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Institutional AI support and digital citizenship in teacher education: exploring the mediating role of AI self-efficacy in an underexplored context

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Artificial intelligence is reshaping teacher education, yet how institutional investment in AI relates to responsible professional conduct remains underexamined, particularly in Arab contexts. Grounded in organizational support theory and social cognitive theory, this study examined whether perceived institutional support for AI was associated with pre-service teachers' digital citizenship practices, both directly and indirectly through AI self-efficacy. A cross-sectional survey was administered to 618 pre-service teachers, and the hypothesized mediation model was tested using covariance-based structural equation modeling. Perceived institutional support for AI was positively associated with both AI self-efficacy and digital citizenship practices, while AI self-efficacy was positively associated with digital citizenship practices. The indirect association between institutional support and digital citizenship practices through AI self-efficacy was statistically significant and consistent with partial mediation. These findings extend institutional AI support research by positioning digital citizenship as a professional and ethical outcome and offer implications for coordinated institutional strategies aimed at cultivating responsible, competent, and ethically informed AI engagement in teacher education.

KEYWORDS
AI self-efficacy, digital citizenship practices, perceived institutional support for AI, pre-service teachers, teacher education

1 Introduction

As reflected in UNESCO's *AI Competency Framework for Teachers*, AI has the potential to revolutionize education, yet preparing future teachers for this transformation requires more than access to technological tools and demands the ethical, human-centered, and responsible competencies needed to preserve human agency and accountability (UNESCO, 2024). Complementarily, as crystallized in the OECD's (2026) guidance, realizing AI's educational potential requires supportive institutional policies, equitable infrastructure, sustained professional development, and safeguards for responsible and trustworthy use. Given that the move into the teaching career may be especially traumatic for pre-service teachers (Pamu, 2010; Taylor et al.,

2019), scholarly attention has increasingly focused on the institutional and psychological resources that support their professional readiness.

Teacher preparation represents a formative period during which enduring technology-related beliefs as well as practices are established (Tondeur et al., 2012), while also equipping prospective teachers to thrive—not merely survive—by developing the competence, resilience, and commitment required for effective professional practice (Beltman et al., 2011). Conceptually, digital responsibility is increasingly recognized as an integral component of professional digital competence rather than an optional addition (Instefjord & Munthe, 2017). Accordingly, the digital citizenship practices developed during this stage shape how future teachers use and model technology throughout their professional careers. As can be inferred from social cognitive theory, much of what students learn about appropriate conduct is acquired vicariously through observing others (Bandura, 1986). Building on this, teachers' visible technology practices may provide students with models of responsible digital conduct. UNESCO's AI Competency Framework for Teachers similarly emphasizes teachers' ethical responsibilities in using AI and supporting learners' safe and responsible engagement with these technologies (UNESCO, 2024). Nevertheless, formal instruction may not be sufficient to translate digital citizenship principles into consistent practice. A cluster-randomized digital citizenship curriculum, for example, improved students' knowledge and self-efficacy more consistently than their actual behavior (Jones et al., 2024). This knowledge-practice gap highlights the necessity of examining the psychological mechanisms through which responsible digital conduct develops. It also suggests that pre-service teachers may require supportive institutional conditions that enable them to convert knowledge and confidence into sustained practice. Building on foundational teacher education research showing that effective technology integration is contingent upon institutional conditions as well as sustained preparation rather than access alone (Ertmer, 1999; Kopcha, 2012) and is also shaped by teachers' beliefs (Ertmer et al., 2012), institutional AI support may be pivotal in cultivating pre-service teachers' AI self-efficacy and responsible digital citizenship practices, particularly given the responsibility of teacher education to foster professional digital competency (Lund et al., 2014).

Oman Vision 2040 places education, learning, scientific research, and national capabilities among its central priorities and positions digital technologies as key enablers of economic diversification as well as institutional development (Oman Vision 2040 Implementation Follow-up Unit, 2020). This direction is corroborated by the ITU's Oman Digital Innovation Profile (ITU, 2023), which highlights the country's sustained investment in digital infrastructure, higher education, professional capacity building, and the development of a competitive knowledge-based digital economy. Building on this policy foundation, the Council of Ministers formally approved the National Program for Artificial Intelligence and Advanced Digital Technologies in September 2024. Extending through 2026, the program combines sectoral AI adoption with an explicit human capital agenda that includes training graduates in data analysis and AI, educating teachers and school students, and introducing AI-related curricula (Ministry of Transport, Communications and Information Technology [MTCIT], 2024). In parallel, the General Policy for the Safe and Ethical Use of Artificial Intelligence Systems foregrounds human-centered principles, including fairness, transparency, accountability, inclusiveness, privacy, and safety across the design, deployment, and application of AI systems (MTCIT, 2025). Responsible AI engagement therefore extends beyond an educational preference in Oman to form part of a broader national effort to align technological innovation with ethical and societal values. Within this policy context, teacher education institutions play a key role in translating national AI priorities into responsible classroom practice.

Although a substantial body of quantitative research has examined AI in higher education, existing studies have largely concentrated on individual-level factors, including attitudes, acceptance, literacy, anxiety, and adoption intentions (Acosta-Enriquez et al., 2024; Nikolic et al., 2024), while critical and ethical dimensions remain comparatively underexplored (Zawacki-Richter et al., 2019). Recent systematic evidence similarly highlights limited attention to the mechanisms, implementation conditions, ethical considerations, and contextual diversity shaping AI-related educational outcomes (Ikram et al., 2026). Existing scholarship further points to a substantial lack of research examining institutional AI support in teacher education. The limited studies addressing this construct have focused mainly on perceived AI-supported learning experiences and general learning outcomes (Jeilani & Abubakar, 2025; Wang et al., 2023), rather than responsible-use outcomes such as digital citizenship practices. Moreover, higher education technology adoption research remains geographically concentrated in Asia, North America, and Western Europe (Xue et al., 2024). Despite the ambitious national AI agendas pursued across the Arab Gulf, the region remains underrepresented in the evidence base, while pre-service teachers' digital citizenship practices remain particularly underexplored.

Accordingly, this study develops and empirically tests a structural model examining whether institutional support for AI (PIS-AI), as perceived by pre-service teachers, is associated with their digital citizenship practices (DCP) both directly and indirectly through the mediating role of AI self-efficacy (AISE). To the authors' knowledge, searches of Web of Science, Scopus, ERIC, and EBSCO did not identify a prior empirical study that simultaneously examined perceived institutional AI support, AI self-efficacy, and digital citizenship practices within a unified mediation model in teacher education. Conducted in Oman, the study also responds to the limited evidence available from Arab Gulf contexts, where responsible AI engagement has become a national policy priority. By integrating an institutional condition, a psychological factor, and a responsible behavioral outcome, the study seeks to clarify how these constructs are related within teacher education.

2 Conceptual framework and hypothesis formulation

2.1 Perceived institutional support for AI

Perceived organizational support reflects individuals' perceptions that their organization recognizes their contributions

and demonstrates concern for their well-being (Eisenberger et al., 1986). Rhoades and Eisenberger (2002) attributed its explanatory power to two mechanisms, namely, the norm of reciprocity, whereby felt support elicits favorable attitudes and behavior in return, and the socioemotional signals that communicate organizational expectations and endorsed conduct. As reflected in technology acceptance research, facilitating conditions denote individuals' belief that sufficient organizational and technical resources are available to enable effective system use (Venkatesh et al., 2003). In higher education, institutional support, examined through organizational support theory, has also been shown to enhance self-efficacy and innovative behavior while shaping technology adoption behavior (Zhao et al., 2020). Wang et al. (2023) conceptualized higher education institutions' AI capability as a higher-order construct of resources, skills, and consciousness, linking it to student self-efficacy and performance. According to Jeilani & Abubakar (2025), PIS-AI predicted university students' technology self-efficacy and perceived AI-supported learning. Along this line, institutional and technical support influence teachers' readiness and beliefs, which in turn shape classroom technology use (Inan & Lowther, 2010; Petko et al., 2018). In PSTs, PIS-AI represents a multidimensional commitment reflecting the degree to which teacher education institutions make available resources, infrastructure, policies, training, technical assistance, ethical guidance, and pedagogical opportunities that enable PSTs to use AI meaningfully and responsibly (Ceallaigh et al., 2025; Mwananyama & Ngao, 2026). In their study of 400 teachers, Hazzan-Bishara et al. (2025) identified institutional support as an external determinant of AI adoption intention through both a direct pathway and an indirect pathway transmitted through self-efficacy and intrinsic motivation.

2.2 AI self-efficacy

AI self-efficacy denotes individuals' confidence in their capacity to understand and successfully use AI technologies to accomplish specific tasks as well as achieve intended outcomes (Wang & Chuang, 2024). A substantial body of research has established that supportive institutional and learning conditions strengthen AI-related efficacy beliefs by providing access to resources, training, and opportunities for meaningful engagement with AI (Jeilani & Abubakar, 2025; Wang et al., 2023; Xia, 2026). Along this line of thought, stronger self-efficacy in generative AI-mediated settings has been associated with improved learning outcomes (Xia, 2026), enhanced learner well-being in AI-supported environments (Fang et al., 2025), and greater creativity and performance (Wang et al., 2023). Among teachers, AI self-efficacy is related to their AI literacy, attitudes toward AI, and capacity to incorporate AI into teaching practice (Bergdahl & Sjöberg, 2025; Xu et al., 2026). Hazzan-Bishara et al. (2025) identified self-efficacy as an internal predictor of teachers' intentions to use generative AI and as a mechanism that partially transmitted the influence of institutional support. According to Mah and Groß (2024), AI self-efficacy differentiated meaningful profiles of faculty engagement with AI and anchored their professional-development needs. As an operative mechanism, AI self-efficacy positively predicted teaching innovation among public school teachers in Oman and mediated the link between change leadership and teaching innovation (Al-Mahdy & Elwakil, 2026).

2.3 Digital citizenship practices

Mossberger (2008) conceptualized digital citizenship as the capacity to engage consistently and competently in online communities, emphasizing access, digital competence, and meaningful participation as essential conditions for inclusion in a digitally mediated polity. In education, Ribble (2015) defined digital citizenship in terms of standards of safe, ethical, and responsible technology use and organized the construct into nine teachable elements, ranging from digital etiquette and communication to rights, security, and well-being. Choi (2016) synthesized the literature into interconnected dimensions encompassing ethical conduct, media and information literacy, civic participation, and critical resistance, thereby portraying digital citizenship as a multidimensional construct expressed through practice. Within teacher education, digital responsibility is therefore regarded as an integral dimension of professional digital competence rather than an optional addition to it (Instefjord & Munthe, 2017).

Examining the literature, digital citizenship appears to vary according to individuals' attitudes, capabilities, and patterns of technology engagement. Internet attitudes were associated with higher digital citizenship among Saudi education students (Al-Zahrani, 2015), and participation skills significantly influenced the formation of digital citizenship among 906 Peruvian university students (Gutiérrez-Aguilar et al., 2024). Along this line, Choi et al. (2018) reported that teachers' digital citizenship differed according to their individual backgrounds, patterns of Internet use, and psychological attributes, with Internet self-efficacy emerging as one of its strongest correlates. Given that AI is increasingly embedded in digital environments, responsible digital conduct now entails evaluating the credibility of algorithmically generated content, protecting personal data, transparently acknowledging AI-assisted work, and using intelligent systems ethically and equitably, as reflected in international competency frameworks (UNESCO, 2024).

2.4 The link between PIS-AI, AISE, and DCP

Based on the literature reviewed, no prior empirical study was identified that simultaneously examined the relationships among PIS-AI, AISE, and DCP among pre-service teachers. The proposed relationships are organized around the complementary roles of Social Cognitive Theory (SCT) and Organizational Support Theory (OST). As can be inferred from SCT, institutional support for AI can strengthen PSTs' self-efficacy by providing mastery experiences through training and structured AI use, vicarious experiences through successful peer and instructor modeling, and social persuasion through institutional encouragement and support (Bandura, 1977, 1997). Bergdahl and Sjöberg (2025) emphasized the contribution of institutional support, accessible resources, and professional training to the development of teachers' AI self-efficacy. Hoi et al., (2023) similarly reported that students were more inclined to adopt AI language models when they perceived strong organizational

support, with this association operating through perceived usefulness and ease of use. In teachers, Hazzan-Bishara et al. (2025) found that institutional support influenced intentions to use generative AI both directly and indirectly, with self-efficacy and intrinsic motivation serving as mediating mechanisms. Additionally, Sultana et al. (2026) identified a positive association between AI self-efficacy and AI-related learning outcomes, with institutional support partially mediating this relationship. Wu et al. (2024) further demonstrated that teacher support enhanced students' self-efficacy indirectly through the development of learning strategies, after which self-efficacy transmitted its effects to learning motivation. Accordingly, perceived institutional support may improve students' academic performance by fostering conditions that support effective AI-enhanced learning while also strengthening their confidence in using AI technologies (Jeilani & Abubakar, 2025).

Reviewing the literature, direct empirical tests of the relationship between AISE and DCP remain scarce. Grounded in SCT, efficacy beliefs shape individuals' choices, effort, and persistence (Bandura, 1977, 1997). PSTs with stronger AI self-efficacy may be better equipped to engage responsibly in AI-rich environments, whereas low-efficacy PSTs may use AI passively and uncritically (Bandura, 1997; Guan et al., 2025). During the validation of the digital citizenship scale, Choi et al. (2017) situated the construct within a nomological network that included Internet self-efficacy as a positive correlate, establishing capability beliefs as theoretically proximate to citizenship conduct. Özüdoğru and Durak (2025) further reported that AI-enhanced innovation, a construct reflecting confident and capability-based engagement with AI, exerted a substantial positive effect on digital citizenship in their study of 816 pre-service teachers, with AI-readiness dimensions contributing to this pathway. As inferred from SCT (Bandura, 1986, 1997), domain-specific efficacy translates into domain-relevant conduct. Along this line, AI self-efficacy has been identified as a predictor of pre-service teachers' intentions to use AI (Sadaf et al., 2025) and creative performance among AI-adopting professionals (Jeong & Jeong, 2025). Given that AI systems increasingly shape the environments in which digital citizenship is exercised (UNESCO, 2024), AI-capability beliefs should function as proximal determinants of citizenship enactment.

A plethora of research emphasizes the crucial role of contextual factors provided by teacher education institutions in facilitating or hindering PSTs' development, competence, and motivation (Granero-Gallegos et al., 2024; Özüdoğru & Durak, 2025; Wong & Liu, 2026). Prior research suggests that AI-oriented learning and institutional support in teacher education can enhance PSTs' digital citizenship practices. OST informs the proposed direct link between PIS-AI and DCP. As can be inferred from OST, when institutional provisions are understood as investment in pre-service teachers' development, they may encourage engagement with the practices supported by the institution (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). As indicated by Chan (2023), institutional AI training, support, and education policies can provide students and teachers with the competencies required to engage with AI professionally, participate in its advancement, and respond to its ethical, social, and economic implications. This argument is further reinforced by Daher (2025), emphasizing that AI literacy, continuous professional development, and ethical principles should be incorporated into teacher education to promote responsible AI usage and inclusive, future-ready teaching. Building on this, these capacities can foster the enactment of responsible digital citizenship practices. Simões et al. (2024) emphasized that digital citizenship development depends on institutional pillars comprising policies, stakeholders, strategies, infrastructure, resources, and evaluation. These foundations underpin competencies associated with online participation, digital well-being, and digital rights, indicating that stronger institutional support for AI may foster preservice teachers' responsible and ethical digital citizenship practices. Accordingly, PIS-AI is expected to be directly associated with PSTs' digital citizenship practices.

The available empirical literature appears not to have examined PIS-AI, AISE, and DCP within a unified mediation framework. By combining organizational support theory and technology acceptance frameworks, Zhao et al. (2020) established that institutional support enhances employees' self-efficacy as well as innovative behavior, which mediates actual system adoption. Shen et al. (2024) revealed that ICT self-efficacy partially mediates the link between perceived organizational support as well as technology integration. This mechanism is paralleled in the digital citizenship context, as Al-Zahrani (2015) found that computer self-efficacy, as a critical motivator, was significantly linked with greater levels of digital citizenship among higher education students. Given that self-efficacy can function as a mechanism linking environmental support to digital capability, Chen and Ma (2022) revealed that ICT self-efficacy significantly mediated the link between teacher support as well as students' information literacy. According to Liu et al. (2025), digital self-efficacy as well as negative emotions operate as sequential mediators between institutional support and teachers' engagement in online work. In the AI context, Yang et al.'s (2025) AI ethics literacy framework links AI ethics literacy with students' perceived competence in learning through AI, supporting the connection between AI confidence and ethical AI engagement. Analogously, Chiu et al.'s (2025) framework links AI self-efficacy to ethical, human centered, and confident AI use, supporting its relevance to responsible digital citizenship. Building on this, AISE may function as the psychological pathway through which PIS-AI contributes to stronger DCP.

2.5 The current study

The current study is centered on Organizational Support Theory and Social Cognitive Theory. OST informs the interpretation of institutional AI provision as support for pre-service teachers' development and constructive engagement, while SCT provides the primary explanation for AISE as a capability-based pathway linking the perceived environment to conduct (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Drawing on the social cognitive paradigm, PIS-AI occupies the environmental corner of the triadic system (Bandura, 1986), while AISE functions as the psychological mechanism through which institutional provision is translated into individual practice. PIS-AI, AISE, and DCP thus represent perceived environmental support, personal capability beliefs, and self-

reported behavior. PIS-AI provides the mastery and persuasive experiences from which efficacy beliefs develop (Bandura, 1997). As these beliefs develop, they may encourage PSTs to engage with AI deliberately as well as responsibly.

Given the existing gap in research concerning the association between PIS-AI, AISE, and DCP among PSTs, this study examines whether PIS-AI is associated with DCP and whether AISE mediates this relationship. More specifically, it examines the direct and indirect associations between perceived institutional AI support and future teachers' self-reported digital citizenship practices. To address these objectives, a conceptual model was developed on the basis of relevant theoretical and empirical literature, specifying the proposed relationships among PIS-AI, AISE, and DCP. Guided by this model, illustrated in Figure 1, the following hypotheses were formulated:

H1. Perceived institutional support for AI is positively related to AI self-efficacy.

H2. AI self-efficacy is positively related to digital citizenship practices.

H3. Perceived institutional support for AI is positively related to digital citizenship practices.

H4. AI self-efficacy mediates the positive relationship between perceived institutional support for AI and digital citizenship practices.

This study contributes to the literature by addressing an important gap in understanding the relationships among PIS-AI, AISE, and DCP, particularly within Omani teacher education programs. The proposed model provides an empirical framework for examining these associations and generating evidence that may inform strategies to strengthen institutional AI support and promote responsible engagement with AI in teacher education.

3 Methodology

3.1 Research design

This study adopted a cross-sectional predictive survey design to investigate the structural relationships among perceived institutional support for AI, AI self-efficacy, and digital citizenship practices, with AI self-efficacy specified as a mediating construct. A cross-sectional design was appropriate for examining theoretically specified relationships among variables and evaluating the proposed structural model within a naturally occurring educational setting (Creswell and Creswell, 2018; Kline, 2016). Covariance-based structural equation modeling with maximum likelihood estimation was employed because it permits the concurrent evaluation of the measurement and structural models while accounting for measurement error (Kline, 2016). Given the cross-sectional design, the modeled paths and mediation estimates were interpreted as statistical associations and do not establish temporal or causal relationships.

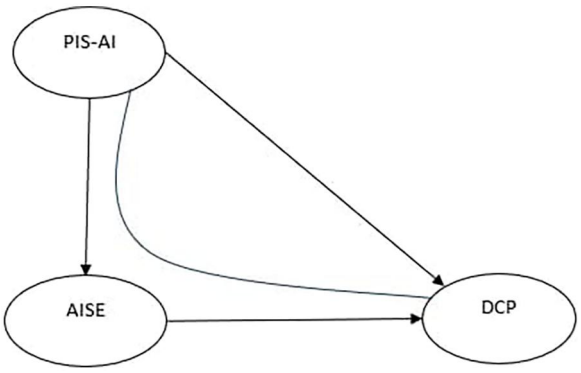

FIGURE 1
Hypothesized mediation model linking perceived institutional support for artificial intelligence, AI self-efficacy, and digital citizenship practices. H1–H3 represent the direct paths, whereas H4 represents the indirect effect of PIS-AI on DCP through AISE. PIS-AI, perceived institutional support for artificial intelligence; AISE, AI self-efficacy; DCP, digital citizenship practices.

3.2 Participants and data collection

The target population consisted of all pre-service teachers registered in the fourth and fifth years of the College of Education during the Spring 2026 semester. These cohorts had completed a substantial proportion of their pedagogical and professional preparation and had comparatively greater exposure to digitally mediated learning and practice-oriented teacher preparation. Following ethical approval, an invitation email providing information about the study along with access to the online questionnaire was sent to the institutional email accounts of all eligible students. Data collection began in the first week of May 2026 and remained open for two weeks. Because all 886 students in the defined target population were invited to participate, a whole-population recruitment strategy was employed. A total of 618 students completed the questionnaire, yielding a response rate of 69.8%.

Of the participants, 295 (47.7%) were in the fourth year and 323 (52.3%) were in the fifth year. The respondents comprised 243 males (39.3%) and 375 females (60.7%). By specialization, 205 participants (33.2%) were enrolled in Arabic language and humanities programs, 90 (14.6%) in English language education, 172 (27.8%) in science, mathematics, and technology-related programs, and 151 (24.4%) in other programs, including art education and physical education. The demographic characteristics of the participants are summarized in Table 1.

TABLE 1 Demographic characteristics of the participants.

Characteristic	Category	n	%
Sex	Male	243	39.3
	Female	375	60.7
Year of study	Fourth year	295	47.7
	Fifth year	323	52.3
Specialization	Arabic language and humanities	205	33.2
	English language education	90	14.6
	STEM	172	27.8
	Other	151	24.4
Total		618	100.0

STEM = science, mathematics, and technology-related programs. Other includes art education, physical education, and related programs.

The resulting sample was deemed adequate for covariance-based SEM and offered a sound basis for testing the hypothesized direct and indirect relationships (Hair et al., 2019; Kline, 2016).

Participation was anonymous and voluntary. Before accessing the questionnaire, students received information about the study's purpose, the measures taken to protect confidentiality, and their right to withdraw at any point before submission. Digital informed consent was secured, and no information capable of identifying individual participants was gathered. Ethical approval was granted by the Research Ethics Committee of the College of Education at Sultan Qaboos University (approval reference: REAAF/EDU/DEFA/2026/03).

3.3 Instruments

The questionnaire comprised three measures. The English-language items were translated into Arabic using an independent forward- and back-translation procedure (Brislin, 1970). One bilingual researcher translated the items from English into Arabic, and a second bilingual researcher, working independently and without consulting the original wording, back-translated the Arabic version into English. The source and back-translated versions were then compared, and minor wording adjustments were made to preserve semantic equivalence and contextual relevance to Omani pre-service teacher education. Because the measures were drawn from previously validated instruments and the adaptations were limited to contextual wording, no separate pilot study was conducted; the psychometric performance of the adapted Arabic measures was subsequently evaluated through confirmatory factor analysis and reliability and validity analyses in the study sample. Responses were assessed on a five-point Likert-type scale extending from 1 (strongly disagree) to 5 (strongly agree). The full wording of the 15 items used in the study is provided in Appendix A.

Perceived institutional support for AI was measured using four items reported by Jeilani and Abubakar (2025). The items assessed students' perceptions of whether their institution made resources available for AI-supported learning, provided training in the use of AI tools, promoted responsible AI integration into educational activities, and established explicit policies governing AI use in education. Minor contextual wording adaptations were made while retaining the intended meaning of the source items. A sample item was, "My university provides resources that support my use of AI tools for learning."

AI self-efficacy was assessed using five items adapted from the technology self-efficacy measure employed by Jeilani and Abubakar (2025), which draws on the computer self-efficacy tradition of Compeau and Higgins (1995). The items were contextualized to AI use and teacher preparation while preserving the intended capability-focused meaning of the source items. The adapted items reflected students' confidence in learning about, troubleshooting, and applying AI tools in their academic studies and teacher preparation. An illustrative item was "I feel confident in my ability to learn to use AI tools in my studies and teacher preparation."

Digital citizenship practices were measured using six practice-oriented items selected and contextually adapted from the Skills and Practice dimension of the Critical Digital Citizenship Scale developed by Dass and Kumar (2025). The selected items reflected responsible and ethical technology use, respectful interaction, avoidance of harmful online conduct, respect for diverse perspectives, information verification, and equitable digital participation. Because the parent construct is multidimensional, the six items were intended to operationalize the practice-oriented component of digital citizenship without encompassing the full breadth of critical digital citizenship. A sample item was, "I verify the accuracy of information and the credibility of its sources before sharing or relying on it."

3.4 Data analysis

Data were analyzed using SPSS 28 and AMOS 24. Preliminary screening was undertaken to identify missing data and evaluate the distributional characteristics of the dataset. Confirmatory factor analysis was subsequently performed to assess the adequacy of the three-factor measurement model. Internal consistency was examined using Cronbach's alpha and composite reliability (CR). Convergent validity was evaluated through standardized factor loadings and average variance extracted (AVE), whereas discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015).

Model fit was examined using the chi-square statistic, χ^2/df, comparative fit index (CFI), Tucker–Lewis index (TLI), normed fit index (NFI), root mean square error of approximation (RMSEA) with its 90% confidence interval and test of close fit, and root mean square residual (RMR). The interpretation of fit relied on the pattern of indices rather than any single cut-off (Kline, 2023).

After establishing the measurement model, CB-SEM with maximum likelihood estimation was employed to examine the structural paths and the mediation hypothesis. Given evidence of multivariate non-normality, bias-corrected bootstrapping with 5,000 resamples was used to obtain confidence intervals for the key direct, indirect, and total effect estimates, thereby reducing reliance on normal-theory inference (MacKinnon et al., 2004; Preacher & Hayes, 2008). An indirect effect was regarded statistically significant when its 95% bias-corrected confidence interval excluded zero (Preacher & Hayes, 2008). Because all constructs were measured through a single self-report questionnaire, anonymity and neutral instructions were used as procedural safeguards. Harman's single-factor test was also used as a diagnostic assessment of common method variance. Consistent with recommendations in the method-bias literature, it was treated as a limited diagnostic and did not establish the absence of common method bias (Podsakoff et al., 2012).

4 Results

The findings are presented in two stages: first, the model is validated, followed by an examination of the study hypotheses.

4.1 Preliminary analyses and common method variance

No missing values were identified across the 15 measurement items; therefore, all 618 cases were retained for analysis. Item-level skewness ranged from −1.105 to −0.498, and kurtosis ranged from −0.123 to 2.210, indicating acceptable univariate distributional properties (West et al., 1995). Multivariate kurtosis was elevated (coefficient = 93.193, critical ratio = 51.294), indicating departure from multivariate normality. Maximum likelihood estimation was retained for model estimation, while inferential emphasis was placed on bias-corrected bootstrap confidence intervals based on 5,000 resamples for the key structural path, indirect, and total effect estimates (Kline, 2023). The bootstrap confidence intervals excluded zero for all hypothesized paths and for the indirect association.

Common method variance was evaluated using Harman's single-factor test (Podsakoff et al., 2012). The analysis extracted three factors with eigenvalues exceeding 1, while the first unrotated factor explained 35.59% of the total variance, below the commonly used 50% heuristic (Fuller et al., 2016). This result did not indicate a dominant single-factor structure. However, because Harman's test has limited diagnostic power, common method bias cannot be ruled out, and the findings involving same-source self-report measures should be interpreted with this limitation in mind.

4.2 Measurement model

A confirmatory factor analysis was performed to evaluate the three-factor model comprising perceived institutional support for AI, AI self-efficacy, and digital citizenship practices. The initially specified model demonstrated acceptable-to-good fit, $\chi^2(87) = 230.834$, $p < .001$, $\chi^2/df = 2.653$, CFI = .961, TLI = .953, NFI = .940, and RMSEA = .052. Inspection of the modification indices identified a localized residual association between DCP_3 and DCP_4. Because both items concerned closely related aspects of interpersonal respect in digital environments -avoiding harmful or demeaning conduct and respecting others' cultures, views, and right to expression- their residuals were allowed to covary. This single modification was therefore supported by both the modification indices and a substantive content rationale (Brown, 2015; Kline, 2016). The standardized residual correlation was.240. No cross-loadings or residual covariances between indicators of different constructs were specified.

Following this theoretically justified residual covariance, model fit improved modestly to $\chi^2(86) = 208.533$, $p < .001$, $\chi^2/df = 2.425$, CFI = .967, TLI = .960, NFI = .946, RMR = .026, and RMSEA = .048, 90% CI [.040,.056], PCLOSE = .638. All standardized factor loadings were positive and statistically significant ($p < .001$), ranging from.624 to.734 for perceived institutional support for AI,.626 to.820 for AI self-efficacy, and.654 to.734 for digital citizenship practices.

Cronbach's alpha and CR exceeded.77 for all three constructs, supporting internal consistency (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). The AVE for AI self-efficacy (.569) exceeded the recommended.50 benchmark, whereas the AVE values for perceived institutional support for AI (.471) and digital citizenship practices (.485) were slightly below.50 (Fornell & Larcker, 1981). Thus, evidence of convergent validity was strongest for AI self-efficacy and somewhat more marginal for perceived institutional support for AI and digital citizenship practices. Nevertheless, all standardized loadings exceeded.60 and CR values were satisfactory, supporting retention of the indicators.

4.3 Descriptive statistics, correlations, and discriminant validity

Table 2 reports the descriptive statistics, reliability coefficients, and correlations among the three constructs, whereas Table 3 presents evidence of convergent and discriminant validity.

Digital citizenship practices recorded the highest mean score (M = 4.150, SD = 0.546), followed by AI self-efficacy (M = 3.942, SD = 0.632) and perceived institutional support for AI (M = 3.516, SD = 0.743). This pattern indicates that participants reported relatively strong engagement in responsible digital practices, while their perceptions of institutional AI support were comparatively more moderate. All latent correlations were positive and statistically significant. Perceived institutional support for AI was positively correlated with AI self-efficacy (r = .169) and digital citizenship practices (r = .317), while AI self-efficacy showed a stronger positive correlation with digital citizenship practices (r = .599). Discriminant validity was established because the square root of the AVE for each construct exceeded its correlations with the remaining constructs (Fornell & Larcker, 1981), and HTMT values ranged from.181 to.597, well below the.85 threshold (Henseler et al., 2015). These results confirm that the three constructs were empirically distinguishable.

4.4 Structural model and mediation analysis

The hypothesized structural model retained the good fit of the three-factor measurement model, $\chi^2(86) = 208.533$, $p < .001$, $\chi^2/$

TABLE 2 Descriptive statistics, reliability coefficients, and correlations.

Construct	x	SD	*A*	CR	1	2	3
1. Perceived Institutional Support for AI (PIS-AI)	3.516	.743	.779	.781	1		
2. AI Self-efficacy (AISE)	3.942	.632	.865	.868	.148**	1	
3. Digital Citizenship Practices (DCP)	4.150	.546	.854	.850	.265**	.509**	1

$n = 618$; **$p < .01$.

df = 2.425, CFI = .967, TLI = .960, NFI = .946, RMR = .026, and RMSEA = .048, 90% CI [.040,.056] (Hu & Bentler, 1999; Kline, 2023). Because the direct path from perceived institutional support for AI to digital citizenship practices was included, the structural model was saturated at the latent level; therefore, overall model fit was identical to that of the measurement model (Kline, 2023).

Table 4 reports the direct structural path estimates used to test H1–H3. Perceived institutional support for AI was positively associated with AI self-efficacy ($\beta = .169$, $p < .001$, 95% BC CI [.080,.263]), supporting H1. AI self-efficacy was positively associated with digital citizenship practices ($\beta = .561$, $p < .001$, 95% BC CI [.486,.638]), supporting H2. Perceived institutional support for AI also showed a positive direct association with digital citizenship practices ($\beta = .222$, $p < .001$, 95% BC CI [.149,.301]), supporting H3. The bias-corrected bootstrap intervals for all three paths excluded zero. The standardized structural relationships are illustrated in Figure 2.

The model accounted for 2.9% of the variance in AI self-efficacy and 40.6% of the variance in digital citizenship practices. Thus, perceived institutional support accounted for only a modest proportion of variation in AI self-efficacy, whereas the two predictors together accounted for a considerably larger proportion of variation in digital citizenship practices.

The mediation hypothesis was then evaluated using bias-corrected bootstrapping with 5,000 resamples. Table 5 presents the standardized total, indirect, and direct effects (Preacher & Hayes, 2008).

As shown in Table 5, the standardized indirect effect estimate linking perceived institutional support for AI with digital citizenship practices through AI self-efficacy was positive and statistically significant, $\beta = .095$, SE = .032, 95% BC CI [.045,.151], $p = .002$. This pattern supported H4 and was consistent with partial mediation. The direct effect remained significant after AI self-efficacy was included, $\beta = .222$, SE = .046, 95% BC CI [.149,.301], $p < .001$, and the total standardized effect was also significant, $\beta = .317$, SE = .051, 95% BC CI [.232,.400], $p < .001$.

Because the direct and indirect effect estimates were both positive and statistically significant, the pattern was consistent with complementary partial mediation (Zhao et al., 2010). Building on this, all four hypotheses were supported. In this cross-sectional model, AI self-efficacy represented one statistically significant indirect pathway linking perceived institutional support for AI with digital citizenship practices. The remaining direct association indicates that other unmeasured factors may also account for part of the relationship between perceived institutional support and digital citizenship practices.

5 Discussion

The present study investigates the relationships among pre-service teachers' perceived institutional support for AI, AI self-efficacy, and digital citizenship practices, including the indirect association through AI self-efficacy. The findings extend research that has primarily linked institutional AI support to technology adoption, creativity, learning performance, and innovation (Hazzan-Bishara et al., 2025; Hoi et al., 2023; Wang et al., 2023) by positioning responsible digital citizenship as an important professional outcome of institutional AI support. Because digital citizenship encompasses ethical conduct, critical engagement, digital participation, safety, and responsible technology use (Choi, 2016; Mossberger, 2008; Ribble, 2015), the findings indicate that institutional AI preparedness may influence whether PSTs use AI and the responsibility with

TABLE 3 Convergent and discriminant validity of the main constructs.

Construct	Loading Range	AVE	PIS-AI	AISE	DCP
Perceived Institutional Support for AI (PIS-AI)	.624–.734	.471	**.687**	.181	.324
AI Self-efficacy (AISE)	.626–.820	.569	.169	**.754**	.597
Digital Citizenship Practices (DCP)	.654–.734	.485	.317	.599	**.697**

Square roots of AVE appear in bold on the diagonal. $n = 618$.

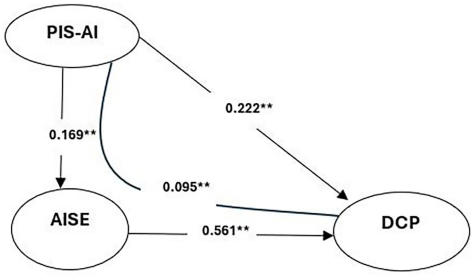

FIGURE 2
Results of the structural equation model. Model fit indices were χ^2/df = 2.425, CFI = .967, NFI = .946, TLI = .960, and RMSEA = .048. $n = 618$; $^{**}p < .01$. PIS-AI, perceived institutional support for artificial intelligence; AISE, AI self-efficacy; DCP, digital citizenship practices.

TABLE 4 Structural path estimates and hypothesis testing.

Hypothesis	Structural path	B	SE	C.R.	β	95% BC CI	Decision
H1	PIS-AI → AISE	.143	.042	3.402	.169	[.080,.263]	Supported
H2	AISE → DCP	.517	.052	9.952	.561	[.486,.638]	Supported
H3	PIS-AI → DCP	.172	.035	4.875	.222	[.149,.301]	Supported

B = unstandardised estimate; SE = standard error; C.R. = critical ratio; β = standardised estimate; BC CI = bias-corrected confidence interval. All three direct paths were significant at $p < .001$. Confidence intervals were based on 5,000 bootstrap resamples.

TABLE 5 Bootstrapping results for the effects of perceived institutional support for AI on digital citizenship practices through AI self-efficacy.

Variables	Point estimate	Product of coefficients		Bias corrected 95% CI		Percentile 95% CI		Two-tailed Sig
		SE	Z	Lower	Upper	Lower	Upper	
Standardized total effect								
PIS-AI-DCP	0.317	0.051	6.22	0.232	0.400	0.227	0.395	**
Standardized indirect effect								
PIS-AI-AISE-DCP	0.095	0.032	2.97	0.045	0.151	0.042	0.148	**
Standardized direct effect								
PIS-AI-DCP	0.222	0.046	4.83	0.149	0.301	0.144	0.294	**

$N = 618$; 5,000 bootstrap samples. PIS-AI, perceived institutional support for artificial intelligence; AISE, artificial intelligence self-efficacy; DCP, digital citizenship practices. $^{**}p < .01$.

which they engage with it. The following section discusses the findings in relation to the proposed hypotheses.

5.1 PIS-AI, AISE, and DCP

The findings indicate significant positive associations among PIS-AI, AISE, and DCP, with a partial mediation pattern in which PIS-AI is associated with DCP both directly and indirectly through AISE. The positive association between PIS-AI and AISE is consistent with the central premise of social cognitive theory that efficacy beliefs develop through interactions between individuals and their environments (Bandura, 1977, 1986, 1997). This result corroborates previous research linking institutional AI capability, conceptualized in terms of resources, skills, and organizational awareness, with students' self-efficacy, creativity, and performance (Wang et al., 2023). Analogously, Jeilani and Abubakar (2025) found that perceived institutional support for AI was associated with students' technology self-efficacy and perceptions of AI-supported learning. The finding also accords with Bergdahl and Sjöberg (2025), emphasizing the importance of training, resources, and professional support in relation to teachers' AI self-efficacy. Importantly, however, PIS-AI explained only 2.9% of the variance in AISE. The association was therefore statistically reliable but modest in explanatory magnitude, indicating that AI self-efficacy is likely related to additional personal and contextual factors not represented in the present model. Taheri et al. (2025) identified institutional support and resource availability as important contextual factors in educators' AI adoption, emphasizing transparent AI policies as well as targeted professional development. In teacher education, Ceallaigh et al. (2025) highlighted the need for comprehensive institutional support encompassing AI competencies and policies for responsible integration. Along this line, Al-khresheh et al. (2026) linked institutional support to practicing EFL teachers' perceptions of AI usefulness as well as the need to reform teacher education programs.

The positive relationship between AISE and DCP is consistent with the enabling and key role of capability beliefs in SCT (Bandura, 1986, 1997). It links confidence in using AI to digital citizenship practices, but does not establish that confidence is sufficient for ethical behavior. The finding extends earlier research connecting technology-related efficacy beliefs with digital citizenship. Choi et al. (2017) situated internet self-efficacy within the nomological network of digital citizenship, while Choi et al. (2018) identified Internet self-efficacy as one of the strongest psychological correlates of teachers' digital citizenship. Similarly, Al-Zahrani (2015) revealed that computer self-efficacy was significantly associated with digital citizenship among higher education students. Özüdoğru and Durak (2025) found that AI-enhanced innovation positively influenced digital citizenship among PSTs. AISE has also been associated with PSTs' intentions to use AI and with the creative performance of professionals adopting AI technologies (Jeong & Jeong, 2025; Sadaf et al., 2025). Responsible participation in AI environments requires users to evaluate algorithmically generated information, recognize possible bias or inaccuracy, maintain human oversight, protect data, and acknowledge AI-assisted work transparently (UNESCO, 2024). Chiu et al. (2025) similarly connected AI self-efficacy with confident, ethical, and human-centered AI engagement, while Yang et al. (2025) linked AI ethics literacy with students' perceived competence in learning with AI. This is consistent with calls to embed AI literacy, ethical principles, and continuous professional development within teacher education rather than focusing exclusively on technical proficiency (Chan, 2023; Daher, 2025; UNESCO, 2024). It also reinforces the view that digital responsibility constitutes a core dimension of professional digital competence rather than a peripheral or discretionary element (Instefjord & Munthe, 2017).

The positive direct relationship between PIS-AI and DCP is consistent with the interpretation, grounded in OST, that institutional investment in pre-service teachers' preparation may encourage constructive engagement with supported professional practices (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Given that PSTs recognize their institution as actively supporting and valuing responsible AI engagement, they may be more inclined to enact conduct consistent with these expectations. This is reinforced by Simões et al. (2024), identifying policies, stakeholders, strategies, infrastructure, resources, and evaluation as interconnected institutional pillars of digital citizenship development. These pillars support competencies associated with online participation, digital well-

being, and digital rights, indicating that digital citizenship cannot be developed through individual knowledge alone. Chan (2023) likewise argued that institutional AI training, support, and educational policies can equip teachers and students to engage with AI professionally and address its ethical, social, and economic implications. Daher (2025) further emphasized the integration of AI literacy, continuous professional development, and ethical principles into teacher education to promote responsible and inclusive AI use. Based on this, the present findings indicate a positive association between PSTs' perceived institutional support for AI and their reported digital citizenship practices, reflecting the role of institutional conditions in shaping responsible digital conduct.

5.2 AISE as a mediator in the relationship between PIS-AI and DCP

Prior empirical research has provided limited evidence regarding the association between perceived institutional support for AI and digital citizenship practices, while the process through which this relationship operates remains insufficiently understood. The present study addressed this gap by examining AI self-efficacy as a mediator of the relationship between PIS-AI and DCP. Specifically, the fourth hypothesis proposed that AISE functions as a psychological mechanism through which institutional support for AI is translated into responsible digital conduct. In this model, PIS-AI is associated with DCP both directly and indirectly through its relationship with AISE. To the authors' knowledge, searches of Web of Science, Scopus, ERIC, and EBSCO did not identify a prior empirical study integrating PIS-AI, AISE, and DCP within the same mediation model in teacher education. The findings indicate that AI self-efficacy significantly mediates the link between PIS-AI and digital citizenship practices, indicating that institutional support exerts both direct and indirect effects, with AISE serving as a key psychological pathway through which this influence is enacted.

The indirect effect through AISE corresponds with findings from Zhao et al. (2020), showing that institutional support enhanced self-efficacy and innovative behavior, which subsequently contributed to technology adoption. Shen et al. (2024) found that ICT self-efficacy partially mediated the association between perceived organizational support and technology integration, while Chen and Ma (2022) reported that ICT self-efficacy mediated the link between teacher support and students' information literacy. Similarly, Liu et al. (2025) identified digital self-efficacy as part of the mechanism connecting institutional support with teachers' online work engagement. Hazzan-Bishara et al. (2025) found that self-efficacy carried part of the association between institutional support and teachers' adoption intentions. Because the direct PIS-AI → DCP relationship remained significant after AISE was included, the findings indicate partial rather than full mediation. AISE, therefore, explains an important part of the link, as other mechanisms include AI literacy, ethical awareness, policy clarity, institutional trust, perceived accountability, professional identity, and perceptions of AI usefulness as well as ease of use. Along this line, Hoi et al. (2023) found that organizational support was related to students' adoption of AI language models through perceived usefulness and ease of use. Facilitating-conditions research also indicates that organizational as well as technical infrastructure can influence technology use by making supported behavior easier to perform (Venkatesh et al., 2003). Institutional policies and ethical guidance may therefore influence DCP directly by clarifying appropriate conduct, even beyond their contribution to PSTs' self-efficacy (Chan, 2023; Daher, 2025; Simões et al., 2024).

The findings make several theoretical contributions. Conceptually, they are consistent with the complementary explanatory value of organizational support theory and social cognitive theory. Organizational support theory provides a basis for understanding how institutional investment may encourage constructive engagement with supported professional practices (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Social cognitive theory explains how these environmental conditions may be internalized through AI-related capability beliefs and translated into conduct (Bandura, 1986, 1997). First, the findings extend institutional AI support research beyond its conventional focus on acceptance, adoption intention, creativity, and performance (Hazzan-Bishara et al., 2025; Hoi et al., 2023; Wang et al., 2023) by featuring DCP as a professional and ethical outcome. Second, the findings extend self-efficacy research by showing that AISE is relevant not only to intentions and performance but also to responsible citizenship conduct (Choi et al., 2017, 2018; Sadaf et al., 2025). Third, the mediation model integrates environmental, psychological, and behavioral levels of explanation, as PIS-AI represents the institutional environment, AISE represents a domain-specific personal cognition, and DCP represents enacted professional behavior.

Practically, the findings suggest that teacher education institutions should complement individual workshops with a coordinated system of AI support. This approach should integrate reliable infrastructure, equitable access, guided practice, technical assistance, and opportunities to apply AI in authentic pedagogical contexts (Bandura, 1997; Ceallaigh et al., 2025; Mwananyama & Ngao, 2026). It should also cultivate a learning climate that encourages experimentation, collaboration, knowledge sharing, and pedagogical innovation, reducing uncertainty surrounding emerging technologies (Al-Mahdy & Elwakil, 2026; Hwang et al., 2020; Skrbinjek et al., 2024). Along this line of thought, these conditions can foster the mastery, vicarious learning, and social persuasion experiences through which AI self-efficacy develops while also accommodating differences in PSTs' confidence and experience (Mah and Groß, 2024). Along this line, institutional efforts should embed digital citizenship and ethical AI use across teacher education curricula. This includes establishing clear expectations regarding information verification, disclosure of AI-assisted work, data protection, authorship, algorithmic bias, equitable access, and the preservation of human oversight (Chan, 2023; Daher, 2025; UNESCO, 2024). These competencies should be reinforced through authentic assessments, reflective portfolios, and practical demonstrations that enable PSTs to critically evaluate AI outputs and make informed pedagogical decisions (Chiu et al., 2025; Yang et al., 2025). Accordingly, professional development for teacher educators remains important because their practices provide key models for responsible technology use (Bergdahl & Sjöberg, 2025; Hazzan-Bishara et al., 2025).

6 Limitations and future directions

Several limitations should be acknowledged. First, the cross-sectional design restricts causal interpretation and does not permit firm conclusions about the temporal sequence of perceived institutional AI support, AI self-efficacy, and digital citizenship practices. The mediation findings should therefore be interpreted as statistical indirect associations. Longitudinal and experimental studies are needed to test temporal ordering more rigorously (Maxwell & Cole, 2007). Second, all constructs were assessed through pre-service teachers' self-reports. Although anonymity and neutral instructions were used and Harman's test did not indicate a dominant single-factor structure, common method bias and social desirability bias cannot be ruled out (Podsakoff et al., 2003, 2012). Future studies should incorporate multiple sources of evidence, including objective indicators of institutional support, performance-based assessments, observations, or digital trace data. Third, convergent validity for PIS-AI and DCP should be interpreted cautiously because their AVE values (.471 and.485, respectively) were slightly below the conventional.50 benchmark. In addition, the six-item DCP measure captured the practice-oriented Skills and Practice component without encompassing the full multidimensional breadth of critical digital citizenship. Fourth, the study was conducted among fourth and fifth year students at a single public university in Oman, which may limit generalizability across institutions, program levels, and cultural settings. Replication across public and private universities and diverse national settings, including multisite and longitudinal designs, would strengthen the external validity and temporal interpretation of the findings (Hox et al., 2018).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were approved by the Research Ethics Committee of the College of Education at Sultan Qaboos University (approval reference: REAAF/EDU/DEFA/2026/03). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided informed consent to participate in this study.

Author contributions

KA-H: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. YA-M: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. MA-A: Conceptualization, Validation, Formal analysis, Writing – review & editing, Visualization. FE: Conceptualization, Validation, Formal analysis, Writing – review & editing, Visualization.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Appendix A. Measurement Items Used in the Study

The items below are English renderings of the Arabic wording administered to participants. All items were rated from 1 (strongly disagree) to 5 (strongly agree). PIS-AI and AISE items were adapted from Jeilani and Abubakar (2025), DCP items were selected and adapted from the Skills and Practice dimension of Dass and Kumar (2025).

Construct	Item	Source item	English rendering of administered item
PIS-AI	1	1	My university provides resources that support my use of AI tools for learning.
PIS-AI	2	2	My university provides training or workshops that help me use AI tools effectively for learning purposes.
PIS-AI	3	3	My university encourages the responsible use of AI tools in courses and educational activities.
PIS-AI	4	4	My university has clear policies regarding the use of AI in education.
AISE	1	1	I feel confident in my ability to learn to use AI tools in my studies and teacher preparation.
AISE	2	2	I can troubleshoot minor technical problems when using AI tools on my own.
AISE	3	3	I can use AI tools effectively to support coursework and teaching-related tasks.
AISE	4	4	I believe I have the skills needed to benefit from AI tools in education.
AISE	5	5	I can understand how to use and work with AI tools with little assistance.
DCP	1	S43	I use digital technologies responsibly and ethically, and I encourage learners to do the same.
DCP	2	S45	I use respectful and appropriate language in my digital interactions and avoid causing others discomfort.
DCP	3	S50	I avoid threatening, insulting, ridiculing others, or spreading rumors about them online.
DCP	4	S51	I respect others' cultures, views, and right to expression in digital environments.
DCP	5	S52	I verify the accuracy of information and the credibility of its sources before sharing or relying on it.
DCP	6	S58	I support equal opportunities for everyone to express themselves and participate in digital discussions.