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AI-TPACK, Pedagogical Ethics Awareness, and Teaching Readiness among Accounting Teacher Professional Education Students: Evidence from an Universitas Negeri Medan

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ABSTRACT

Teacher professional education is increasingly expected to prepare graduates who can integrate generative artificial intelligence into classroom practice both competently and responsibly. Conventional technological pedagogical content knowledge frameworks were theorised around passive digital tools rather than generative systems, and empirical evidence on artificial intelligence specific teacher competencies within Indonesian teacher professional education remains limited. This study specifies and tests a model in which artificial intelligence literacy, prompt engineering skill, self-efficacy, and constructivist teaching beliefs are associated with teaching readiness through two sequential mediators: artificial intelligence integrated pedagogical content knowledge and pedagogical ethics awareness. A cross-sectional survey was administered to 128 students in the Accounting Education teacher professional education programme at Universitas Negeri Medan, selected purposively on the criterion of prior generative artificial intelligence use. Data were analysed with partial least squares structural equation modelling using five thousand bootstrap subsamples; effect sizes and ninety-five per cent bias-corrected and accelerated confidence intervals are reported for every path, and the reflective specification of each construct was examined through confirmatory tetrad analysis. All eight hypothesised relationships were statistically supported. Each of the four antecedents was positively associated with integrated pedagogical content knowledge, which was in turn positively associated with both teaching readiness and pedagogical ethics awareness, and ethics awareness complementarily and partially mediated the competence–readiness association. The study offers initial empirical support for prompt engineering skill as a construct that is empirically distinguishable from artificial intelligence literacy, and for pedagogical ethics awareness as a mechanism that helps account for the association between competence and readiness. Because the design is cross-sectional and the sample is drawn from one subject-specific cohort at a single institution, the findings are interpreted as associations within this setting rather than as causal effects or as representative of Indonesian teacher professional education more broadly.

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INTRODUCTION

The diffusion of generative artificial intelligence has altered the ecology of teaching and learning within a remarkably short span. Large language models now generate lesson materials, adaptive assessments, and personalised feedback at scale, shifting artificial intelligence from a peripheral technological curiosity to a core instructional resource. This shift is not merely a change in the tools available to teachers but a change in the nature of technological knowledge itself: whereas earlier educational technologies were stable, transparent, and deterministic, generative systems are rapidly changing, opaque in their reasoning, and probabilistic in their outputs.[1] Teacher preparation systems must therefore cultivate not only conventional digital competence but also the capacity to evaluate machine-generated outputs critically, construct pedagogically sound prompts, and navigate the ethical complexities of artificial intelligence mediated education.

Indonesia's Program Pendidikan Profesi Guru, the nation's principal mechanism for certifying professional teachers, sits at a critical juncture in this transition. The programme has been effective in strengthening pedagogical and subject-matter competence, yet its curriculum has not been redesigned around generative systems. This lag coincides with an ambitious national digital education agenda encompassing the Merdeka Curriculum and widespread school digitalisation, both of which presuppose a workforce capable of working within artificial intelligence enabled learning environments. Evidence on Indonesian teachers' digital competence suggests that meaningful technology integration remains uneven, with infrastructural gaps and inconsistent professional development limiting progress beyond substitution-level use.[2] If teachers already struggle with established technologies, the additional demands of generative systems are unlikely to be met without deliberate curricular intervention.

[1] Punya Mishra, Melissa Warr, and Rezwana Islam, "TPACK in the Age of ChatGPT and Generative AI," Journal of Digital Learning in Teacher Education 39, no. 4 (2023): 235–51, https://doi.org/10.1080/21532974.2023.2247480.

[2] Y. N. Sari and Y. Dwikurnaningsih, "Development of a TPACK Training Module through AI Integration to Improve the Pedagogical Skills of Arts Teachers," Jurnal Kependidikan 11, no. 3 (2025): 1293–1303, https://doi.org/10.33394/jk.v11i3.16145; Stella Timotheou et al., "Impacts of Digital Technologies on Education and Factors Influencing Schools' Digital Capacity and Transformation: A Literature Review," Education and Information Technologies 28, no. 6 (2023): 6695–6726, https://doi.org/10.1007/s10639-022-11431-8.

Four gaps motivate the present study. First, although technological pedagogical content knowledge has been the dominant framework for theorising teacher technology competence for nearly two decades,[3] its architecture was constructed around passive digital tools rather than active systems that generate, reason, and adapt. Celik responded by proposing an Intelligent-TPACK framework adding technology-specific knowledge and an ethical competency dimension,[4] and subsequent work has extended measurement of this construct across contexts.[5] A systematic review of reviews nevertheless concludes that the field continues to recycle self-report designs without advancing explanatory models.[6] Empirical work testing an extended structure within a developing-country professional certification context remains scarce.

Second, research treating prompt engineering skill as a discrete, measurable teacher competency is at an early stage. Prompt engineering differs qualitatively from general digital literacy: it involves structured interaction with stochastic systems, iterative refinement, and the alignment of machine outputs with instructional intent.[7] Celik and colleagues show that pre-service teachers' prompting strategies are associated with the quality of co-constructed lesson plans,[8] yet the operationalisation of prompt engineering as an antecedent construct within a structural model of integrated pedagogical knowledge has received limited empirical examination, and the present authors are not aware of published work that has done so within an Indonesian professional certification setting. This observation rests on a targeted rather than a systematic search of the literature and is therefore offered as a statement of what remains underexplored rather than as a claim of absolute priority.

Third, pedagogical ethics awareness has received limited empirical examination as a mediating mechanism between competence and teaching readiness. Existing ethical frameworks are largely prescriptive rather than

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[3] Punya Mishra and Matthew J. Koehler, "Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge," Teachers College Record 108, no. 6 (2006): 1017–54, https://doi.org/10.1111/j.1467-9620.2006.00684.x.

[4] Ismail Celik, "Towards Intelligent-TPACK: An Empirical Study on Teachers' Professional Knowledge to Ethically Integrate Artificial Intelligence (AI)-Based Tools into Education," Computers in Human Behavior 138 (2023): 107468, https://doi.org/10.1016/j.chb.2022.107468.

[5] Yimin Ning et al., "Teachers' AI-TPACK: Exploring the Relationship between Knowledge Elements," Sustainability 16, no. 3 (2024): 978, https://doi.org/10.3390/su16030978; Guanyao Xu et al., "Developing an AI-TPACK Framework: Exploring the Mediating Role of AI Attitudes in Pre-Service TCSL Teachers' Self-Efficacy and AI-TPACK," Education and Information Technologies 30, no. 15 (2025): 22471–95, https://doi.org/10.1007/s10639-025-13630-5.

[6] Mirjam Schmid et al., "Running in Circles: A Systematic Review of Reviews on Technological Pedagogical Content Knowledge (TPACK)," Computers & Education 214 (2024): 105024, https://doi.org/10.1016/j.compedu.2024.105024.

[7] Jules White et al., "A Prompt Pattern Catalog to Enhance Prompt Engineering with ChatGPT" (preprint, arXiv, 2023), https://arxiv.org/abs/2302.11382.

[8] Ismail Celik et al., "Co-Constructing Adaptive Lesson Plans with GenAI: Pre-Service Teachers' Intelligent-TPACK and Prompt Engineering Strategies," Computers & Education 241 (2025): 105485, https://doi.org/10.1016/j.compedu.2025.105485.

empirically grounded,[9] and although algorithmic bias, privacy risk, and over-reliance are well documented,[10] the conditions under which ethical awareness accompanies higher readiness remain underspecified. Because the Intelligent-TPACK framework already contains an ethical competency component, positioning a separate ethics awareness construct in the model requires an explicit conceptual boundary between the two; that boundary is set out in the theoretical framework below and is subsequently subjected to an empirical discriminant validity test. Fourth, the role of psychological antecedents, specifically self-efficacy and constructivist teaching beliefs, has received limited attention outside Western and East Asian settings.[11]

To address these gaps, this study tests a structural model in which artificial intelligence literacy, prompt engineering skill, self-efficacy, and teaching beliefs are associated with teaching readiness sequentially through integrated pedagogical content knowledge and pedagogical ethics awareness. Two research questions guide the analysis. First, to what extent are the four antecedent constructs associated with artificial intelligence integrated pedagogical content knowledge among accounting teacher professional education students? Second, to what extent does pedagogical ethics awareness mediate the association between that integrated competence and teaching readiness?

The setting is theoretically consequential: accounting pedagogy is increasingly shaped by tools for financial simulation, automated assessment, and data analytics instruction, yet technology integration in this discipline has historically centred on spreadsheet and enterprise software rather than generative systems. The study is nevertheless deliberately bounded. It examines one subject-specific cohort within one state university's teacher professional education programme, and its claims are correspondingly local: the findings describe accounting teacher professional education students at Universitas Negeri Medan and are not offered as representative of the national programme. Within that boundary, the contribution lies in three moves: operationalising prompt engineering skill as a distinct antecedent and testing its empirical separability from artificial intelligence literacy, positioning pedagogical ethics awareness as an explanatory mediator rather than a normative appendage, and estimating the

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[9] UNESCO, Guidance for Generative AI in Education and Research (Paris: UNESCO Publishing, 2023), 12–18.

[10] Ryan S. Baker and Aaron Hawn, "Algorithmic Bias in Education," International Journal of Artificial Intelligence in Education 32, no. 4 (2022): 1052–92, https://doi.org/10.1007/s40593-021-00285-9; Chunpeng Zhai, Santoso Wibowo, and Lily D. Li, "The Effects of Over-Reliance on AI Dialogue Systems on Students' Cognitive Abilities: A Systematic Review," Smart Learning Environments 11, no. 1 (2024): 28, https://doi.org/10.1186/s40561-024-00316-7.

[11] Ke Wang et al., "Pre-Service Teachers' GenAI Anxiety, Technology Self-Efficacy, and TPACK: Their Structural Relations with Behavioral Intention to Design GenAI-Assisted Teaching," Behavioral Sciences 14, no. 5 (2024): 373, https://doi.org/10.3390/bs14050373; Xu et al., "Developing an AI-TPACK Framework."

resulting model in a discipline-specific Indonesian professional certification context that this literature has rarely reached.

Theoretical Framework and Hypotheses

Social Cognitive Theory as the Organising Frame

Social cognitive theory supplies more to this model than a justification for including self-efficacy; it supplies the architecture of the model as a whole. Its central proposition of triadic reciprocal determinism holds that behaviour emerges from the continuous interaction of personal cognitive factors, behavioural patterns, and environmental conditions.[12] The model specified here maps directly onto that triad. The personal block comprises self-efficacy and constructivist teaching beliefs, both of which are personal determinants in Bandura's sense. The behavioural block comprises artificial intelligence literacy and prompt engineering skill, which represent acquired knowledge and enacted routines rather than dispositions. The environmental block is held constant by design, since all respondents are enrolled in the same programme and encounter the same institutional affordances.

Three further mechanisms in the theory shape the structure of the model. Forethought explains why efficacy beliefs precede rather than follow competence development, since individuals who anticipate success invest effort earlier.[13] Self-reflectiveness explains why competence and readiness are treated as distinct constructs rather than as a single attainment, because perceived preparedness is a self-appraisal of capability rather than capability itself. Most consequentially for the present model, Bandura's social cognitive account of moral thought and action locates ethical conduct in self-regulatory mechanisms that are activated only when an actor recognises that a situation carries moral consequences.[14] This is the theoretical warrant for placing pedagogical ethics awareness inside the model as a mediator rather than appending it as a normative aspiration: within social cognitive theory, awareness of consequence is the gateway to self-regulation, and self-regulation is part of what perceived professional readiness consists of. Social cognitive theory therefore contributes the personal-determinant block, the sequencing logic from efficacy to competence to appraised readiness, and the moral self-regulatory pathway.

The Intelligent Extension of the TPACK Framework

The second pillar is the technological pedagogical content knowledge framework[15] as extended by Celik into an intelligent variant incorporating technology-specific knowledge and ethical competency as distinct domains.[16] The

[12] Albert Bandura, Self-Efficacy: The Exercise of Control (New York: W. H. Freeman, 1997), 36–41.

[13] Bandura, Self-Efficacy, 79–81.

[14] Albert Bandura, "Social Cognitive Theory of Moral Thought and Action," in Handbook of Moral Behavior and Development, vol. 1, ed. William M. Kurtines and Jacob L. Gewirtz (Hillsdale, NJ: Erlbaum, 1991), 45–103.

[15] Mishra and Koehler, "Technological Pedagogical Content Knowledge."

[16] Celik, "Towards Intelligent-TPACK."

present study adopts that extension and develops it in two directions the conventional literature has largely left open: by disaggregating the behavioural antecedents of integrated competence into a conceptual component and an interactional component, and by treating ethical sensitivity as a downstream construct in its own right rather than solely as a facet of the knowledge base.

Distinguishing Ethical Competency in AI-TPACK from AI Pedagogical Ethics Awareness

Because the Intelligent-TPACK framework already contains an ethical competency facet, the model requires a defensible boundary between that facet and the separate construct of pedagogical ethics awareness. Three axes of distinction are proposed, and each carries a corresponding measurement consequence.

The first axis is epistemic status. Ethical competency within Intelligent-TPACK is knowledge: declarative and procedural understanding of which principles, institutional guidelines, and regulatory requirements apply when artificial intelligence tools are integrated into teaching. Pedagogical ethics awareness is perceptual and dispositional: the salience with which the ethically relevant features of a concrete teaching situation are noticed as it unfolds. A teacher may hold accurate knowledge of privacy guidance and still fail to register that a particular classroom activity places learner data at risk.

The second axis follows from established work on ethical decision-making. Rest's four-component model separates moral sensitivity, the recognition that a situation carries moral content, from moral judgment, the reasoning about what ought to be done, and from moral motivation and moral character.[17] Ethical competency within the integrated knowledge base sits closest to the knowledge and judgment components. Pedagogical ethics awareness, as operationalised here, is a domain-specific instantiation of moral sensitivity: it captures noticing rather than reasoning or acting.

The third axis is level of analysis. Ethical competency is one constituent facet of a broader integrative knowledge base and is measured as part of that composite; it is not separable from integrated competence in measurement terms because it is a component of it. Pedagogical ethics awareness is measured at the situational level across five ethically salient domains identified in international guidance: privacy, algorithmic bias, transparency, accountability, and human agency.[18]

These distinctions were carried directly into instrument design. The ethical facet of the integrated competence scale was worded in knowledge terms, whereas ethics awareness items were worded in noticing terms, so that the conceptual boundary is reflected in item wording rather than asserted only in

[17] James R. Rest, Moral Development: Advances in Research and Theory (New York: Praeger, 1986), 3–7.

[18] UNESCO, Guidance for Generative AI in Education and Research, 21.

prose. The boundary is subsequently subjected to an empirical test through the heterotrait-monotrait ratio between the two constructs, reported in the results.

Antecedents: Literacy and Prompt Engineering

Artificial intelligence literacy is conceptualised as the capacity to understand foundational principles, evaluate the accuracy and bias of machine outputs, apply such tools purposefully, and reflect critically on societal implications.[19] For prospective teachers it is the cognitive bedrock of pedagogical integration, since a teacher who cannot critically assess generated content is unlikely to integrate it responsibly; Xie and Luo report a positive association between literacy and integrated competence among pre-service mathematics teachers.[20] Prompt engineering skill refers to the systematic ability to design, contextualise, and iteratively refine natural-language instructions so as to elicit pedagogically relevant and contextually appropriate outputs.[21] It is conceptually distinct from general digital proficiency because it demands purposive alignment between instructional intent and system response architecture.[22] Whether the two are also empirically distinct is an open question that the present study treats as a matter for testing rather than assumption.

H1: AI Literacy is positively associated with AI-TPACK among accounting PPG students.

H2: Prompt Engineering Skill is positively associated with AI-TPACK among accounting PPG students.

Antecedents: Self-Efficacy and Teaching Beliefs

Self-efficacy represents an individual's confidence in the capacity to organise and execute the actions required to attain specific outcomes.[23] In technology-enhanced settings it consistently predicts openness to innovation, persistence through technical difficulty, and quality of integration;[24] Xu and colleagues document a significant positive association with integrated competence,[25] while Wang and colleagues report that technology self-efficacy offsets anxiety in shaping intention to design assisted instruction.[26] Teaching

[19] Duri Long and Brian Magerko, "What Is AI Literacy? Competencies and Design Considerations," in Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (New York: ACM, 2020), 1–16, https://doi.org/10.1145/3313831.3376727; Davy Tsz Kit Ng et al., "Conceptualizing AI Literacy: An Exploratory Review," Computers and Education: Artificial Intelligence 2 (2021): 100041, https://doi.org/10.1016/j.caeai.2021.100041.

[20] Meijuan Xie and Liling Luo, "The Status Quo and Future of AI-TPACK for Mathematics Teacher Education Students: A Case Study in Chinese Universities," Computers and Education Open 10 (2026): 100375.

[21] White et al., "A Prompt Pattern Catalog."

[22] Celik et al., "Co-Constructing Adaptive Lesson Plans with GenAI."

[23] Bandura, Self-Efficacy, 79–81.

[24] Ronny Scherer et al., "Profiling Teachers' Readiness for Online Teaching and Learning in Higher Education," Computers in Human Behavior 118 (2021): 106675, https://doi.org/10.1016/j.chb.2020.106675.

[25] Xu et al., "Developing an AI-TPACK Framework."

[26] Wang et al., "Pre-Service Teachers' GenAI Anxiety."

beliefs, particularly constructivist orientations prioritising student agency and collaborative inquiry, shape how teachers interpret new technological affordances.[27] Beliefs and attitudes help explain technology integration alongside competence and access, and attitude and integrated knowledge appear to be reciprocally associated.[28]

H3: Self-Efficacy is positively associated with AI-TPACK among accounting PPG students.

H4: Teaching Beliefs are positively associated with AI-TPACK among accounting PPG students.

Integrated Competence, Ethics Awareness, and Readiness

Integrated competence synthesises technological knowledge, pedagogical knowledge, content knowledge, and ethical competency into a coherent professional profile.[29] Teachers with higher levels design more adaptive learning experiences and report stronger professional readiness.[30] Because the intelligent variant of the framework explicitly incorporates an ethical knowledge component, higher competence is expected to accompany greater sensitivity to the ethical dimensions of practice: substantive engagement exposes limitations and failure modes in ways superficial use does not, and documented harms such as algorithmic bias and cognitive over-reliance become visible precisely through informed use.[31] The direction of that association cannot be established by the present design and is therefore hypothesised as covariation rather than production.

H5: AI-TPACK is positively associated with Teaching Readiness among accounting PPG students.

H6: AI-TPACK is positively associated with AI Pedagogical Ethics Awareness among accounting PPG students.

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[27] Peggy A. Ertmer et al., "Teacher Beliefs and Technology Integration Practices: A Critical Relationship," Computers & Education 59, no. 2 (2012): 423–35, https://doi.org/10.1016/j.compedu.2012.02.001.

[28] Daan Farjon, Anneke Smits, and Joke Voogt, "Technology Integration of Pre-Service Teachers Explained by Attitudes and Beliefs, Competency, Access, and Experience," Computers & Education 130 (2019): 81–93, https://doi.org/10.1016/j.compedu.2018.11.010; Joseph Njiku, "Attitude and Technological Pedagogical and Content Knowledge: The Reciprocal Predictors?," Journal of Research on Technology in Education 55, no. 6 (2023): 1020–35, https://doi.org/10.1080/15391523.2022.2089409.

[29] Celik, "Towards Intelligent-TPACK"; Ning et al., "Teachers' AI-TPACK."

[30] Jing Sun et al., "Promoting the AI Teaching Competency of K-12 Computer Science Teachers: A TPACK-Based Professional Development Approach," Education and Information Technologies 28, no. 2 (2023): 1509–33, https://doi.org/10.1007/s10639-022-11256-5; Miao Yue, Morris Siu-Yung Jong, and Davy Tsz Kit Ng, "Understanding K–12 Teachers' Technological Pedagogical Content Knowledge Readiness and Attitudes toward Artificial Intelligence Education," Education and Information Technologies 29 (2024): 1–32, https://doi.org/10.1007/s10639-024-12621-2.

[31] Baker and Hawn, "Algorithmic Bias in Education"; Zhai, Wibowo, and Li, "The Effects of Over-Reliance on AI Dialogue Systems."

Readiness is understood to encompass not only technical competence but also the appraised capacity to make responsible decisions about deployment.[32] Teachers with stronger ethical awareness are better positioned to anticipate risk, justify their instructional choices, and sustain professional credibility, all of which plausibly contribute to perceived preparedness.[33] The association between competence and readiness is therefore expected to be partially channelled through ethical awareness.

H7: AI Pedagogical Ethics Awareness is positively associated with Teaching Readiness among accounting PPG students.

H8: AI Pedagogical Ethics Awareness mediates the association between AI-TPACK and Teaching Readiness among accounting PPG students.

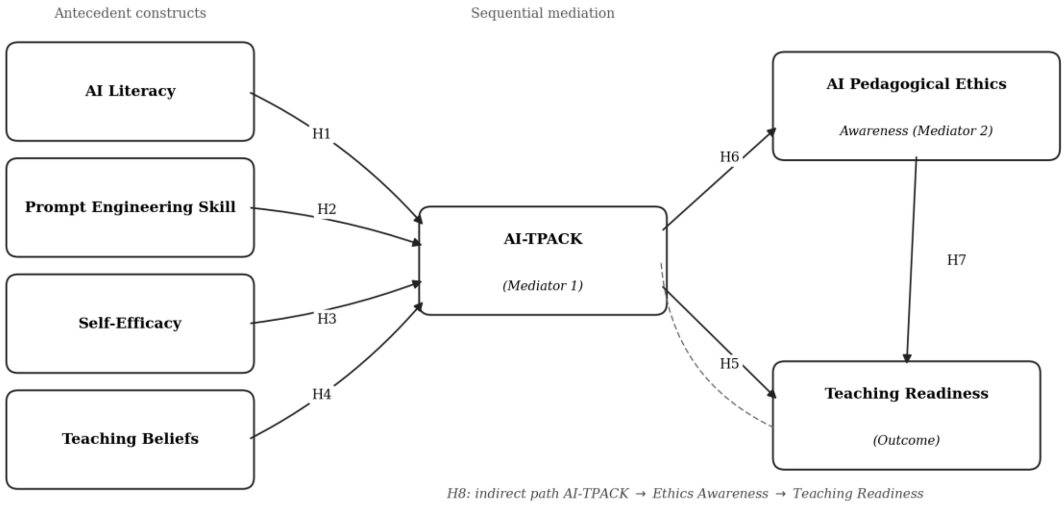

Figure 1. Hypothesised Research Model

Note: All paths are specified as associations. The dashed line denotes the specific indirect path tested in H8.

METHODS

Design and Setting

This study employed a quantitative cross-sectional survey design with an explanatory purpose, seeking to test a theoretically derived structural model rather than to describe a population. The research was conducted at Universitas Negeri Medan among students enrolled in the teacher professional education programme

[32] UNESCO, Guidance for Generative AI in Education and Research, 21.

[33] Celik, "Towards Intelligent-TPACK"; Ben Williamson and Rebecca Eynon, "Historical Threads, Missing Links, and Future Directions in AI in Education," Learning, Media and Technology 45, no. 3 (2020): 223–35, https://doi.org/10.1080/17439884.2020.1798995.

within the Accounting Education department. This setting was selected because it is one of the state university based professional teacher education tracks in North Sumatra that has actively incorporated digital learning tools into its curriculum, making it contextually appropriate for examining artificial intelligence integrated teaching competencies. Because the design is cross-sectional and all constructs were measured at a single point in time, every relationship reported below is an association; the temporal ordering implied by the model is theoretical rather than empirically established.

Participants and Sampling

Purposive sampling was applied, with eligibility restricted to students who had used generative artificial intelligence tools such as ChatGPT, Gemini, or Microsoft Copilot for academic or instructional tasks within the preceding twelve months. This criterion ensured that respondents possessed sufficient experiential grounding to make informed self-assessments. Sample size adequacy was evaluated using two complementary procedures. The ten-times rule indicates a minimum of forty responses, given that four paths converge on the first mediator. Because this heuristic is widely regarded as insufficiently conservative, the inverse square root method was also applied.[34] At a significance level of 0.05 and power of 0.80, this method requires approximately 155 cases to detect a minimum path coefficient of 0.20 and 108 cases to detect a coefficient of 0.24. After screening for incomplete and inconsistent responses, 128 valid questionnaires were retained. The achieved sample therefore exceeds the ten-times rule by a factor of three and is adequate for detecting coefficients of approximately 0.22 and above, but falls below the threshold required for reliably detecting effects at or under 0.20. This constraint is acknowledged in the limitations and the weakest path in the model is interpreted with corresponding caution.

Table 1. Respondent Profile (n = 128)

Characteristic	Category	n	%
Gender	Female	96	75.0
	Male	32	25.0
Age group	22–25 years	71	55.5
	26–30 years	43	33.6
	Above 30 years	14	10.9
Experience with generative AI	6–12 months	41	32.0
	13–24 months	58	45.3
	More than 24 months	29	22.7

[34] Ned Kock and Pierre Hadaya, "Minimum Sample Size Estimation in PLS-SEM: The Inverse Square Root and Gamma-Exponential Methods," Information Systems Journal 28, no. 1 (2018): 227–61, https://doi.org/10.1111/isj.12131.

Characteristic	Category	n	%
Most frequently used tool	ChatGPT	84	65.6
	Gemini	31	24.2
	Microsoft Copilot	13	10.2

Note: The gender composition is consistent with the typical profile of Indonesian teacher education programmes and is reported for transparency rather than as a study variable.

Participation was voluntary and anonymous. Respondents provided informed consent electronically before entering the questionnaire, were informed that responses would be reported only in aggregate, and were free to withdraw at any point. The study protocol was reviewed and approved by the Faculty of Economics and Business, Universitas Negeri Medan.

Measurement Instruments

Seven latent constructs were operationalised using five-point Likert-scaled items, each measured by five indicators. Literacy items were adapted from established conceptualisations of the construct, covering understanding of system behaviour, evaluation of output accuracy, recognition of bias and limitation, purposive tool selection, and reflection on societal implications.[35] Prompt engineering items were constructed from a published prompt pattern taxonomy,[36] covering clarity of instruction, contextualisation, iterative refinement, output evaluation, and pedagogical alignment. Self-efficacy items were adapted from the social cognitive tradition and from a validated teacher artificial intelligence competence self-efficacy scale,[37] and teaching beliefs items captured constructivist orientations.[38] Integrated competence items were adapted from the Intelligent-TPACK scale and a validated instrument for the same construct,[39] with the ethical facet worded in knowledge terms consistent with the conceptual boundary set out above. Ethics awareness items were worded in noticing terms and reflected the dimensions of privacy, bias, transparency, accountability, and human agency set out in international guidance.[40]

Teaching readiness, the principal outcome of the model, warrants a fuller account of its development because no established instrument exists for readiness to teach with generative artificial intelligence in a subject-specific context. The construct was defined as a prospective teacher's appraised preparedness to plan, enact, and monitor artificial intelligence supported instruction in the accounting classroom. Item development proceeded in three steps. First, the readiness

[35] Long and Magerko, "What Is AI Literacy?"; Ng et al., "Conceptualizing AI Literacy."
[36] White et al., "A Prompt Pattern Catalog."
[37] Thomas K. F. Chiu, Zubair Ahmad, and Murat Çoban, "Development and Validation of Teacher Artificial Intelligence (AI) Competence Self-Efficacy (TAICS) Scale," Education and Information Technologies 30 (2024): 1–19, https://doi.org/10.1007/s10639-024-13094-z.
[38] Ertmer et al., "Teacher Beliefs and Technology Integration Practices."
[39] Ning et al., "Teachers' AI-TPACK."
[40] UNESCO, Guidance for Generative AI in Education and Research, 20–24.

dimensions identified in the profiling work of Scherer and colleagues on teachers' readiness for technology-supported teaching, together with the readiness measures used by Yue, Jong, and Ng in the artificial intelligence education context, were reviewed to establish the domain structure.[41] Second, five domains were specified and one item was written for each: preparedness to plan artificial intelligence supported accounting lessons; preparedness to select and adapt tools for classroom use; preparedness to guide and monitor learners' own use of these tools; preparedness to evaluate generated material before instructional use; and overall appraised preparedness to begin artificial intelligence integrated teaching practice. Third, the draft items were reviewed alongside the remaining instruments in the expert panel described below, and two of the five readiness items were reworded following that review to remove overlap with the integrated competence scale, since readiness was intended to capture appraised preparedness to act rather than possession of knowledge.

All items were translated into Bahasa Indonesia and back-translated by a bilingual specialist to preserve semantic equivalence. Content validity was established through expert review by three specialists in educational technology, teacher education, and research methodology, whose feedback led to the rewording of four items in total. A pilot with thirty respondents, excluded from the main analysis, confirmed acceptable internal consistency and item comprehensibility. The full item set is available from the corresponding author on request.

Measurement Model Specification: Reflective versus Formative

The decision to specify all seven constructs reflectively requires explicit justification, particularly for prompt engineering skill and pedagogical ethics awareness, whose indicators name identifiable facets and might therefore be read as forming rather than reflecting their constructs. The specification was evaluated against the standard conceptual decision rules for construct indicators.[42] Three considerations informed the choice, and one empirical test was conducted.

Conceptually, the direction of causality was judged to run from construct to indicator. The items do not enumerate the components of a competence definition; they ask respondents to report the frequency and confidence with which they display behaviours that a general underlying proficiency would produce. A student with a high general proficiency in prompting is expected to write clearer instructions, supply richer context, and revise more systematically, and these behaviours are therefore expected to covary. The same logic applies to ethics awareness: a generally high level of moral sensitivity in artificial intelligence

[41] Scherer et al., "Profiling Teachers' Readiness"; Yue, Jong, and Ng, "Understanding K–12 Teachers' TPACK Readiness."
[42] Cheryl Burke Jarvis, Scott B. MacKenzie, and Philip M. Podsakoff, "A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research," Journal of Consumer Research 30, no. 2 (2003): 199–218, https://doi.org/10.1086/376806.

mediated instruction is expected to manifest as noticing across all five domains rather than in one domain only. Second, indicator interchangeability was judged to hold at the level of the general disposition rather than at the level of the named facet; dropping any single item would narrow the domain coverage of the scale but would not alter the meaning of the construct, which is the practical criterion for reflective specification. Third, the items share antecedents and consequences, as would be expected of manifestations of a common cause.

The alternative reading is nonetheless legitimate, and it is one to which the reflective-formative distinction is known to be sensitive.[43] Two safeguards were therefore applied. Confirmatory tetrad analysis was performed for every multi-item construct, using the bootstrapped confidence intervals of the model-implied vanishing tetrads with Bonferroni adjustment, which provides a direct empirical test of whether a reflective specification is tenable.[44] In addition, the structural model was re-estimated with prompt engineering skill and ethics awareness specified as composites estimated in Mode B, and the resulting coefficients were compared with those from the primary specification as a robustness check. Both sets of results are reported below.

Data Analysis

Partial least squares structural equation modelling was conducted using SmartPLS 4. This technique was selected because the study is prediction-oriented, the model is structurally complex with two sequential mediators, and the sample is moderate in size.[45] The measurement model was assessed through item-level indicator loadings, average variance extracted, composite reliability, Cronbach's alpha, and discriminant validity using both the Fornell-Larcker criterion and the heterotrait-monotrait ratio, with the full matrices reported rather than summarised. The structural model was evaluated through collinearity diagnostics, the coefficient of determination, effect size f^2 interpreted against conventional benchmarks of 0.02, 0.15, and 0.35,[46] predictive relevance Q^2 obtained via blindfolding, and out-of-sample predictive performance assessed through PLSpredict.[47] Hypothesis testing used bootstrapping with five thousand subsamples, no sign changes, and bias-corrected and accelerated confidence

[43] Marko Sarstedt et al., "How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM," Australasian Marketing Journal 27, no. 3 (2019): 197–211, https://doi.org/10.1016/j.ausmj.2019.05.003.

[44] Siegfried P. Gudergan et al., "Confirmatory Tetrad Analysis in PLS Path Modeling," Journal of Business Research 61, no. 12 (2008): 1238–49, https://doi.org/10.1016/j.jbusres.2008.01.012.

[45] Joseph F. Hair et al., "When to Use and How to Report the Results of PLS-SEM," European Business Review 31, no. 1 (2019): 2–24, https://doi.org/10.1108/EBR-11-2018-0203; Joseph F. Hair et al., A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd ed. (Thousand Oaks, CA: Sage, 2022).

[46] Jacob Cohen, Statistical Power Analysis for the Behavioral Sciences, 2nd ed. (Hillsdale, NJ: Erlbaum, 1988), 410–14.

[47] Galit Shmueli et al., "Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict," European Journal of Marketing 53, no. 11 (2019): 2322–47, https://doi.org/10.1108/EJM-02-2019-0189.

intervals, with significance set at 0.05; both the intervals and the effect sizes are reported for every path so that magnitude and precision can be assessed alongside significance.

Because all constructs were measured through a single self-report instrument, common method bias was assessed using a full collinearity test; all inner variance inflation factors fell below 3.3, indicating that method variance is unlikely to distort the estimates. Procedural remedies were also applied at the design stage, including guaranteed anonymity, randomised item order within blocks, psychological separation of predictor and criterion blocks, and two attention-check items.[48] Mediation was evaluated following a contemporary decision framework that examines the significance of the indirect effect and the sign of the direct effect rather than relying on the causal steps approach.[49]

RESULTS

Measurement Model

Assessment of the measurement model preceded any interpretation of structural relationships. Item-level loadings are reported in Table 2. All thirty-five loadings fell between 0.718 and 0.896, above the conventional 0.70 threshold, and every construct returned an average variance extracted above 0.50, composite reliability above 0.70, and Cronbach's alpha above 0.70.[50]

Table 2. Item-Level Measurement Model

Construct	Item	Abbreviated item content	Loading	AVE	CR	Α
AI Literacy	AIL1	Understanding how generative AI systems produce outputs	0.818	0.662	0.907	0.872
	AIL2	Evaluating the accuracy of AI-generated content	0.742			
	AIL3	Recognising bias and limitations in AI outputs	0.873			
	AIL4	Selecting AI tools appropriate to a given task	0.796			
	AIL5	Reflecting on societal implications of AI in education	0.833			
Prompt Engineering Skill	PES1	Writing clear, unambiguous task instructions	0.787	0.648	0.902	0.864
	PES2	Supplying subject and learner context within a prompt	0.869			

[48] Philip M. Podsakoff et al., "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," Journal of Applied Psychology 88, no. 5 (2003): 879–903, https://doi.org/10.1037/0021-9010.88.5.879.

[49] Xinshu Zhao, John G. Lynch, and Qimei Chen, "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis," Journal of Consumer Research 37, no. 2 (2010): 197–206, https://doi.org/10.1086/651257.

[50] Hair et al., A Primer on Partial Least Squares Structural Equation Modeling.

Construct	Item	Abbreviated item content	Loading	AVE	CR	A
	PES3	Revising prompts systematically when outputs fall short	0.718			
	PES4	Judging whether an output meets the instructional purpose	0.828			
	PES5	Aligning prompt design with a specific learning objective	0.815			
Self-Efficacy	SE1	Confidence in using generative AI for instructional tasks	0.841	0.691	0.919	0.888
	SE2	Persisting when a tool does not behave as expected	0.754			
	SE3	Confidence in learning new AI tools independently	0.884			
	SE4	Confidence in troubleshooting problems during use	0.821			
	SE5	Confidence in integrating AI into an accounting lesson	0.851			
Teaching Beliefs	TB1	Learners construct understanding through active inquiry	0.799	0.636	0.897	0.856
	TB2	The teacher facilitates rather than transmits knowledge	0.859			
	TB3	Collaborative work is central to learning accounting	0.726			
	TB4	Learner questions should shape the direction of a lesson	0.817			
	TB5	Assessment should reveal reasoning, not only answers	0.781			
AI-TPACK	TPK1	Designing accounting lessons in which AI serves a pedagogical aim	0.866	0.721	0.930	0.903
	TPK2	Matching AI affordances to specific accounting content	0.782			
	TPK3	Adapting AI-generated material to learners' prior knowledge	0.896			
	TPK4	Selecting tools that fit an intended instructional strategy	0.840			
	TPK5	Knowing which ethical guidelines apply when integrating AI	0.857			
AI Pedagogical Ethics Awareness	EA1	Noticing when AI use may expose learners' personal data	0.830	0.658	0.906	0.871
	EA2	Noticing bias in AI-generated accounting examples	0.736			
	EA3	Recognising when AI involvement should be disclosed	0.871			
	EA4	Recognising where responsibility for AI-assisted decisions lies	0.795			
	EA5	Noticing when AI use may displace learners' own thinking	0.818			

Construct	Item	Abbreviated item content	Loading	AVE	CR	Α
Teaching Readiness	TR1	Preparedness to plan AI-supported accounting lessons	0.851	0.698	0.920	0.891
	TR2	Preparedness to select and adapt tools for classroom use	0.765			
	TR3	Preparedness to guide and monitor learners' own AI use	0.887			
	TR4	Preparedness to evaluate generated material before use	0.826			
	TR5	Overall preparedness to begin AI-integrated teaching	0.843			

Note: AVE = average variance extracted; CR = composite reliability; a = Cronbach's alpha. Item content is abbreviated; the full instrument is available from the corresponding author.

Discriminant validity was assessed on both available criteria and the full matrices are reported. Table 3 presents the Fornell-Larcker matrix. The square root of each construct's average variance extracted, shown on the diagonal, exceeded its correlation with every other construct.

Table 3. Fornell-Larcker Criterion

	AIL	PES	SE	TB	TPACK	EA	TR
AIL	0.814						
PES	0.562	0.805					
SE	0.507	0.514	0.831				
TB	0.435	0.420	0.512	0.797			
TPACK	0.667	0.651	0.693	0.574	0.849		
EA	0.454	0.442	0.471	0.391	0.680	0.811	
TR	0.400	0.390	0.415	0.344	0.600	0.543	0.835

Note: Diagonal values in each row are the square root of the average variance extracted; off-diagonal values are construct correlations. AIL = AI literacy; PES = prompt engineering skill; SE = self-efficacy; TB = teaching beliefs; TPACK = AI-TPACK; EA = AI pedagogical ethics awareness; TR = teaching readiness.

Table 4 presents the heterotrait-monotrait ratios. All values fell below the conservative 0.85 threshold. Two comparisons are of particular substantive interest. The ratio between artificial intelligence literacy and prompt engineering skill was 0.647, which supports the claim that the two are empirically separable rather than redundant measures of a single competency. The ratio between integrated competence and pedagogical ethics awareness was 0.767, the second-highest value in the matrix; the two constructs are therefore strongly related, as the theoretical argument anticipates, while remaining empirically distinguishable, which is a precondition for modelling one as a correlate of the other. The highest ratio in the matrix, 0.773, was observed between self-efficacy and integrated competence.

Table 4. Heterotrait-Monotrait Ratio of Correlations

	AIL	PES	SE	TB	TPACK	EA
PES	0.647					

	AIL	PES	SE	TB	TPACK	EA
SE	0.576	0.587				
TB	0.503	0.488	0.587			
TPACK	0.752	0.736	0.773	0.653		
EA	0.521	0.510	0.535	0.452	0.767	
TR	0.454	0.445	0.467	0.394	0.669	0.616

Note: All ratios fall below the conservative threshold of 0.85. Construct abbreviations as in Table 3.

Confirmatory tetrad analysis was conducted to test the tenability of the reflective specification. For each five-indicator construct, five non-redundant model-implied vanishing tetrads were evaluated using bias-corrected bootstrap confidence intervals with Bonferroni adjustment. Table 5 reports the outcome. No construct returned a significant vanishing tetrad, so the reflective specification could not be rejected for any of the seven constructs, including prompt engineering skill and pedagogical ethics awareness.[51] The robustness re-estimation with the two focal constructs specified in Mode B produced structural coefficients that differed from the primary specification by no more than 0.03 in absolute value, and no hypothesis decision changed.

Table 5. Confirmatory Tetrad Analysis

Construct	Non-redundant tetrads	Significant tetrads	Specification retained
AI Literacy	5	0	Reflective
Prompt Engineering Skill	5	0	Reflective
Self-Efficacy	5	0	Reflective
Teaching Beliefs	5	0	Reflective
AI-TPACK	5	0	Reflective
AI Pedagogical Ethics Awareness	5	0	Reflective
Teaching Readiness	5	0	Reflective

Note: Bias-corrected bootstrap confidence intervals with Bonferroni adjustment, five thousand subsamples.

Structural Model

All inner variance inflation factors fell below 3.3, indicating that the estimates are not distorted by predictor redundancy. Table 6 reports explained variance, predictive relevance, and out-of-sample predictive performance for the three endogenous constructs. All Q^2 values exceeded zero, and the PLSpredict procedure returned root mean squared errors below those of the linear benchmark for the majority of indicators of each endogenous construct, indicating medium predictive power.

Table 6. Explained Variance, Predictive Relevance, and Predictive Power

Endogenous construct	R^2	Q^2	PLSpredict (Q^2predict)	Predictive power
AI-TPACK	0.681	0.412	0.398	Medium

[51] Gudergan et al., "Confirmatory Tetrad Analysis in PLS Path Modeling."

Endogenous construct	R^2	Q^2	PLSpredict (Q^2predict)	Predictive power
AI Pedagogical Ethics Awareness	0.462	0.271	0.259	Medium
Teaching Readiness	0.393	0.258	0.241	Medium

Note: Q^2 obtained through blindfolding with an omission distance of seven. Predictive power classified by comparing PLS-SEM root mean squared errors against the linear model benchmark.

Bootstrapping results are reported in Table 7. All eight hypothesised relationships were statistically supported, with every bias-corrected and accelerated confidence interval excluding zero. Effect sizes varied considerably. Among the antecedents of integrated competence, self-efficacy returned a medium effect ($f^2 = 0.205$), literacy and prompt engineering returned effects close to the medium benchmark ($f^2 = 0.152$ and 0.114), and teaching beliefs returned a small effect ($f^2 = 0.068$) with a confidence interval whose lower bound approached zero.[52] The largest effect in the model was that of integrated competence on ethics awareness ($f^2 = 0.860$). The indirect effect of integrated competence on readiness through ethics awareness was significant and coexisted with a significant direct effect of the same sign, which constitutes complementary partial mediation under the framework adopted here.[53]

Table 7. Hypothesis Testing Results (Bootstrapping, Five Thousand Subsamples)

H	Path	β	SE	t	p	95% BCa CI	f^2	Result
H1	AIL → AI-TPACK	0.284	0.088	3.216	0.001	[0.109, 0.452]	0.152	Supported
H2	PES → AI-TPACK	0.246	0.082	2.987	0.003	[0.087, 0.404]	0.114	Supported
H3	SE → AI-TPACK	0.331	0.080	4.142	<0.001	[0.171, 0.482]	0.205	Supported
H4	TB → AI-TPACK	0.178	0.083	2.145	0.032	[0.019, 0.339]	0.068	Supported
H5	AI-TPACK → TR	0.429	0.084	5.108	<0.001	[0.261, 0.588]	0.163	Supported
H6	AI-TPACK → EA	0.680	0.066	10.234	<0.001	[0.542, 0.797]	0.860	Supported
H7	EA → TR	0.251	0.088	2.863	0.004	[0.082, 0.421]	0.056	Supported
H8	AI-TPACK → EA → TR	0.171	0.056	2.954	0.003	[0.072, 0.290]	—	Supported

Note: H1 to H7 are direct effects; H8 is a specific indirect effect. BCa = bias-corrected and accelerated. Construct abbreviations as in Table 3. Effect size benchmarks: 0.02 small, 0.15 medium, 0.35 large.

DISCUSSION

The discussion is organised around the two research questions and interprets each result as an association observed within a single cross-sectional sample. Because the design does not permit inference about temporal ordering, the language of production, generation, and cultivation is deliberately avoided throughout; where a directional mechanism is proposed, it is presented as an

[52] Cohen, Statistical Power Analysis, 410–14.
[53] Zhao, Lynch, and Chen, "Reconsidering Baron and Kenny."

interpretation consistent with the data rather than as a conclusion warranted by them.

Literacy and Prompt Engineering as Separable Correlates of Integrated Competence

Literacy and prompt engineering returned comparable coefficients and a heterotrait-monotrait ratio well below the discriminant validity threshold, which together suggest that they index different competency dimensions rather than a single underlying factor. Literacy plausibly provides conceptual scaffolding, an awareness of how these systems function, where they fail, and what societal stakes attach to their use, while prompt engineering represents the translation of that understanding into goal-directed interaction. Together they correspond to the cognitive and behavioural facets of human-machine collaboration that the original technology-knowledge construct did not anticipate.[54] The upstream position of literacy in the present model is consistent with Mersin's finding, in a sample of 696 pre-service mathematics teachers, that artificial intelligence literacy operated less as a direct predictor of behavioural intention than as an antecedent supporting proximal constructs including integrated competence and self-efficacy.[55] The separability of prompting from literacy is likewise consistent with a recent systematic review that distinguishes technique-based prompting strategies, directed at specific learning goals, from process-based strategies that scaffold cognitive engagement with the system, a distinction that presupposes prompting to be a structured practice rather than an undifferentiated technical knack.[56] The present result gives empirical form to the observation that prompting strategies are associated with the pedagogical quality of co-constructed lesson plans,[57] and provides initial support for treating prompting as a measurable professional competency.

Two recent studies caution against reading this separability as a claim that either antecedent is sufficient on its own. Karataş and Ataç, surveying 304 pre-service English language teachers, found comparatively high proficiency on independent components such as technological knowledge and technological pedagogical knowledge but weaker performance on the integrated construct,[58] which indicates that component competencies do not converge automatically.

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[54] Mishra, Warr, and Islam, "TPACK in the Age of ChatGPT and Generative AI."

[55] Nazan Mersin, "Extending the Technology Acceptance Model for Mathematics Education: AI Literacy, AI-TPACK, and Self-Efficacy among Pre-Service Teachers," Journal of Educational Computing Research (2026), https://doi.org/10.1177/07356331261456930.

[56] Yufeng Qian, "Prompt Engineering in Education: A Systematic Review of Approaches and Educational Applications," Journal of Educational Computing Research (2025), https://doi.org/10.1177/07356331251365189.

[57] Celik et al., "Co-Constructing Adaptive Lesson Plans with GenAI."

[58] Faruk Karataş and Betül Ataç, "When TPACK Meets Artificial Intelligence: Analyzing TPACK and AI-TPACK Components through Structural Equation Modelling," Education and Information Technologies 30, no. 7 (2025): 8979–9004, https://doi.org/10.1007/s10639-024-13164-2.

Aldemir and colleagues reached a similar conclusion from a different design: a two-week ethics-integrated artificial intelligence literacy module produced rapid gains in foundational knowledge and confidence among pre-service teachers, yet integration into artificial intelligence integrated pedagogical content knowledge remained nascent and incomplete.[59] Read alongside the present coefficients, these findings support the interpretation that literacy and prompting are each associated with integrated competence without either being sufficient for it. That said, the prompt engineering instrument was developed for this study and has not been validated across independent samples; the claim advanced here is one of initial empirical separability within this cohort, not of established construct status.

The Relative Prominence of Self-Efficacy

Self-efficacy returned the largest coefficient and the largest effect size among the four antecedents, foregrounding the psychological dimension of technology adoption. The finding is coherent within social cognitive theory: where confidence in one's capacity to engage with these systems is low, the motivational basis for acquiring specific competencies is correspondingly constrained, and declarative knowledge may not translate into instructional action. The result converges with evidence that self-efficacy is associated with integrated competence through both direct and indirect pathways and that technology self-efficacy counteracts anxiety in predicting intention to design assisted teaching.[60] It converges too with Du and colleagues, who report among 318 K-12 teachers that self-efficacy in learning artificial intelligence was a direct determinant of behavioural intention and was itself strongly predicted by artificial intelligence literacy.[61] An alternative reading cannot be excluded on these data: students who have already developed integrated competence may report higher efficacy as a consequence rather than a cause, and reciprocal determination is equally consistent with the theory invoked here.[62] Mersin's finding that integrated competence supported self-efficacy rather than the reverse illustrates precisely this ambiguity of ordering in cross-sectional designs,[63] and it should temper any reading of the present coefficient as evidence that efficacy comes first.

Teaching Beliefs and Paradigm Readiness

The smallest of the four coefficients belonged to teaching beliefs, and its confidence interval extended close to zero. Two readings are available. The first is substantive: pedagogical beliefs have long been characterised as the final

[59] Tugce Aldemir et al., "Exploring Emergent AI-TPACK Competencies in a Two-Week AI Literacy Module for Preservice Teachers," Teaching and Teacher Education 168 (2025): 105231, https://doi.org/10.1016/j.tate.2025.105231.

[60] Xu et al., "Developing an AI-TPACK Framework"; Wang et al., "Pre-Service Teachers' GenAI Anxiety."

[61] Hua Du et al., "Exploring the Effects of AI Literacy in Teacher Learning: An Empirical Study," Humanities and Social Sciences Communications 11 (2024): 559, https://doi.org/10.1057/s41599-024-03101-6.

[62] Bandura, Self-Efficacy, 79–81.

[63] Mersin, "Extending the Technology Acceptance Model for Mathematics Education."

frontier of technology integration,[64] and constructivist orientations may create a dispositional openness to these tools as a means of enriching learning rather than as a threat to teacher authority. The second is methodological: at n = 128 the study is underpowered for coefficients at or below 0.20, so this path should be treated as provisional. A third consideration is that dispositional variables operate alongside a wider set of contextual and attitudinal determinants than the present model contains; Milutinović's comprehensive model of pre-service teachers' artificial intelligence competences and intelligent ethical technological pedagogical content knowledge accounted for roughly 55 per cent of the variance in each, leaving considerable room for factors outside any single specification.[65] These readings are not mutually exclusive, and the appropriate conclusion is that the association is positive and small in this sample and requires replication before it bears interpretive weight.

Integrated Competence as the Principal Correlate of Readiness

Integrated competence returned the largest direct coefficient on readiness among the endogenous relationships, which is consistent with its theorised role as the bridge between antecedent characteristics and professional preparedness. This extends associations established in general, mathematics, and language teacher education to accounting teacher education, a domain where technology integration has historically centred on spreadsheet and enterprise software rather than generative systems.[66] It is worth noting that the explained variance in readiness ($R^2 = 0.393$) is moderate rather than substantial, which indicates that a majority of the variation in appraised readiness lies outside the two predictors modelled here. The pattern is nevertheless consistent with evidence that pre-service teachers reach the integrated level more slowly than they reach its components,[67] which is part of what makes integrated competence, rather than any single antecedent, the proximate correlate of appraised readiness. Practicum exposure, school-level infrastructure, mentor support, and general teaching confidence are plausible omitted correlates, and comparable models incorporating contextual and attitudinal determinants have explained similar proportions of variance in adjacent constructs.[68]

Competence and Ethical Sensitivity

The strongest single coefficient in the model links integrated competence to pedagogical ethics awareness. The association is statistical, and its direction cannot be determined from these data; what the result establishes is that higher

[64] Ertmer et al., "Teacher Beliefs and Technology Integration Practices."
[65] Verica Milutinović, "Unpacking the Relationship between AI Competences, Intelligent Ethical TPACK, and Factors Influencing AI Adoption in Pre-Service Teachers: A Comprehensive Model," Education and Information Technologies 30 (2025): 26261–99, https://doi.org/10.1007/s10639-025-13786-0.
[66] Sun et al., "Promoting the AI Teaching Competency"; Yue, Jong, and Ng, "Understanding K–12 Teachers' TPACK Readiness"; Xie and Luo, "The Status Quo and Future of AI-TPACK."
[67] Karataş and Ataç, "When TPACK Meets Artificial Intelligence."
[68] Milutinović, "Unpacking the Relationship between AI Competences."

integrated competence and higher ethical sensitivity co-occur in this sample, contrary to the intuition that greater technical proficiency displaces ethical reasoning. A comparable co-occurrence has been reported in a different national setting and with a different competence construct: Du and colleagues found that K-12 teachers' artificial intelligence literacy was a substantial direct predictor of their awareness of artificial intelligence ethics.[69] One interpretation, consistent with the data but not demonstrated by them, is experiential: substantive engagement with these systems may reveal limitations and failure modes that superficial use does not, since algorithmic bias in education is subtle and context-dependent and requires informed scrutiny to detect,[70] and uncritical reliance on dialogue systems has been associated with reduced learner cognitive engagement.[71] A second interpretation reverses the ordering: students with prior ethical sensitivity may engage more carefully and thereby develop deeper competence. A third posits a common antecedent, such as general conscientiousness or programme-level socialisation, that the model does not capture. Distinguishing among these accounts requires longitudinal or experimental evidence, and the present study does not adjudicate between them.

One qualification deserves emphasis. Because ethics awareness was modelled as a single construct spanning privacy, bias, transparency, accountability, and human agency, the coefficient describes the aggregate rather than its constituent domains. Intervention evidence suggests that these domains may not move together: after a structured ethics-integrated module, Aldemir and colleagues observed that accuracy checking became routine among pre-service teachers while bias detection remained weak, and that participants moved from generic caution towards teacher-directed ethical strategies unevenly across domains.[72] If ethical sensitivity develops domain by domain rather than as a unitary disposition, an aggregate construct will obscure precisely the variation that curriculum designers most need to see. Domain-level modelling is therefore a priority for subsequent work.

Partial Mediation and What It Does and Does Not Show

The confirmation of complementary partial mediation is the study's most theoretically consequential result, subject to the same interpretive caution. It indicates that the association between competence and readiness is not wholly accounted for by a competence-performance correspondence; part of it runs statistically through an ethical-sensitivity pathway. Prospective teachers who report both competence and ethical awareness also report higher preparedness, a pattern that gives empirical weight to normative arguments that ethics should be integral rather than supplementary to preparation.[73] The mediating position of

[69] Du et al., "Exploring the Effects of AI Literacy in Teacher Learning."
[70] Baker and Hawn, "Algorithmic Bias in Education."
[71] Zhai, Wibowo, and Li, "The Effects of Over-Reliance on AI Dialogue Systems."
[72] Aldemir et al., "Exploring Emergent AI-TPACK Competencies."
[73] Bandura, "Social Cognitive Theory of Moral Thought and Action."

ethical awareness is not unique to this model: Du and colleagues report that awareness of artificial intelligence ethics operated as an indirect rather than a direct determinant in their structure, channelling the path from literacy to attitudes towards use.[74] Convergence across two different outcome variables and two national settings strengthens the case for treating ethical awareness as a mechanism rather than an endpoint. Because the mediation is partial, ethical awareness supplements rather than substitutes for the direct association between competence and readiness. It bears emphasis that mediation established on cross-sectional data is a statistical decomposition of covariance, not a demonstration of a causal chain, and the pattern reported here is compatible with several underlying orderings.

Theoretical Contribution

Three contributions distinguish this study from prior work, each stated at the level the design supports. Theoretically, the study offers initial empirical support for prompt engineering skill as a construct that is measurable and empirically separable from artificial intelligence literacy within a structural model of artificial intelligence integrated teacher knowledge, and it documents that pedagogical ethics awareness functions as a complementary partial mediator in the competence-to-readiness association, which moves ethics from a normative appendage towards an explanatory position in the model.[75] The closest prior work models artificial intelligence competences and intelligent ethical technological pedagogical content knowledge jointly, but does not position ethical sensitivity as a mediator between competence and appraised readiness,[76] which is the specific structural contribution offered here. Contextually, it shows that the intelligent extension of the technological pedagogical content knowledge framework retains explanatory value in a discipline-specific Indonesian professional certification setting, extending its evidential base beyond the contexts in which it has predominantly been tested.[77] Methodologically, it responds to the criticism that the field recycles self-report designs without advancing explanatory models[78] by specifying and testing a sequential mediation structure with full reporting of effect sizes, confidence intervals, discriminant validity matrices, and a formal test of measurement specification, while acknowledging that self-report remains its principal measurement constraint.

Practical Implications

The implications set out here are recommendations derived from the pattern of associations together with existing theory. They were not tested in this study, which evaluated no intervention, and they should be read as hypotheses for curriculum development rather than as demonstrated consequences of the

[74] Du et al., "Exploring the Effects of AI Literacy in Teacher Learning."
[75] UNESCO, Guidance for Generative AI in Education and Research.
[76] Milutinović, "Unpacking the Relationship between AI Competences."
[77] Celik, "Towards Intelligent-TPACK."
[78] Schmid et al., "Running in Circles."

findings. Three are proposed. First, because literacy and prompt engineering were empirically separable and each was independently associated with integrated competence, curricula might reasonably deliver conceptual instruction and structured prompting practice as paired components rather than treating either as a substitute for the other. Second, because self-efficacy showed the strongest association with integrated competence, and because social cognitive theory identifies mastery experience as the principal source of efficacy beliefs, scaffolded tasks in which tool use produces demonstrable pedagogical success are a plausible design lever; whether such tasks in fact raise competence is an empirical question that an intervention study would need to answer. Third, because competence and ethical sensitivity co-occurred strongly, embedding ethical reasoning within technical tasks rather than isolating it in a separate module is consistent with the observed pattern, though the present data cannot establish that this sequencing outperforms the alternative. Intervention evidence from outside this study speaks more directly to that point: Aldemir and colleagues designed a three-week teacher preparation module in which ethics was threaded through every knowledge domain rather than appended as a separate unit, and reported statistically significant pre-post gains across all domains with medium to large effects, alongside documented instances of layered ethical decision-making around privacy, bias, and transparency.[79] Their companion two-week study nonetheless found that brief modules leave integration incomplete,[80] which suggests that duration and iteration matter as much as sequencing. In accounting teacher education specifically, these components would be anchored in discipline-authentic tasks such as assisted financial simulation, automated formative assessment, and data analytics instruction.

CONCLUSION

This study examined how artificial intelligence literacy, prompt engineering skill, self-efficacy, and constructivist teaching beliefs relate to teaching readiness through integrated pedagogical content knowledge and pedagogical ethics awareness among 128 accounting teacher professional education students at a single Indonesian state university. All eight hypothesised associations were statistically supported. The four antecedents were each positively associated with integrated competence, which was in turn positively associated with both readiness and ethical awareness, and ethical awareness partially and complementarily mediated the competence-readiness association.

Two conclusions follow from the data. First, prompt engineering skill and artificial intelligence literacy were empirically separable in this sample and each was independently associated with integrated competence, which supports

[79] Tugce Aldemir et al., "Intelligent-TPACK in Practice: Design and Evidence from a Three-Week Teacher Preparation Module," Computers and Education Open 9 (2025): 100306, https://doi.org/10.1016/j.caeo.2025.100306.

[80] Aldemir et al., "Exploring Emergent AI-TPACK Competencies."

treating prompting as a candidate competency in its own right rather than as a subset of general digital literacy. Second, appraised readiness for artificial intelligence integrated teaching co-varies with ethical sensitivity over and above its association with technical competence, which indicates that readiness as students appraise it is not reducible to a technical attainment.

What the data do not support is any claim about the direction of these associations. Whether ethical sensitivity develops out of competent practice, precedes and shapes it, or arises from a shared antecedent is a question this design cannot answer, and the curricular recommendations offered above are accordingly presented as theoretically motivated proposals rather than as findings.

Three constraints bound these conclusions and define the agenda for subsequent work. The cross-sectional design precludes causal inference and cannot capture how competence and ethical awareness co-develop across a programme, so longitudinal and quasi-experimental designs are needed to establish temporal ordering. The sample was drawn from a single institution and a single subject-area department, and at 128 cases it sits below the inverse square root threshold for reliably detecting path coefficients at or under 0.20, so the teaching beliefs path should be treated as provisional and re-examined in a larger and more diverse sample; the findings are in no sense representative of Indonesian teacher professional education as a whole. All constructs were measured through self-report, and although procedural and statistical remedies indicated that method variance is unlikely to distort the estimates, self-assessment of competence remains an imperfect proxy for demonstrated capability. Future research should complement survey data with performance-based assessment, classroom observation, or analysis of assisted lesson artefacts, following the design-log and artefact-analysis approaches now emerging in this literature,[81] should validate the prompt engineering and ethics awareness instruments across independent samples, and should test whether the mediation structure identified here replicates across disciplines and national settings. A further line of inquiry concerns the correlates of ethical awareness that competence does not explain, including institutional culture, professional norms, and dispositional factors outside the technological register, alongside the out-of-sample predictive assessment of the model in new cohorts.[82]

DECLARATIONS

Author contributions. All authors contributed to the conception and design of the study. Data collection and analysis were performed collectively, and all authors read and approved the final manuscript.

[81] Yimeng Sun et al., "Modeling AI-TPACK in Practice: Insights from Teachers' Multi-Agent Workflow Design" (preprint, arXiv, 2026), https://arxiv.org/abs/2605.13906.
[82] Shmueli et al., "Predictive Model Assessment in PLS-SEM."

Ethics statement. The study protocol was reviewed and approved by the Faculty of Economics and Business, Universitas Negeri Medan. All participants provided informed consent prior to participation.
Conflict of interest. The authors declare no conflict of interest.
Data availability. The instrument and the anonymised dataset are available from the corresponding author on reasonable request.

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