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Exploring the Readiness for AI Innovation in Higher Education at the Serbian Universities

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Abstract

Purpose

This study explores the readiness of Serbian higher education institutions for adopting artificial intelligence (AI), situating local findings within broader global debates on digital transformation in universities. The aim is to identify how awareness, competences, cultural norms, and perceived risks shape openness to AI training and implementation, thereby highlighting opportunities and governance challenges.

Methodology

An exploratory mixed-methods design was employed. Quantitative data were gathered through a structured survey (N = 150) distributed across Serbian universities, measuring awareness, digital competences, perceived usefulness, risks, governance concerns, and cultural impact. The survey instrument was developed through a review of established AI adoption models and contextualized with faculty consultations. Descriptive and inferential analyses were conducted to examine group differences and contextual variables such as academic role, field of study, and international exposure.

Findings

The results reveal relatively high levels of digital competence and perceived usefulness of AI, contrasted with low awareness and persistent concerns regarding risks, ethics, and governance. Faculty and students reported higher engagement compared to administrative staff, who remain least prepared yet stand to benefit most from efficiency gains. Private university participants and those with international experience demonstrated higher AI awareness. Importantly, awareness was significantly associated with reduced perceptions of cognitive and cultural risks.

Research limitations/implications

The findings are limited by the sample's concentration in Serbian universities and by ongoing institutional instability, which constrained more systematic sampling. Nevertheless, the exploratory results provide a foundation for future large-scale validation, cross-country comparisons, and integration of interviews and infrastructure analyses. The study underscores the need for transparent communication, targeted training, and ethical frameworks to guide AI integration in higher education.

Originality/Value

This paper contributes one of the first empirical analyses of AI readiness in Serbian higher education, extending adoption research beyond technical models to include cultural and contextual variables such as collectivism, power distance, ethnocentrism, and uncertainty avoidance. By situating findings within both local and international discourses, it offers actionable insights for policymakers, institutional leaders, and educators navigating AI transformation.

Keywords

Artificial intelligence, higher education, AI adoption, digital competence, cultural impact, Serbia, governance, readiness

Paper type

Research paper

1. Introduction & Literature Review

Artificial Intelligence (AI) is no longer an experimental add-on in higher education. It is increasingly regarded as a core driver of data-rich, adaptive, and personalized learning ecosystems. Global exemplars of predictive analytics, intelligent tutoring, and generative feedback illustrate AI's transformative promise, yet their diffusion remains uneven and contingent on the sociotechnical fabric of individual institutions (OECD, 2023; Zawacki-Richter et al., 2019). Empirical studies consistently demonstrate that successful adoption depends less on algorithmic sophistication than on the interplay among governance structures, digital infrastructure, faculty competences, and culturally embedded attitudes toward innovation. At the same time, AI is not merely a technological innovation but a catalyst for rethinking the fundamental relationship between universities, learners, and society. Bearman, Ryan, and Ajjawi (2023) highlight how discourses oscillate between narratives of imperative change and altered authority, positioning technology as both an inevitable driver of transformation and a force redistributing power among teachers, students, institutions, and commercial actors.

Recent research underscores the accelerating scope of AI in higher education. Systematic reviews report a two- to three-fold increase in publications between 2016 and 2022 (Crompton & Burke, 2023). Much of this scholarship highlights perceived benefits across domains such as assessment, intelligent tutoring, skill acquisition, achievement analysis, and administrative automation (Hannan & Liu, 2023; Wang, Liu & Tu, 2021; Zouhaier, 2023), while also cautioning against risks to rigor, transparency, and ethical practice (Castillo-Martínez et al., 2024). Students generally perceive generative AI positively for brainstorming, writing, and individualized support, though they also voice concerns about accuracy, plagiarism, and over-reliance (Chan & Hu, 2023). Faculty adoption remains more tentative, shaped by digital literacy, awareness, and perceived usefulness and risks (Helmiatin et al., 2024; Rahiman & Kodikal, 2024). Multicultural surveys further reveal that perceived benefits and risks vary substantially across contexts, underscoring the need for ethically grounded, culturally sensitive strategies (Yusuf et al., 2024).

Beyond these infrastructural and cultural determinants, perceived cognitive risk has emerged as an urgent research frontier. Neuroscientific evidence suggests that AI-enabled cognitive offloading may attenuate neural engagement during complex tasks; students relying on generative tools have shown diminished memory retention and reduced metacognitive awareness (Kosmyna et al., 2025). Tlili et al. (2023) likewise caution that algorithmic personalization, while increasing efficiency, can narrow epistemic exposure and constrain critical thinking. Such findings resonate with UNESCO's (2021) call for intentional integration frameworks that scaffold human–AI collaboration without eroding learners' agency or analytical competencies. Ethical questions, such as academic integrity, algorithmic bias, and data governance, thus remain central, with some warning of a "dumbing down" effect and threats to academic honesty (Fowler, 2023). From a systemic perspective, others envision "smart universities" where AI reshapes pedagogy, credentialing, administration, and competitiveness (George & Wooden, 2023). Yet the success of such models ultimately hinges on human readiness. In higher education this translates into faculty AI literacy, which UNESCO (2021) identifies as foundational, but which lags significantly behind student uptake. The asymmetry risks widening pedagogical dissonance and deepening cognitive vulnerabilities, unless adoption is paired with frameworks that build critical literacy and help educators and learners alike to mitigate risks of bias, inaccuracy, and overreliance (Ivanov et al., 2024; Yusuf et al., 2024).

To explain adoption patterns, most recent studies draw on classical models and theories of technology acceptance. Several conceptual frameworks provide complementary perspectives on why individuals and institutions accept or resist innovative technologies. Among the most cited is the Technology Acceptance Model (TAM) (Davis, 1989), which emphasizes perceived usefulness and ease of use as key predictors of adoption intention. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) expands this view with constructs such as social influence and facilitating conditions, particularly relevant in hierarchical educational institutions. The Diffusion of Innovations Theory (DOI) (Rogers, 2003) highlights compatibility, trialability, and observability, offering insight into how entrenched academic norms shape AI uptake. The Theory of Planned Behaviour (TPB) (Ajzen, 1991) enriches this picture by incorporating attitudes, subjective norms, and perceived behavioral control — constructs that help explain both intention and actual use behavior.

Beyond individual acceptance, as previously mentioned, the literature underscores that successful AI integration depends on the interplay between technical systems and organizational and cultural environments. It is therefore worth mentioning the Socio-technical Systems Theory (Trist & Bamforth, 1951) which underscores the co-evolution of technical tools and organizational culture, arguing that implementation succeeds only when social and technical subsystems are jointly optimized. This insight is particularly relevant in contexts with entrenched informal practices and collective attitudes, such as Serbian universities, as discussed later. Together, all these frameworks illuminate both individual-level adoption and systemic determinants of AI integration.

Building on these foundations, contemporary AI readiness and maturity models offer structured, institutional perspectives. For example, Microsoft's AI Maturity Model (2019) charts staged progression from exploration to optimization across dimensions of culture, talent, data, and tools. Commonly used in business settings, Cisco's AI Readiness Index (2024) assesses governance, security, infrastructure, and workforce preparedness, while the IMF AI Preparedness Framework (2023) emphasizes institutional governance, transparency, and accountability. It is also worth mentioning the Stanford's Human-Centered AI framework (2025), which adds a complementary perspective, stressing responsible innovation, human oversight, and the alignment of AI adoption with institutional values, while warning against "AI exceptionalism," the assumption that existing policies do not apply to AI (Stanford University, 2025). Additional models such as BCG's Digital Acceleration Index, which offers a diagnostic approach to measuring digital maturity across strategy, offerings, technology, and culture, and McKinsey's 7S Framework (2018), which similarly emphasizes the alignment of strategy, structure, systems, shared values, skills, style, and staff, further situate AI readiness within broader digital transformation strategies, stressing the interplay of leadership commitment, organizational culture, and infrastructural alignment. These frameworks go beyond classical adoption models by embedding AI within organizational, ethical, and geopolitical contexts.

As briefly mentioned, previous studies show that cultural dimensions play a critical role in shaping how technologies such as AI are perceived and adopted in higher education. Beyond individual attitudes captured by models like TAM or DOI, cultural orientations influence trust, legitimacy, and the pace of institutional change. Hofstede's (2010) framework, particularly the dimensions of power distance and collectivism, can help explain why faculty and administrators in many contexts defer to hierarchical mandates rather than proactively champion innovation. In collectivist societies, social consensus and authoritative endorsement weigh heavily in determining the acceptance of new technologies. Innovation Resistance Theory (Ram & Sheth, 1989) also highlights how perceived risks, inertia, and traditions can inhibit adoption, even when the benefits are recognized. Empirical studies confirm this dynamic, with, for example, Tarhini et al. (2017) who found that social norms strongly predict technology adoption in Arab universities, while Kovacic (2009) demonstrated that power distance and uncertainty avoidance shape ICT acceptance in Eastern European contexts. More recent surveys highlight the same pattern. Yusuf et al. (2024) showed that cultural orientations mediate perceptions of AI's benefits and risks across 76 countries, while Helmiatin et al. (2024) found that in Indonesian universities, facilitating conditions and perceived risks interact with collectivist norms to shape adoption. Similarly, Rahiman and Kodikal (2024) observed that awareness, performance expectancy, and perceived risk strongly influenced faculty attitudes in Asian higher education contexts, pointing again to the importance of organizational culture in moderating adoption outcomes. Chan and Tsi (2024) add that cultural orientations also mediate perceptions of AI's legitimacy, including concerns over academic depersonalization and algorithmic bias. According to some authors, cultural identity and ethnocentric tendencies may further shape attitudes toward AI adoption, as individuals in collectivist and high-uncertainty-avoidance contexts often display skepticism toward foreign-developed technologies, preferring solutions that are culturally familiar and endorsed within their own institutions (Tarhini et al., 2017). However, exposure to international academic environments has been shown to broaden awareness of educational technologies and increase openness to experimentation, which may act as a facilitator to technology adoption regardless of culture of origin (Rogers, 2003; Yusuf et al., 2024).

Against this backdrop, Serbia presents a paradoxical case. Its universities boast long-standing strengths, particularly in STEM disciplines, and are formally aligning with EU digital transformation strategies (European Commission, 2019; Kuleto et al., 2022). Yet they continue to operate within legacy information systems, constrained fiscal environments, and a historical ambivalence toward disruptive reform (Kuleto et al., 2022). Studies point to persistent deficits in AI infrastructure and faculty preparedness, with many institutions still unfamiliar with applications beyond basic functions (Kuleto et al., 2021; Pisica et al., 2023). Uneven levels of digital literacy further heighten vulnerability: students with lower technological self-efficacy may experience amplified cognitive risks when relying on AI, potentially entrenching existing educational inequities (Kuleto et al., 2021). Policy initiatives such as the National AI Supercomputing Platform and the Strategy for the Development of Artificial Intelligence signal ambition, but their benefits remain unevenly distributed across sectors (OECD OPSI, 2023; Government of the Republic of Serbia, 2025). Crucially, Serbia's cultural configuration, marked by collectivism, high power distance, and uncertainty avoidance, exerts a profound influence on AI acceptance (Hofstede, 2010; Zakić & Kovačić, 2022). In such contexts, technology adoption often hinges on hierarchical mandates and peer consensus rather than individual initiative (Tarhini et al., 2017; Kovacic, 2009). This dynamic carries two consequences: first, adoption trajectories may depend disproportionately on institutional leadership and formal endorsements; second, collective skepticism, amplified by ethnocentric tendencies toward foreign technologies (Marinković, Kostić & Stanišić, 2011), may attenuate readiness despite strong policy imperatives. Global studies further suggest that such cultural orientations shape perceptions of AI's legitimacy and risks, including fears of academic depersonalization and algorithmic bias (Chan & Tsi, 2024). Taken together, Serbia's structural, cultural, and cognitive paradoxes complicate AI adoption and expose the limits of universalist readiness models that focus narrowly on infrastructure and policy while overlooking organizational culture, governance maturity, ethics, and faculty–student competencies.

Although the global literature on AI in higher education has expanded rapidly, these limitations are not unique to Serbia. Existing adoption models, largely derived from TAM and UTAUT, reduce the complexity of AI to a narrow set of constructs (e.g., perceived usefulness, ease of use), while overlooking governance, transparency, cultural legitimacy, and contextual factors (Zawacki-Richter et al., 2019; Abbas et al., 2023; Rahiman & Kodikal, 2024). Empirical research has been dominated by Western or high-income contexts, leaving middle-income countries such as Serbia underexamined despite their distinct infrastructural constraints and cultural dynamics (Kuleto et al., 2021; Pisica et al., 2023). Moreover, while European and Serbian policy frameworks articulate ethical principles for AI, little is known about how these are operationalized at the institutional level, particularly with regard to faculty roles in algorithmic governance. Research also rarely extends beyond students and instructors to include other higher education stakeholders, nor does it account for contextual variables such as field of study, GPA, or study duration (Helmiatin, Hidayat, & Kahar, 2024). Although such variables remain underexplored in AI adoption research, existing work in related digital learning contexts suggests that indicators such as GPA and timely study progression may plausibly shape openness to innovation, as achievement often correlates with self-efficacy and willingness to experiment with new tools (Helmiatin et al., 2024; Yusuf et al., 2024).

Accordingly, this study seeks to address these gaps by developing an evidence-based, context-sensitive approach to AI readiness in Serbian universities. While the long-term aim is to build a comprehensive, data-driven readiness framework tailored to Serbia's higher education sector, integrating classical adoption theories with contemporary maturity and governance models, this exploratory phase is more modest in scope. Bearing in mind the current state of formalized AI use in Serbian higher education, we opted to examine a limited set of basic adoption-related concepts first, leaving deeper analysis of personal attitudes toward AI tools for a later stage, when such tools may be more widely implemented or at least introduced to most participants. Building on established models, recent research, and practical observation, the survey was structured around the following variables: AI Awareness, Digital Competence (DC), Perceived Usefulness (PU), Perceived Cognitive Risks (PCR), Governance & Ethical Concerns (GEC), Cultural Impact (CI), and their influence on Openness to AI Training and Implementation (OTI). Awareness, PU, and DC reflect core TAM/UTAUT drivers of performance and effort expectancy (Davis, 1989; Venkatesh, 2003), further informed by the EC Digital Competence Framework (European Commission, 2022). PCR and GEC capture risk and governance dimensions highlighted in UTAUT extensions and in AI-focused readiness frameworks such as those developed by Cisco (2024) and the IMF (2023), while CI draws on socio-technical systems theory (Trist & Bamforth, 1951), the Theory of Planned Behaviour (Ajzen, 1991), Hofstede's (2010) cultural dimensions, and Microsoft's (2019) AI Maturity Model, which will be applied more fully in future iterations. OTI, our key dependent variable, serves as a proxy for Behavioral Intention (BI) and early adoption readiness, as posited in multiple adoption models (Ajzen, 1991; Davis, 1989; Venkatesh, 2003). In addition, the survey tested the feasibility of introducing redefined factors into AI adoption research in higher education, thereby addressing the literature's tendency to concentrate on a narrow set of recurring constructs (e.g., TAM/UTAUT variables) and neglect broader governance and cultural determinants (Zawacki-Richter et al., 2019; Crompton & Burke, 2023; Rahiman & Kodikal, 2024). Finally, we sought to adopt a more nuanced approach to individual differences by including contextual variables beyond gender, age, and role, examining whether field of study, duration of studies, GPA, and international academic exposure influenced the above concepts, responding to calls to move beyond limited demographic controls (Helmiatin, Hidayat, & Kahar, 2024; Chan & Hu, 2023).

Recent literature lends further support to this selection — performance/effort expectancy and awareness often predict attitudes and intention in higher education adoption settings (Helmiatin et al., 2024; Rahiman & Kodikal, 2024), perceived cognitive risks and ethical concerns can shape both attitudes and intentions (Ivanov et al., 2024; Yusuf, Pervin, & Román-González, 2024), and governance and integrity issues, including plagiarism and bias, seem to be central (Fowler, 2023; Michel-Villarreal et al., 2023), while cultural orientations mediate perceived legitimacy, benefits, and risks (Chan & Hu, 2023; Yusuf et al., 2024). Systemic perspectives further stress that “smart universities” succeed only when adoption is paired with governance maturity and organizational culture (George & Wooden, 2023). Building on this as well other reviewed literature, several hypotheses can be derived regarding the determinants of AI readiness in higher education.

First, core adoption drivers emphasized by TAM and UTAUT suggest that *AI Awareness, Perceived Usefulness, and Digital Competence may positively predict Openness to AI Training and Implementation (OTI)*. Prior studies have shown that awareness and competence directly influence perceived ease of use and performance expectancy, which in turn shape adoption intentions (Davis, 1989; Venkatesh et al., 2003; Helmiatin et al., 2024; Rahiman & Kodikal, 2024). Second, *Perceived Cognitive Risks and Governance & Ethical Concerns are expected to negatively influence OTI*, as concerns about accuracy, bias, plagiarism, and transparency have repeatedly been linked to lower willingness to adopt educational technologies (Fowler, 2023; Ivanov et al., 2024; Yusuf et al., 2024). At the same time, where governance maturity is perceived as high, these negative effects may be mitigated (George & Wooden, 2023). Third, *Cultural Impact is hypothesized to be negatively associated with adoption outcomes,* with collectivist orientations, high power distance, uncertainty avoidance and ethnocentric attitudes reducing the likelihood of individual initiative and making adoption more dependent on hierarchical endorsement (Hofstede, 2010; Tarhini et al., 2017; Kovacic, 2009; Marinković, Kostić & Stanišić, 2011). In such contexts, organizational legitimacy and social consensus outweigh individual perceptions of usefulness. Contextual and demographic variables are expected to further shape adoption patterns. *Faculty members are hypothesized to exhibit lower OTI than students,* reflecting findings of slower adoption and lower AI literacy among educators (Chan & Hu, 2023; UNESCO, 2021). *Among students, higher GPA and on-time study progression are expected to predict higher OTI,* as achievement correlates with openness to digital learning innovations (Helmiatin et al., 2024). Furthermore, *participants from private institutions are expected to report higher OTI,* given evidence of greater organizational flexibility and resource allocation compared to state institutions in Serbia and Eastern Europe (Kuleto et al., 2021; Pisica et al., 2023). Finally, *individuals with prior academic experience abroad are expected to demonstrate higher OTI,* consistent with DOI’s emphasis on trialability and exposure as adoption facilitators (Rogers, 2003; Yusuf et al., 2024).

2. Methodology:

2.1 Research Design

This study employs a mixed-methods exploratory research design to assess the readiness for artificial intelligence (AI) implementation in higher education across different faculties in Serbia. The design integrates quantitative data from a structured questionnaire and qualitative insights from open-ended questions within the survey, as well as from the institutional document review. Such triangulation responds to calls in the literature for context-sensitive, multi-method approaches that can capture the interplay of technological, cultural, and ethical factors shaping AI adoption in higher education (Crompton & Burke, 2023; Castillo-Martínez et al., 2024; Yusuf et al., 2024). As this phase is exploratory, no factor analysis or scale validation is attempted, the aim is to map perceptions and identify directions for further research in Serbia.

2.2 Method

The methodological approach combined instrument development, item selection, and data collection procedures into a single process, ensuring both theoretical grounding and contextual validity. The questionnaire was developed based through a synthesis of theoretical and practical sources. Classical adoption frameworks (TAM, UTAUT, DOI, TPB) informed the inclusion of awareness, usefulness, competence, and intention constructs (Davis, 1989; Venkatesh et al., 2003; Rogers, 2003; Ajzen, 1991). At the same time, institutional and governance dimensions were derived from contemporary readiness models such as Microsoft's AI Maturity Model, Cisco's AI Readiness Index, and the IMF Preparedness Framework, which highlight culture, infrastructure, and governance capacity as critical determinants of readiness (Microsoft, 2019; Cisco, 2024; IMF, 2023). In addition, item development drew on hands-on contextual experience and consultations with professors and faculty management at the University of Belgrade (Faculty of Organizational Sciences). This practice ensured both content validity and contextual appropriateness, addressing the observation that AI adoption is strongly shaped by local organizational routines, leadership endorsement, and cultural norms rather than abstract constructs alone (Rahiman & Kodikal, 2024; Helmiatin, Hidayat & Kahar, 2024).

The finalized instrument includes 60 items across the following sections:

1. **Demographic and institutional background** (13 items) – e.g. institutional type, field of study, GPA, study duration, and international experience, representing contextual factors such as achievement and exposure which have been shown to influence openness to educational technologies (Helmiatin et al., 2024; Yusuf et al., 2024).

2. **AI Awareness** (5 items) – familiarity with AI applications in learning and administration, as awareness has been identified as a critical precursor of adoption readiness (Chan & Hu, 2023; Crompton & Burke, 2023).

3. **Digital Competence** (DC, 5 items) – self-efficacy in digital and AI-supported tasks, anchored in the European Commission's Digital Competence Framework (2022), and supported by studies showing that competence predicts performance expectancy (Rahiman & Kodikal, 2024).

4. **Perceived Usefulness** (PU, 5 items) – perceived benefits for teaching, research, and administration, as a core TAM/UTAUT variable repeatedly found to predict adoption (Helmiatin et al., 2024; Rahiman & Kodikal, 2024).

5. **Governance & Ethical Concerns** (GEC, 5 items) – concerns about plagiarism, bias, data security, and transparency, highlighted as central issues in AI adoption in higher education (Fowler, 2023; Michel-Villarreal et al., 2023; Yusuf et al., 2024).

6. **Perceived Cognitive Risks** (PCR, 10 items) – concerns about memory, critical thinking, and overreliance, supported by neuroscientific findings on cognitive offloading (Kosmyna et al., 2025) and warnings about constrained epistemic exposure (Tlili et al., 2023).

7. **Cultural Impact** (CI, 10 items) – focused on the four cultural dimensions most relevant for AI adoption bearing in mind the global and local context: *collectivism*, as group consensus and peer endorsement strongly shape adoption decisions (Hofstede, 2010; Tarhini et al., 2017; Yusuf et al., 2024), *power distance*, because hierarchical authority seems to determine whether individuals feel free to adopt innovations independently (Hofstede, 2010; Kovacic, 2009), *uncertainty avoidance*, highlighting that heightened caution toward risk and error discourages experimentation with novel AI systems (Hofstede, 2010; Yusuf et al., 2024), and ethnocentrism, reflecting the Serbian preference for locally developed technologies over foreign solutions, potentially limiting openness to external AI tools (Marinković, Kostić & Stanišić, 2011; Tarhini et al., 2017). This selection reflects both theory (Hofstede's dimensions, Innovation Resistance Theory) and empirical findings from Eastern European and Southeast Asian contexts, where these cultural traits most directly moderate AI adoption.

8. **Openness to AI Training and Implementation** (OTI, 5 items) – the core dependent variable, serving as a proxy for Behavioral Intention and early adoption readiness (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003).

The instrument combines Likert-scale items with open-ended questions, in line with recommendations that exploratory studies in under-researched contexts should capture both measurable constructs and nuanced perceptions (Castillo-Martínez et al., 2024; Ivanov et al., 2024). The two open-ended questions targeted participants' views on the most important cultural and/or ethical dilemmas regarding the adoption of AI tools in their institution, and their views of the local cultural characteristics they saw as main AI adoption enablers and obstacles. Institutional documentation (e.g., ICT strategies, AI initiatives, internal communications) will be collected and reviewed with management staff. In later phases, semi-structured interviews with faculty leaders are planned to deepen insights into governance, infrastructure, and cultural readiness, further guiding more detailed research planning and conducting.

2.3 Hypotheses

As previously positioned in line with previous research, we expected to confirm the following hypotheses in our survey result analysis:

H1: *AI Awareness, Perceived Usefulness, and Digital Competence will positively predict Openness to AI Training and Implementation (OTI).*

H2: *Perceived Cognitive Risks and Governance & Ethical Concerns will negatively predict OTI (unless governance support is perceived as high).*

H3: *Cultural orientations (power distance, ethnocentrism, uncertainty avoidance, collectivism) will be negatively associated with Openness to AI Training and Implementation.*

H4a: *Faculty members will report lower OTI than students.*

H4b: *Students with higher GPA and on-time progression will report higher OTI.*

H4c: *Participants from private institutions will show higher OTI than those from public ones.*

H4d: *Prior international academic exposure will increase OTI.*

2.4 Sampling & Data Collection

First data collection was conducted using an online survey platform, with the questionnaire distributed to academic and administrative staff, students, and faculty leadership. A purposive sampling strategy was implemented to ensure role-based representation across the institution. Participation was voluntary, anonymous, and aligned with institutional ethical guidelines.

In the next phase, institutional documents such as digitalization strategies, ICT infrastructure reports, and internal communication on innovation initiatives will be reviewed to contextualize the self-reported data and identify gaps between policy and perception.

2.5 Data Analysis

Quantitative data was analyzed using descriptive statistics and group comparisons (e.g. ANOVA, regression) to test the hypotheses. No factor analysis or scale validation is intended in this phase, as the purpose is exploratory, i.e. to map readiness and identify future research directions in Serbia. Qualitative responses were coded thematically to capture perceptions of opportunities and risks.

Document review findings will further contextualize survey responses, highlighting alignment or divergence between institutional strategy and user experiences.

2.5 Research Design Limitations

As an exploratory study, this research does not claim to establish validated measurement scales or psychometric properties. The questionnaire is a diagnostic tool to highlight trends and gaps, not a finalized instrument. Factor analysis and validation are deliberately deferred to later phases, contingent on larger and more diverse samples.

In addition, the scope of cultural impact is limited to four dimensions, collectivism, power distance, ethnocentrism, and uncertainty avoidance, because these have been identified in previous research as the most salient in shaping AI and ICT adoption in higher education, particularly in collectivist and high power-distance contexts (Tarhini et al., 2017; Kovacic, 2009; Marinković et al., 2011; Yusuf et al., 2024). Other Hofstede dimensions (masculinity, long-term orientation, and indulgence) were excluded as they have shown weaker or less consistent associations with technology adoption and including them at this early stage would dilute focus. Future research may expand to these dimensions once core relationships are established.

3. Results:

3.1 Sample Description

The first sample consisted of 150 respondents (54.7% female, 45.3% male). Participants' ages ranged from 19 to 74 years (M = 35.7, SD = 13.6). Around 80% of the sample consisted of students and/or academic instructors, while the rest encompassed affiliated researchers, managerial and administrative staff. Among students, the majority were undergraduate students (62.5%), followed by doctoral students (28.7%) and master's students (8.8%), with less than 20% of students falling behind in their academic progress, and the mean self-reported GPA 8.8 (SD = 1.38).

Most faculties consisted of less than 5000 students (71.3%), with a fewer percentage counting more than 5000 students. Majority of institutions belonged to state universities (72%) and were mainly headquartered in Belgrade (88%) or Novi Sad (22%). The most common fields of studies (67.3%) included social sciences (including psychology, political science, education, law and economics), followed by natural and technical sciences, and humanities, with many participants belonging to multidisciplinary institutions. The participants' average number of years of experience in the institution was 11.5 (SD=11), and approximately 19% of respondents reported international academic/professional experience longer than 6 months.

3.2. Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables. Among the constructs, Digital Competence (M = 3.85, SD = 0.82) and Perceived Usefulness (M = 3.82, SD = 0.84) showed the highest mean values, suggesting that participants generally felt confident in their digital skills and recognized the benefits of AI. Openness to AI Training and Implementation was also relatively high (M = 3.68, SD = 1.11), indicating a general positive orientation toward engaging with AI-related learning opportunities. Governance and Ethical Concerns scored moderately (M = 3.50, SD = 0.53), while AI Awareness (M = 2.79, SD = 0.93) and Cultural Impact (M = 2.90, SD = 0.58) were somewhat lower, pointing to more limited familiarity with AI and nuanced cultural considerations. The lowest overall mean was observed for Perceived Cognitive Risks (M = 2.60, SD = 1.05), suggesting that concerns about potential negative consequences of AI were present but not predominant.

Normality was assessed using the Shapiro–Wilk test, skewness/kurtosis indices, and visual inspection of histograms. While Shapiro–Wilk tests indicated significant deviations for several composites, skewness and kurtosis values were within acceptable ranges (–1 to +1). Therefore, the distributions were treated as approximately normal.

Table 1. Descriptive Statistics

N=150

Variable	***M***	***SD***
AI Awareness	2.79	0.93
Digital Competence	3.85	0.82
Governance & Ethical Concerns	3.50	0.53
Perceived Usefulness	3.82	0.84
Cultural Impact	2.90	0.58
Perceived Cognitive Risks	2.60	1.05
Openness to AI Training & Implementation	3.68	1.11

3.3. Quantitative Data Analysis

Bivariate correlations confirmed that Openness to AI Training and Implementation (OTI) was positively associated with Perceived Usefulness ($r = 0.53$, $p < 0.001$), AI Awareness ($r = 0.39$, $p < 0.001$), and Digital Competence ($r = 0.29$, $p < 0.001$), while Perceived Cognitive Risks (PCR) were negatively related ($r = –0.29$, $p < 0.001$). On the other hand, Governance and Ethical Concerns and the composite Cultural Impact score showed no significant associations with OTI. These results provide support for H1 and partial support for H2, highlighting perceived usefulness, awareness, digital competence, and cognitive risk as the primary correlates of openness to AI training and implementation in this sample.

To examine whether individual cultural orientations revealed more nuanced effects, we analyzed the four sub-dimensions separately. Results indicated that Power Distance was positively related to OTI ($r = 0.24$, $p = .003$), whereas Ethnocentrism was negatively related ($r = –0.22$, $p = 0.007$). In contrast, Uncertainty Avoidance ($r = –0.04$, $p = 0.619$) and Collectivism ($r = 0.06$, $p = 0.489$) did not show significant associations. These findings partially support H3 by suggesting that certain cultural dispositions, particularly hierarchical deference and ethnocentric attitudes, shape adoption trajectories, though in divergent ways: power distance appears to increase reliance on institutional mandates as a pathway to openness, while ethnocentrism diminishes readiness by constraining legitimacy for foreign-developed technologies.

Table 2: Intercorrelations Among Study Variables

Variable	1	2	3	4	5	6	7
1. AI Awareness	—						
2. Digital Competence (DC)	.485***	—					
3. Perceived Usefulness (PU)	.440***	.225**	—				
4. Perceived Cognitive Risks (PCR)	-.251**	-.097	-423***	—			
5. Governance & Ethical Concerns (GEC)	-.281***	-.148	-.124	-290***	—		
6. Cultural Impact (CI)	-.051	-.068	-44	.161*	.292***	—	
7. Openness to AI Training & Implementation (OTI)	.39***	.29***	.53***	-.29***	.01	.06	—

Note: N = 150. Correlations are Pearson's r. *p < 0.05, **p < 0.01, ***p < 0.001.

Among the demographic variables, no significant gender differences were observed on any of the study variables, while age was positively correlated with openness to AI training and implementation (OTI; $r = 0.20$, $p < 0.05$), although it did not correlate significantly with any of the other composite constructs. Furthermore, years of experience at the institution showed no significant associations with any variable. Among students, grade point average (GPA) was not related to OTI ($r = 0.10$, $p = 0.37$), but it was positively associated with Digital Competence ($r = 0.24$, $p < 0.05$), suggesting that students with higher academic achievement reported greater self-rated digital skills.

Regarding demographic–cultural associations, age was negatively correlated with uncertainty avoidance ($r = –0.19$, $p < 0.05$) and ethnocentrism ($r = –0.17$, $p < 0.05$), suggesting that older respondents expressed lower tendencies toward caution in the face of uncertainty and weaker ethnocentric orientations. No other significant correlations were observed between age and the remaining cultural subdimensions.

To further test the first three hypotheses, a multiple regression analysis was conducted to examine predictors of Openness to AI Training and Implementation (OTI). The overall model was significant, $F(6, 143) = 13.10$, $p < 0.001$, with $R^2 = 0.36$ and Adjusted $R^2 = 0.33$, indicating that the predictors explained approximately 36% of the variance in OTI. As shown in Table 3, Perceived Usefulness was the strongest positive predictor ($\beta = 0.39$, $p < 0.001$), followed by AI Awareness ($\beta = 0.17$, $p = 0.050$) and Governance and Ethical Concerns ($\beta = 0.15$, $p = 0.048$). Digital Competence showed a small positive but non-significant effect ($\beta = 0.14$, $p = 0.080$). Perceived Cognitive Risks were negatively associated with OTI, but this effect was not statistically significant in the full model ($\beta = –0.12$, $p = 0.119$). Cultural Impact was unrelated to OTI ($\beta = 0.04$, $p = 0.573$). We also conducted mulitple regression to check whether subdimensions of cultural orientations predicted OTI. The overall model was significant, $F(4, 145) = 5.24$, $p < 0.001$, with $R^2 = 0.13$ and Adjusted $R^2 = 0.10$, indicating that the cultural dimensions explained about 13% of the variance in openness. Power Distance was a significant positive predictor ($\beta = 0.26$, $p < 0.05$), while Ethnocentrism was a significant negative predictor ($\beta = –0.28$, $p < 0.05$). Uncertainty Avoidance ($\beta = 0.02$, $p = 0.852$) and Collectivism ($\beta = 0.08$, $p = 0.356$), as previously signaled, were not significant predictors. In addition, because age was correlated with some cultural dimensions, partial correlations were used to test whether links with OTI held after controlling for age. Results showed that Power Distance remained positively related to OTI ($r = 0.25$, $p < 0.05$), while Ethnocentrism was negatively related ($r = –0.19$, $p < 0.05$). Uncertainty Avoidance and Collectivism were not significant once age was controlled. Although the cultural dimensions were interrelated, only Power Distance and Ethnocentrism showed unique associations with OTI independent of age.

Table 3: Multiple Regression Predicting Openness to AI Training and Implementation (OTI)

Predictor	**B**	**SE B**	**t**	**p**	**β**
AI Awareness	0.2008	0.1015	1.98	0.050	0.17
Digital Competence (DC)	0.1828	0.1038	1.76	0.080	0.14
Perceived Usefulness (PU)	0.5133	0.1063	4.83	<0.001	0.39
Perceived Cognitive Risks (PCR)	-0.1279	0.0817	-1.57	0.119	-0.12
Governance & Ethical Concerns (GEC)	0.3128	0.1566	2.00	0.048	0.15
Cultural Impact (CI)	0.0762	0.1350	0.56	0.573	0.04
Intercept	-0.526	0.788	-0.67	0.506	—

Note. N = 150. B = unstandardized regression coefficient; SE B = standard error; β = standardized coefficient. Overall model: $F(6, 143) = 13.1$, $p < 0.001$, $R^2 = 0.36$, Adjusted $R^2 = 0.33$.

A one-way Welch's ANOVA was conducted to test whether Openness to AI Training and related variables differed by role (student, faculty, administration, management, researcher). The analyses indicated no statistically significant differences across roles for Openness to AI (OTI), $F(4, 11.4) = 1.96$, $p = 0.168$, or for any of the other main study variables, all $p > 0.05$. The only variable approaching significance was AI Awareness, $F(4, 11.2) = 2.79$, $p = 0.079$, suggesting a possible trend toward differences in awareness across roles. However, post-hoc Tukey comparisons did not reveal any significant pairwise differences between groups.

Since one-way ANOVA was first conducted using participants' main role (e.g. student OR faculty) as a factor, and given the frequently present overlap between role categories (many participants simultaneously assumed multiple roles, e.g. studying and teaching), independent samples t-tests were subsequently run to explore the most relevant subgroup contrasts. Results indicated that, analyzed in this way, students differed significantly from non-students on Openness to AI Training ($t(148) = 3.06$, $p < 0.05$, $d = 0.50$), as well as Perceived Cognitive Risks ($t(148) = -2.51$, $p < 0.05$, $d = -0.41$) with students being more open and non-students perceiving higher risks.

Faculty members differed from non-faculty in Openness to AI Training ($t(148) = -2.44$, $p < 0.05$, $d = -0.40$), as well as Governance & Ethical Concerns ($t(148) = -2.72$, $p < 0.05$, $d = -0.44$), Cultural Impact ($t(148) = 2.69$, $p < 0.05$, $d = 0.44$), and Perceived Cognitive Risks ($t(148) = 2.25$, $p < 0.05$, $d = 0.37$). In addition, the small group of tested administrative staff, while no significant difference in OTI was shown, scored significantly lower than all non-administrative staff in AI Awareness ($t(148) = 2.51$, $p < 0.05$, $d= 1.27$), Digital Competence ($t(148) = 2.50$, $p < 0.05$, $d = 1.26$), and Governance Concerns ($t(148) = 2.41$, $p = .017$, $d = 1.22$). No significant differences were observed between management or researchers and other groups ($p > .05$ across all variables).

To test whether GPA and study progression predicted Openness to AI Training (OTI), a regression analysis was conducted including only student participants. The overall model was not significant, $F(2, 70) = 1.53$, $p = 0.223$, $R^2 = .04$, indicating that GPA and study progression together explained little variance in openness. Neither GPA ($\beta = 0.06$, $p = 0.597$) nor being late with studies ($\beta = 0.58$, $p = 0.130$) significantly predicted openness to AI training. Thus, H4b was not supported. No significant differences in OTI were found across study levels either (i.e. undergraduate, master's, and doctoral), $F(2, 14.7) = 0.98$, $p = 0.400$. Although master's ($M = 3.80$) and doctoral students ($M = 3.65$) scored slightly higher than undergraduates ($M = 3.29$), post-hoc comparisons were nonsignificant. No differences between study levels were observed in relation to any of the other study variables.

Finally, independent samples t-tests showed no significant differences between private and state institutions for OTI, PCR, CI, PU, GEC, or DC (all $p > 0.12$), but participants from private institutions reported higher AI Awareness, $t(148) = -3.94$, $p < 0.001$, $d = -0.72$. Similarly, no differences emerged between participants with and without international academic experience on these variables (all $p > 0.14$), except for AI Awareness, which was higher among those with international experience, $t(148) = 2.55$, $p < 0.05$, $d = 0.53$.

Cronbach's α values ranged from 0.63 (Cultural Impact) to 0.92 (Perceived Cognitive Risks), suggesting acceptable to excellent internal consistency for most scales (Nunnally & Bernstein, 1994). The Governance & Ethical Concerns scale, however, showed a very low reliability coefficient ($\alpha = 0.14$), indicating that its items may not cohere well. Given the exploratory nature of this study, these values were deemed sufficient for preliminary analysis, though the Governance & Ethical Concerns construct should be interpreted with caution and refined in future research.

3.4. Qualitative Data Analysis

Analysis of the two open-ended questions revealed several recurring themes. Participants most often pointed to insufficient information, training, and legal frameworks as key dilemmas for the meaningful use of AI, alongside ethical concerns related to data protection, plagiarism, and the replacement of human interaction. Many emphasized risks for critical thinking and creativity, warning that overreliance on AI could foster passivity and reduce originality in both students and faculty. Institutional barriers such as weak infrastructure and the absence of clear policies were also highlighted, while neutral or indifferent responses typically reflected low perceived usefulness. When asked about local cultural characteristics, respondents noted that high power distance and bureaucratic inertia may hinder bottom-up initiatives, whereas collectivist tendencies could both accelerate adoption through collaboration and slow it down through corruption and lack of transparency. High uncertainty avoidance was described as a double-edged trait, producing caution and resistance but also careful reflection, while younger generations' curiosity and openness were recognized as potential drivers of adoption. Overall, several comments also reflected an ethnocentric stance, emphasizing greater trust in locally developed solutions and skepticism toward foreign technologies.

A more detailed interpretation of these findings is presented in the Discussion section.

4. Discussion

The aim of this exploratory study was to examine readiness for AI adoption in Serbian higher education. By testing established constructs from TAM, UTAUT, DOI, TPB, and socio-technical perspectives, we sought to identify drivers and barriers of openness to AI training and implementation. The findings provide partial support for the hypotheses, alongside several meaningful descriptive patterns that enrich understanding of the local context.

The results offered strong support for H1, as AI Awareness, Perceived Usefulness, and Digital Competence were positively associated with Openness to AI Training and Implementation (OTI). Perceived Usefulness emerged as the strongest predictor in regression analysis, consistent with TAM/UTAUT research that links usefulness perceptions to adoption intentions (Davis, 1989; Venkatesh et al., 2003; Helmiatin et al., 2024; Rahiman & Kodikal, 2024). H2 was only partially supported. Perceived Cognitive Risks correlated negatively with openness at the bivariate level, but did not remain significant in the regression model, suggesting that risks may be secondary to perceived benefits when individuals evaluate adoption. Governance and Ethical Concerns unexpectedly showed a small positive effect on openness, implying that recognition of ethical issues may in fact heighten interest in training opportunities, as also suggested by Yusuf et al. (2024) and Castillo-Martínez et al. (2024). H3 was also partially supported. Among cultural orientations, Power Distance was positively associated with openness, while Ethnocentrism showed a negative effect, confirming previous findings that hierarchical deference can channel adoption when endorsed by leadership (Tarhini et al., 2017; Kovacic, 2009), whereas ethnocentric preferences may hinder openness to foreign-developed tools (Marinković, Kostić, & Stanišić, 2011). Collectivism and Uncertainty Avoidance were unrelated to openness in this sample. The role-based hypotheses (H4) were mixed. As expected, students showed higher openness and lower perceived risks compared to non-students, while faculty reported higher concerns about governance, culture, and risks. However, contrary to expectations, GPA and study progression were unrelated to openness, and no differences were observed across study levels, suggesting that achievement indicators may not strongly shape adoption at this stage. Likewise, private versus public institutional affiliation and international experience did not predict openness, though both subgroups reported higher awareness.

Although the group differences were not statistically significant, several meaningful patterns emerged in the descriptive results. Students and researchers reported the highest familiarity with AI concepts, while administrative staff consistently scored the lowest across both familiarity and methods of use. Importantly, only four administrative staff members completed the survey, which is itself an indicator of limited engagement from this group. Similarly, managerial staff were underrepresented compared to students and teachers. Interestingly, researchers and management personnel indicated relatively greater engagement with methods of AI use, aligning with their roles in shaping institutional practices. At the disciplinary level, organizational and technical sciences stood out as the most familiar with both concepts and methods, which resonates with prior findings that STEM-oriented fields often display earlier uptake of emerging technologies (OECD, 2023; Zawacki-Richter et al., 2019).

In terms of digital competence, no significant differences were observed between participants with or without international experience, nor across age groups. Nevertheless, administrative staff rated themselves lowest in both tool use and adaptation to new technologies, suggesting potential vulnerabilities in support functions where efficiency gains from AI could be most impactful. From an organizational design and development perspective, this gap indicates a misalignment between those most responsible for routine processes and the very technologies that could streamline their work. Unless structures are adapted to include and empower administrative roles, institutions risk uneven adoption that reinforces existing bottlenecks (George & Wooden, 2023; Trist & Bamforth, 1951).

Regarding attitudes, administration automation emerged as the most valued application (M = 3.8), reflecting recognition of AI's potential to reduce routine workloads. Perceived usefulness overall outweighed perceived cognitive risks (M = 3.8 vs. 2.6), and while concerns were relatively uniform across risk items, slightly higher apprehension was reported concerning AI's potential negative consequences for intellectual development (Fowler, 2023; Chan & Hu, 2023). Correlational analyses supported these impressions: nearly all items of perceived usefulness correlated positively with awareness, and negatively with perceived cognitive risks. Likewise, awareness items themselves were mostly negatively correlated with perceived risks, with the strongest effects observed for staying updated with the latest AI news and developments — indicating that greater exposure to information may mitigate perceived threats (Crompton & Burke, 2023; Castillo-Martínez et al., 2024). In terms of knowledge management, this highlights the central role of knowledge flows and learning systems: institutions that create channels for continuous updating and knowledge sharing are better positioned to reduce resistance and build trust in innovation (Nonaka & Takeuchi, 1995; UNESCO, 2021).

An additional unexpected finding was that older participants were less influenced by cultural orientations in their AI interest. This contrasts with personality research showing that openness to new experience typically declines with age, making space for more prominent conservatism (McCrae et al., 2005). At least in this Serbian sample, cultural dimensions may play a smaller role among older cohorts than previously assumed, raising interesting implications for strategic innovation: even groups traditionally perceived as more conservative may be willing to embrace change if provided with appropriate structures and incentives (Christensen, 1997; Teece, 2010).

The findings also suggest ways of framing AI adoption within strategic project management and strategic management perspectives. The fact that governance and ethical concerns correlated positively with openness implies that projects which explicitly integrate ethical risk management may gain legitimacy and stakeholder buy-in (Müller et al., 2019). From a strategic management standpoint, the strong predictive role of Perceived Usefulness underlines the need to connect AI adoption directly with institutional performance and value creation (Hannan & Liu, 2023). Meanwhile, the underrepresentation of managerial staff points to a strategic gap: without visible leadership engagement, innovation risks becoming fragmented, driven by pockets of student or faculty enthusiasm rather than coordinated institutional vision (Zahra & George, 2002).

Finally, the unexpectedly high response rate, greater than anticipated under the current political circumstances influencing the Serbian higher education system , suggests a reservoir of interest and willingness to engage with AI. For universities, this represents a clear opportunity for strategic innovation: building on grassroots enthusiasm through structured programs, while also creating governance frameworks to ensure ethical, equitable, and sustainable adoption (OECD, 2023).

Practical Implications

The findings point to several priorities for future project planning. Administrative staff emerged as the least engaged and least confident group, yet also the one that could benefit most from AI-driven efficiency in routine tasks, making them a key target for tailored training and awareness initiatives. The limited participation of managerial staff suggests that institutional leadership has not yet fully engaged with AI adoption, highlighting a governance gap that needs to be addressed at the strategic level (George & Wooden, 2023). At the same time, disciplinary strengths in organizational and technical sciences could serve as entry points for cross-disciplinary knowledge transfer and institutional capacity-building. The strong link between awareness and reduced risk perceptions further underlines the importance of transparent communication, professional development, and clear ethical frameworks (Rahiman & Kodikal, 2024; Yusuf et al., 2024).

The already mentioned unexpectedly high response rate, despite political instability and ongoing strikes in Serbian higher education, signals strong grassroots interest in AI adoption. This enthusiasm provides a foundation for more structured research and long-term capacity-building, even as current institutional challenges complicate systematic planning and implementation. To build on these insights, later phases of this project will include a systematic review of institutional documents such as ICT strategies, AI policies, and internal reports, combined with semi-structured interviews with faculty leaders, administrators, and technical staff. These qualitative components will help further contextualize survey results, capture nuanced perspectives on governance and infrastructure, and guide the design of a tailored AI Adoption Readiness Framework for Serbian higher education.

5. Conclusion

This study provides an initial exploratory mapping of AI readiness in Serbian higher education. Hypotheses testing confirmed that awareness, perceived usefulness, and digital competence support openness to AI adoption, while perceived risks and cultural orientations play uneven roles. Descriptive analyses revealed role- and discipline-based patterns, highlighting students and researchers as the most familiar groups, and administrative staff as the least engaged. Administration automation was perceived as the most useful AI application, and awareness consistently emerged as a mitigating factor for risk perceptions.

Although exploratory, the unexpectedly high participation demonstrates substantial interest in AI adoption across Serbian higher education, even under challenging political and institutional conditions. These findings underline both the potential and the necessity of further research and policy development. By building on existing capacities, addressing gaps in administration and governance, and leveraging disciplinary strengths, Serbian universities can create pathways for responsible and equitable AI integration.

6. Limitations

Several limitations should be acknowledged. First, the sample was uneven, with only four administrative staff and a small number of managerial staff compared to students and teachers, restricting group comparisons. Second, the Governance and Ethical Concerns scale showed low reliability and requires refinement in future iterations. Third, the cross-sectional and exploratory design limits causal inference, and factor validation was not attempted at this stage. Fourth, the study was conducted during a period of political instability and university strikes, which complicated advanced planning and a more complete data collection. Finally, the surprising finding regarding age and cultural orientations should be treated with caution and further tested in larger, more balanced samples. Future work should expand to qualitative interviews, institutional infrastructure analysis, and longitudinal designs to deepen understanding of AI readiness trajectories in Serbia.

Annex: AI-Readiness Survey for Higher Education

Instructions: *Unless otherwise noted, please rate items on a 1–5 scale, where 1 = "Strongly disagree / No competence / Not useful / Not interested" and 5 = "Strongly agree / Very high competence / Very useful / Very interested."*

A. Demographic Information

1. Gender: ☐ Male ☐ Female ☐ Other / Prefer not to say

2. Age: _____

3. Role (check all that apply): ☐ Teaching staff ☐ Non-teaching staff / Administration ☐ Management (Dean, Vice-Dean, Director) ☐ Student ☐ Researcher

4. Type of institution: ☐ Public ☐ Private

5. Faculty / Study or work area (e.g., Organizational Sciences, Engineering, Social Sciences): _____

6. Location of institution: __________________

7. Years of experience at this institution: _____

8. Approximate size of your institution (number of students): ☐ < 5 000 ☐ 5 000–15 000 ☐ > 15 000

9. Have you studied or worked abroad for ≥ 6 months? ☐ Yes ☐ No

10. (For students only) Year of enrolment: _____

11. (For students only) Current level of studies: (Bachelor, Master, PhD): _____

12. (For students only) Current year of studies: ______

13. (For students only) GPA: _____

B. Awareness of Artificial Intelligence

14. I am familiar with the basic concepts and applications of artificial intelligence (AI).

15. I have attended formal or informal training related to AI.

16. I know how AI is currently used in higher education globally.

17. My institution has communicated plans or strategies related to AI adoption.

18. I regularly follow news and developments about AI in education.

C. Digital Competencies

Please rate your competence in the following areas (1 = No competence, 5 = Very high competence):

19. Using basic digital tools for teaching/learning (e.g., LMS, e-mail, video-conferencing)

20. Evaluating digital content for relevance, quality, and accuracy

21. Adapting to new digital systems or platforms at my institution

22. Understanding data privacy and security in digital environments

23. Interpreting data generated by digital/AI tools (e.g., learning analytics)

D. Governance & Ethical Concerns

24. I am concerned about data privacy when using AI tools in education.

25. I believe AI can amplify existing inequalities in education.

26. My institution has clear ethical guidelines for the use of AI.

27. I feel sufficiently informed about the ethical risks of AI in education.

28. There should be a regulatory framework governing AI use at universities.

E. Perceived Usefulness of AI in Higher Education

Please rate how useful you consider applying AI in the following areas (1 = Not useful at all, 5 = Very useful):

29. Personalized learning and student support

30. Automation of administrative tasks

31. Academic advising and career guidance

32. Early detection of at-risk students (e.g., potential dropouts)

33. Enhancing research and knowledge discovery

F. Cultural Dimensions and Norms Related to AI Adoption

34. At my institution, decisions about adopting new technologies are always made by top management and rarely by frontline individuals.

35. Before I accept a new technology, it is important to me to see that colleagues in my group are already using it.

36. Uncertainties and potential errors in AI systems are approached with a high degree of caution.

37. AI solutions originating from “Western” companies are viewed skeptically in my environment.

38. Open criticism of decisions made by an AI system is rare due to respect for hierarchy.

39. I value solutions developed within our own culture more than foreign technology, even if performance is similar.

40. Colleagues I work with believe AI could replace some of their tasks, which creates latent resistance.

41. Successful AI implementation at my university depends on receiving a clear “top-down” signal that it is a priority.

42. I feel a moral obligation to adopt AI if the university leadership recommends it.

43. I trust human judgment more than algorithmic recommendations, even when the algorithm is statistically more accurate.

G. Perceived Impact of AI on Cognitive Abilities

44. Using AI tools (e.g., ChatGPT) makes it harder for me to develop my own solutions and ideas.

45. Because I use AI, I try less often to solve complex problems independently.

46. I feel that AI reduces my ability for critical thinking.

47. I believe that over-reliance on AI limits my creativity.

48. I think using AI negatively affects my long-term learning ability.

49. I notice a decrease in my confidence in personal cognitive abilities because of using AI.

50. When I use AI, I am less motivated to think deeply about a topic.

51. I believe AI supports my intellectual development. (R)

52. Using AI makes me more passive in problem-solving.

53. I am convinced that AI has more advantages than disadvantages for my cognitive abilities. (R)

H. Interest in Training and Implementation

Please rate your level of interest in the following activities (1 = Not interested at all, 5 = Very interested):

54. Attending workshops on AI applications in education

55. Participating in the design or implementation of AI tools

56. Learning about AI ethics and responsible use

57. Advocating for the development of AI-related policies at my institution

58. Collaborating on research projects about AI in education

I. Open-Ended Questions (optional)

59. What are your most important cultural or value-based dilemmas regarding the introduction of AI at your institution?

60. Which local cultural characteristics do you see as advantages and which as obstacles to wider AI adoption?

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