and pedagogically informed human AI collaboration into science teacher preparation programmes to support responsible and appropriately calibrated trust in AI-based educational technologies.

Gender Differences in Trust in AI-Based Educational Technologies

An independent-samples t-test was conducted to examine whether overall trust in AI-based educational technologies differed significantly by gender.

Table 3

Independent Samples T-Test Results (Overall Trust)

Variable		t	df	p	Mean Difference	SE Difference
Equal Assumed	**Variances**	-1.074	114	.285	-0.098	0.091

Note. Student's t-test (equal variances assumed).

As presented in Table 3, the results indicated that there was no statistically significant difference in overall trust between male and female respondents, t(114) = -1.074, p = .285. Since the p-value is greater than .05, the difference is not statistically significant. However, this finding should be interpreted cautiously because the construction, directional coding, and factorial validity of the aggregate trust score have not been sufficiently established. As trust is examined through three distinct dimensions, gender comparisons at the dimensional level provide a more comprehensive understanding of potential variations in AI-related perceptions and willingness. This approach is consistent with the multidimensional measurement perspective of Nazaretsky et al. (2022) and the importance of establishing construct validity when interpreting composite scores (Cronbach & Meehl, 1955).

Table 4

Group Descriptive Statistics by Gender

Variable	Gender	N	Mean	SD
Benefits	Female	80	4.381	0.613
	Male	36	4.398	0.498
Distrust	Female	80	3.653	0.651
	Male	36	3.602	0.862
Willingness	Female	80	4.024	0.610
	Male	36	4.352	0.528

As shown in Table 4, gender differences in perceived benefits and reasons for distrust were negligible. Female respondents (M = 4.381, SD = 0.613) and male respondents (M = 4.398, SD = 0.498) reported nearly identical levels of perceived benefits, with no statistically significant difference, Welch's t(82.09) = 0.158, p = .875, Hedges' g = 0.029. Similarly, no significant gender difference was identified in reasons for distrust, with female respondents (M = 3.653, SD = 0.651) and male respondents (M = 3.602, SD = 0.862) reporting comparable levels, t(53.70) = −0.317, p = .753, Hedges' g = −0.070. The confidence intervals for both comparisons included zero, suggesting limited evidence of gender-related differences in perceived benefits

and distrust. Nevertheless, non-significant findings should not be interpreted as evidence of complete equivalence between gender groups.

In contrast, a statistically significant gender difference was identified in willingness to work alongside AI. Male respondents (M = 4.352, SD = 0.528) reported higher willingness than female respondents (M = 4.024, SD = 0.610), with a mean difference of 0.328, Welch's t(77.31) = 2.946, p = .004, 95% CI [0.106, 0.550], and Hedges' g = 0.556. The moderate effect size indicates that the observed difference may have practical relevance beyond statistical significance. Moreover, the result remained statistically significant after adjustment for multiple comparisons using the Holm procedure (adjusted p ≈ .013). These additional inferential statistics were calculated from the reported group summary statistics and should be interpreted in light of this methodological limitation.

These findings suggest that gender-group differences in AI-related evaluations may be more pronounced in willingness to collaborate with AI than in perceptions of its benefits or reasons for distrust. Although the overall trust comparison was not significant, the dimension-specific analysis revealed a difference that would otherwise remain less apparent when examining only the aggregate score. This distinction highlights the importance of adopting a multidimensional analytical approach, as different aspects of AI-related trust may exhibit different patterns across demographic groups. A related methodological implication emerges from Fuchs and Lenzgeiger (2026): teachers with different trust and perceived-risk profiles also differed in current and intended GenAI use. Although this was a person-centred study of in-service primary teachers rather than a gender comparison, it strengthens the argument that aggregating distinct evaluations can obscure meaningful heterogeneity. The present findings identify a gender-group contrast specifically in reported willingness, not a generalised difference in AI competence or trustworthiness.

Previous research has reported inconsistent gender-related patterns in technology acceptance (Marquez Garcia et al., 2024). However, the higher willingness reported by male respondents in the present study should not be attributed to inherent gender characteristics or assumed differences in technological confidence, competence, risk tolerance, or prior experience. Such factors were not directly measured and therefore cannot be established as explanations for the observed difference. Similarly, the lower average willingness among female respondents should not be interpreted as resistance to AI or evidence of greater caution in evaluating technological risks. Differences in previous experiences, learning opportunities, AI literacy, and institutional contexts may offer alternative explanations that warrant further investigation.

Recent research on pre-service life sciences teachers further illustrates why contextual explanations are preferable to gender-essentialist interpretations. Mnguni et al. (2026) documented variation in AI readiness, perceived agency and access across socioeconomic teaching contexts in South Africa. Their qualitative findings do not explain the observed gender-group difference in Malaysia, but they reinforce the need to examine training opportunities, technological access and educational settings before drawing explanatory conclusions.

From a broader theoretical perspective, the findings underscore the importance of distinguishing favourable evaluations of AI from willingness to engage with AI-based technologies. Long and Magerko (2020) emphasised that AI literacy involves competencies extending beyond awareness of technological capabilities, including understanding and critically evaluating AI systems. Similarly, Kasneci et al. (2023) highlighted the importance of addressing the opportunities and challenges associated with AI integration in educational environments. These perspectives suggest that willingness to work alongside AI may need to be considered alongside technological understanding, critical judgement, and pedagogical preparedness. Nevertheless, the present study did not directly assess these relationships, and no causal mechanism can be inferred from the observed gender differences.

The findings have implications for science teacher education programmes, particularly in providing equitable opportunities for pre-service teachers to develop informed and responsible engagement with AI-based educational technologies. Rather than assuming that all trainees possess similar levels of readiness, teacher education institutions could incorporate structured AI literacy activities, guided exploration of AI-supported instructional tools, and opportunities to critically evaluate AI-generated scientific content. Such approaches may support the development of informed willingness and responsible human–AI collaboration without reinforcing gender-based assumptions about technological abilities or preferences.

Emerging empirical evidence from teacher education provides further insights into the development of structured professional learning. Y. Hu and Wang (2026) observed uneven self-reported AI-literacy profiles across competency domains, whereas Wang, Chen, and Li (2026) reported greater posttest GenAI-literacy outcomes under teacher-guided use than under comparison conditions in a quasi-experimental study. These results support evaluating structured, guided and ethically informed professional learning as a future intervention; they do not demonstrate that such training would eliminate the willingness difference found here.

Overall, the findings demonstrate that although gender differences in overall trust were not statistically significant, a meaningful difference emerged in the willingness dimension. This provides empirical support for examining AI-related trust through distinct dimensions rather than relying exclusively on an aggregate score. Nevertheless, because the study employed convenience sampling and a cross-sectional design, the findings should be interpreted as dimension-specific associations within the present sample rather than generalisable or causal gender effects. Future research should investigate whether factors such as AI literacy, prior technological experience, self-efficacy, and pedagogical training help explain variations in willingness to work alongside AI among pre-service science teachers.

Theoretical and Practical Implications for Science Teacher Education

The first contribution is conceptual and methodological: positive perceptions of AI benefits, distrust-related concerns, and willingness should not automatically be collapsed into a single trust indicator. The results illustrate how aggregation can conceal a dimension-specific comparison, while the adapted instrument's structural validity remains an open question. This interpretation complements the notion of calibrated trust or appropriate reliance developed by Lee and See (2004), but it is not a test of causal pathways or of the Technology

Acceptance Model (Davis, 1989). Since perceived ease of use and the remaining central TAM constructs were not measured, TAM can serve only as a secondary interpretive perspective.

For science teacher education, the combination of perceived benefits, concerns and willingness supports a curriculum emphasis on responsible rather than unconditional AI uptake. Structured tasks could require pre-service teachers to verify AI-generated scientific claims, identify fabricated or weakly supported explanations, compare outputs with authoritative scientific resources, and document when teacher judgement supersedes AI suggestions. Kasneci et al. (2023) emphasise critical thinking, fact-checking and human oversight in educational AI use; Long and Magerko (2020) outline competencies for understanding and evaluating AI; and Miao and Cukurova (2024) foreground ethics and human-centred teacher competencies. Such instructional activities are proposed implications, not interventions evaluated in this study.

The willingness contrast also suggests the value of providing equitable, guided opportunities for all trainees to practise AI-supported lesson planning, microteaching and reflective evaluation, without assigning needs or capacities on the basis of gender. Teacher educators could diagnose individual support needs using validated measures and evaluate whether training improves responsible AI use. These proposals are consistent with the professional-development emphasis of Nazaretsky et al. (2022), but their effectiveness requires separate intervention research.

Conclusion

This study examined three dimensions of trust in AI-based educational technologies among Malaysian pre-service science teachers: perceived benefits, reasons for distrust, and willingness to work alongside AI. The findings revealed favourable perceptions and high willingness alongside substantial distrust-related concerns, highlighting the multidimensional nature of AI-related trust. Although no significant gender difference was found in overall trust, dimension-specific analyses identified significantly higher willingness among male respondents, with a moderate effect size. No significant differences were observed in perceived benefits or distrust. These findings emphasise the importance of examining trust dimensions separately rather than relying exclusively on an overall score.

The study contributes to understanding AI-related trust among pre-service science teachers and underscores the importance of integrating critical AI literacy, ethical awareness, and responsible human AI collaboration into teacher education programmes. AI-supported microteaching, lesson planning, and scientific content evaluation may promote informed trust and professional judgement.

Nevertheless, the cross-sectional design, convenience sampling, and limited validation of the adapted instrument constrain generalisability. The dimension-specific results also require verification using participant-level data. Future research should employ validated measures and longitudinal approaches to investigate relationships between trust dimensions and actual AI adoption. Overall, responsible AI integration requires balancing pedagogical benefits with critical evaluation, ethical responsibility, and appropriately calibrated trust.

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