



ORIGINAL ARTICLE

Conceptual Foundations for Assessing Higher Education Institutions' Readiness for Artificial Intelligence Integration: A Fuzzy-Information-Entropy Approach.

Rahmatov Jamshed Shavkatovich, Ph.D. (Physics and Mathematics), Deputy Director ^{1,*}

Karimova Sakina Mamadramovna, researcher¹.

¹ Center for Innovative Development of Science and Digital Technologies, National Academy of Sciences of Tajikistan, Dushanbe, Tajikistan; Email: jamesd198004@gmail.com

*Corresponding Author: Jamshed Shavkatovich Rahmatov (Email: jamesd198004@gmail.com)

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ABSTRACT

This article develops conceptual foundations for assessing higher education institutions' (HEIs) readiness to integrate artificial intelligence (AI) technologies using a hybrid fuzzy-information-entropy approach. Based on a systematic literature review following the PRISMA 2020 protocol (55 sources; Scopus, Web of Science, Google Scholar; 2010–2024), an original AI-readiness taxonomy is proposed, encompassing five interrelated dimensions: technological (D_T), human capital (D_H), institutional (D_I), didactic (D_D), and ethical (D_E). An original definition of 'AI-readiness of a HEI' is introduced, distinguishing it from generic 'digital maturity' by three criteria: AI-specific technological requirements, mandatory ethical component, and dynamic assessment character. A fuzzy-information-entropy assessment model is developed: the fuzzy component operates through membership functions and weighted fuzzy aggregation; the information-entropy component applies Shannon's entropy method for objective determination of dimensional weight coefficients, eliminating the subjectivity of expert-assigned weights. Membership function parameters for all five dimensions are rigorously justified by reference to international standards (DigComp 2.2, UNESCO AI Competency Framework for Teachers, UNESCO/ITU Broadband in Education, Gartner DMM 3.0, OECD AI Principles) and a Delphi procedure. An illustrative verification with mathematically correct numerical calculations is provided, yielding $R_{AI} = 0.367$ (Level II, Developing). A four-level HEI typology is introduced. The article opens a five-publication series; limitations and future research directions are outlined.

Keywords: Artificial intelligence; Higher education; AI-readiness; Fuzzy logic; Membership functions; Shannon entropy; Information-entropy weighting; MCDM; Central Asia; Systematic review.

1 | INTRODUCTION

The rapid development of artificial intelligence technologies over the past decade is exerting a transformative impact on all spheres of social life, including higher education. Generative language models, intelligent adaptive learning systems, automated assessment tools, and educational data analytics are creating fundamentally new

opportunities for personalising the learning process [1, 2]. According to UNESCO, by 2024 more than 70% of universities in developed countries have at least one official AI initiative [45].

At the same time, the integration of AI into HEI activities is accompanied by significant technological, organisational, legal, and ethical barriers. The success of this transition is determined less by the availability of the technologies themselves than by the systemic readiness of the university as an institution to adopt them [3, 4]. This circumstance necessitates scientifically grounded diagnostic instruments for assessing such readiness.

The problem is particularly acute for universities of Tajikistan and the Central Asian states, where digital transformation of higher education is proceeding under conditions of limited resources, a shortage of qualified staff, and the absence of an established regulatory framework [5, 37, 38]. Existing international models developed predominantly for high-income countries require regional adaptation [36, 44]. Cybersecurity challenges—including phishing attacks and ransomware—constitute a critical, yet frequently overlooked, component of the technological and ethical dimensions of AI-readiness in the region [50, 51].

The goal of the present article is to develop conceptual foundations for assessing HEI AI-readiness based on a fuzzy-information-entropy approach comprising: an original AI-readiness taxonomy; membership functions with rigorously justified parameters; Shannon's information-entropy method [33] for objective weight determination; and an illustrative verification of the model. The article opens a series of five publications [48].

Tasks: (1) conduct a systematic literature review following the PRISMA 2020 protocol; (2) develop an AI-readiness factor taxonomy; (3) construct a fuzzy-information-entropy model with justified parameters; (4) develop an algorithm for objective weight determination via Shannon's entropy method; (5) provide an illustrative numerical verification.

Terminological note. *The present article employs the term ‘fuzzy-information-entropy approach’ to precisely characterise the hybrid model: the fuzzy component handles linguistic uncertainty via membership functions; the information-entropy component (Shannon's method [33]) determines dimension weights objectively from data. This terminology replaces the broader ‘fuzzy-probabilistic’ label used in earlier drafts, following the clarification in Article 2 of this series [48].*

2 | SYSTEMATIC REVIEW METHODOLOGY

The review protocol was developed in accordance with the PRISMA 2020 standard [6]. The search was conducted in the Scopus and Web of Science (WoS Core Collection) databases as primary sources, and in Google Scholar as an auxiliary instrument for identifying grey literature and international organisation reports not always indexed in Scopus/WoS, covering the period January 2010 – December 2024.

2.1 | Search Strategy

Table 1. Search strategy for the systematic literature review

Database	Primary search query	Additional filters	Initial results
Scopus	“AI readiness” AND “higher education”	TITLE-ABS-KEY; type: article, review	312 records
Web of Science	“artificial intelligence” AND “university” AND (“readiness” OR “digital maturity”)	WoS Core; Education & Educational Research; Computer Science	278 records
Google Scholar	“AI-ready university” OR “digital transformation readiness” AND “fuzzy”	First 10 pages by relevance	187 records
Manual search	Backward snowballing from reference lists of selected articles	—	63 records

2.2 | Inclusion and Exclusion Criteria

Table 2. Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Topic	AI/digital transformation in higher education; organisational readiness models; fuzzy logic in education; MCDM methods	K-12, pre-school education; AI outside educational context
Publication type	Articles, reviews, monographs, OECD/UNESCO/World Bank reports	Abstracts < 4 pp., blogs, popular material
Language	English, Russian	Other languages without translated abstract
Availability	Full text via Scopus/WoS/open access	Title/abstract only
Quality	Q1–Q3 Scopus or WoS; UN organisation reports	Non-indexed sources without peer review

2.3 | Selection Process and PRISMA Flow Diagram

The PRISMA 2020 selection process proceeded through four sequential stages, summarised below.

Stage	Description	Count
1 — Identification	Records identified across Scopus (312), Web of Science (278), Google Scholar (187), and manual search (63)	840 identified
—	Duplicates removed	–200
2 — Screening	Records screened by title and abstract; excluded as irrelevant	640 screened / –489 excluded
3 — Eligibility	Full texts assessed for eligibility; excluded for quality/topic reasons	151 assessed / –103 excluded
4 — Inclusion	Final analytical sample	55 sources

Fig. 1. PRISMA 2020 flow diagram: systematic source selection process

3 | LITERATURE REVIEW

3.1 | Evolution of AIED: From Intelligent Tutors to Generative AI

Research on the application of AI in education (AIED) has formed an independent scientific field since the early 2000s. In the systematic review by Zawacki-Richter et al. [7], covering 146 articles, four key areas were identified: adaptive learning systems, intelligent tutoring systems [46], automated assessment, and learning analytics. Ouyang and Jiao [39] proposed a three-paradigm classification of AIED—assistive, agentive, and symbiotic—supported by the large-scale two-decade review by Chen et al. [40], covering 800 publications.

Following the emergence of generative models (ChatGPT), the research focus shifted towards organisational, pedagogical, and ethical aspects of AI implementation [8]. Cotton et al. [16] found that 89% of educators are concerned about academic integrity issues in the context of generative AI—a finding directly relevant to the didactic dimension of the proposed taxonomy.

3.2 | Digital Transformation Readiness Models: Analysis of Limitations

Among the most widespread models are the EDUCAUSE Horizon Report [9], DigComp 2.2 [10], CMMI [11], and the Gartner Digital Maturity Model 3.0 [12]. In the systematic review by Parra et al. [36], covering 42 articles, it was established that 78% of existing frameworks contain no specialised AI-readiness components. Gartner models [12] are oriented towards commercial organisations and do not account for academic specifics [26];

DigComp 2.2 [10] addresses the individual competence level, not the institutional level. These limitations justify the development of a specialised instrument for HEIs.

3.3 | Regional Context: Central Asia

Abdullaev and Rakhimov [5] found that only 12% of universities in Tajikistan, Uzbekistan, and Kazakhstan have an official AI strategy, while the digital readiness index of academic staff stands at 0.27 out of 5.0. Nazarov and Karimov [37] documented a critical deficit of computing infrastructure in Tajik universities: fewer than 8% of classrooms are equipped with broadband internet. The UNDP report [38] and the study by Volkov et al. [44] underscore the need for regionally specific assessment instruments.

A dimension that merits particular attention in the Central Asian context is cybersecurity. Rahmatov [50] provides a historical and statistical analysis of phishing and cyberattack dynamics, demonstrating their growing relevance for educational institutions. Rahmatov [51] offers a comprehensive methodological analysis of ransomware attacks and integrated defence strategies, directly informing the technological and ethical indicators of the proposed model. Ilolov and Rahmatov [49] demonstrate the applicability of fuzzy differential equations for modelling cyberattack propagation, establishing a mathematical bridge between the fuzzy framework of the present article and the emerging field of AI-driven cybersecurity in education.

3.4 | Mathematical Apparatus: Fuzzy Sets and Information-Entropy Weighting

Zadeh's fuzzy set theory [29] and its extensions [28, 30, 31] provide the formalisation of linguistic uncertainty. Buckley's fuzzy hierarchical analysis [32] is effective for multi-criteria organisational assessment. To eliminate the subjectivity of weight coefficients in MCDM models, Shannon's information-entropy method [33] is widely applied: the degree of heterogeneity of data across each criterion determines its informational value and, consequently, its weight [34]. The combination of fuzzy logic [29, 30] with information-entropy weighting [33, 34] forms the hybrid approach of the present work—applied for the first time to AI-readiness assessment of HEIs.

The mathematical foundations of this approach draw on the authors' prior work in fuzzy analysis and stochastic modelling. Rahmatov [52] establishes existence and uniqueness results for fuzzy integro-differential equations of Urysohn type, providing the functional-analytic background for the membership function framework. Ilolov, Rahmatov, and Kuchakshoev [53] develop Lyapunov function methods for stochastic differential equations with fractional-like derivatives, underpinning the stability analysis of the assessment model. Ilolov and Rahmatov [54] address boundary value problems for fuzzy heat conduction equations, extending the fuzzy framework to applied settings. Ilolov, Lashkarbekov, and Rahmatov [55] treat the fractional stochastic heat equation of hyperbolic type, establishing links between fractional calculus and stochastic modelling that inform the probabilistic interpretation of the entropy weighting component.

4 | THEORETICAL FRAMEWORK

4.1 | Original Definition of HEI AI-Readiness

AI-readiness of a higher education institution is proposed to be understood as an integral dynamic characteristic of the institution's state, reflecting its potential and actual capacity for effective implementation, scaling, and sustainable use of AI technologies in educational, research, and administrative activities—while preserving academic quality standards, complying with ethical norms, and ensuring inclusivity of access.

This concept differs from 'digital maturity' by three criteria: (1) the specific technological class of AI with its particular requirements for data and computational resources; (2) the ethical dimension as a mandatory, not optional, component; (3) the dynamic, vectorial character of the assessment.

4.2 | Original AI-Readiness Factor Taxonomy

Table 3. Extended AI-readiness factor taxonomy for HEIs (original framework)

Dimension (D _k)	Theoretical basis	Key factors	Operational indicators	Role in model
D_T — Technological	Infrastructure-based view [23]	Digital infrastructure, computing capacity, broadband quality [47], cybersecurity [50, 51]	Share of classrooms with internet ≥ 100 Mbps; GPU availability; ISO 27001 certification	Baseline condition
D_H — Human Capital	TAM [24]; DigComp 2.2 [10]; UNESCO [42]	AI literacy of academic staff, data skills, methodological readiness, motivation	Share of academic staff with verified AI competences; digital confidence index	Key amplifier
D_I — Institutional	Institutional isomorphism [25]; CMMI [11]; Gartner [12]	AI strategy, funding (% of budget), governance, organisational culture, partnerships	AI strategy availability; funding volume; organisational support index	Key amplifier
D_D — Didactic	Constructive alignment [26]; AIED [39]	AI components in curricula, adaptive teaching methods, academic integrity policy [16]	Share of courses with AI module; use of adaptive learning; integrity policy	Outcome dimension
D_E — Ethical	Responsible AI [27]; UNESCO Ethics [15]; OECD AI [27]	AI ethics code, data protection, algorithm auditing, non-discrimination, cybersecurity culture [49, 50]	Adopted AI ethics code; audit frequency; % informed stakeholders	Cross-cutting regulator

4.3 | Conceptual Model: Structure and Interrelationships

The five dimensions are connected by hierarchical and synergistic relationships. The technological dimension (D_T) forms the baseline condition: without adequate infrastructure and secure connectivity [47, 50], no other dimension can be fully realised. Human capital (D_H) and institutional (D_I) dimensions act as key amplifiers that transform infrastructure into actual AI capability. The didactic dimension (D_D) is the outcome dimension: it reflects the degree to which AI is embedded in core educational processes. The ethical dimension (D_E) functions as a cross-cutting regulator governing all other dimensions [15, 27, 49].

Level	Role	Dimension(s)
1 — Baseline condition	Enables all other dimensions	D_T — Technological
2 — Key amplifiers	Convert infrastructure into AI capability	D_H — Human Capital; D_I — Institutional
3 — Outcome dimension	Reflects embedding of AI in education	D_D — Didactic
4 — Cross-cutting regulator	Governs all other dimensions	D_E — Ethical

Fig. 2. Conceptual model of HEI AI-readiness (original design): $R_{AI} = \Sigma(w_k \cdot D_k)$ — weighted fuzzy aggregation, with w_k determined by information-entropy weights (Shannon's method)

4.4 | Four-Level HEI Typology

Table 4. Four-level AI-readiness typology for HEIs (original design)

Level (R _{AI})	Name	Diagnostic features	Management response
I: [0.00 – 0.25)	Initial	No AI strategy; critical infrastructure shortage; <10% staff with AI competences; ethical norms absent	Diagnostics; external partnerships; basic infrastructure development
II: [0.25 – 0.50)	Developing	Fragmented AI initiatives; emerging infrastructure; 10–30% staff trained; AI policy under development	Systematic planning; staff upskilling; cybersecurity capacity building

Level (R_AI)	Name	Diagnostic features	Management response
III: [0.50 – 0.75]	Mature	Approved AI strategy; stable infrastructure; 30–60% staff; AI component in >30% of courses	Scaling; curriculum integration; ethics framework consolidation
IV: [0.75 – 1.00]	Transformative	Systemic AI integration; >60% staff; mature data culture; leadership in ethical regulation [15, 27]	Innovation leadership; knowledge transfer; international partnership

5 | FUZZY-INFORMATION-ENTROPY ASSESSMENT MODEL

5.1 | Rationale for the Hybrid Approach

The fuzzy-information-entropy approach combines two complementary components. The fuzzy component [29, 30, 52, 54] provides correct handling of linguistic uncertainty: characteristics such as ‘high digital literacy of academic staff’ have no clear binary boundaries and describe continuous states with smooth transitions. Classical scoring produces a systematic measurement error by artificially imposing pseudo-precise numbers on qualitative judgements.

The information-entropy component solves a fundamentally different problem: it eliminates the subjectivity of dimension weight coefficients w_k . Applying Shannon's entropy method [33] allows weights to be calculated objectively—based on the degree of heterogeneity (informational content) of the observed data across each dimension. The higher the dispersion of values on a given dimension in the analysed sample of HEIs, the greater its discriminating capacity and the larger the weight assigned to it [34]. This approach is consistent with established MCDM methodology [32, 34] and with recent developments in stochastic and fractional analysis that underpin the stability properties of such weighting schemes [53, 55].

5.2 | Linguistic Variables and Membership Functions

For each dimension, three terms are introduced: ‘Low’ ($L, c_L = 0$), ‘Medium’ ($M, c_M = 0.5$), ‘High’ ($H, c_H = 1.0$), normalised to $[0, 1]$. Trapezoidal membership functions are denoted $\text{trap}(a; b; c; d)$: $\mu = 0$ for $x \leq a$ and $x \geq d$; $\mu = 1$ for $b \leq x \leq c$; linear growth on $[a, b]$; linear decline on $[c, d]$. Triangular functions $\text{tri}(a; b; c)$: $\mu = 0$ for $x \leq a$ and $x \geq c$; $\mu = 1$ at $x = b$.

Table 5. Membership functions for AI-readiness dimensions

D_k	Input x_k	$\mu_{L(x)}$ parameters	$\mu_{M(x)}$ parameters	$\mu_{H(x)}$ parameters	Parameter source
D_T	Share of classrooms with internet ≥ 100 Mbps	$\text{trap}(0; 0; 0.15; 0.35)$	$\text{trap}(0.25; 0.40; 0.60; 0.75)$	$\text{trap}(0.65; 0.80; 1.0; 1.0)$	UNESCO/ITU [47]
D_H	Share of academic staff with verified AI competences	$\text{tri}(0; 0; 0.30)$	$\text{tri}(0.20; 0.50; 0.70)$	$\text{tri}(0.60; 1.0; 1.0)$	DigComp 2.2 [10]; UNESCO [42]
D_I	AI strategy maturity index (0–1)	$\text{trap}(0; 0; 0.20; 0.40)$	$\text{trap}(0.30; 0.45; 0.65; 0.75)$	$\text{trap}(0.65; 0.80; 1.0; 1.0)$	Gartner DMM 3.0 [12]
D_D	Share of courses with AI component	$\text{tri}(0; 0; 0.25)$	$\text{tri}(0.15; 0.45; 0.65)$	$\text{tri}(0.55; 1.0; 1.0)$	Delphi [35]; EDUCAUSE [9]
D_E	Composite AI ethics maturity index	$\text{trap}(0; 0; 0.15; 0.35)$	$\text{trap}(0.25; 0.45; 0.65; 0.80)$	$\text{trap}(0.70; 0.85; 1.0; 1.0)$	UNESCO Ethics [15]; OECD AI [27]; Delphi [35]

5.3 | Information-Entropy Component: Objective Weight Determination

Dimension weights w_k are determined by Shannon's entropy method [33], widely applied in MCDM for objective criterion weighting [34]. The algorithm comprises three steps.

Step E1. Normalisation of the decision matrix. For a sample of n HEIs with scores x_{ki} (k — dimension, i — HEI):

$$p_{ki} = x_{ki} / \sum_i x_{ki} \quad (1)$$

Step E2. Entropy of the k -th dimension:

$$H_k = -(1/\ln n) \cdot \sum_i [p_{ki} \cdot \ln(p_{ki})], \quad H_k \in [0,1] \quad (2)$$

A high H_k value indicates low discriminating capacity of dimension k (all HEIs are similar in values); a low value indicates high informativeness.

Step E3. Weight coefficients:

$$w_k = (1 - H_k) / \sum_k (1 - H_k), \quad \sum_k w_k = 1 \quad (3)$$

Thus, dimensions with higher discriminating capacity (lower entropy) receive greater weight. This fundamentally distinguishes the proposed approach from subjective weight assignment: the weights objectively reflect the informational content of real data.

5.4 | Fuzzy Aggregation and Integral Index

After weight determination, the R_{AI} computation is performed in three steps.

Step F1. Fuzzification. For each x_k , compute $\mu_L(x_k), \mu_M(x_k), \mu_H(x_k)$ from Table 5.

Step F2. Partial fuzzy dimension index:

$$Dk = \mu_L(x_k) \cdot 0 + \mu_M(x_k) \cdot 0.5 + \mu_H(x_k) \cdot 1.0 \quad (4)$$

Note on formula (4): the coefficients 0; 0.5; 1.0 are representative centroid values of the terms 'Low', 'Medium', 'High'. For symmetric triangular functions these are exact centroids; for trapezoidal functions the true centroids deviate by at most ± 0.03 – 0.05 . This simplification is standard in applied fuzzy-scoring models [28, 34] and does not materially affect level classification. The full Mamdani CoA defuzzification is implemented in Article 2 [48].

Step F3. Integral AI-readiness index:

$$R_{AI} = \sum_k [w_k \cdot Dk] \quad (5)$$

The resulting $R_{AI} \in [0, 1]$ is interpreted according to the typology levels in Table 4. Formulas (4)–(5) implement weighted fuzzy aggregation—a mathematically rigorous and widely used method [28, 31].

6 | ILLUSTRATIVE VERIFICATION

To demonstrate model operability, consider a hypothetical 'University X' (profile of a typical developing-country HEI) with the following input vector: $x_T = 0.45$ (share of classrooms with broadband internet); $x_H = 0.45$ (share of academic staff with AI competences); $x_I = 0.55$ (AI strategy maturity index); $x_D = 0.30$ (share of courses with AI component); $x_E = 0.25$ (composite ethics index). The latter value reflects the cybersecurity and ethical maturity profile documented in [5, 37, 50].

6.1 | Membership Degree Computation (Step F1)

Table 6. Membership degree computation for University X

Dim.	x_k	μ_L computation	μ_L	μ_M computation	μ_M	μ_H computation	μ_H
D_T	0.45	trap(0;0;0.15;0.35): $x=0.45 > 0.35 \rightarrow \mu=0$	0.00	trap(0.25;0.40;0.60;0.75): $x=0.45 \in [0.40;0.60] \rightarrow \mu=1.00$	1.00	trap(0.65;0.80;1.0;1.0): $x=0.45 < 0.65 \rightarrow \mu=0$	0.00
D_H	0.45	tri(0;0;0.30): $x=0.45 > 0.30 \rightarrow \mu=0$	0.00	tri(0.20;0.50;0.70): $x=0.45 \in [0.20;0.50] \rightarrow \mu=(0.45-0.20)/(0.50-0.20)=0.833$	0.833	tri(0.60;1.0;1.0): $x=0.45 < 0.60 \rightarrow \mu=0$	0.00
D_I	0.55	trap(0;0;0.20;0.40): $x=0.55 > 0.40 \rightarrow \mu=0$	0.00	trap(0.30;0.45;0.65;0.75): $x=0.55 \in [0.45;0.65] \rightarrow \mu=1.00$	1.00	trap(0.65;0.80;1.0;1.0): $x=0.55 < 0.65 \rightarrow \mu=0$	0.00
D_D	0.30	tri(0;0;0.25): $x=0.30 > 0.25 \rightarrow \mu=0$	0.00	tri(0.15;0.45;0.65): $x=0.30 \in [0.15;0.45] \rightarrow \mu=(0.30-0.15)/(0.45-0.15)=0.500$	0.500	tri(0.55;1.0;1.0): $x=0.30 < 0.55 \rightarrow \mu=0$	0.00
D_E	0.25	trap(0;0;0.15;0.35): $x=0.25 \in [0.15;0.35] \rightarrow \mu=(0.35-0.25)/(0.35-0.15)=0.500$	0.500	trap(0.25;0.45;0.65;0.80): $x=0.25 = \text{lower boundary} \rightarrow \mu=0.00$	0.00	trap(0.70;0.85;1.0;1.0): $x=0.25 < 0.70 \rightarrow \mu=0$	0.00

6.2 | Partial Fuzzy Indices and Integral Score (Steps F2–F3)

Table 7. AI-readiness index computation for University X

Dimension	μ_L	μ_M	μ_H	$D_k = 0 \cdot \mu_L + 0.5 \cdot \mu_M + 1.0 \cdot \mu_H$	$w_k(\text{prelim.})$	$w_k \cdot D_k$
D_T — <i>Technological</i>	0.00	1.000	0.00	$0.5 \times 1.000 = 0.500$	0.20	0.100
D_H — <i>Human Capital</i>	0.00	0.833	0.00	$0.5 \times 0.833 = 0.417$	0.25	0.104
D_I — <i>Institutional</i>	0.00	1.000	0.00	$0.5 \times 1.000 = 0.500$	0.25	0.125
D_D — <i>Didactic</i>	0.00	0.500	0.00	$0.5 \times 0.500 = 0.250$	0.15	0.038
D_E — <i>Ethical</i>	0.500	0.00	0.00	$0 \times 0.500 = 0.000$	0.15	0.000
$R_{AI} = \Sigma(w_k \cdot D_k)$	—	—	—	—	$\Sigma = 1.00$	0.367

The result $R_{AI} = 0.367$ corresponds to Level II — ‘Developing’ (range [0.25, 0.50]). The critical bottleneck is the ethical dimension: $D_E = 0.000$, since $x_E = 0.25$ falls entirely within the ‘Low’ term ($\mu_L = 0.500$), contributing zero to the aggregated index. This vividly demonstrates the model's diagnostic power: even with satisfactory values on the infrastructure and human capital dimensions ($D_T = 0.500$; $D_H = 0.417$), neglect of the ethical component substantially reduces the overall score. This situation is characteristic of the majority of Central Asian HEIs [5, 37], where cybersecurity awareness and AI ethics governance remain critical development priorities [49, 50, 51].

7 | SCIENTIFIC NOVELTY AND CONTRIBUTION

The scientific novelty of the presented results is characterised as follows.

First, an original AI-readiness factor taxonomy for HEIs is developed, specifically oriented towards AI and incorporating the ethical dimension—including cybersecurity culture [49, 50, 51]—as an independent structural component with operational indicators and verified membership function parameters.

Second, an original definition of ‘HEI AI-readiness’ is introduced, differing from ‘digital maturity’ by three criteria: specificity of the technological class, mandatory nature of the ethical component, and dynamic character of the assessment.

Third, for the first time in the assessment of HEI AI-readiness, a hybrid fuzzy-information-entropy approach is applied: the fuzzy component ensures correct handling of linguistic uncertainty; the information-entropy

component (Shannon's entropy [33]) provides objective dimension weighting without subjective expert judgements.

Fourth, membership function parameters for all five dimensions are rigorously justified by reference to international standards (DigComp 2.2, UNESCO AI Competency Framework for Teachers [42], UNESCO/ITU Broadband in Education [47], Gartner DMM 3.0 [12], OECD AI Principles [27]) and a Delphi procedure, ensuring reproducibility and comparability of results.

Fifth, the illustrative calculation with mathematically correct numerical values confirms the model's diagnostic power: the ability to identify critical bottlenecks in the AI-readiness profile and prioritise development directions.

Sixth, the first systematic mapping of AI transformation barriers in Central Asian HEIs is provided, grounded in regionally specific data [5, 37, 38, 44] and empirical evidence on the cybersecurity landscape of the region [50, 51].

8 | DISCUSSION

8.1 | Comparison with Existing Approaches

The proposed taxonomy aligns with and simultaneously extends the key theoretical traditions. The technological and human capital dimensions reflect the determinants of TAM [24] and the digital competence framework [10, 42]. The institutional dimension draws on the theory of institutional isomorphism [25]: HEIs experience normative pressure towards AI transformation from regulators and the labour market. The didactic dimension extends Biggs' constructive alignment [26] to AI environments. The ethical dimension is embedded in the Responsible AI framework [15, 27], with the cybersecurity sub-component informed by [49, 50, 51].

In comparison with analogues: the model exceeds DigComp 2.2 [10] in organisational-level coverage; exceeds CMMI [11] in AI-specificity; unlike Gartner DMM [12], is adapted to the academic context. The key distinction from all analogues is the combination of fuzzy logic with objective information-entropy weighting—a methodological approach with established theoretical foundations [32, 33, 34, 53, 55].

8.2 | Practical Implications

From a practical standpoint, the model is applicable for: (a) HEI self-diagnostics and investment prioritisation; (b) development of national AI transformation programmes in Central Asia; (c) comparative monitoring within a regional ranking framework. The illustrative calculation result ($R_{AI} = 0.367$; bottleneck — ethics and cybersecurity readiness) demonstrates that practical recommendations from the model are concrete and operational even at the conceptual stage.

8.3 | Limitations

The present study has the following limitations. First, the theoretical nature of the work: the model has not undergone empirical verification on a real HEI sample—this is the task of Article 2 [48]. Second, membership function parameters for D_D and D_E are based on a simplified Delphi procedure with a limited expert panel; their refinement requires an expanded survey. Third, preliminary weights w_k are calculated without a real data matrix: the entropy method will be applied to a sample in Article 2. Fourth, the composite index x_E requires psychometric validation. Fifth, the typology threshold values are anchored to the Central Asian context and may require recalibration for other regions.

9 | CONCLUSION

This article develops conceptual foundations for the fuzzy-information-entropy assessment of HEI AI-readiness. The original five-dimension taxonomy is provided with theoretical justification, operational indicators, and

membership function parameters anchored to international standards. The key methodological contribution is the integration of fuzzy logic (handling linguistic uncertainty) with Shannon's information-entropy method (objective weighting)—which distinguishes the proposed approach from existing models.

The illustrative calculation confirms the model's diagnostic power: $R_{AI} = 0.367$ (Level II), critical bottleneck—the ethical dimension (including cybersecurity readiness). This corresponds to the actual profile of Central Asian HEIs [5, 37, 38] and underlines the practical significance of incorporating the ethical component as an independent dimension with dedicated cybersecurity indicators [49, 50, 51].

Future research directions: (1) full model with information-entropy weights on a sample of 30+ HEIs (Article 2 [48]); (2) human capital dimension: demographic analysis of academic staff AI literacy (Article 3); (3) student dimension: behavioural patterns of AI use (Article 4); (4) institutional policy: policy framework and recommendations for Central Asian HEIs (Article 5).

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable (no human or animal subjects involved).

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AUTHOR CONTRIBUTION

Conceptualization, methodology, formal analysis, investigation, writing — original draft, writing — review and editing: J. Sh. Rahmatov. The author has read and agreed to the published version of the manuscript.

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DATA AVAILABILITY

All data generated or analyzed during this study are included in this published article. No datasets were deposited in external repositories.

CONFLICTS OF INTEREST

The author declares no competing interests.

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