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Validation of an Instrument for Assessing Iranian Higher Education Readiness for Artificial Intelligence Adoption: Exploratory and Confirmatory Factor Analysis

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A B S T R A C T

Purpose: This study aimed to develop and validate a context-specific instrument for assessing the readiness of Iranian higher education institutions for the adoption and application of artificial intelligence.

Methods and Materials: A sequential exploratory mixed-methods design was employed. In the qualitative phase, 25 participants, including artificial intelligence specialists, university faculty members, and employers or managers, were selected purposively and interviewed using semi-structured interviews. Thematic analysis generated the conceptual domains and initial questionnaire items. Following expert review and pilot testing, the instrument was administered to 248 faculty members and academic or educational managers using purposive-snowball sampling. Construct validity was examined using polychoric correlations, minimum residual exploratory factor analysis with Promax rotation, parallel analysis, Velicer's MAP, VSS, exploratory graph analysis, hierarchical clustering, and confirmatory factor analysis using DWLS/WLSMV estimation. Reliability, composite reliability, average variance extracted, and HTMT were also evaluated.

Findings: Sampling adequacy was excellent (KMO = 0.94), and Bartlett's test was significant ($\chi^2 = 7178.013$, df = 1711, $p < 0.001$). Although alternative one-, two-, five-, and ten-factor solutions were examined, the five-factor structure provided the most defensible balance of fit, interpretability, and psychometric stability. In the full-sample CFA, the five-factor model showed CFI = 0.979, TLI = 0.976, RMSEA = 0.037, robust CFI = 0.930, robust TLI = 0.921, robust RMSEA = 0.053, and SRMR = 0.049. All factor loadings were significant ($p < 0.001$). Composite reliability ranged from 0.735 to 0.825, Cronbach's alpha from 0.751 to 0.829, and all HTMT values were below 0.85. The five factors represented research and industry interaction, governance and ethics, technological infrastructure, organizational culture and maturity, and education, skills, and employability.

Conclusion: The developed instrument demonstrated satisfactory reliability, structural validity, and discriminant validity and provides a promising framework for assessing institutional AI readiness in Iranian higher education, although further validation in larger independent samples is warranted.

Keywords: *Artificial Intelligence Readiness; Higher Education; Instrument Validation; Exploratory Factor Analysis; Confirmatory Factor Analysis; Iran*

1. Introduction

Artificial intelligence (AI) has rapidly moved from a specialized technological domain into a general-purpose capability with substantial implications for education, research, organizational governance, labor markets, and professional practice. Higher education institutions are increasingly expected not only to teach AI-related knowledge but also to integrate AI into teaching, assessment, research, administrative processes, student support, institutional decision-making, and engagement with external stakeholders. This transformation has accelerated with the emergence of generative AI systems capable of producing text, code, images, analytical outputs, and personalized educational content. Consequently, universities are confronting a transition in which the central question is no longer whether AI will affect higher education, but whether institutions possess the technological, human, organizational, educational, ethical, and governance capacities required to adopt it responsibly and effectively. International evidence indicates that AI applications are already expanding across learning analytics, adaptive instruction, automated feedback, academic support, research assistance, and administrative decision-making, while institutional policies and capabilities often develop more slowly than technological possibilities (Crompton & Burke, 2023; Pablo-Martí et al., 2024; Pedreño Muñoz et al., 2024).

The significance of AI for higher education derives partly from its capacity to transform the fundamental processes through which teaching and learning are organized. AI-supported environments can facilitate personalized instruction, provide differentiated learning resources, assist students with complex tasks, and enable faculty members to identify learning needs more rapidly. Recent evidence concerning faculty perceptions suggests that AI is increasingly viewed as a potentially valuable mechanism for personalized instruction and learning facilitation, although successful implementation depends heavily on faculty competence, trust, access, institutional support, and clarity regarding pedagogical purposes (Saki et al., 2026). At the same time, generative AI has complicated traditional assumptions regarding the relationship among students, teachers, knowledge, and assessment. Rather than functioning merely as an additional educational technology, generative AI can participate directly in processes previously regarded as indicators of individual learning, including essay writing, coding, problem solving, summarization, idea generation, and feedback. This development requires universities to reconsider instructional design, learning outcomes, academic assessment, and the role of teachers in AI-rich educational environments (Holmes & Miao, 2023; Lye & Lim, 2024; Nguyen et al., 2025).

The educational implications of AI extend beyond the use of specific tools. AI integration increasingly requires a shift from content transmission toward forms of learning that emphasize judgment, critical evaluation, problem formulation, creativity, ethical reasoning, and collaboration with intelligent systems. Assessment practices are particularly important because conventional assignments may no longer provide valid evidence of individual learning when generative AI can perform substantial portions of the required cognitive work. Accordingly, assessment redesign needs to focus more strongly on authentic tasks, process evidence, oral defense, iterative work, contextualized problem solving, and the ability to critically evaluate AI-generated outputs (Lye & Lim, 2024; Nguyen et al., 2025). This transformation also changes the competencies required of instructors. Teachers need more than operational familiarity with AI applications; they require competencies related to pedagogical integration, data literacy, ethical awareness, critical evaluation of AI outputs, learner support, and responsible selection of technologies (Cukurova & Miao, 2024). Institutional readiness must therefore include mechanisms for continuous faculty development rather than assuming that technology adoption can be achieved simply through access to software.

At the institutional level, AI adoption also raises substantial governance questions. Universities must establish policies governing acceptable AI use, transparency, data protection, academic integrity, intellectual property, accountability, bias, cybersecurity, and the use of AI-generated or AI-assisted outputs in education and research. The rapid diffusion of generative AI has often preceded the development of comprehensive institutional rules, producing uncertainty among faculty members, students, administrators, and researchers regarding permissible and responsible practices. UNESCO's guidance emphasizes that generative AI should be adopted through human-centered approaches that protect agency, inclusion, privacy, academic integrity, and educational quality (Holmes & Miao, 2023). More broadly, AI has become an arena of global educational governance in which international organizations increasingly influence national and institutional understandings of responsible adoption, competencies, regulation, and educational policy

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(Christodoulou & Zembylas, 2026). Therefore, readiness cannot be reduced to technical availability; it must include institutional governance capacity and the ability to translate broad ethical principles into operational rules and practices.

Ethical readiness is particularly important because universities operate in environments in which AI decisions and outputs can directly influence learning opportunities, evaluation, research practices, and academic careers. Responsible implementation requires attention to algorithmic bias, explainability, fairness, privacy, informed use, human oversight, and the risk that AI may weaken critical thinking or create inappropriate dependence on automated systems. Institutional readiness for responsible AI therefore precedes or should accompany technological deployment. Recent work has emphasized the importance of pre-deployment governance frameworks through which institutions identify ethical risks, establish accountability structures, specify decision rights, and develop procedures before AI systems become deeply embedded in university processes (Abdelaziz, 2026). Similarly, strategic AI governance research demonstrates that effective adoption depends on coordinated governance mechanisms rather than isolated technological initiatives (Bashir & Ravi, 2025). AI safety and misuse concerns surrounding foundation models also reinforce the necessity of structured risk-management practices, particularly where powerful general-purpose systems can be used in ways that exceed their originally intended applications (Shahi & Conner, 2024).

Readiness must also be understood in relation to organizational culture and human acceptance. Universities may possess technological infrastructure while lacking the willingness, competencies, incentives, or leadership necessary to use it effectively. Faculty members may simultaneously recognize the value of AI and remain concerned about academic integrity, diminished human interaction, job displacement, reliability, professional autonomy, or the quality of AI-supported learning. Institutional strategies therefore need to address not only technological acquisition but also trust, participation, communication, professional development, and the perceived legitimacy of AI-enabled change. Studies of AI integration in higher education indicate that faculty and institutional stakeholders frequently identify insufficient training, lack of clear policy, inadequate infrastructure, ethical ambiguity, and uncertainty regarding effective pedagogical use as significant barriers to innovation (Schmidt et al., 2025). These barriers suggest that institutional readiness is multidimensional and that weakness in one domain can constrain progress in others.

The relationship between higher education and the labor market further strengthens the importance of institutional AI readiness. AI is altering occupational tasks, the distribution of skill demand, and the combination of technical and nontechnical competencies required in contemporary employment. Labor-market analyses indicate that AI is likely to reshape rather than simply eliminate many forms of work, increasing demand for combinations of digital competence, problem solving, communication, adaptability, analytical judgment, and the capacity to work effectively with AI-enabled systems (Green, 2024; Green et al., 2023). Future-work analyses similarly suggest that the period to 2030 will involve substantial shifts in skill profiles and organizational structures as automation and intelligent systems become more widely embedded in economic activity (Thamarasseri, 2025). Universities therefore face pressure to ensure that curricula, teaching approaches, internships, research projects, and professional development pathways remain aligned with changing occupational requirements.

Evidence from the AI sector demonstrates that the skills gap between higher education and industry is not confined to technical proficiency. Employers seek graduates who can translate problems into workable AI solutions, manage data, understand deployment environments, communicate findings, work in interdisciplinary teams, and understand organizational and commercial constraints. Research on the higher education–industry skills gap has shown that academic preparation may lag behind rapidly evolving industrial requirements, creating mismatches between what universities teach and what employers require (Jaiswal et al., 2025). Similar concerns have been raised regarding the European AI skills ecosystem, where the development of specialized technical roles must be complemented by broader organizational and interdisciplinary capacities (Van Haeften et al., 2024). The pathway from education to high-quality employment also depends on whether institutions create structured links among academic learning, professional experience, employers, and labor-market opportunities (Bates et al., 2025). Accordingly, AI readiness in higher education should incorporate employability, university–industry collaboration, practical learning, and the capacity to anticipate emerging skills requirements.

Research and innovation constitute another essential dimension. Universities are central institutions in national innovation systems because they generate knowledge,

Iranian Journal of Educational Sociology
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develop human capital, support entrepreneurship, and connect scientific activity with social and economic needs. AI can increase research productivity and expand opportunities for interdisciplinary innovation, but these benefits depend on access to computing infrastructure, high-quality data, software platforms, research collaboration, and mechanisms for converting academic outputs into usable solutions. Universities that lack advanced computational resources, institutional data management, cloud access, or partnerships with industry may remain consumers of AI technologies rather than active producers and developers. This problem is especially relevant where access to advanced technologies is uneven or constrained by economic, geopolitical, linguistic, and organizational conditions. National AI readiness indices similarly demonstrate that the capacity to benefit from AI depends on combinations of infrastructure, governance, human capital, institutional capability, and innovation ecosystems rather than on any single technological indicator (Hankins et al., 2023).

These issues are especially significant in the Iranian higher education context. Iranian universities operate within a distinctive institutional environment characterized by differences in resources across universities, centralized elements of educational governance, economic constraints, uneven access to technological infrastructure, rapidly changing labor-market requirements, and the need for Persian-language technological resources. At the same time, Iranian faculty members and students increasingly encounter generative AI tools through teaching, research, language learning, academic writing, programming, and everyday knowledge work. Evidence specifically addressing AI in Iranian higher education indicates that users recognize substantial educational opportunities while simultaneously confronting ethical tensions, uncertainty regarding appropriate use, and pedagogical challenges (Isaee, 2025, 2026). These conditions make it inappropriate to assume that readiness frameworks developed in other countries can be transferred directly to Iranian higher education without contextual evaluation.

The Iranian context also highlights the difference between individual AI use and institutional AI readiness. Faculty members or students may independently adopt generative AI even when their universities have no coherent AI strategy, formal ethical policy, dedicated computational infrastructure, structured professional training, or mechanisms for monitoring outcomes. Conversely, an institution may possess hardware or digital platforms without the organizational culture, curriculum reform, leadership, or industry relationships needed to convert these resources into meaningful educational outcomes. Therefore, readiness is better conceptualized as a systemic institutional capability rather than as simple access to technology or positive attitudes toward AI. It requires alignment among technological infrastructure, people, culture, governance, ethics, education, research, external engagement, employability, and institutional learning.

This multidimensionality creates a measurement challenge. Reliable institutional decision-making requires an instrument that can distinguish between areas of readiness and vulnerability rather than relying on broad perceptions of whether a university is "ready" or "not ready." A meaningful readiness instrument should capture both enabling conditions and implementation capacities. It should assess whether institutions have appropriate computing resources and integrated data systems; whether faculty members, managers, and staff possess relevant knowledge and motivation; whether governance structures, funding mechanisms, and ethical rules are established; whether curricula and teaching methods are responsive to AI-related change; whether students develop practical and professional competencies; whether research and innovation connect with society and industry; and whether universities evaluate their own progress toward sustainable institutional maturity.

The measurement problem is further complicated by the rapid evolution of AI. Instruments that focus exclusively on conventional digitalization may fail to capture issues that have become particularly important with generative AI, including prompt literacy, critical evaluation of generated outputs, hallucination and error awareness, intellectual-property concerns, responsible use, preservation of human learning, and the need to redesign assessment. Contemporary higher education must therefore distinguish between generic digital maturity and specific preparedness for AI-enabled institutional transformation (Pablo-Martí et al., 2024; Pedreño Muñoz et al., 2024). Likewise, an instrument developed solely from international frameworks may inadequately represent contextual issues such as local governance structures, Persian-language AI resources, resource disparities, restricted technological access, or particular relationships between Iranian universities and the labor market.

A psychometrically sound instrument is also necessary because readiness is a latent construct that cannot be directly observed. Individual questionnaire items serve as indicators of broader underlying dimensions, and their adequacy must

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

therefore be established empirically. High internal consistency alone cannot demonstrate that an instrument measures the intended structure. Exploratory analysis is required when the dimensional organization of a new context-specific measure is uncertain, whereas confirmatory analysis is needed to evaluate whether a hypothesized measurement structure provides an acceptable representation of the observed data. Comparison of competing structures is especially important in a domain such as AI readiness because conceptually distinct dimensions may be strongly correlated and may empirically consolidate into broader latent factors.

Existing scholarship has provided valuable insights into AI applications, faculty competencies, educational design, governance, ethics, and labor-market effects, but these streams are often studied separately. Research on AI in higher education documents the expanding range of applications (Crompton & Burke, 2023); competency frameworks identify the capacities required of educators (Cukurova & Miao, 2024); generative-AI guidance addresses responsible pedagogical integration (Holmes & Miao, 2023); assessment research emphasizes redesign of learning and evaluation (Lye & Lim, 2024; Nguyen et al., 2025); governance scholarship addresses institutional and strategic mechanisms (Abdelaziz, 2026; Bashir & Ravi, 2025); and labor-market studies demonstrate emerging skill requirements (Green, 2024; Jaiswal et al., 2025; Van Haeften et al., 2024). What remains insufficiently developed is an integrated, context-sensitive, empirically validated instrument capable of measuring these domains together within Iranian higher education.

Developing such an instrument is important for both research and policy. For researchers, a validated scale can support systematic investigation of institutional differences, antecedents of AI adoption, relationships between readiness and educational outcomes, and changes over time. For university leaders, it can provide a structured diagnostic framework for identifying weaknesses and prioritizing investment. For policymakers, a readiness instrument can reveal whether national initiatives are supported by sufficient organizational capacity at the institutional level. For faculty-development units, it can identify areas where professional learning is most needed. For curriculum planners, it can help determine whether educational programs are keeping pace with technological and labor-market transformation. Finally, repeated use of a validated measure can enable institutions to monitor progress rather than treating AI adoption as a one-time technological intervention.

The urgency of this work is reinforced by the growing expectation that universities will play a proactive role in shaping, rather than merely reacting to, AI-driven transformation. Higher education institutions are increasingly responsible for preparing students for employment in AI-affected labor markets, ensuring responsible use of intelligent systems, maintaining academic standards, supporting faculty development, generating relevant research, and contributing to national innovation capacity (Green et al., 2023; Thamarasseri, 2025). At the same time, faculty experience and institutional evidence indicate that adoption without sufficient preparation can intensify ethical uncertainty, pedagogical inconsistency, inequity, and resistance (Isaee, 2025; Schmidt et al., 2025). A readiness framework must therefore be sufficiently broad to reflect systemic transformation while sufficiently parsimonious to function as a practical measurement instrument.

Accordingly, the present study addressed this gap through the development and psychometric validation of a context-specific instrument grounded initially in qualitative evidence from AI specialists, faculty members, employers, and managers and subsequently evaluated quantitatively through exploratory and confirmatory factor analysis. By integrating stakeholder-derived content with empirical tests of dimensionality, reliability, convergent validity, discriminant validity, and competing measurement structures, the study sought to move beyond the direct transfer of external readiness frameworks and establish a measurement structure responsive to the realities of Iranian higher education. The aim of this study was to develop and validate an instrument for assessing the readiness of Iranian higher education institutions for the adoption and application of artificial intelligence using exploratory and confirmatory factor analyses.

2. Methods and Materials

This study employed a sequential exploratory mixed-methods design within a pragmatic research paradigm to develop and validate an instrument for assessing the readiness of Iranian higher education institutions for the adoption and application of artificial intelligence (AI). The pragmatic paradigm was considered appropriate because the construct under investigation encompasses both context-dependent meanings and empirically measurable

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

dimensions. Accordingly, the study integrated qualitative exploration with quantitative psychometric validation rather than privileging either approach independently. The sequential exploratory design followed a QUAL → quan sequence, in which the qualitative phase had an exploratory and instrument-development function and the subsequent quantitative phase was used to examine the latent structure, reliability, and construct validity of the resulting measurement instrument. This design was particularly appropriate because no validated indigenous instrument was available for comprehensively assessing AI readiness within the organizational, technological, educational, ethical, human, and labor-market context of Iranian higher education. Existing international digital maturity and AI-readiness frameworks were considered useful conceptual references but could not be assumed to adequately represent the institutional, cultural, regulatory, technological, and educational conditions of Iranian universities without contextual adaptation and empirical validation.

The qualitative phase was conducted using thematic analysis and involved 25 participants selected through criterion-based purposive sampling. Participants were drawn from three complementary stakeholder groups to ensure that the construct of AI readiness was examined from technological, educational, organizational, and labor-market perspectives. The first group consisted of seven AI specialists with academic or professional experience in areas such as machine learning, natural language processing, large language models, computer vision, software development, networking, infrastructure, and organizational applications of AI. The second group included nine faculty members from Iranian higher education institutions representing disciplines such as computer engineering, electrical engineering, agricultural engineering, educational sciences, educational management, and social sciences. They were affiliated with different types of institutions, including public universities, Islamic Azad University, Payame Noor University, and Farhangian University. The third group comprised nine employers and managers working in AI and software companies, banking, education, industry, digital content production, data science, and organizational training. Participants were geographically diverse and included individuals working in Razavi Khorasan, Tehran, Golestan, as well as Iranian professionals residing in Germany and the Netherlands. This diversity was deliberately sought to increase the breadth of perspectives represented during item generation.

Eligibility criteria were tailored to the three qualitative groups. AI specialists were required to possess relevant postgraduate education or substantial professional experience in AI-related projects. Faculty participants were required to hold an academic appointment and have sufficient teaching or university experience to evaluate institutional and educational readiness. Employers and managers were required to occupy managerial, technical, or professional positions in organizations that either used AI technologies or employed personnel with AI-related competencies. Data collection continued beyond the point at which all major organizing themes had emerged in order to verify saturation across participant groups. The eighteenth and final organizing theme emerged during the eighth interview, while the remaining interviews contributed elaboration and confirmation rather than additional organizing themes. The final three interviews were used specifically as additional confirmation of thematic saturation. All participants were identified through coded labels rather than personal names to protect confidentiality.

The quantitative phase targeted faculty members and academic or educational managers from Iranian universities, including public universities, Islamic Azad University, Payame Noor University, University of Applied Science and Technology, Farhangian University, and universities of medical sciences. Academic managers included individuals holding positions such as department chair, dean, educational vice-chancellor, research vice-chancellor, or other middle- and senior-level university administrative responsibilities. Faculty members were included because of their direct involvement in teaching, research, student learning, and the implementation of emerging technologies, whereas academic managers were included because of their involvement in institutional policy, strategic planning, resource allocation, governance, and organizational decision-making. Eligibility for the quantitative phase required current academic employment or an academic managerial position in an Iranian higher education institution.

Because a complete national sampling frame that could be practically accessed was unavailable, participants in the quantitative phase were recruited using purposive-snowball sampling. The online questionnaire was initially distributed through professional faculty networks, university-related messaging groups, institutional and professional contacts, and electronic communication channels. Initial respondents were also invited to share the questionnaire with eligible colleagues. Therefore, although the population of Iranian

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

faculty members is large, the quantitative sample should be regarded as a non-probability validation sample rather than as a probability sample intended to produce nationally representative prevalence estimates. A total of 248 valid questionnaires were obtained and retained for the main psychometric analyses. The sample size was considered adequate for the factor-analytic objectives of the study, particularly when evaluated in conjunction with empirical measures of factorability, the magnitude and stability of factor loadings, communalities, and overall model identification. The study therefore used the final sample primarily for measurement validation and examination of latent structure rather than for population-level statistical generalization.

Before the main quantitative data collection, a pilot study was conducted with 27 faculty members to examine the preliminary internal consistency and comprehensibility of the instrument. The overall Cronbach's alpha for the 60-item questionnaire was 0.9376, indicating high overall internal consistency. Dimension-level analysis showed stronger reliability for several dimensions, whereas technological readiness and governance demonstrated borderline coefficients and the ethics and university–industry linkage dimensions showed comparatively weaker preliminary coefficients. Item-level examination, including alpha-if-item-deleted statistics, was consequently used diagnostically rather than as an automatic deletion criterion. Three items concerning responsible generative AI use, institutional collaboration with industry, and observable educational outcomes were reworded before the main administration to improve conceptual clarity and alignment with their intended dimensions. No dimension was removed solely on the basis of the small pilot sample because the definitive assessment of dimensionality and construct reliability was reserved for the main factor analyses.

The study was conducted in accordance with established ethical principles for research involving human participants. Participation in both phases was voluntary. Before participation, individuals were informed about the purpose of the study, the use of the collected information, confidentiality safeguards, and their right to discontinue participation without adverse consequences. Personally identifying information was excluded from analytical reports, qualitative participants were represented by coded identifiers, and interview excerpts were handled in a manner designed to minimize direct or indirect identification. Data were analyzed and reported without intentional alteration of participants' views or empirical findings.

Qualitative data were collected through in-depth semi-structured interviews. The interview protocol was developed following a review of the literature on AI readiness, digital maturity, responsible AI, educational digital transformation, and institutional technology adoption, with particular attention to international frameworks such as UNESCO guidance on AI in education, OECD digital education perspectives, the NIST AI Risk Management Framework, and institutional digital maturity frameworks. The interview guide was subsequently reviewed in consultation with academic supervisors and subject-matter experts. Semi-structured interviewing was selected because it provided a common framework across participants while retaining sufficient flexibility to explore unanticipated issues arising from their professional experiences. Interviews began with a broad question asking participants to evaluate the readiness of Iranian universities to use AI in education and research. Follow-up probes addressed technological infrastructure and access to data, human readiness and organizational culture, faculty and managerial competencies, governance and institutional policy, financing, curricula and teaching practices, responsible and ethical AI use, university–industry relationships, labor-market alignment, student professional competencies, research and innovation, major barriers, and priorities for institutional improvement.

The 25 qualitative interviews were conducted through face-to-face meetings, telephone conversations, and asynchronous voice or written responses through digital communication platforms, depending on participant preference and accessibility. All interview material was transcribed and systematically organized for qualitative analysis. Thematic analysis was performed using ATLAS.ti version 23. The analytical process incorporated the six phases of familiarization with the data, generation of initial codes, identification of candidate themes, review and refinement of themes, definition and naming of themes, and production of an interpretive account. The thematic network logic of Attride-Stirling was also used to organize the findings hierarchically into basic themes, organizing themes, and a global theme. The analysis ultimately produced 101 basic themes and 18 organizing themes, which were synthesized into the overarching concept of systemic AI-based higher education readiness. For the purposes of scale development, the 18 organizing themes were further consolidated on the basis of conceptual similarity, shared theoretical domain, and measurement parsimony into 10 broader readiness dimensions.

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

Several procedures were employed to enhance the trustworthiness of the qualitative findings before they were transformed into questionnaire items. Theoretical saturation was monitored throughout data collection, with no new organizing themes emerging after the eighth interview and subsequent interviews serving to elaborate or confirm the established thematic structure. Member checking was conducted with seven participants drawn from all three stakeholder groups. Each participant evaluated the 18 organizing themes using categories of full confirmation, confirmation with minor modification, or rejection. Across 126 individual evaluations, 119 were fully confirmed, seven were confirmed with minor modifications, and none were rejected, corresponding to a direct full-confirmation rate of 94.44%. Suggested refinements were reviewed and incorporated where appropriate without changing the overall structure of the 18 organizing themes. Intercoder reliability was additionally assessed using six interviews, representing 24% of the qualitative dataset, with two interviews selected from each stakeholder group. An independent coder assessed the presence or absence of the 18 organizing themes without access to the original coding decisions. Across 108 coding judgments, the observed agreement was 96.30%, and Cohen's kappa was approximately 0.93, indicating almost perfect agreement. Disagreements concerned boundaries between closely related themes rather than fundamentally different interpretations and were resolved through discussion.

The questionnaire-development process began after completion of the qualitative analysis. An initial pool of 107 items representing 21 provisional dimensions was generated from the qualitative themes and supplemented, where necessary, by concepts identified in relevant international literature. Additional attention was given to areas such as data literacy, employability outcomes, and smart-university maturity to ensure adequate conceptual coverage. Because a 107-item, 21-dimension instrument would impose substantial respondent burden and contained several conceptually overlapping domains, the item pool was subsequently refined using the principle of conceptual parsimony. Related dimensions were combined on the basis of theoretical and semantic similarity, resulting in an intermediate 62-item instrument representing 10 broader constructs.

The 62-item version underwent expert face-validity assessment by eight specialists in higher education, AI, and educational management. Each item was evaluated on clarity, relevance, and simplicity using a four-point rating scale. The overall expert evaluation resulted in a mean score of approximately 3.2 out of 4. Both numerical ratings and qualitative comments were considered during revision. Two redundant or insufficiently clear items were removed, conceptually overlapping item pairs were consolidated, ambiguous wording was revised, and new items were introduced where experts identified insufficient content coverage. Additions addressed topics such as cybersecurity, access to diverse AI tools, faculty motivation, AI use in nontechnical disciplines, awareness of AI limitations, intellectual property, Persian-language AI content, targeted internships, institutional self-assessment, and graduate employment monitoring. Following iterative review, the instrument was finalized at 60 items across 10 dimensions.

The final instrument assessed technological infrastructure readiness, human readiness and organizational culture, governance and policy readiness, educational and curriculum readiness, responsible and ethical AI use, university interaction with industry, government and society, research, innovation and entrepreneurship, students' professional skill development, employability and labor-market alignment, and educational outcomes and smart-university maturity. The technological infrastructure dimension contained six items, human readiness and organizational culture seven items, governance and policy seven items, educational and curriculum readiness seven items, responsible and ethical AI use six items, university–industry–government–society linkage five items, research and innovation five items, professional skill development five items, employability and labor-market alignment six items, and educational outcomes and smart-university maturity six items. Together, these domains constituted the hypothesized multidimensional structure of systemic readiness for AI adoption in Iranian higher education.

Responses to the 60 substantive items were recorded on a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. One negatively worded item concerning faculty resistance to AI was reverse-scored before scale computation and psychometric analysis. In addition to the 60 scale items, the questionnaire contained eight demographic and professional questions covering characteristics such as gender, age, academic rank, institutional type, disciplinary field, professional experience, geographic location, and familiarity with AI. Three supplementary open-ended questions were also included to allow respondents to identify additional concerns or recommendations not adequately represented by the fixed-response items. Average completion time was approximately 15–20 minutes.

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

Qualitative data were managed and analyzed in ATLAS.ti version 23, while quantitative psychometric analyses were conducted in R using packages appropriate for exploratory factor analysis, confirmatory factor analysis, and reliability and validity assessment, including psych, lavaan, semTools, and EGAnet. Data screening preceded the main factor analyses and included examination of response completeness, coding accuracy, response distributions, reverse scoring of the negatively worded item, and the empirical suitability of the item set for factor analysis. Because the questionnaire items were measured on a five-category ordinal Likert scale, factor analyses were based on methods appropriate for ordinal indicators rather than treating the items uncritically as continuous normally distributed variables.

Exploratory factor analysis was first performed to investigate the empirical dimensionality of the newly developed instrument without imposing the complete qualitative structure on the quantitative data. A polychoric correlation matrix was used because polychoric correlations provide a more appropriate representation of associations among ordered categorical items than conventional Pearson correlations when Likert-type responses are analyzed as ordinal variables. Sampling adequacy and factorability were evaluated using the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity before extraction. The number of factors was determined through a combination of empirical factor-retention procedures and substantive interpretability rather than reliance on a single mechanical rule. Exploratory procedures included evaluation of the eigenvalue pattern and factor-retention evidence available from the R analytical workflow. Because the dimensions of institutional AI readiness were theoretically expected to be correlated rather than statistically independent, an oblique rotation, specifically oblimin rotation, was employed. Items were evaluated in terms of the magnitude of their primary loadings, cross-loadings, communalities, conceptual coherence, and contribution to interpretable factors. Decisions to retain or remove items were therefore based jointly on statistical evidence and substantive consistency with the qualitative construct-development phase.

Following exploratory analysis, confirmatory factor analysis was conducted to evaluate whether the empirically derived measurement structure adequately reproduced the observed relationships among the ordinal questionnaire items. CFA was estimated with the weighted least squares mean and variance adjusted estimator (WLSMV), which is particularly appropriate for ordered categorical indicators and does not require multivariate normality to the same extent as conventional maximum-likelihood estimation. The CFA stage was not restricted to a single hypothesized solution. Competing measurement structures were examined in order to determine whether AI readiness was better represented by a broad general factor or by a differentiated multidimensional structure. These analyses included alternative one-factor, two-factor, and five-factor representations, while more differentiated correlated-factor and higher-order structures were also evaluated where model identification and the empirical distribution of items permitted. Models producing inadequately identified factors, including structures resulting in unstable or single-item latent factors, were not retained merely because they corresponded to the original qualitative categorization. Final model selection was therefore based on the combined evidence of global fit, factor reliability, convergent and discriminant validity, item performance, interpretability, parsimony, and consistency with the qualitative findings.

Model fit was assessed using multiple complementary indices because no single statistic provides a sufficient evaluation of measurement-model adequacy. The chi-square statistic and the chi-square-to-degrees-of-freedom ratio were reported as indicators of absolute model discrepancy, while the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI) were used as incremental fit indices. The Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) were examined as indices of approximate and residual fit. As general interpretive criteria, CFI and TLI values of at least 0.90 were considered acceptable and values approaching or exceeding 0.95 were interpreted as evidence of stronger fit. RMSEA values of 0.08 or lower were considered acceptable, with values around or below 0.06 indicating close fit, and SRMR values of 0.08 or lower were regarded as desirable. The relative chi-square was interpreted cautiously because chi-square statistics are sensitive to sample size and model complexity. Where statistically appropriate, competing nested models were additionally compared using procedures compatible with the WLSMV estimator rather than conventional uncorrected chi-square difference testing.

The measurement quality of the retained factor solution was evaluated through standardized factor loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant-validity indices. Standardized loadings approaching or exceeding 0.70 were considered strong evidence of indicator reliability, although items below this value were not automatically discarded when they

Iranian Journal of Educational Sociology
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demonstrated substantive importance and acceptable overall psychometric behavior. Cronbach's alpha and composite reliability values of at least 0.70 were used as general criteria for adequate internal consistency. Convergent validity was assessed through the average variance extracted, with AVE values of at least 0.50 indicating that a latent factor accounted for at least half of the variance of its indicators on average. Discriminant validity was evaluated using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations. Under the Fornell–Larcker criterion, the square root of a construct's AVE was expected to exceed its correlations with other latent constructs, while HTMT values below 0.85 were interpreted as supporting adequate distinction between conceptually related dimensions. Reliability and validity evidence was interpreted collectively rather than by deleting items solely to maximize any individual coefficient.

Because the central purpose of the study was scale validation, the final interpretation integrated evidence from item development, expert appraisal, the pilot study, exploratory factor analysis, confirmatory factor analysis, internal-consistency estimates, convergent validity, discriminant validity, and global model fit. The quantitative factor structure was also compared with the qualitative thematic architecture to determine the extent to which the psychometrically supported dimensions corresponded to the domains initially identified by experts. This integration was an essential component of the sequential exploratory design: qualitative findings established the contextual content domain of AI readiness, whereas EFA and CFA determined whether that conceptual structure could be supported as a stable measurement model in the quantitative data. The final instrument was therefore selected on the basis of combined qualitative relevance and quantitative psychometric evidence rather than on either source of evidence alone.

3. Findings and Results

Analysis of the 25 semi-structured interviews produced 101 basic themes, which were organized into 18 organizing themes and ultimately integrated under the global theme of systemic readiness of higher education for artificial intelligence. The qualitative findings indicated that AI readiness in higher education is not limited to technological infrastructure; rather, it involves a network of interdependent technological, human, organizational, educational, ethical, research, labor-market, governance, and sustainability conditions. The complete thematic classification is presented in Table 1.

Table 1

Final Classification of the Qualitative Findings

Organizing theme	Basic themes
Technological and hardware infrastructure readiness for AI in universities	Provision of GPU servers and up-to-date graphics processing resources; stable, high-speed, high-bandwidth Internet; modernization of computer systems and laboratory equipment; development of cloud platforms, storage systems, and intelligent platforms; integration and organization of institutional data systems; dedicated and sustainable funding for AI infrastructure; reduction of infrastructural inequalities among universities; development of shared computing centers and national laboratories
Integration of theory and practice in graduates' applied AI competencies	Coding and algorithmic thinking; data engineering and real-data cleaning; use of major frameworks and industrial tools; competence in large language models and natural language processing; image processing and computer vision; machine-learning operations and deployment in real settings; translation of real-world problems into AI solutions; data analysis, visualization, and interpretation; exposure to organizational data and real working conditions; end-to-end problem solving
Development of soft skills and professional readiness	Teamwork and collaboration in authentic projects; presentation, public speaking, and stakeholder communication; time management, personal discipline, and work commitment; understanding business environments and product-oriented thinking; professional documentation and organizational reporting; realistic career expectations and gradual professional development
Revision of faculty evaluation and promotion criteria	Inclusion of industry collaboration in promotion criteria; recognition of products, software, and industrial contracts; reduction of excessive teaching loads; financial incentives for industrial projects; encouragement of faculty industrial experience
Changing stakeholder attitudes and organizational culture toward AI	Increasing managers' practical awareness of AI; reducing faculty resistance to changes in teaching; reducing administrative staff resistance; managing the coexistence of enthusiasm and fear; building trust in and acceptance of AI; moving from conservatism toward innovation; translating slogans and directives into operational action
Governance, policymaking, and targeted financing	Development of strategic documents and operational plans; reduction of bureaucracy and acceleration of decision making; sustainable targeted budgeting; equitable distribution of resources and opportunities; relative university autonomy accompanied by accountability; establishment of a national AI coordinating body; reduction of the policy–implementation gap; systems thinking and data-driven decision making

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

Updating AI-oriented curricula and course content	Continuous and rapid curriculum revision; labor-market-oriented curriculum design; movement toward project-based education; compulsory basic AI education across disciplines; inclusion of soft skills and ethics; curriculum flexibility and delegation of authority; industry representation in curriculum committees
Responsible and professionally ethical use of AI	Institutionalization of professional ethics; transparency and explainability of AI outputs; prevention of AI-assisted academic misconduct; explicit regulations and usage frameworks; preservation of learning quality and critical thinking; awareness of algorithmic bias
Familiarity with generative AI	Professional use of generative AI; prompt engineering and critical evaluation of outputs; use of AI as an assistant in coding and reporting; ability to identify appropriate and inappropriate uses
Collaboration among universities, the private sector, government, and society	Formal university–industry mechanisms; long-term joint industrial projects; access to real organizational data; facilitative role of government; private sector as an active partner; institutionalized university–government–industry collaboration
Continuous learning and professional development of stakeholders	Continuous faculty development; administrative staff training; managerial digital literacy; self-directed and lifelong learning culture; change-management and culture-building skills
Alignment of emerging AI-related skills with industrial applications	Systematic identification of labor-market needs; specialist competencies in high-demand fields; alignment with contemporary industrial technologies; cultivation of practically competent rather than solely theoretical graduates; familiarity with industrial standards and regulations
AI-based innovation and entrepreneurship	Support for student start-ups; conversion of research into commercially viable products; linking university innovation with market needs
Revision of teaching and learning methods	Reframing faculty members as learning facilitators; AI-supported personalized learning; integration of AI with innovative teaching approaches; process-oriented rather than purely outcome-oriented assessment; purposeful use of generative AI in instruction
Intra-university and interdisciplinary collaboration	Joint research between technical and nontechnical disciplines; removal of structural barriers to interdisciplinary collaboration; interdisciplinary teams for complex problems
International cooperation and localization	Learning from successful international models; localization of AI tools and Persian-language models; access to international projects and tools
Alignment of university and industry goals	Reducing the difference between the pace of change in universities and industry; problem-oriented and industry-based theses; systematic targeted internships; joint university–industry offices; management of mutual expectations
Foresight and sustainable AI development	Long-term planning and sustained investment; reducing technological dependency and brain drain; attention to economic constraints; continuous development pathways from university to industry; transformational leadership and a shared AI vision

The saturation analysis showed that 17 of the 18 organizing themes emerged during the first six interviews with AI specialists. The seventh interview did not add a new theme. The eighteenth theme, revision of teaching methods, emerged in the first faculty interview, corresponding to Participant 8, and none of the remaining 17 interviews produced an additional organizing theme. The final three employer interviews were conducted specifically as confirmatory saturation interviews. Accordingly, thematic saturation was considered firmly established.

Member checking further supported the credibility of the qualitative structure. Seven participants from the three stakeholder groups evaluated all 18 organizing themes, producing 126 individual evaluations. Of these evaluations, 119 were classified as full confirmation, seven as confirmation with minor modification, and none as rejection. Thus, the direct full-confirmation rate was 94.44%, while all 126 evaluations ultimately supported retention of the thematic content after minor revisions. The proposed modifications concerned wording, boundaries between neighboring themes, or placement of selected basic themes and did not alter the overall 18-theme structure.

Intercoder agreement was examined using six interviews, representing 24% of the qualitative dataset. Two interviews were selected from each participant group. Across 108 theme-presence judgments, the two coders agreed in 104 cases. The observed agreement was therefore 96.30%. Based on the 56 positive agreements, four disagreements, zero instances in which only the second coder identified the theme, and 48 joint absences, Cohen's kappa was 0.93, indicating almost perfect agreement. All four disagreements involved boundary decisions between conceptually adjacent themes rather than substantially different interpretations of the interview content.

The quantitative analyses reported in this section were based on 248 valid respondents and 59 analyzed questionnaire items. The overall Cronbach's alpha was 0.966, and the standardized alpha was likewise 0.966, demonstrating very high overall internal consistency. Dimension-specific Cronbach's alpha coefficients ranged from 0.735 for university interaction with industry, government, and society to 0.816 for educational and curriculum readiness. Thus, all 10 original dimensions achieved coefficients above 0.70 in the main sample. Analysis of alpha if item deleted showed that removal of no

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individual item produced a substantively meaningful increase in dimension-level reliability.

The average inter-item correlations ranged from 0.328 to 0.439 across the 10 dimensions, with an overall average inter-item correlation of 0.327. These values were within the commonly acceptable range of approximately 0.15–0.50, indicating that the items were sufficiently related without showing evidence of excessive redundancy. The highest average inter-item correlation was observed for professional skill development, whereas the lowest values were observed for governance and responsible AI use.

Table 2

Reliability and Dimension-Level Descriptive Statistics

Dimension	Code	Items	Cronbach's α	Mean	SD	Average inter-item correlation
Technological infrastructure readiness	TECH	6	0.782	2.367	0.638	0.375
Human readiness and organizational culture	HUM	6	0.770	2.608	0.616	0.361
Governance, policymaking, and faculty evaluation	GOV	7	0.773	2.306	0.550	0.328
Educational and curriculum readiness	EDU	7	0.816	2.163	0.612	0.389
Responsible and ethical AI use	ETH	6	0.743	2.476	0.593	0.328
University interaction with industry, government, and society	LINK	5	0.735	2.258	0.624	0.358
Research, innovation, and entrepreneurship	RES	5	0.787	2.435	0.669	0.425
Professional skill development of students	PRO	5	0.796	2.423	0.670	0.439
Employability and labor-market alignment	EMP	6	0.767	2.333	0.581	0.356
Educational outcomes and smart-university maturity	OUT	6	0.756	2.120	0.554	0.346
Total instrument	—	59	0.966	—	—	0.327

The descriptive results consistently indicated that respondents perceived Iranian higher education as being below the midpoint of the five-point scale across most readiness domains. Technological infrastructure readiness had an overall mean of 2.37. At the item level, means ranged from 2.11 to 2.85. Educational and research data received the highest evaluation at 2.85, whereas access to required infrastructure received the lowest evaluation at 2.11. The remaining technological items included hardware readiness at 2.27, AI platforms at 2.36, security protocols at 2.17, and technological support or readiness among managers and faculty at 2.45. Standard deviations ranged from approximately 0.90 to 0.95, skewness from -0.14 to 0.61, and kurtosis from -0.65 to 0.12.

Human readiness and organizational culture showed somewhat greater variability. Item means ranged from 2.13 to 3.42. Faculty enthusiasm for using AI received the highest mean of 3.42 and was the only item in this domain clearly above the scale midpoint. Organizational culture was close to the midpoint at 2.96. Awareness of AI among university managers had a mean of 2.47, continuous-learning culture 2.38, one faculty-readiness indicator 2.28, and administrative and staff readiness 2.13. Standard deviations ranged from 0.81 to 0.97, skewness from -0.33 to 0.60, and kurtosis from -0.80 to 0.24.

Governance, policymaking, and faculty evaluation exhibited a consistently weak pattern, with item means ranging from 2.00 to 2.62. Practical university action received the highest mean of 2.62, followed by the existence of a national coordinating mechanism at 2.53. Financial and professional incentives averaged 2.33, administrative processes 2.31, strategic university documents 2.17, faculty promotion regulations 2.17, and targeted AI budgeting only 2.00. Standard deviations ranged from 0.79 to 0.92. Skewness ranged from -0.06 to 0.36 and kurtosis from -0.53 to -0.17, indicating no serious distributional abnormality.

Educational and curriculum readiness was among the weakest domains. Item means ranged from 1.88 to 2.33. Curriculum content received the lowest mean of 1.88, followed by labor-market alignment of programs at 2.05, basic AI education at 2.08, availability of educational infrastructure at 2.19, student assessment practices at 2.27, and teaching approaches and the condition of relevant student programs at 2.33. Standard deviations ranged from 0.81 to 1.03, skewness from 0.37 to 0.71, and kurtosis from -0.55 to 0.43.

For responsible and ethical AI use, item means ranged from 1.96 to 3.33. The highest item mean, 3.33, related to a faculty-level practice, whereas education and learning concerning responsible use approached the midpoint at 2.97. Other items averaged 2.40, 2.19, 2.01, and 1.96, with the lowest value corresponding to institutional attention to AI ethical principles. Standard deviations ranged from 0.78 to

Iranian Journal of Educational Sociology
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1.00, skewness from -0.23 to 0.62, and kurtosis from -0.68 to 0.15.

University interaction with industry, government, and society was also evaluated below the midpoint. Item means ranged from 2.04 to 2.55. Joint research obtained the highest mean of 2.55, followed by utilization or exchange of experience at 2.36, theses and research projects at 2.24, institutional collaboration mechanisms at 2.10, and tripartite university–government–industry collaboration at 2.04. Standard deviations ranged from 0.81 to 0.96, skewness from 0.42 to 0.74, and kurtosis from -0.28 to 0.47.

For research, innovation, and entrepreneurship, item means ranged from 2.17 to 2.98. University research and scientific capacity was closest to the scale midpoint at 2.98. Innovation initiatives averaged 2.53, AI-related research activity 2.28, supporting organizational structures 2.22, and scientific or applied production 2.17. Standard deviations ranged from 0.83 to 1.02, skewness from 0.07 to 0.49, and kurtosis from -0.73 to 0.04.

Professional skill development among students was uniformly below the midpoint, with item means ranging narrowly from 2.35 to 2.51. The highest mean was 2.51 for a work-related student skill indicator, followed by 2.46, 2.43, 2.36, and 2.35 for the remaining competence indicators. Standard deviations ranged from 0.87 to 0.95, skewness from 0.32 to 0.56, and kurtosis from -0.61 to 0.09.

Employability and labor-market alignment showed item means from 2.06 to 2.72. Interaction with organizations and employers had the highest mean of 2.72, followed by perceptions of graduates at 2.52. University preparation of skilled human resources averaged 2.29, effectiveness of learned skills 2.24, systematic attention to skill requirements 2.16, and student internship programs only 2.06. Standard deviations ranged from 0.79 to 0.91, skewness from 0.07 to 0.78, and kurtosis from -0.32 to 0.87.

Educational outcomes and smart-university maturity was the lowest-scoring dimension overall, with a mean of 2.12. Item means ranged from 1.92 to 2.60. Practical application of AI had the highest mean at 2.60. Managerial contribution to AI development averaged 2.19, continuity of institutional AI initiatives 2.08, organizational utilization 1.98, development pathways 1.94, and employment-related outcomes only 1.92. Standard deviations ranged from 0.72 to 0.96, skewness from 0.24 to 0.60, and kurtosis from -0.52 to 0.06. Across all domains, skewness and kurtosis remained within ±2, indicating that no severe univariate distributional problems were evident.

Prior to factor extraction, the suitability of the correlation matrix was evaluated. The overall Kaiser–Meyer–Olkin index was 0.94, indicating excellent sampling adequacy. Item-specific KMO coefficients ranged from 0.86 to 0.97, so no item failed the conventional minimum criterion. Bartlett's test of sphericity was statistically significant, $\chi^2(1711) = 7178.013$, $p < 0.001$, demonstrating that the correlation matrix contained sufficient shared variance for factor analysis.

The first exploratory analysis examined the theoretically proposed 10-factor structure. Because many factor correlations exceeded 0.30, an oblique solution was required. Before final rotation, factor correlations ranged approximately from -0.06 to 0.64. Particularly strong associations were found between MR1 and MR3 (0.64), MR1 and MR6 (0.60), MR3 and MR4 (0.60), MR4 and MR10 (0.58), MR6 and MR9 (0.57), and MR3 and MR5 (0.56). These results demonstrated that the dimensions were not statistically independent. Direct Oblimin rotation was initially attempted but failed to converge after 1,000 iterations. Promax rotation was therefore adopted and converged without warning.

The initial 10-factor Promax solution produced factor loadings ranging widely across the 59 items. Several items displayed clear primary loadings, such as V5 on MR4 at 0.76, V17 on MR5 at 0.72, V31 on MR3 at 0.73, V35 on MR1 at 0.76, V38 on MR1 at 0.73, V41 on MR1 at 0.73, V43 on MR1 at 0.82, V54 on MR1 at 0.73, and V58 on MR8 at 0.59. Other items showed more complex patterns. V15 and V18 had particularly small differences between their strongest and second-strongest loadings. V11, V10, V53, V37, V22, V40, and V56 required further review because of elevated complexity or ambiguous loading patterns. V16, V30, V24, and V7 showed relevant cross-loadings. Moreover, several factors were represented by fewer than three items.

The initial 10-factor solution had a mean item complexity of 2.60, RMSR = 0.02, df-corrected RMSR = 0.03, likelihood $\chi^2 = 2533.67$ with 1166 degrees of freedom, TLI = 0.744, and RMSEA = 0.069, 90% CI [0.065, 0.073]. Factor-score correlations ranged approximately from 0.72 to 0.85 and corresponding multiple R^2 coefficients from 0.51 to 0.73.

A psychometric screening procedure was then applied using primary loading magnitude, loading-gap size, cross-loadings, communality, complexity, and the number of indicators available for each factor. Twenty-nine problematic items were removed: V53, V23, V37, V18,

Iranian Journal of Educational Sociology
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V57, V8, V4, V27, V51, V32, V45, V9, V42, V56, V16, V20, V3, V40, V50, V19, V14, V15, V52, V59, V39, V54, V46, V33, and V55. The resulting 30-item solution retained 10 factors. Primary loadings in the refined solution included 0.60–0.79 for the principal indicators of MR2, 0.65–0.72 for several MR5 indicators, 0.58–0.66 for MR10 indicators, 0.95 for V36 on MR1, 1.08 for V31 on MR3 in the pattern matrix, 0.82 for V29 on MR7, and 0.63 for V58 on MR4. Communalities were generally above 0.40.

However, although fit improved substantially, the 10-factor structure remained psychometrically problematic because several factors contained only one or two indicators. The final allocation consisted of five items in Factor 1, six in Factor 2, four in Factor 3, four in Factor 4, three in Factor 5, two each in Factors 6, 7, and 8, and only one item each in Factors 9 and 10. Consequently, a conventional CFA based on this 10-factor solution would have contained poorly identified or unstable latent factors.

After Promax rotation, factor correlations ranged from -0.19 to 0.60. The largest correlations were MR1–MR4 = 0.60, MR1–MR6 = 0.59, MR4–MR6 = 0.57, MR1–MR2 = 0.56, MR4–MR5 = 0.53, and MR2–MR5 = 0.52. These findings further justified use of an oblique rather than orthogonal rotation.

Because the 10-factor solution produced underidentified or weakly represented factors, the optimal dimensionality of the instrument was reassessed using several complementary approaches: parallel analysis, the scree criterion, Velicer's minimum average partial test, the Very Simple Structure criterion, empirical BIC, sample-size-adjusted BIC, exploratory graph analysis, hierarchical cluster analysis, and comparisons of fit across factor solutions.

VSS at complexity 1 was highest for the one-factor solution at 0.91, whereas VSS at complexity 2 reached its maximum of 0.68 for the two-factor solution. Velicer's MAP also favored two factors, with its minimum value of 0.0098 at the two-factor solution. Empirical BIC reached its lowest value at two factors, -1927, whereas the sample-size-adjusted BIC favored six factors, with SABIC = -242. Parallel analysis likewise indicated that only the first two empirical eigenvalues clearly exceeded their random-data counterparts. In contrast, the scree plot showed a major decline after the first factor but a more gradual decline through approximately the fifth factor, after which the curve became substantially flatter. The Kaiser criterion also identified five eigenvalues greater than one.

Table 3

Factor-Retention Evidence Across One- to Ten-Factor Solutions

Factors	VSS1	VSS2	MAP	df	χ^2	Fit	TLI	RMSEA	RMSR	SRMR	BIC	SABIC	Complexity	Variance explained
1	0.91	0.00	0.0141	594	1544	0.91	0.766	0.080	0.049	0.0487	-1731	152	1.0	0.385
2	0.57	0.68	0.0098	559	1155	0.68	0.843	0.065	0.034	0.0340	-1927	-155	1.1	0.437
3	0.48	0.67	0.0104	525	1046	0.65	0.854	0.063	0.031	0.0309	-1849	-185	1.4	0.458
4	0.32	0.56	0.0109	492	935	0.57	0.867	0.060	0.028	0.0276	-1778	-218	1.7	0.480
5	0.29	0.48	0.0117	460	850	0.53	0.874	0.058	0.025	0.0255	-1686	-228	1.8	0.498
6	0.25	0.44	0.0125	429	763	0.51	0.884	0.056	0.023	0.0234	-1602	-242	2.0	0.515
7	0.25	0.43	0.0138	399	700	0.50	0.887	0.055	0.022	0.0218	-1500	-235	2.0	0.538
8	0.23	0.34	0.0149	370	635	0.46	0.893	0.054	0.020	0.0200	-1405	-232	2.3	0.553
9	0.22	0.32	0.0164	342	566	0.44	0.901	0.051	0.018	0.0184	-1319	-235	2.3	0.566
10	0.22	0.32	0.0177	315	524	0.44	0.900	0.052	0.017	0.0171	-1213	-214	2.4	0.577

The eigenvalues derived from the polychoric correlation matrix were 14.481, 2.338, 1.275, 1.243, 1.048, 0.986, 0.939, 0.911, 0.824, and 0.811 for the first 10 factors, respectively. These factors explained 40.23%, 6.49%, 3.54%, 3.45%, 2.91%, 2.74%, 2.61%, 2.53%, 2.29%, and 2.25% of the variance. Cumulative explained variance

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therefore reached 40.23% after Factor 1, 46.72% after Factor 2, 50.26% after Factor 3, 53.71% after Factor 4, 56.63% after Factor 5, and 69.05% after Factor 10.

Exploratory graph analysis using a GLASSO network identified two major communities of items. The first community consisted primarily of V1, V2, V3, V4, V5, V8, V10, V11, V12, V13, V16, V17, V18, V19, V27, V28, V30, V31, V32, V37, V52, V53, V55, V56, V58, and V59. The second community contained V6, V7, V20, V21, V22, V24, V26, V29, V34, V35, V36, V38, V39, V40, V41, V42, V43, V44, V45, V46, V47, V48, V50, V51, and V54. V9, V14, V15, V23, V25, V33, V49, and V57 occupied more peripheral or boundary positions. The within-community connections were generally denser than connections between communities, supporting the existence of two broad latent clusters.

Hierarchical cluster analysis based on polychoric correlations and Ward's minimum-variance method produced a compatible pattern. Numerous item pairs and small groups merged at low linkage distances, whereas the final merger of the two largest clusters occurred at a substantially higher distance of approximately 1.5. This indicated that the instrument possessed a strong general structure but also contained two broad subclusters. The convergence between parallel analysis, MAP, VSS, empirical BIC, EGA, and hierarchical clustering provided substantial statistical support for a parsimonious two-factor interpretation, whereas the scree plot and Kaiser criterion justified examination of a five-factor alternative.

A one-factor EFA initially produced loadings between 0.41 and 0.72. Most items loaded above 0.50, although V19, V31, and V58 showed comparatively weak performance. Seven items—V2, V3, V8, V19, V25, V31, and V58—were subsequently removed according to the stated screening criteria. In the resulting 52-item solution, factor loadings ranged from 0.55 to 0.72 and communalities from approximately 0.30 to 0.52. The proportion of explained variance increased from 38% before deletion to 40% after deletion. Model fit also improved, with RMSR decreasing from 0.05 to 0.04, TLI increasing from 0.667 to 0.728, and RMSEA decreasing from 0.080 to 0.076. Factor-score adequacy remained extremely high: the correlation between estimated factor scores and the latent factor was 0.99 both before and after deletion, with factor-score $R^2 = 0.97$.

The two-factor solution initially explained approximately 42% of the total variance. The first and second factors had SS loadings of 13.78 and 10.79 and accounted for approximately 23% and 18% of the total variance, respectively. Their correlation was 0.75, indicating that the two dimensions were distinguishable but strongly related. Twenty-three problematic items—V3, V4, V5, V9, V12, V14, V19, V23, V25, V31, V33, V42, V43, V44, V45, V46, V47, V48, V49, V50, V51, V52, and V57—were removed. The final 36-item two-factor solution produced primary loadings predominantly above 0.40, factor correlation r = 0.73, and cumulative explained variance of approximately 44%. Following item removal, mean complexity declined from 1.20 to 1.10, RMSR from 0.04 to 0.03, TLI increased from 0.715 to 0.844, and RMSEA decreased from 0.074 to 0.065. Factor-score correlations remained satisfactory at 0.86 and 0.85, with R^2 values of 0.74 and 0.73.

The five-factor solution was then examined because the first five eigenvalues exceeded one, the scree plot suggested a meaningful elbow near the fifth factor, and a five-factor interpretation allowed the statistical structure to be related more readily to the broader qualitative domains. In the initial five-factor analysis, primary loadings were generally moderate to strong, but 33 items displayed insufficient simple structure according to loading magnitude, cross-loading, communality, or complexity criteria. These items were V3, V6, V7, V9, V11, V13, V14, V15, V16, V20, V23, V24, V26, V27, V29, V30, V32, V33, V40, V42, V43, V45, V46, V47, V48, V49, V50, V52, V53, V54, V57, V58, and V59. Reanalysis of the remaining 26 items produced primary loadings from approximately 0.47 to 0.89 and communalities from 0.35 to 0.66. The five factors collectively explained 49% of the variance. Factor correlations after refinement ranged from approximately 0.47 to 0.70.

The five-factor model was also re-estimated in a randomly selected 60% exploratory subsample of 149 participants. The sample split was generated reproducibly using set.seed(123), leaving 99 participants for subsequent CFA. The EFA again used polychoric correlations, minimum residual extraction, and Promax rotation. Items were screened using primary loading, secondary loading, loading difference, number of cross-loadings ≥0.30 and ≥0.40, communality, and complexity. The retained 21-item solution comprised six items in the first factor, six in the second, and three in each of the remaining three factors. Communalities ranged from 0.428 to 0.705. The five factors explained 54% of the variance, distributed as approximately 16%, 14%, 9%, 8%, and 8%. Factor correlations ranged from 0.461 to 0.685. Fit was acceptable, with RMSR = 0.02, RMSEA = 0.059, 90% CI [0.042, 0.077], TLI = 0.914, and BIC = -399.16. V20 and V42 showed relatively weaker

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factor-structural performance and were identified as items requiring additional attention in subsequent validation.

Table 4

Comparison of Refined Exploratory Factor Solutions

Solution	N	Retained items	Cumulative variance	Mean complexity	RMSR	df-corrected RMSR	χ^2	df	TLI	RMSEA	90% CI RMSEA	BIC
One-factor	248	52	40%	1.00	0.04	0.04	3097.32	1274	0.728	0.076	0.073–0.080	-3926.79
Two-factor	248	36	44%	1.10	0.03	0.04	1154.96	630	0.844	0.065	0.060–0.071	-1927.05
Five-factor	248	26	49%	1.30	0.02	0.03	394.51	205	0.886	0.061	0.052–0.070	-735.74
Five-factor, 60% exploratory subsample	149	21	54%	1.50	0.02	0.03	176.29	115	0.914	0.059	0.042–0.077	-399.16
Ten-factor	248	30	59%	2.10	0.02	0.02	295.57	180	0.915	0.051	0.040–0.061	-696.85

The 10-factor model explained the largest proportion of variance and displayed the strongest EFA fit statistics, but this apparent advantage was offset by structural instability: three of its factors contained only two indicators and two factors contained only a single indicator. In contrast, the two-factor model was parsimonious and strongly supported by factor-retention statistics, while the five-factor solution achieved a more interpretable compromise between statistical parsimony, adequate indicator counts, explained variance, and correspondence with the qualitative domains.

The final item distributions in the refined solutions reflected this contrast. The one-factor model contained all 52 retained items in a single dimension. The refined two-factor model allocated V6, V7, V15, V20, V21, V22, V24, V26, V29, V34, V35, V36, V38, V39, V40, V41, and V54 to the first factor and V1, V2, V8, V10, V11, V13, V16, V17, V18, V27, V28, V30, V32, V37, V53, V55, V56, V58, and V59 to the second factor. The refined full-sample five-factor model allocated V35, V36, V38, V39, and V41 to MR1; V8, V17, V18, V19, V28, and V31 to MR2; V1, V2, V4, and V5 to MR3; V10, V12, V25, V37, V55, and V56 to MR4; and V21, V22, V34, V44, and V51 to MR5.

In the 60% exploratory subsample, the five-factor arrangement was somewhat different but preserved the same five broad conceptual domains. MR1 contained V20, V21, V22, V26, V34, and V44; MR2 contained V35, V36, V39, V40, V41, and V42; MR3 contained V10, V12, and V53; MR4 contained V3, V18, and V28; and MR5 contained V1, V2, and V4. The change in factor order reflected differences in extraction rather than emergence of substantively unrelated constructs.

Table 5

Five-Factor Structures Obtained in the Full Sample and the 60% Exploratory Subsample

Analysis	Factor	Conceptual interpretation	Items	No. of items	Eigenvalue/SS loading	Variance
Full-sample EFA	MR1	Research, innovation, and interaction with industry and society	V35, V36, V38, V39, V41	5	2.79	11%
	MR2	AI governance, leadership, and ethics	V8, V17, V18, V19, V28, V31	6	2.57	10%
	MR3	Technological infrastructure readiness	V1, V2, V4, V5	4	2.08	8%
	MR4	Organizational culture and institutional maturity	V10, V12, V25, V37, V55, V56	6	2.80	11%
	MR5	Education, skills development, and employability	V21, V22, V34, V44, V51	5	2.55	10%
60% exploratory subsample	MR1	Education, skills development, and employability	V20, V21, V22, V26, V34, V44	6	3.33	16%

Iranian Journal of Educational Sociology
E-ISSN: 2645-3460

	MR2	Research, innovation, and interaction with industry and society	V35, V36, V39, V40, V41, V42	6	2.88	14%
	MR3	Organizational culture and institutional maturity	V10, V12, V53	3	1.85	9%
	MR4	AI governance, leadership, and ethics	V3, V18, V28	3	1.77	8%
	MR5	Technological infrastructure readiness	V1, V2, V4	3	1.60	8%

Thus, the full-sample five-factor solution explained 49% of total variance, whereas the five-factor solution in the 60% exploratory subsample explained 54%. Despite item-level changes, five broad conceptual domains remained recognizable in both analyses. This reproducibility was one of the reasons for advancing the five-factor model to confirmatory testing.

CFA was performed using DWLS/WLSMV estimation because the questionnaire items were ordinal. Competing one-factor, two-factor, and five-factor models were examined. The five-factor model based on the full sample showed the strongest combination of conventional and robust fit indices.

For the one-factor model, standard fit indices appeared strong: CFI = 0.995, TLI = 0.995, RMSEA = 0.032, 90% CI [0.027, 0.037], and SRMR = 0.060. The scaled solution produced CFI = 0.959, TLI = 0.957, and RMSEA = 0.041; however, the explicitly robust indices were substantially weaker, with robust CFI = 0.777, robust TLI = 0.768, and robust RMSEA = 0.075, 90% CI [0.071, 0.079]. Thus, the apparent excellent fit of the conventional indices overstated the strength of the unidimensional model.

The one-factor CFA loadings ranged from 0.549 to 0.728 and were all significant at $p < 0.001$. The highest loadings included V41 = 0.728, V46 = 0.721, V22 = 0.720, V54 = 0.717, V11 = 0.694, V26 = 0.692, V56 = 0.692, and V39 = 0.691. The lowest included V5 = 0.549, V12 = 0.555, V28 = 0.560, V17 = 0.568, V53 = 0.571, and V13 = 0.574. Reliability was extremely high, with Cronbach's $\alpha = 0.9649$, ordinal $\alpha = 0.9712$, $\omega = 0.9653$, and CR = 0.9782. AVE, however, was only 0.4013, indicating incomplete convergent validity despite excellent reliability.

The two-factor CFA demonstrated better fit. Standard indices were CFI = 1.000, TLI = 1.001, RMSEA = 0.000, and SRMR = 0.052. The scaled indices were CFI = 0.975, TLI = 0.974, and RMSEA = 0.036, while robust CFI, robust TLI, and robust RMSEA were 0.884, 0.877, and 0.061, respectively. All 36 loadings were significant at $p < 0.001$. For MR1, standardized loadings ranged from 0.608 for V6 to 0.770 for V41. Other relatively strong indicators were V22 = 0.738, V54 = 0.721, V26 = 0.712, V39 = 0.710, and V24 = 0.708. For MR2, loadings ranged from 0.507 for V58 to 0.739 for V11, with V56 = 0.719, V16 = 0.688, V30 = 0.685, V32 = 0.683, and V18 = 0.679. MR1 demonstrated $\alpha = 0.922$, ordinal $\alpha = 0.934$, $\omega = 0.929$, CR = 0.929, and AVE = 0.460. MR2 demonstrated $\alpha = 0.910$, ordinal $\alpha = 0.929$, $\omega = 0.916$, CR = 0.916, and AVE = 0.412. HTMT was 0.771, supporting discriminant validity. Overall two-factor scale reliability was $\alpha = 0.948$, ordinal $\alpha = 0.957$, $\omega = 0.961$, CR = 0.964, and AVE = 0.435.

The five-factor CFA produced the most favorable overall pattern. The standard solution yielded CFI = 1.000, TLI = 1.002, RMSEA = 0.000, and SRMR = 0.049. The scaled values were CFI = 0.979, TLI = 0.976, and RMSEA = 0.037. More importantly, the explicitly robust indices reached CFI = 0.930, TLI = 0.921, and RMSEA = 0.053, providing stronger robust fit than either the one-factor or two-factor structures.

Table 6

Confirmatory Fit of the Competing Measurement Models

Index	One-factor standard	One-factor robust/scaled	Two-factor standard	Two-factor robust/scaled	Five-factor standard	Five-factor robust/scaled	Five-factor, 40% sample standard	Five-factor, 40% sample robust/scaled
N	248	248	248	248	248	248	99	99
χ^2	1605.717	1795.549	571.513	784.486	260.493	386.776	197.019	253.518
df	1274	1274	593	593	289	289	179	179
p	—	<0.001	—	<0.001	—	<0.001	—	<0.001
CFI	0.995	0.959	1.000	0.975	1.000	0.979	0.996	0.951
TLI	0.995	0.957	1.001	0.974	1.002	0.976	0.995	0.943
Robust CFI	—	0.777	—	0.884	—	0.930	—	0.833
Robust TLI	—	0.768	—	0.877	—	0.921	—	0.804
RMSEA	0.032	0.041	0.000	0.036	0.000	0.037	0.032	0.065

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90% CI for RMSEA	0.027–0.037	0.036–0.045	0.000–0.016	0.029–0.043	0.000–0.013	0.027–0.046	0.000–0.057	0.046–0.083
Robust RMSEA	—	0.075	—	0.061	—	0.053	—	0.098
Robust RMSEA 90% CI	—	0.071–0.079	—	0.055–0.067	—	0.043–0.063	—	0.079–0.117
SRMR	0.060	0.060	0.052	0.052	0.049	0.049	0.080	0.080

All standardized loadings in the full-sample five-factor CFA were statistically significant at $p < 0.001$. For MR1, loadings were V35 = 0.673, V36 = 0.719, V38 = 0.718, V39 = 0.742, and V41 = 0.826. For MR2, the loadings were V8 = 0.678, V17 = 0.677, V18 = 0.738, V19 = 0.499, V28 = 0.701, and V31 = 0.541. For MR3, loadings were V1 = 0.711, V2 = 0.646, V4 = 0.738, and V5 = 0.646. For MR4, loadings were V10 = 0.661, V12 = 0.592, V25 = 0.547, V37 = 0.688, V55 = 0.673, and V56 = 0.769. For MR5, loadings were V21 = 0.663, V22 = 0.779, V34 = 0.699, V44 = 0.711, and V51 = 0.620. With the exception of V19 at 0.499, all standardized loadings were at least approximately 0.54, and every loading was highly statistically significant.

The corresponding standard errors were 0.045, 0.041, 0.042, 0.038, and 0.035 for V35–V41 in MR1; 0.041, 0.049, 0.045, 0.059, 0.044, and 0.051 for V8–V31 in MR2; 0.043, 0.047, 0.049, and 0.051 for V1–V5 in MR3; 0.041, 0.042, 0.055, 0.042, 0.043, and 0.040 for V10–V56 in MR4; and 0.046, 0.037, 0.043, 0.042, and 0.047 for V21–V51 in MR5. The resulting z statistics ranged from 8.457 to 23.390.

Table 7

Reliability and Validity of the Final Full-Sample Five-Factor CFA Model

Factor	Cronbach's α	Ordinal α	Omega	CR	AVE	Highest HTMT with another factor
MR1: Research, innovation, and interaction with industry and society	0.829	0.853	0.823	0.825	0.543	0.786 with MR5
MR2: AI governance, leadership, and ethics	0.772	0.808	0.774	0.767	0.416	0.725 with MR4
MR3: Technological infrastructure readiness	0.751	0.782	0.739	0.735	0.471	0.755 with MR4
MR4: Organizational culture and institutional maturity	0.784	0.818	0.779	0.779	0.434	0.760 with MR5
MR5: Education, skills development, and employability	0.794	0.823	0.790	0.791	0.485	0.786 with MR1
Total scale	0.920	0.933	0.932	0.941	0.466	—

Internal consistency was therefore satisfactory for all five dimensions. Cronbach's alpha ranged from 0.751 to 0.829, ordinal alpha from 0.782 to 0.853, omega from 0.739 to 0.823, and composite reliability from 0.735 to 0.825. MR1 achieved AVE = 0.543 and therefore exceeded the conventional 0.50 threshold. The remaining dimensions had AVE values of 0.416, 0.471, 0.434, and 0.485. Accordingly, convergent validity was strongest for MR1 and approached the conventional criterion for MR3 and MR5, whereas MR2 and MR4 showed more limited extracted variance. Nevertheless, all five factors exhibited acceptable reliability.

Discriminant validity was evaluated primarily through HTMT. The complete HTMT matrix showed values of 0.725 for MR1–MR2, 0.617 for MR1–MR3, 0.679 for MR1–MR4, 0.786 for MR1–MR5, 0.615 for MR2–MR3, 0.725 for MR2–MR4, 0.576 for MR2–MR5, 0.755 for MR3–MR4, 0.663 for MR3–MR5, and 0.760 for MR4–MR5. All were below 0.85, supporting satisfactory discriminant validity.

The corresponding latent-factor correlations were also positive but lower than unity. They were 0.468 for MR1–MR2, 0.500 for MR1–MR3, 0.574 for MR1–MR4, 0.698 for MR1–MR5, 0.568 for MR2–MR3, 0.615 for MR2–MR4, 0.519 for MR2–MR5, 0.613 for MR3–MR4, 0.521 for MR3–MR5, and 0.614 for MR4–MR5. Thus, the factors shared a meaningful common readiness domain while retaining distinguishable content.

The 21-item five-factor solution derived from the 60% exploratory subsample was subsequently tested in the independent 40% holdout subsample of 99 respondents. Standard fit statistics remained favorable: CFI = 0.996, TLI = 0.995, RMSEA = 0.032, and SRMR = 0.080. The scaled values were CFI = 0.951, TLI = 0.943, and RMSEA = 0.065. However, the explicitly robust fit indices were weaker: robust CFI = 0.833, robust TLI = 0.804, and robust RMSEA = 0.098, 90% CI [0.079, 0.117]. This deterioration indicated that model stability was more limited when the CFA was estimated with only 99 participants.

Iranian Journal of Educational Sociology
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All 21 standardized loadings remained statistically significant at $p < 0.001$. For the first factor, the loadings were V34 = 0.717, V44 = 0.599, V22 = 0.788, V21 = 0.624, V20 = 0.738, and V26 = 0.682. For the technological infrastructure factor, V1 = 0.670, V2 = 0.447, and V4 = 0.790. For the organizational culture/institutional maturity factor, V10 = 0.690, V12 = 0.536, and V53 = 0.570. The research and innovation factor contained V42 = 0.579, V41 = 0.766, V40 = 0.634, V39 = 0.761, V35 = 0.689, and V36 = 0.748. The governance and ethics factor contained V3 = 0.567, V18 = 0.736, and V28 = 0.691. Thus, the factor-loading range was 0.447–0.790, with V2 providing the weakest but still statistically significant loading.

Reliability in the holdout sample was uneven. Cronbach's alpha was 0.817 for MR1, 0.647 for MR2, 0.585 for MR3, 0.806 for MR4, and 0.642 for MR5. Ordinal alpha coefficients were 0.844, 0.682, 0.618, 0.837, and 0.695, respectively. Omega coefficients were 0.827, 0.615, 0.580, 0.843, and 0.654, while composite reliability values were identical or nearly identical at 0.827, 0.615, 0.580, 0.843, and 0.654. AVE values were 0.482, 0.424, 0.363, 0.489, and 0.447. Thus, none of the five holdout factors reached AVE = 0.50, although MR1 and MR4 came close. At the total-scale level, Cronbach's alpha was 0.904, ordinal alpha 0.919, and omega approximately 0.933, indicating that the instrument retained high global reliability despite weaker dimension-level precision in the smaller sample.

The holdout-sample HTMT values were 0.573 for MR1–MR2, 0.768 for MR1–MR3, 0.881 for MR1–MR4, 0.617 for MR1–MR5, 0.751 for MR2–MR3, 0.461 for MR2–MR4, 0.754 for MR2–MR5, 0.642 for MR3–MR4, 0.819 for MR3–MR5, and 0.701 for MR4–MR5. The value of 0.881 between MR1 and MR4 exceeded the strict 0.85 criterion, suggesting weaker discrimination between those dimensions in the smaller validation sample. The result was interpreted cautiously because the CFA subsample contained only 99 cases for a five-factor, 21-item model and approximately 110 estimated parameters.

The overall evidence did not support retention of the original qualitative 10-factor structure as the final quantitative measurement model. Although the refined 10-factor EFA produced TLI = 0.915, RMSEA = 0.051, and 59% explained variance, it contained factors represented by only one or two items. Such factors would have limited reliability estimation, unstable parameter estimates, and weak latent-variable identification.

The one-factor model was highly reliable and represented a strong general AI-readiness dimension, but the robust CFA indices were comparatively weak and the model did not preserve meaningful differentiation among institutional readiness domains. The two-factor model was strongly supported by parallel analysis, MAP, VSS2, empirical BIC, EGA, and hierarchical clustering and therefore represented the most statistically parsimonious solution. Nevertheless, the five-factor structure provided a better compromise between dimensional differentiation and psychometric stability. Unlike the 10-factor model, each factor retained an interpretable set of indicators; unlike the one-factor solution, it preserved substantively important institutional domains; and relative to the two-factor CFA, the full-sample five-factor CFA showed superior robust fit.

In the full-sample five-factor EFA, the first factor represented research, innovation, and interaction with industry and society; the second reflected AI governance, leadership, and ethics; the third represented technological infrastructure readiness; the fourth reflected organizational culture and institutional maturity; and the fifth represented education, skill development, and employability. The corresponding EFA structure explained 49% of variance. When the EFA was repeated in the 60% exploratory subsample, the ordering and individual membership of some factors changed, but the same broad conceptual domains reappeared and the cumulative explained variance increased to 54%.

Consequently, the full-sample five-factor solution was adopted as the principal proposed measurement structure, while the split-sample analysis was treated as a partial cross-validation exercise. The full-sample five-factor model had substantially better robust CFA indices than either the one-factor or two-factor models and satisfactory reliability and discriminant validity. At the same time, the lower AVE of four dimensions and the weaker robust performance in the 99-person holdout sample indicate that the instrument should be regarded as promising and preliminarily validated rather than definitively finalized. Independent validation with a larger sample would therefore strengthen evidence for structural stability.

To preserve the content supported by either the full-sample five-factor model or the 60% exploratory solution, a consolidated 32-item pool was retained. These items jointly covered technological infrastructure, governance and ethics, organizational culture and institutional maturity, education and employability, research and innovation, collaboration with industry and society, and institutional AI-readiness monitoring.

Iranian Journal of Educational Sociology
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Table 8

Final 32-Item Pool for Assessing Higher Education Readiness for AI Adoption

No.	Item	English wording
1	V1	The university has sufficient computing hardware, including servers, GPUs, and network infrastructure, to implement AI projects.
2	V2	The university uses appropriate cloud platforms, data-analysis tools, and integrated systems for AI education and research.
3	V3	The university's educational, research, and administrative data are managed in an integrated manner and used in intelligent processes.
4	V4	The university provides faculty members and students with access to a diverse range of AI software and tools.
5	V5	The university has the cybersecurity protocols required to protect sensitive data in AI projects.
6	V8	Faculty members have sufficient enthusiasm and motivation to use AI tools in teaching and research.
7	V10	Faculty members regularly participate in AI retraining and professional-development programs.
8	V12	A culture of continuous and self-directed learning in AI is prevalent within the university.
9	V17	A coordinating institution and a clearly defined mechanism for AI policymaking in higher education exist at the national level.
10	V18	Faculty promotion regulations assign appropriate weight to applied and research activities in AI.
11	V19	Appropriate financial and professional incentives are available to faculty members participating in applied AI projects.
12	V20	University curricula are continuously updated in accordance with developments in AI.
13	V21	Curricula are designed on the basis of real labor-market needs and the requirements of the knowledge-based economy.
14	V22	University teaching is moving toward project-based learning, real-world problem solving, and active learning.
15	V25	Basic AI education is incorporated into the curricula of students across all academic disciplines.
16	V26	Student assessment is based on practical competence and the learning process rather than solely on examination outcomes.
17	V28	Faculty members have adequate awareness of the limitations, errors, and weaknesses of AI tools.
18	V31	Educational practices preserve human learning quality and critical thinking and prevent excessive dependence on AI.
19	V34	Student theses and projects are deliberately focused on real problems faced by organizations and industry.
20	V35	Interdisciplinary joint research on AI is conducted among different academic departments within the university.
21	V36	The university draws on successful international experiences in AI education and adapts them to local conditions.
22	V37	Tripartite university–government–industry collaboration in the development of AI education is institutionalized nationally.
23	V38	The university's scientific and research capacity in AI has increased substantially in recent years.
24	V39	The university supports innovative and entrepreneurial AI initiatives undertaken by students.
25	V40	The university has structures for transforming AI research into commercially viable products and solutions.
26	V41	University AI research is linked to actual societal and labor-market needs and contributes to the development of locally relevant solutions.
27	V42	The university actively contributes to the development of Persian-language AI educational content and tools.
28	V44	Students acquire the ability to understand workplace environments, organizational needs, and problem-oriented thinking.
29	V51	The university develops capable, practically oriented human resources who are ready for the labor market rather than possessing only theoretical knowledge.
30	V53	Organizations and employers are satisfied with the practical capabilities of graduates from this university.
31	V55	The university continuously evaluates and improves its level of digital and smart-university maturity.
32	V56	Using explicit indicators, the university regularly assesses its readiness to adopt and apply AI.

Overall, the findings demonstrated a clear progression from a broad qualitative framework of 18 organizing themes and 10 provisional dimensions toward a more parsimonious quantitative structure. The original instrument showed excellent total-scale reliability, but factor-analytic evidence suggested that the qualitative domains did not operate as 10 statistically independent latent constructs. Statistical evidence ranged from a broad two-factor organization identified by parallel analysis, MAP, VSS, EGA, and hierarchical clustering to a five-factor structure supported by the scree pattern, theoretical interpretability, stable indicator representation, and superior confirmatory fit. Among the competing CFA models, the full-sample five-factor solution provided the strongest overall balance of model fit, reliability, discriminant validity, conceptual interpretability, and correspondence with the qualitative evidence. Its five dimensions were therefore identified as research, innovation, and interaction with industry and society; AI governance, leadership, and ethics; technological infrastructure readiness; organizational culture and institutional maturity; and education, skills development, and employability. The reduced stability observed in the 40% holdout subsample, particularly with respect to robust fit, AVE, and selected HTMT coefficients, nevertheless indicates that further independent validation with a larger sample is warranted before the factor structure is regarded as definitive.

Iranian Journal of Educational Sociology
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4. Discussion and Conclusion

The present study developed and psychometrically evaluated a context-sensitive instrument for assessing the readiness of Iranian higher education institutions for the adoption and application of artificial intelligence. The findings provide evidence that AI readiness in higher education is best understood as a systemic and multidimensional phenomenon rather than as a purely technological condition. The qualitative phase initially identified 101 basic themes organized into 18 organizing themes and 10 provisional dimensions, while the quantitative phase demonstrated that these domains were substantially interrelated and could be represented more parsimoniously by a smaller number of latent factors. The final evidence favored a five-factor structure comprising research, innovation, and interaction with industry and society; AI governance, leadership, and ethics; technological infrastructure readiness; organizational culture and institutional maturity; and education, skills development, and employability. This structure reflects the increasing recognition in the literature that successful AI adoption in higher education depends on the interaction of technological, organizational, pedagogical, ethical, and workforce-related capacities rather than on the acquisition of AI tools alone (Crompton & Burke, 2023; Pablo-Martí et al., 2024; Pedreño Muñoz et al., 2024).

The qualitative findings showed that technological infrastructure constituted an essential but insufficient foundation for AI readiness. Participants emphasized access to GPU-enabled computing resources, high-speed Internet, modern hardware, cloud services, integrated data systems, cybersecurity, sustainable funding, and equitable distribution of infrastructure among universities. The quantitative findings supported the importance of this domain but also revealed that technological readiness was perceived as relatively weak, with an overall mean below the midpoint of the response scale. The particularly low ratings for access to required infrastructure and cybersecurity protocols suggest that many Iranian universities may face practical barriers to deploying AI at scale. This result is consistent with broader assessments of AI readiness, which emphasize that technological infrastructure, data accessibility, institutional digital capacity, and governance capabilities jointly determine whether organizations can meaningfully benefit from AI (Hankins et al., 2023). It also aligns with discussions of universities in the AI era that identify computational infrastructure and access to advanced digital platforms as necessary conditions for research, teaching, and institutional transformation (Pablo-Martí et al., 2024; Pedreño Muñoz et al., 2024).

At the same time, the findings demonstrate that infrastructure alone does not explain readiness. Human readiness and organizational culture emerged strongly in the qualitative phase and were reflected in the final factors through items concerning faculty motivation, continuous learning, professional development, and institutional maturity. Faculty enthusiasm toward AI received one of the highest descriptive means in the instrument, whereas continuous professional development, staff readiness, and managerial awareness remained relatively weak. This apparent contrast is important: willingness to use AI may be developing faster than the institutional mechanisms required to support competent and sustainable adoption. Recent studies have similarly shown that faculty often recognize the potential of AI for personalized instruction and learning support while simultaneously reporting uncertainty about implementation, competence, and institutional support (Saki et al., 2026). Research on academic innovation likewise indicates that successful integration requires systematic training, clear strategies, sufficient resources, and institutional leadership rather than depending solely on individual enthusiasm (Schmidt et al., 2025). The present findings therefore suggest that Iranian higher education may already possess an emerging motivational foundation for AI adoption but lacks equivalent maturity in professional development and organizational implementation.

Governance, leadership, and ethics constituted another central component of the final measurement structure. In the descriptive findings, governance-related items were consistently rated below the midpoint, particularly targeted budgeting, strategic planning, promotion regulations, and financial or professional incentives. The qualitative interviews also highlighted the need for a national coordinating body, clearer institutional policies, reduced bureaucracy, greater accountability, and a narrower gap between policy and implementation. These findings are consistent with the literature on strategic AI governance, which argues that fragmented initiatives and isolated technology adoption are insufficient when institutions lack coherent decision structures, accountability arrangements, risk-management mechanisms, and clearly defined responsibilities (Bashir & Ravi, 2025). The importance of governance is further reinforced by the emergence of AI as a global educational policy issue in which universities increasingly operate within broader national and

Iranian Journal of Educational Sociology
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international frameworks of regulation, ethics, and accountability (Christodoulou & Zembylas, 2026).

The close empirical association between governance and ethics is also theoretically meaningful. Responsible AI use depends on institutional structures that convert general ethical principles into operational rules. Participants in the present study emphasized academic integrity, transparency, explainability, algorithmic bias, responsible use of generative AI, and preservation of critical thinking. These concerns correspond closely with international guidance emphasizing human oversight, privacy, equity, transparency, and protection of educational quality in AI-enabled environments (Holmes & Miao, 2023). The finding that AI governance and ethics formed part of the same broader latent domain is also consistent with the argument that ethical readiness should precede or accompany deployment, because institutions need mechanisms for risk identification, accountability, and responsible implementation before AI becomes embedded in teaching and organizational decision making (Abdelaziz, 2026). Concerns surrounding misuse and safety of foundation models likewise support the need for explicit institutional governance rather than relying on informal or individual judgment (Shahi & Conner, 2024).

The results concerning educational and curriculum readiness were among the most concerning descriptive findings. This dimension had one of the lowest overall means, and respondents rated curriculum updating, basic AI education, educational infrastructure, assessment systems, and alignment with contemporary teaching approaches below the scale midpoint. These findings indicate that institutional adoption of AI may be occurring more rapidly than formal curricular reform. This pattern is consistent with international discussions suggesting that generative AI requires substantial redesign of teaching and assessment rather than incremental incorporation into existing educational practices (Lye & Lim, 2024; Nguyen et al., 2025). When AI can generate essays, code, summaries, and problem solutions, traditional assessments may no longer adequately represent independent student learning. Consequently, authentic assessment, process-based evaluation, project work, oral explanation, iterative feedback, and critical evaluation of AI-generated outputs become increasingly important (Lye & Lim, 2024). The qualitative finding that faculty roles should move toward facilitation and that teaching should become more project-based and personalized is therefore closely aligned with contemporary recommendations for AI-integrated learning design (Nguyen et al., 2025).

The importance of faculty competence within this transformation was also evident. AI readiness requires teachers to understand not only how to operate AI systems but also how to determine when and why they should be used. The emergence of issues such as prompt design, critical evaluation of AI outputs, recognition of errors, ethical use, and preservation of human judgment means that traditional digital literacy is no longer sufficient. This finding is consistent with AI competency frameworks for educators, which emphasize human-centered values, ethical awareness, AI foundations, pedagogy, and professional learning as interdependent areas of competence (Cukurova & Miao, 2024). The current results therefore reinforce the need to conceptualize faculty readiness as a continuing developmental process rather than a one-time training requirement.

A further major finding concerned the relationship between higher education and the labor market. The qualitative phase identified applied technical competence, soft skills, interdisciplinary collaboration, internships, industry-based projects, and alignment with emerging occupational requirements as fundamental components of readiness. The quantitative findings likewise showed that employability and student professional skills remained below the desired level. Student internship programs received especially low evaluations, while respondents also reported weaknesses in systematic identification of labor-market needs and preparation of practically capable graduates. These results are consistent with evidence that AI-related employment increasingly requires a combination of technical expertise, communication, teamwork, applied problem solving, data competence, and familiarity with organizational contexts (Green, 2024; Jaiswal et al., 2025). Research on the AI skills gap has similarly indicated that higher education and industry often differ in their expectations regarding the practical competencies graduates should possess (Van Haeften et al., 2024).

The strong role assigned to university–industry interaction in the final structure is therefore unsurprising. In the qualitative findings, participants repeatedly emphasized long-term industrial projects, access to real organizational data, problem-based theses, structured internships, private-sector participation, and tripartite cooperation among universities, government, and industry. These themes suggest that institutional AI readiness is partly relational: universities cannot develop relevant AI capacity in isolation

Iranian Journal of Educational Sociology
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from the ecosystems in which graduates, technologies, organizations, and public institutions operate. Pathways from higher education to employment are strengthened when academic learning is connected to authentic professional experiences and employer needs (Bates et al., 2025). More broadly, the effects of AI on employment suggest that universities must respond not only to current job descriptions but also to changing combinations of tasks and skills as AI alters the organization of work (Green et al., 2023; Thamarasseri, 2025).

Research, innovation, and entrepreneurship also emerged as a distinct factor in the final model. The findings suggest that universities need more than the capacity to teach students how to use AI; they must also be able to generate AI-related knowledge, conduct interdisciplinary research, support entrepreneurial initiatives, commercialize outputs, localize technologies, and respond to social and industrial needs. The relatively moderate descriptive ratings for research capacity, coupled with weaker evaluations of institutional structures supporting commercialization and production, indicate that research capability may exist without a fully developed innovation ecosystem. This distinction is important because the capacity to produce publications is not equivalent to the capacity to transform research into socially or economically useful AI applications. Contemporary analyses of AI and universities similarly emphasize that institutions must increasingly link research, innovation, entrepreneurship, and external engagement if they are to contribute meaningfully to AI-driven transformation (Pablo-Martí et al., 2024; Pedreño Muñoz et al., 2024).

The Iranian context provides a particularly important setting for these findings. Previous research on AI in Iranian higher education has identified both opportunities and ethical tensions associated with AI use, including uncertainty about responsible use, challenges in language learning, and concerns about academic practice (Isaee, 2025, 2026). The present study extends this evidence by showing that these issues are embedded within a broader institutional system that includes infrastructure, governance, organizational culture, curriculum, research, employability, and external collaboration. The findings therefore suggest that the principal challenge is not simply whether Iranian students or faculty members are using AI, but whether institutions possess coordinated capacities to govern, support, evaluate, and sustain such use.

An important psychometric contribution of the study is the discrepancy between the original 10-domain qualitative framework and the more parsimonious empirical factor structure. The qualitative phase distinguished 10 conceptually meaningful readiness domains, but the EFA showed substantial correlations among these dimensions, and the 10-factor quantitative solution generated several factors represented by only one or two indicators. Although that model explained 59% of the variance and produced relatively favorable fit indices after item deletion, such underrepresented factors are difficult to justify psychometrically. This suggests that stakeholders may conceptually distinguish many aspects of AI readiness, while respondents experience these dimensions as more integrated at the institutional level. For example, governance, ethics, leadership, and faculty incentives may operate as parts of a shared institutional-control system, while education, professional skills, and employability may function together as a broader educational-output domain.

The two-factor findings reinforce this interpretation. Parallel analysis, MAP, VSS, empirical BIC, exploratory graph analysis, and hierarchical clustering all provided evidence for a comparatively simple two-dimensional structure. The two factors were also highly correlated, suggesting the existence of a broad overarching readiness construct. The very high overall Cronbach's alpha of 0.966 and the strong one-factor reliability estimates further support a substantial general readiness dimension. Nevertheless, the one-factor CFA produced weaker robust fit and an AVE below 0.50, demonstrating that a single global factor does not fully represent the structure of the instrument. The two-factor model improved fit and discriminant validity but remained less informative conceptually than the five-factor model.

The five-factor model therefore appears to represent the most defensible compromise between parsimony and substantive differentiation. In the full sample, its robust CFI of 0.930, robust TLI of 0.921, robust RMSEA of 0.053, and SRMR of 0.049 indicated the strongest overall confirmatory fit among the competing structures. Reliability was acceptable across all five factors, with composite reliability values between 0.735 and 0.825. HTMT values were all below 0.85, supporting adequate discriminant validity. Although AVE was below 0.50 for four of the five factors, the values were relatively close to the threshold for several dimensions and were accompanied by acceptable composite reliability and significant factor loadings. Accordingly, the model provides stronger evidence for reliability and discriminant validity than for fully established convergent validity. This distinction is important because high

E-ISSN: 2645-3460

reliability alone does not guarantee that a factor explains a sufficiently large proportion of its indicators' variance.

The split-sample analysis provides a more cautious perspective on the stability of the model. The EFA conducted on 60% of the sample reproduced a five-factor organization and explained 54% of the variance, providing evidence that the broad structure was not unique to the full-sample analysis. However, when the corresponding 21-item model was tested in the 40% holdout sample, the standard fit indices remained acceptable while the robust indices deteriorated substantially, including robust CFI = 0.833, robust TLI = 0.804, and robust RMSEA = 0.098. Dimension-level reliability also weakened for several factors, and one HTMT coefficient exceeded the 0.85 criterion. These results do not necessarily contradict the five-factor interpretation; rather, they indicate that the holdout sample of 99 respondents was likely too small to provide stable estimates for a relatively complex ordinal CFA model. The appropriate conclusion is therefore that the five-factor structure is supported provisionally but requires replication in a larger independent sample.

Overall, the findings are consistent with the broader literature showing that institutional AI transformation requires coordinated development across technology, people, pedagogy, ethics, governance, and external engagement. AI readiness is therefore better viewed as an institutional capability than as a simple technology-adoption variable. The final five-factor framework captures this logic by linking technological preparedness with governance, organizational maturity, education and employability, and research and external engagement. This systemic interpretation is also consistent with the growing policy emphasis on responsible AI, teacher competence, labor-market responsiveness, and institutional governance (Bashir & Ravi, 2025; Cukurova & Miao, 2024; Green, 2024; Holmes & Miao, 2023). The instrument consequently offers a promising basis for diagnosing institutional readiness while recognizing that further validation is required before the factor structure can be considered definitive.

Several limitations should be considered when interpreting the findings. First, the quantitative sample was obtained through purposive-snowball recruitment rather than probability sampling, which limits the extent to which the observed readiness levels can be generalized statistically to all Iranian higher education institutions. Second, although the overall sample of 248 respondents was adequate for the principal factor analyses, the 40% holdout sample contained only 99 participants, which was relatively small for a five-factor ordinal CFA and likely contributed to instability in robust fit indices, reliability coefficients, and discriminant-validity estimates. Third, the initial qualitative model was substantially broader than the final quantitative structure, and the need to delete multiple items during competing EFA solutions indicates that some aspects of the original conceptual framework were not represented with sufficient psychometric precision. Fourth, several final factors had AVE values below 0.50, indicating that convergent validity was not uniformly optimal. Fifth, all quantitative information was based on self-reported perceptions rather than direct institutional indicators such as computing capacity, AI budgets, curriculum documents, research outputs, or employment outcomes. Finally, because AI technologies and institutional practices are evolving rapidly, some items that are currently salient may require revision as technological capabilities, policies, and educational practices change.

Future studies should validate the five-factor structure using substantially larger and fully independent samples drawn from different types of Iranian higher education institutions and geographic regions. Stratified probability sampling, where feasible, would improve population-level generalizability and enable meaningful comparisons among public, private, medical, teacher-training, applied-science, and distance-learning institutions. Further research should also evaluate measurement invariance across gender, academic rank, disciplinary field, university type, managerial status, level of AI experience, and geographic region. The weaker AVE observed in several dimensions indicates that additional item development may improve convergent validity, particularly for governance, organizational maturity, and education-related factors. New items should be generated to strengthen underrepresented conceptual domains without unnecessarily increasing respondent burden. Future work could also examine bifactor and hierarchical models to determine whether the five dimensions operate under a higher-order general AI-readiness factor. Longitudinal studies would be especially valuable for assessing whether institutional readiness scores are sensitive to policy interventions, infrastructure investment, faculty training, or curriculum reform. Finally, predictive validity should be investigated by testing whether readiness scores are associated with observable outcomes such as actual AI adoption, faculty and student AI competence, research productivity, innovation outputs, educational quality, graduate employability, or institutional digital maturity.

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For practice, universities should use the instrument primarily as a diagnostic and developmental tool rather than as a ranking mechanism. Institutional leaders should interpret readiness profiles across the five dimensions to identify specific bottlenecks and prioritize interventions accordingly. Universities with weak technological readiness should focus on computing infrastructure, integrated data systems, secure digital environments, and equitable access to AI tools. Weaknesses in governance should be addressed through explicit AI strategies, clear ethical regulations, defined accountability structures, dedicated funding, and incentive systems that reward applied and interdisciplinary AI activity. Faculty development should move beyond introductory workshops and include sustained training in AI-supported pedagogy, assessment redesign, responsible generative AI use, critical evaluation of outputs, and discipline-specific applications. Curriculum reform should emphasize project-based learning, practical problem solving, internships, authentic assessment, and alignment with emerging labor-market requirements. Universities should also strengthen formal partnerships with industry, government, and society so that students and researchers have access to authentic problems, real datasets, applied projects, and commercialization opportunities. Finally, readiness assessment should be repeated periodically so that institutions can monitor progress, identify emerging risks, and adapt their strategies as AI technologies and educational expectations continue to evolve.

Authors' Contributions

Authors equally contributed to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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All procedures performed in studies involving human participants were under the ethical standards of the institutional and, or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

References

Abdelaziz, M. H. (2026). Ethical Readiness for Responsible AI in Higher Education: A Pre-deployment Institutional Governance Framework. *Journal of Ethics in Higher Education*(8.2), 89-117. https://doi.org/10.26034/fr.jehe.2026.9532

Bashir, H., & Ravi, M. (2025). A systematic review of strategic artificial intelligence governance frameworks and mechanisms in studies from 2017-2025. *Virtual Space and Social Media Studies*, *2*(3), 9-54.

Bates, M., Cashdollar, S., Mitchell, E., Nagaoka, J., & Clinton, C. (2025). *Promising Pathways: College and Industry Routes to Good Jobs for Illinois Youth from Low-Income Families* (Illinois High School to Career Series, Issue.

Christodoulou, E., & Zembylas, M. (2026). Artificial intelligence as a site of global educational governance: the case of UNESCO. *Journal of Education Policy*, 1-24. https://doi.org/10.1080/02680939.2026.2646218

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Cukurova, M., & Miao, F. (2024). *AI Competency Framework for Teachers*.

Green, A. (2024). *Artificial Intelligence and the Changing Demand for Skills in the Labour Market* (OECD Artificial Intelligence Papers, Issue.

Green, A., Salvi del Pero, A., & Verhagen, A. (2023). OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market. In (pp. 103-127). Organisation for Economic Co-operation and Development.

Hankins, E., Nettel, P. F., Martinescu, L., Grau, G., & Rahim, S. (2023). *2023 Government AI Readiness Index*.

Holmes, W., & Miao, F. (2023). *Guidance for Generative AI in Education and Research*.

Isaee, H. (2025). AI in Iranian higher education: A mixed-methods study of ethical tensions and L2 learning challenges. *Forum for Education Studies*, *3*, 81-91. https://doi.org/10.59400/fes3881

Isaee, H. (2026). AI in Iranian higher education: A mixed-methods study of ethical tensions and L2 learning challenges. *Forum for Education Studies*. https://doi.org/10.59400/fes3881

E-ISSN: 2645-3460

Jaiswal, K., Kuzminykh, I., & Modgil, S. (2025). Understanding the skills gap between higher education and industry in the UK in artificial intelligence sector. *Industry and Higher Education*, *39*(2), 234-246. https://doi.org/10.1177/09504222241280441

Lye, C. Y., & Lim, L. (2024). Generative artificial intelligence in tertiary education: Assessment redesign principles and considerations. *Education Sciences*, *14*(6), 569. https://doi.org/10.3390/educsci14060569

Nguyen, A., Duong, A. T., Nguyen, D. T. B., Lai, V. T. T., & Dang, B. (2025). Guidelines for learning design and assessment for generative artificial intelligence-integrated education: a unified view. *Information and Learning Sciences*, *126*(7-8), 491-512. https://doi.org/10.1108/ILS-11-2024-0148

Pablo-Martí, F., Mir Fernández, C., & Navarro-Meneses, F. J. (2024). Reimagining higher education in the age of AI.

Pedreño Muñoz, A., González Gosálbez, R., Mora Illán, T., del Pérez Fernández, E., Ruiz Sierra, J., & Torres Penalva, A. (2024). *Artificial Intelligence in Universities: Challenges and Opportunities*. https://andrespedreno.com/ai-universities.pdf

Saki, S., Zeinabadi, H., Abbasian, H., & Abdollahi, B. (2026). Faculty perceptions of AI for personalized instruction and learning facilitation in higher education. *Scientific reports*. https://doi.org/10.1038/s41598-026-42980-4

Schmidt, D. A., Alboloushi, B., Thomas, A., & Magalhaes, R. (2025). Integrating artificial intelligence in higher education: Perceptions, challenges, and strategies for academic innovation. *Computers and Education Open*, *9*, 100274. https://doi.org/10.1016/j.caeo.2025.100274

Shahi, M., & Conner, A. (2024). *Re: Request for Comments on the US Artificial Intelligence Safety Institute's Draft Document: Managing Misuse Risk for Dual-Use Foundation Models, Docket No. NIST-2024-0002*.

Thamarasseri, I. (2025). The Future of Work: Navigating Transformations in the Global Labour Market (2025-2030). *i-Manager's Journal on Management*, *19*(3). https://doi.org/10.26634/jmgt.19.3.21582

Van Haeften, W., Zhang, R., Boesen-Mariani, S., Lub, X., Ravesteijn, P., & Aertsen, P. (2024). *Bridging the AI skills gap in Europe: A detailed analysis of AI skills and roles* 37th Bled eConference Resilience Through Digital Innovation: Enabling the Twin Transition, https://doi.org/10.18690/um.fov.4.2024.22

E-ISSN: 2645-3460