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Non-compensatory Decision-Making in the Integration of Artificial Intelligence in Higher Education in Azerbaijan

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Abstract. The accelerated development of artificial intelligence (AI) is changing the landscape of higher education, creating new opportunities to enhance teaching and learning processes. The aim of this study is to assess the potential of AI technology integration in Azerbaijani universities. The study combines a review of the literature on digitalization and AI in education with empirical data obtained from an online survey conducted among faculty and students of higher education institutions in Azerbaijan (305 respondents), analyzed using logistic regression models.

The results show that perceived benefits significantly increase the probability of AI adoption (average marginal effect of about 3.5 percentage points per additional perceived benefit), whereas perceived risks, the benefit–risk interaction, and perceived teacher competence have no statistically significant effect. The effect of perceived benefits is concentrated among academic staff, while students' use of AI depends neither on perceived benefits nor on perceived risks. This pattern provides no evidence of a compensatory benefit–risk trade-off and is consistent with a benefit-dominated, non-compensatory decision rule reflecting bounded rationality. The literature review indicates the high potential of AI application in educational practice: AI technologies contribute to the personalization of learning trajectories, automation of routine academic and administrative tasks, provision of timely and high-quality feedback, and the development of adaptive and scalable educational content. At the same time, the literature points to challenges such as ethical issues related to data privacy and security; insufficient levels of digital competence among the teaching staff; the need for continuous professional development; and the need to ensure compliance with existing legal and regulatory frameworks. The study concludes that addressing these issues is essential to the responsible, sustainable implementation of AI technologies in academic environments. Overall, the integration of AI into higher education represents a highly promising direction for future development, with the potential to significantly improve the quality, accessibility, and personalization of education, as well as enhance graduate readiness for the changing demands of the global labor market.

Keywords: Digital Education, Artificial Intelligence, Artificial Intelligence Strategy, Non-Compensatory Model, Technology Adoption

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Author contributions

A. Muradov and L. Hajiyeva contributed to the literature review, interpretation of the findings, and formulation of the conclusions. N. Huseynova and M. Samadova were responsible for questionnaire development, data collection, and survey administration. E. Ahmadova conducted the econometric analysis.

1. Introduction

Amid accelerating global transformations, contemporary societies are increasingly shaped by volatility, uncertainty, and the rapid evolution of digital technologies. The pervasive diffusion of digital solutions across economic and social systems not only intensifies systemic vulnerabilities but also drives the restructuring of established institutional frameworks. In this context, the continuous examination of digitalization processes has become a critical area of scholarly inquiry (Urekeshova et al., 2023). The education sector, traditionally characterized by institutional rigidity and path dependency, is particularly exposed to these dynamics and thus requires comprehensive adaptation to emerging technological, economic, and sociocultural conditions.

Digital transformation has emerged as a central catalyst for innovation in higher education systems. It enables the deployment of advanced instruments for the organization and governance of the educational process, the modernization of assessment and certification mechanisms, and the development of digital ecosystems that facilitate interaction among key stakeholders, including faculty, students, researchers, and employers. These changes contribute to the formation of more flexible, data-driven, and interconnected educational environments. At the institutional level, digitalization allows universities to integrate and optimize their resources through unified information infrastructures, implement sophisticated electronic document management systems, and institutionalize knowledge management practices across organizational units. Furthermore, digital technologies support continuous monitoring and analytics of learning outcomes and teaching effectiveness, foster the development of individualized educational trajectories, and enhance the efficiency of knowledge generation, dissemination, and application.

The digitalization of education has gone through three stages (Bolsunovskaya and Ganina, 2025): (1) the development of computer literacy and the emergence of the first computer labs in schools and universities; (2) the introduction of information and communication technologies into the educational process; (3) digital transformation in all educational processes.

Two forms of digitalization of education are distinguished: (1) digitalization of the educational process (implementation of interactive whiteboards, projectors, and other interactive technologies); (2) digitalization of administrative work (electronic document management, implementation of electronic journals, etc.).

Within this transformative landscape, artificial intelligence (AI) is increasingly recognized as a pivotal enabler of educational innovation. The integration of AI-driven solutions, such as adaptive learning systems and intelligent tutoring technologies, facilitates the personalization of learning experiences, improves decision-making processes in institutional management, and broadens access to education for diverse population groups. However, the growing reliance on AI also raises critical concerns related to ethics, data governance, and the reproduction of social inequalities. As emphasized by UNESCO (UNESCO, 2025), the implementation of AI in education should adhere to a human-centered paradigm that ensures inclusivity, transparency, and equity.

Despite the growing body of literature on digital transformation in education, there remains a limited understanding of how these processes unfold in specific national contexts, particularly in emerging digital economies. In this regard, Azerbaijan represents a relevant case for examining the interplay between digitalization policies and the adoption of AI in higher education.

Accordingly, the aim of this study is to investigate the specific features of education digitalization, analyze the decision-making mechanism underlying the adoption of AI technologies by students and

academic staff of higher education institutions in Azerbaijan, and evaluate the associated opportunities and risks within this evolving landscape.

2. Literature review

2.1. Conceptual Foundations of Artificial Intelligence in Education

Artificial intelligence has increasingly become an integral component of modern educational systems, offering tools capable of addressing the heterogeneous needs of learners, educators, and administrators (Makhzoum, 2025). In a broad sense, AI encompasses a spectrum of technologies designed to replicate or augment cognitive functions traditionally associated with human intelligence, including learning, reasoning, problem-solving, and natural language processing (Russell and Norvig, 2021).

Scholarly interpretations of artificial intelligence vary depending on disciplinary perspectives and research objectives. Some authors conceptualize AI as a property of intelligent systems that enables the execution of creative and cognitive functions characteristic of human thinking (Pavlyuk, 2020). Others define it as a complex of software solutions and algorithmic mechanisms capable of reproducing specific intellectual operations (Rakitov, 2018). From an educational standpoint, AI is frequently understood as a means of modeling cognitive, mental, and learning processes, allowing for the simulation and analysis of educational activities (Amirov and Bilalova, 2020).

A number of authors believe that "artificial intelligence" (AI) is associated with software products that can reproduce human behavior and thought processes (Iqbal et al., 2024). Others examine the integration of artificial intelligence (AI) into education from the perspective of transforming the knowledge and skills of teachers and improving curricula (Amiri et al., 2025).

More comprehensive approaches emphasize AI as the computational modeling of human intellectual processes, encompassing learning, reasoning, self-regulation, and the recognition of verbal and non-verbal signals through machine vision and speech technologies (Paskova, 2019). In this context, Duggan (2020) introduces the concept of augmented intelligence, highlighting AI's role in supporting informed decision-making among educational stakeholders rather than replacing human agency. Similarly, Luchsheva (2020) regards artificial intelligence as an instrumental resource for enhancing pedagogical methods, accelerating instructional processes, and optimizing communication within educational environments. According to Chaudhari (2025), artificial intelligence (AI) has transformed the education sector through the introduction of learning technologies that adapt to each student, automated assessment systems, and AI research tools.

A number of authors note the importance of AI for increasing teacher productivity by automating a range of standard tasks, such as classroom record-keeping, preparing educational materials, analyzing statistics and literature, grading exams, etc. AI is highly significant in terms of saving time and solving routine, standard tasks (Malik and Hasan, 2025).

Synthesizing these perspectives, artificial intelligence in education may be defined as a complex of advanced digital technologies that, through large-scale data collection, analytical processing, and software-based modeling, enable the design and implementation of individualized instructional strategies. These technologies replicate selected elements of human cognitive and communicative activity to support learning, assessment, and educational decision-making.

Within the educational domain, artificial intelligence is capable of performing a wide range of functions, including the recognition and interpretation of visual and auditory information, the formulation and solution of professional and educational tasks, the retrieval and contextual application of knowledge, and the analysis of sociocultural patterns embedded in human speech and behavior (Korovnikova, 2021).

Research in this field shows dynamic growth in the AI education market. According to statistics, the market value of AI education in 2025 was $7.57 billion, representing a 38.4% increase over the previous year. Given the rapid growth of the AI education market, researchers predict that its market value will exceed $30 billion by 2030 and exceed $110 billion by 2034 (Kumar, 2026).

In the digital age, in addition to mastering professional competencies (hard skills), developing soft skills is essential. The ever-increasing volume of information and knowledge has a profound impact on the

human brain. It is impossible to absorb all this information, but artificial intelligence can assist in various tasks, helping develop students' critical thinking and creativity. Today, end-to-end technologies can be excellent aids in collecting and filtering information, helping students learn more effectively and teachers improve the quality of their learning. At the same time, the adoption of AI is characterized by a dual nature, combining significant opportunities with emerging challenges. While AI technologies offer substantial improvements in efficiency and accessibility, they also raise concerns related to reliability, ethical implications, and potential overdependence on automated systems. These challenges highlight the complexity of integrating AI into educational environments and the need to balance technological advancement with critical evaluation of its consequences (Ahmadova, 2022).

Thus, it can be concluded that the essence of artificial intelligence in education lies in the effective and flexible use of cutting-edge technologies to transition to a personalized and results-oriented educational process. The introduction of digital resources increases the accessibility of education anytime and anywhere, making them particularly relevant in the modern world.

2.2. Key types of Artificial Intelligence in education

Mgala (2024) systematizes the key categories of artificial intelligence tools applied within the educational domain, highlighting several major directions of their implementation.

Intelligent Tutoring Systems (ITS) are designed to support personalized learning by dynamically adapting instructional content to individual learner needs. These systems analyze learner behavior and performance data to generate targeted recommendations regarding learning materials, pacing, and instructional strategies, thereby enhancing the effectiveness and precision of pedagogical support (Wang et al., 2023).

Personalized Learning Environments (PLE**s)** facilitate the construction of individualized educational trajectories. Within such environments, the traditional role of the teacher is transformed from a primary source of knowledge to that of a facilitator or mentor, guiding learners through self-directed and adaptive learning processes. This shift contributes to the development of a learner-centered educational paradigm that emphasizes autonomy, flexibility, and personalization.

AI-based assessment technologies introduce more advanced and flexible approaches to evaluating student performance. By leveraging data analytics and machine learning techniques, these tools enable the generation of adaptive tests, automated feedback mechanisms, and performance diagnostics that can be aligned with diverse curricular models. As a result, assessment processes become more responsive to individual learning contexts and educational objectives.

Educational robots represent an emerging class of AI-enabled tools with particular relevance for science, technology, engineering, and mathematics (STEM) education. The systematic review by Zhang et al. (2021) demonstrates that the integration of educational robots into instructional practice has a statistically significant, albeit moderate, positive effect on learning outcomes. These effects are most evident in the development of computational thinking skills, as well as in shaping students' motivation and attitudes toward STEM disciplines.

A literature review reveals the following advantages and disadvantages of using AI in education (Table 1):

Table 1. Advantages and Limitations of Artificial Intelligence in Education

Advantages	**Limitations / Challenges**
Enhancement of the quality of educational process management through monitoring, control, optimization, dynamic planning, and predictive analytics	Absence of emotional and affective interaction between AI systems and learners
Personalization of learning trajectories based on individual cognitive and behavioral data	High financial costs associated with the implementation, maintenance, and technical support of AI systems

Reduction of repetitive and routine elements in teaching, leading to decreased monotony of the educational process	Administrative and technical complexity in managing AI-enabled information systems
Development of dynamic learner models that reflect progress, learning styles, and competencies	Contextual and functional limitations in the application of AI technologies
Increased objectivity in the assessment of learning outcomes through data-driven evaluation	Necessity to develop new professional competencies among educators and administrators
Reduction of subjectivity and human error in instructional and evaluative processes	Insufficient digital literacy among teachers, requiring systematic and continuous professional training
Stimulation of innovation through the development of new learning technologies and instructional formats	Vulnerability to cybersecurity threats, including unauthorized access and data breaches
Compatibility with digital educational platforms and distance learning systems	Need for revision and adaptation of regulatory frameworks and standards governing the use of AI in education
Efficient navigation of integrated information resources and accelerated delivery of educational content	Fragmentation of educational processes, particularly the separation of instruction and value-based education
Rapid processing and analysis of educational content and learning data	Risk of excessive reliance on AI technologies, potentially leading to reduced learner engagement
Adaptive formation of learning groups based on performance and learning needs	Possible decline in students' critical and analytical thinking skills due to extensive use of generative AI tools (e.g., ChatGPT)

Source: Compiled by the authors based on a literature analysis

The listed advantages and disadvantages of using artificial intelligence in education should be taken into account when developing AI programs in universities in Azerbaijan.

2.3. AI Development in Azerbaijan: Policy Context

Analyzing the implementation of AI in Azerbaijan, we note that, as in many countries, the pandemic has been a factor influencing digitalization, increased internet usage, and the development of online services and distance learning. The pandemic has forced many industries to confront the inevitable reality: to survive and develop under conditions of total restrictions, they must adapt to new conditions (Javadov et al., 2025).

As of January 1, 2025, the number of internet users in the Republic of Azerbaijan was 9.6 million, with internet penetration reaching 91.0% of the population. The number of broadband internet users exceeded 2.2 million. In the 2024 UN e-Government Development Index, Azerbaijan ranks 74th out of 193 countries, thus entering the "Very High EGDI" group for the first time, which is considered the index's highest category. According to Azerbaijan's statistical data on ICT development indicators, the ICT development index was 6.64 in 2020 and 80.4 in 2024; these values are not directly comparable, since the methodology and scale of the index were revised (from a 0–10 to a 0–100 scale) (State Statistical Committee of the Republic of Azerbaijan, 2026).

The Artificial Intelligence Strategy for the period 2025–2028 (Artificial Intelligence Strategy of the Republic of Azerbaijan, 2025) represents a comprehensive policy framework aimed at accelerating national development in the field of artificial intelligence, fostering digital transformation, and strengthening Azerbaijan's position within the global AI ecosystem. The adoption of this strategy reflects the state's recognition of artificial intelligence as a critical driver of economic competitiveness, technological sovereignty, and sustainable digital growth.

The strategy defines a set of interrelated objectives, including the stimulation of innovation and digital development, enhancement of economic competitiveness, and the establishment of AI-driven information

management systems. Particular emphasis is placed on the development of human capital through the training of highly qualified specialists and the expansion of AI-related knowledge and skills across various sectors. In addition, the strategy highlights the importance of strengthening public–private partnerships as a mechanism for accelerating technological diffusion and ensuring the effective implementation of AI solutions. Governance mechanisms grounded in information security principles and ethical standards are positioned as a foundational component of the national AI framework.

From an infrastructural perspective, the strategy prioritizes the development of high-performance computing capacities, the creation of open and interoperable data repositories, and the large-scale deployment of artificial intelligence technologies across multiple domains. Special attention is given to Natural Language Processing (NLP) technologies, reflecting their strategic relevance for multilingual environments, public administration, and digital services. The preparation of a national data strategy aimed at improving data quality and enabling the efficient processing of large-scale datasets further underscores the data-centric orientation of Azerbaijan's AI policy.

Support for academic research and the introduction of new AI-oriented educational programs within higher education institutions constitute another key pillar of the strategy. These measures are designed to strengthen the national research ecosystem, facilitate knowledge transfer, and align educational outcomes with labor market demands. At the same time, the strategy emphasizes the expansion of international cooperation, recognizing the transnational nature of AI development and the necessity of integration into global research and innovation networks. In the education sector, Artificial Intelligence is mostly used for digital learning platforms and personalized education models. A number of higher education institutions operating in the country - ADA University, Baku Higher Oil School and Azerbaijan State University of Economics (UNEC) - have specialization and research programs in artificial intelligence. Along with the expansion of digital education in a number of schools, the introduction of artificial intelligence-based learning tools is being implemented in stages. In general, electronic resources, online assessment systems and virtual teacher technologies are already used in some educational institutions.

In economic terms, the strategy envisages increased investment in the AI startup ecosystem, alongside targeted initiatives to support the commercialization of artificial intelligence technologies. By fostering entrepreneurship and attracting both domestic and foreign investors, the strategy seeks to create favorable conditions for the emergence of innovative AI-driven enterprises and the scaling of technological solutions beyond the national market. Ethical governance and cybersecurity are identified as critical dimensions of the national AI agenda. The strategy implies the development of a regulatory framework aimed at ensuring the ethical use of artificial intelligence, enhancing algorithmic transparency, mitigating information bias, and strengthening cybersecurity resilience. These measures align Azerbaijan's AI policy with international discussions on responsible and human-centered AI deployment.

Finally, the strategy places strong emphasis on increasing public awareness of artificial intelligence technologies and promoting their societal benefits through educational and informational initiatives. In this regard, public engagement is viewed as a prerequisite for building trust in AI systems and ensuring their socially responsible adoption. Overall, the implementation of the Artificial Intelligence Strategy 2025–2028 positions Azerbaijan to emerge as a regional leader in AI development, while simultaneously serving as a strategic roadmap for the formation of a sustainable national AI ecosystem and the country's active participation in global AI platforms.

2.4. Hypotheses Development

The existing literature provides mixed evidence regarding the mechanisms underlying AI adoption in education, suggesting the need to test alternative decision-making frameworks.

Traditional technology adoption models assume that individuals evaluate technologies through a compensatory process, balancing perceived benefits and risks (Davis, 1989; Venkatesh et al., 2012). However, behavioral research indicates that real-world decision-making often deviates from such rational trade-offs, especially in complex and uncertain environments (Kahneman and Tversky, 1979; Simon, 1955). In such contexts, individuals may rely on simplified or rule-based decision mechanisms rather than continuous optimization.

Moreover, non-compensatory decision theories suggest that individuals may not integrate all factors into a single utility function but instead base decisions on dominant criteria or threshold conditions (Aleskerov et al., 2007; Aleskerov et al., 2010). In the context of AI adoption, this implies that users may not balance perceived benefits and risks but rather rely on asymmetric evaluation patterns. Based on this reasoning, the following hypothesis is proposed:

H1: AI adoption follows a non-compensatory decision-making rule rather than a compensatory trade-off between benefits and risks.

A substantial body of research suggests that perceived risks may act as barriers to technology adoption, particularly in the context of digital and AI technologies (Dwivedi et al., 2021). However, empirical evidence remains inconsistent, with some studies finding limited or insignificant effects of risk perception on user behavior. This leads to the following hypothesis:

H2: Perceived risks act as a limiting factor in AI adoption.

Perceived benefits are consistently identified as one of the strongest predictors of technology adoption. Users tend to adopt technologies that improve efficiency, productivity, and performance (Dwivedi et al., 2021; Venkatesh et al., 2012). Accordingly:

H3: Perceived benefits positively influence AI adoption.

Prior research suggests that usage intensity and experience may reinforce adoption behavior, as repeated interaction with technology increases familiarity and reduces uncertainty. Thus:

H4: The intensity of AI use positively influences AI adoption.

Finally, institutional factors, including the competence and readiness of educators, are often considered important for technology adoption in educational settings (Borgonovi et al., 2025). However, the extent to which such factors influence individual behavior remains unclear. Therefore:

H5: Perceived institutional competence positively influences AI adoption.

3. Methodology

A quantitative approach based on a structured survey is used to obtain empirical data and examine perceptions and practices related to the use of artificial intelligence (AI) in higher education institutions in Azerbaijan.

Data were collected using an online questionnaire created in Google Forms and distributed to students, master's students, faculty, and academic staff at Azerbaijani higher education institutions. The survey included both closed-ended and Likert-scale questions designed to assess respondents' awareness of artificial intelligence technologies, their frequency of use, their perceived benefits, and their associated risks.

The study sample consisted of 305 respondents, including 160 undergraduate and graduate students, and 145 faculty and academic staff from various universities. Gender is coded as a dummy variable (1 = female, 0 = male); two respondents who preferred not to disclose their gender were excluded from the regression analysis. Age group (five categories) and education level (four categories) are treated as ordinal variables. Since respondent status is a nominal variable, it is recoded into a dummy variable Staff (1 = academic staff or teacher, 0 = bachelor or master student).

Due to accessibility concerns, a convenience sampling method was used. Despite its limitations, this approach is widely used in research examining new technological practices (e.g., Miranda, 2025).

Research shows that the behavior of individuals cannot always be described by compensatory models reflecting rational behavior. A number of researchers emphasize the importance of non-compensatory models, which primarily assume bounded rationality and heuristic decision making (Aribarg et al., 2018; Dieckmann et al., 2009; Rao, 2026). This study departs from the standard classical compensatory approach to technology adoption, which assumes that people weigh perceived benefits against perceived risks. Instead, the results are presented from a non-compensatory decision-making model, where certain criteria act as limiting factors that cannot be compensated for by improvements in other aspects.

Formally, in the compensatory model, the utility of adoption is defined as follows:

$$U_i = \beta_1 BENEFIT_i - \beta_2 RISK_i + \beta_3 COMP_i + \gamma X_i + \varepsilon_i \quad (1)$$

where X_i are control variables (female, academic staff status and education level), and COMP denotes the perceived competence of teachers.

Following the literature on non-compensatory (conjunctive) decision rules (Dawes, 1964; Einhorn, 1970; Gilbride and Allenby, 2004) and the concept of threshold aggregation (Aleskerov et al., 2007; Aleskerov et al., 2010), the decision rule is determined by the following threshold conditions:

$$Adopt_i = \begin{cases} 1, & \text{if } BENEFIT_i \geq \theta_1 \text{ and } RISK_i \leq \theta_2 \\ 0, & \text{otherwise} \end{cases}$$

This formulation implies that high perceived risks cannot be offset by high perceived benefits, reflecting bounded rationality and threshold-based decision-making. To implement this study, variables were aggregated, i.e., index variables were created, followed by econometric modeling.

To model the likelihood of AI adoption as a function of key explanatory variables, the authors of this article used a binary choice model. This specification allows for testing for non-compensatory decision making through interaction effects.

$$P(Adopt_i = 1) = \Lambda(\beta_1 BENEFIT_i + \beta_2 RISK_i + \beta_3 COMP_i + \gamma X_i)$$

where $\Lambda(\cdot)$ is the logistic function. The diversity of AI use (USE) is excluded from the baseline specification, since the number of purposes for which AI is used is largely a consequence of adoption; it is used only in a robustness check. Age group is also excluded because of its strong correlation with academic staff status.

To test the non-compensatory hypothesis, we introduce interaction terms:

$$P(Adopt_i = 1) = \Lambda(\beta_1 BENEFIT_i + \beta_2 RISK_i + \beta_3 (BENEFIT_i \times RISK_i) + \cdots)$$

If β_3<0, then the marginal benefit effect decreases as risk increases. This would indicate non-compensatory decision making. Since in nonlinear models the coefficient of an interaction term does not equal the interaction effect on the probability scale, the interaction should also be evaluated in terms of marginal effects (Ai and Norton, 2003).

To explicitly model threshold behavior, we estimate separate models:

$$P(Adopt_i = 1 \mid RISK_i < c) \text{ and } P(Adopt_i = 1 \mid RISK_i \geq c)$$

where c is the critical threshold (median or empirically estimated value).

A significant reduction in the BENEFIT_i effect in the high-risk regime indicates the presence of risk constraints.

In addition, perceived risk was decomposed into two components, below and above the threshold c, and both components were included in the regression model:

$$RISK_i^{low} = \min(RISK_i, c), RISK_i^{high} = \max(0, RISK_i - c)$$

$$P(Adopt_i = 1) = \Lambda(\beta_1 BENEFIT_i + \beta_2 RISK_i^{low} + \beta_3 RISK_i^{high} + \cdots)$$

This allows us to test for the presence of nonlinear threshold effects.

In general form, a conjunctive (threshold) decision rule can be represented as follows:

$$A(x) = \begin{cases} 1, & \text{if } x_j \geq \theta_j \ \forall j \in J \\ 0, & \text{otherwise} \end{cases}$$

where x_j are the criteria (benefits, risks, institutional trust), and θ_j are the threshold values (for the risk criterion the inequality is reversed, i.e. the risk level must not exceed its threshold). In this approach, RISK serves as a non-compensatory criterion, while BENEFIT acts as a necessary but insufficient condition. This structure demonstrates a fundamental difference from additive utility models.

In other words, adoption requires that the benefit and the risk conditions are satisfied simultaneously. To ensure the reliability of the modeling, standard errors robust to heteroscedasticity were applied, multicollinearity factor (VIF) diagnostics were performed, and an alternative index construction (PCA instead of additive) was employed. Given the small number of non-adopters, penalized-likelihood (Firth) logit estimates are reported as a robustness check, and the predictive ability of the model is assessed using in-sample and 10-fold cross-validated AUC. Heterogeneity in the effect of perceived benefits between students and academic staff is tested by adding a BENEFIT × Staff interaction (Model 3).

The analysis relies on cross-sectional variation in perceptions and AI use across respondents and is therefore correlational rather than causal. Although causal inference is limited, the proposed framework allows inference about behavioral decision-making rules, which is the study's central idea.

4. Results

This section presents the empirical data obtained from a survey of students, faculty members, and academic staff of universities in Azerbaijan. Table 2 presents the dependent, explanatory, institutional, and control variables.

Table 2. Operationalization of variables

Category	Variable	Description
Dependent variable	$Adopt_i$	Binary indicator of AI adoption (1 = uses AI regularly or sometimes; 0 = rarely or never)
Key explanatory variables	$BENEFIT_i$	Number of perceived benefits (items Q1–Q5)
	$RISK_i$	Number of perceived risks (items O1–O7)
	USE_i	Number of purposes of AI use (items J1–J9); robustness check only
Institutional variable	$COMP_i$	Perceived competence of teachers (1 = very low … 5 = very high)
Controls	—	Age group (ordinal: 1 = under 20 … 5 = over 50; robustness check only), Female (1 = female, 0 = male), Staff (1 = academic staff or teacher, 0 = student), Education level (ordinal: 1 = secondary … 4 = PhD)

Source: The authors presented their findings based on survey data

BENEFIT and RISK are count indices equal to the number of benefits (items Q1–Q5) and risks (items O1–O7) selected by the respondent from multiple-response lists. Their internal consistency is modest (Cronbach's alpha/KR-20 = 0.51 and 0.47, respectively), which is expected for formative count indices composed of heterogeneous items; the first principal component explains 34% and 27% of the variance. Therefore, PCA-based indices are used as a robustness check.

Table 3 presents descriptive statistics for the main variables used in the analysis. Overall, 92.5% of respondents (282 of 305) use AI regularly or sometimes and are classified as adopters, while 23 respondents (7.5%) use it rarely or never; the number of non-adopters is almost identical among students (11) and academic staff (12). On average, respondents select 2.91 of five possible benefits and 2.52 of seven possible risks; since the indices are measured on different scales, their means are not directly comparable. On average, respondents use AI for 3.85 of nine listed purposes.

Table 3. Descriptive statistics of key variables

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Adopt	305	0.92	0.26	0	1

BENEFIT	305	2.91	1.27	0	5
RISK	305	2.52	1.45	0	6
USE	303	3.85	2.03	1	9
ATTITUDE	304	18.43	3.37	5	23
COMPETENCE	304	2.69	0.94	1	5

Source: The authors' calculations are based on survey data (N = 305).

BENEFIT reflects the perceived benefits of AI, RISK reflects perceived risks, USE reflects the diversity of AI use, and ATTITUDE represents a composite of opinions on the integration of AI in education (items K, L, M, N and S, reverse-coded so that higher values indicate more favorable attitudes). COMPETENCE reflects perceived institutional readiness. The composite index of attitudes toward AI integration is high (mean = 18.43 on a 5–25 scale), indicating generally favorable perceptions. However, teachers' perceived competence in using AI remains moderate (mean = 2.69 on a 1–5 scale), suggesting potential institutional limitations. Age group, academic staff status and education level are strongly correlated (r = 0.85–0.88); therefore, age group is excluded from the baseline specification and used only in robustness checks.

Descriptive statistics indicate that, although AI is widely used and perceived positively, concerns about risks and institutional readiness remain relevant.

Table 4 presents the results of the logistic regression models explaining AI adoption. In Model 1, perceived benefits have a positive and statistically significant effect on the likelihood of AI adoption ($\beta = 0.552$, $p < 0.05$). This result is consistent with standard models of technology adoption, where expected utility drives individual decisions.

Table 4. Logistic Regression Results for AI Adoption

Variables	**Model 1**	**Model 2**	**Model 3**
BENEFIT	0.552** (0.252)	0.589** (0.241)	0.188 (0.254)
RISK	0.041 (0.193)	0.068 (0.185)	0.015 (0.179)
COMPETENCE	0.276 (0.191)	0.286 (0.195)	0.240 (0.188)
Female	1.205** (0.488)	1.246** (0.495)	1.269*** (0.485)
Staff	-1.313** (0.660)	-1.349** (0.659)	-3.483*** (1.248)
Education level	0.631* (0.339)	0.654* (0.352)	0.598* (0.354)
BENEFIT × RISK	—	0.074 (0.138)	—
BENEFIT × Staff	—	—	1.065** (0.528)
Constant	-1.506 (1.029)	0.078 (1.149)	-0.399 (1.121)
Observations	300	300	300
AIC	153.9	155.6	149.6
McFadden R^2	0.138	0.140	0.177

Note: Heteroskedasticity-robust (HC1) standard errors are given in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is a binary indicator of AI adoption. Model 1 contains the baseline logistic regression results; Model 2 includes an interaction term between mean-centred perceived benefits and risks to test for non-compensatory decision making; Model 3 includes an interaction between perceived benefits and academic staff status. The authors' calculations are based on survey data (N = 300).

Perceived risks, in contrast, do not have a statistically significant effect, suggesting that, in this sample, variation in perceived risks is not systematically associated with adoption decisions. Among the control variables, female respondents are significantly more likely to adopt AI ($p < 0.05$). Academic staff are less likely to adopt AI than students with the same education level ($p < 0.05$), while education level shows a weakly significant positive effect ($p < 0.1$); since staff status and education level are strongly correlated, these two effects should be interpreted jointly. Model 2 extends the baseline specification by adding an interaction term between perceived benefits and risks to test the non-compensatory hypothesis. The interaction term is positive (0.074) but not statistically significant, contrary to the expected negative sign;

the likelihood-ratio test does not support the inclusion of the interaction ($\chi^2 = 0.27$, $p = 0.60$), while the effect of perceived benefits remains positive and significant ($\beta = 0.589$, $p < 0.05$).

Importantly, the lack of a significant interaction effect, coupled with the insignificance of perceived risks, provides no evidence of a compensatory benefit–risk trade-off. Statistically insignificant coefficients do not by themselves prove a non-compensatory rule; however, they are consistent with a decision structure in which perceived benefits dominate and risks do not play a binding role.

For a clearer interpretation of the results, Table 5 presents the average marginal effects. The findings confirm that perceived benefits significantly increase the likelihood of AI adoption. Specifically, a one-unit increase in the benefits index increases the likelihood of adoption by approximately 3.5 percentage points ($p < 0.05$).

Table 5. Average marginal effects from the logistic model

Variables	**AME**	**Std. Error**	**p-value**
BENEFIT	0.0354**	0.0165	0.0324
RISK	0.0027	0.0124	0.8306
COMPETENCE	0.0177	0.0129	0.1697
Female	0.0844**	0.0380	0.0264
Staff	-0.0914*	0.0498	0.0664
Education level	0.0404*	0.0217	0.0629
BENEFIT | students (Model 3)	0.0117	0.0160	0.4661
BENEFIT | academic staff (Model 3)	0.0771***	0.0274	0.0048

Note: Average marginal effects (AMEs) are presented. Robust standard errors are reported in a separate column. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is a binary indicator of AI adoption. Marginal effects are averaged over all observations in the sample. The first six rows are based on Model 1; the last two rows report the average marginal effect of perceived benefits for students and academic staff, estimated from Model 3. The authors' calculations are based on survey data (N = 300).

Marginal effects analysis confirms that perceived benefits significantly increase the likelihood of AI adoption. Specifically, a one-unit increase in the perceived benefits index increases the likelihood of adoption by approximately 3.5 percentage points. In contrast, perceived risks have no statistically significant effect on adoption decisions. This finding suggests that respondents do not appear to trade off risks against benefits when deciding whether to use AI. Instead, decision making appears to be primarily driven by perceived benefits, consistent with a non-compensatory or heuristic model. Gender differences remain statistically significant: female respondents are approximately 8.4 percentage points more likely to adopt AI than male respondents. Education level shows a marginally significant positive effect (4.0 percentage points per level, $p < 0.1$), whereas academic staff are approximately 9.1 percentage points less likely to adopt AI than students with the same education level ($p < 0.1$).

According to the regression analysis results, perceived risks do not have a statistically significant marginal effect on adoption decisions, and neither does the perceived competence of teachers. These results support the conclusion that adoption behavior is primarily determined by perceived benefits, while risks do not play a decisive role.

Additional specifications were estimated to test for threshold (non-compensatory) effects of risk directly. In a piecewise specification with the threshold at the median of the risk index, neither the risk component below the threshold ($\beta = 0.058$, $p = 0.90$) nor the component above it ($\beta = 0.035$, $p = 0.88$) is significant. In separate penalized-likelihood (Firth) models for respondents with low and high perceived risk, the effect of perceived benefits is almost identical ($\beta = 0.55$ and $\beta = 0.50$, respectively), and the marginal effect of benefits does not decline at higher risk levels. Finally, a comparison of decision rules shows that the compensatory model (AIC = 153.9), the best-fitting conjunctive rule (BENEFIT ≥ 3 and RISK ≤ 6; AIC = 154.6) and a benefit-only threshold rule (BENEFIT ≥ 3; AIC = 154.6) fit the data almost

equally well. Since the best risk threshold coincides with the maximum observed value of the risk index, the conjunctive rule effectively reduces to the benefit-only rule. Thus, risk does not act as a binding constraint, and adoption decisions are dominated by perceived benefits.

Model 3 tests whether the effect of perceived benefits differs between students and academic staff. The interaction between perceived benefits and staff status is positive and significant ($\beta = 1.065$, $p < 0.05$), and Model 3 has the lowest AIC (149.6). The average marginal effect of an additional perceived benefit is 7.7 percentage points for academic staff ($p < 0.01$) but only 1.2 percentage points and statistically insignificant for students ($p = 0.47$) (Table 5). Separate Firth models confirm this result: perceived benefits strongly increase AI adoption among academic staff ($\beta = 1.11$, $p < 0.01$) but not among students ($\beta = 0.19$, $p = 0.48$), whereas perceived risks are insignificant in both groups ($p > 0.9$).

The results are robust to alternative specifications. Penalized-likelihood (Firth) estimation, which reduces small-sample bias given the small number of non-adopters, yields virtually the same estimates (BENEFIT: $\beta = 0.522$, $p < 0.05$; RISK: $p = 0.87$). Replacing the additive indices with PCA-based indices (BENEFIT: $\beta = 0.691$, $p < 0.05$; RISK: $p = 0.99$) or adding age group ($\beta = -0.052$, $p = 0.87$) does not change the conclusions. When the diversity of AI use (USE) is added, it is strongly significant ($\beta = 0.683$, $p < 0.01$) and the effect of perceived benefits becomes insignificant; however, the number of purposes for which AI is used is largely a consequence of adoption itself, so USE is treated as endogenous and excluded from the baseline specification.

To ensure the robustness of the estimated models, several diagnostic tests were conducted. First, multicollinearity was assessed using variance inflation factors (VIFs). All VIF values are below 3 (the maximum, 2.75, is observed for education level), indicating no serious multicollinearity. Secondly, the model fit was assessed using the Hosmer–Lemeshow goodness-of-fit test ($\chi^2 = 9.58$, $df = 8$, $p = 0.296$), which shows that the null hypothesis of good fit cannot be rejected, although the power of this test is limited in samples of this size.

Third, the predictive performance of the model was assessed using the receiver operating characteristic (ROC) curve. The area under the curve equals 0.79 (95% CI: 0.71–0.87), and the 10-fold cross-validated AUC equals 0.70, indicating moderate out-of-sample predictive ability.

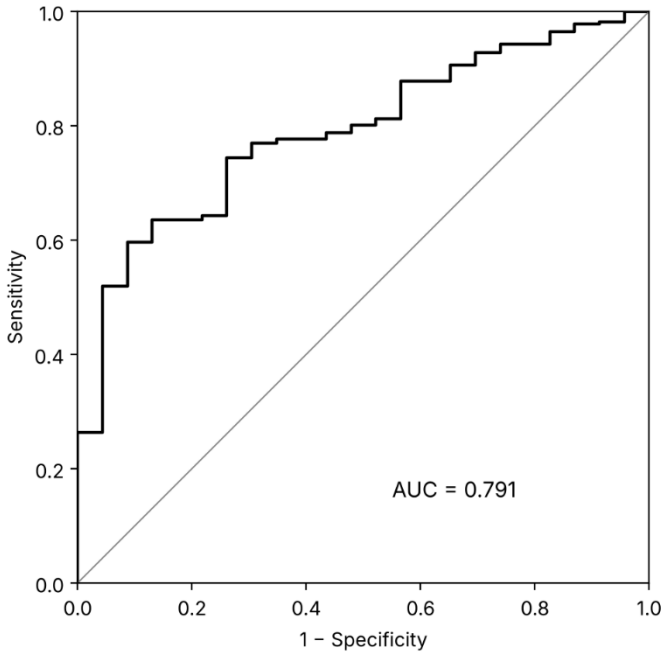


Figure 1. Receiver Operating Characteristic (ROC) Curve for the AI Implementation Model

Note: The ROC curve evaluates the predictive performance of the logistic regression model. The model demonstrates satisfactory classification ability, as the curve lies above the 45-degree reference line, indicating superior performance compared to random classification. The area under the curve (AUC = 0.79)

serves as a summary measure of the model's accuracy. The authors' calculations are based on survey data (N = 300).

Figure 1 illustrates the ROC curve for the estimated logistic model. The curve lies clearly above the 45-degree reference line, indicating that the model performs better than random classification and demonstrates satisfactory predictive accuracy.

Taken together, these diagnostics indicate that the estimated model provides an acceptable fit to the data.

Table 6 summarizes the results of hypothesis testing.

Table 6. Summary of hypothesis testing

Hypothesis	Expected effect	Result
H1: Non-compensatory decision rule	No benefit–risk trade-off	Partially supported: no compensatory benefit–risk trade-off (interaction and LR test insignificant); risk does not act as a threshold constraint; adoption follows a benefit-dominated rule
H2: Perceived risks limit adoption	−	Not supported (RISK insignificant in all specifications and in both subgroups)
H3: Perceived benefits increase adoption	+	Supported ($\beta = 0.552$, $p < 0.05$; AME = 3.5 p.p.); the effect is concentrated among academic staff (AME = 7.7 p.p.)
H4: Intensity of use increases adoption	+	Not tested in the baseline model: USE is endogenous to adoption; positive and significant in the robustness check
H5: Perceived competence increases adoption	+	Not supported (COMPETENCE insignificant)

Source: Compiled by the authors based on Tables 4–5 and robustness checks.

5. Discussion

The obtained empirical results provide important insights into the nature of decision making in AI implementation. Perceived benefits increase the likelihood of adoption in the baseline specification, whereas perceived risks remain statistically insignificant in all specifications and in both subgroups. Furthermore, the inclusion of interaction terms reveals no compensatory tradeoff mechanism. This pattern suggests that individuals do not balance risks and benefits within a continuous utility-maximization model. Instead, decision making appears to rely on simplified heuristics in which perceived benefits predominate and risks do not act as a binding constraint. This behavior is consistent with a non-compensatory model of decision making, where certain criteria (e.g., perceived risks) are not included in the decision-making function in a compensatory manner. Rather than balancing risks and benefits, individuals appear to base their decisions primarily on the presence of perceived benefits. It should be noted that this pattern does not confirm the conjunctive form of the rule specified in Section 3, in which risk acts as a non-compensatory constraint; rather, it is consistent with a benefit-dominated (lexicographic) screening rule.

The results also reveal substantial heterogeneity between groups. Among academic staff, AI adoption is strongly associated with perceived benefits, which suggests a more deliberate, benefit-driven evaluation of AI tools in professional activities. Among students, by contrast, AI use is widespread regardless of perceived benefits and risks, which may reflect habitual use, the ubiquity and accessibility of generative AI tools, and peer norms. This interpretation should be treated with caution given the small number of non-adopters in each group, but it implies that the benefit-dominated decision rule applies primarily to academic staff.

This study expands our understanding of how decisions are made about using artificial intelligence in education. The results show that classical technology acceptance models do not fully explain actual user behavior. Such models assume that people weigh benefits and risks and make decisions based on this

tradeoff. However, in our study, risks do not significantly influence AI adoption, which is not consistent with the assumption of compensatory (balanced) choice (Davis, 1989; Venkatesh et al., 2012).

The results also confirm the importance of a behavioral approach. Users do not always make decisions rationally, but rather rely on simplified assessments. In particular, they focus on the most salient benefits of AI and may ignore potential risks. This behavior is consistent with the concept of bounded rationality (Kahneman and Tversky, 1979; Simon, 1955).

The key contribution of the study lies in the application of a non-compensatory approach. Within this approach, decisions are made not through a balance of factors, but rather through the dominance of individual characteristics. This means that some factors (e.g., benefits) may play a decisive role, while others (e.g., risks) are barely considered (Aleskerov et al., 2007; Aleskerov et al., 2010).

The results are consistent with this view: benefits significantly influence decisions, while risks play no significant role. This points to an asymmetrical decision-making structure. Furthermore, the study shows that institutional factors, such as perceived teacher competence, do not have a strong influence on AI adoption. This suggests that decisions are largely determined by individual behavior, not just the external environment.

Thus, the study complements existing theories of technology acceptance by demonstrating that user behavior in the face of complex digital technologies may be non-compensatory and based on simplified choice rules. This opens up avenues for further research, particularly in the fields of behavioral economics and digital education.

The findings contribute to the literature on technology adoption by challenging the dominance of trade-off models such as the Technology Acceptance Model (TAM) and related frameworks. While such models assume that users evaluate technologies based on a trade-off between perceived utility and perceived risks or costs, this study shows that this assumption may not hold in practice.

Instead, AI adoption behavior appears to be nonlinear, asymmetric, and rule-based rather than trade-off-based. This suggests that traditional models may overestimate the role of risk perception and underestimate the importance of heuristic behavior.

The authors' findings in this article have important implications for policymakers and educational institutions seeking to promote AI adoption. First, since perceived benefits are the most influential, measures to expand AI adoption should focus on clearly and understandably demonstrating its practical value; this is particularly relevant for academic staff, whose adoption decisions are most sensitive to perceived benefits. Focusing on real-world use cases, increased productivity, and usability may be an effective lever for adoption. Second, the weak sensitivity of adoption to perceived risks does not mean that risks are unimportant; rather, it indicates that users may underweight them. Therefore, the promotion of AI should be accompanied by training in AI literacy, academic integrity and data protection, so that adoption is both widespread and responsible. Third, the weak impact of faculty competency assessments suggests that institutional readiness may play a secondary role in decision-making. This suggests that AI adoption is driven largely by user initiatives rather than solely by formal organizational decisions and strategies.

Despite its contributions, this study has several limitations. First, the cross-sectional nature of the data limits causal interpretation. Second, the use of self-reported measures may introduce response bias. Third, operationalizing risks and benefits as additive indices may not fully capture their multidimensional nature. Fourth, the convenience sample drawn from a single country limits the generalizability of the findings. Fifth, the binary adoption variable is unevenly distributed, which reduces the precision of the logit estimates, although penalized-likelihood (Firth) estimates confirm the main results. Sixth, perceived benefits may partly result from prior experience with AI, so reverse causality cannot be ruled out; in addition, the internal consistency of the count indices is modest.

Further research directions in the future to better understand the application and impact of AI in education could include:

1. Using experimental or longitudinal methods to identify causal mechanisms;
2. Examining threshold effects using nonlinear or regime-switching models;
3. Using additional behavioral variables, such as trust, cognitive load, or digital literacy;
4. Comparing results across countries or institutional contexts.

6. Conclusion

The empirical analysis based on a survey of 305 students and academic staff in Azerbaijan shows that perceived benefits are the main driver of AI adoption, whereas perceived risks and perceived teacher competence do not have a statistically significant effect. The effect of perceived benefits is concentrated among academic staff, while students use AI regardless of perceived benefits and risks. These results provide no evidence of a compensatory benefit–risk trade-off and are consistent with a benefit-dominated, non-compensatory decision rule. At the same time, the low sensitivity of users to risks underlines the need for institutional measures that promote the responsible use of AI.

The analysis of the implementation of artificial intelligence in education indicates that the integration of AI technologies produces a structural transformation of educational systems rather than a purely technological enhancement. On the one hand, AI significantly strengthens the managerial and instructional dimensions of education by enabling data-driven decision-making, personalized learning trajectories, and objective assessment mechanisms. These capabilities contribute to increased efficiency, scalability, and adaptability of educational processes, which is particularly relevant in the context of mass and distance education. Artificial intelligence has significant potential to transform education, improve learning outcomes, increase student engagement and motivation, and enhance teacher skills (Saraswat, 2024).

Based on the literature reviewed and the findings of this study, it can be argued that the digital transformation of education significantly reshapes the role of universities. It demands that academic staff acquire new skill sets, including the ability to design digital learning materials, implement blended learning formats, apply digital pedagogy, and develop entrepreneurial thinking. In addition, universities are witnessing the emergence of new professional roles, such as instructional designers, developers of digital learning resources, online course creators and methodologists, MOOC coordinators, tutors, and digital curators. These changes contribute to the evolution of a new type of institution — the digital university. This model is characterized by the active development of comprehensive electronic learning environments and the widespread integration of e-learning and distance learning technologies.

A digital university should not be understood merely as a traditional institution enhanced with technological tools. Its effective implementation requires a fundamental transformation of both curricula and educational strategies. The focus shifts from standardized program requirements to a more student-centered approach that considers individual needs, preferences, and learning capabilities. By leveraging advanced technologies, particularly those based on big data analytics, universities can create personalized learning experiences that address the interests of both students and faculty members.

On the other hand, the identified limitations reveal a set of systemic challenges that constrain the uncritical adoption of AI in educational practice. The absence of emotional and value-based interaction highlights the inherent limitations of AI in addressing the formative and socio-cultural dimensions of education. Furthermore, high implementation costs, cybersecurity risks, and the growing demand for advanced digital competencies among educators underscore the organizational and infrastructural complexity associated with AI-driven educational systems.

Of particular concern is the potential overreliance on generative AI tools, which may lead to a gradual decline in students' analytical and critical thinking skills if such technologies are used as substitutes rather than supplements to cognitive effort. This challenge emphasizes the necessity of maintaining a balance between automation and human intellectual engagement. Consequently, the effective integration of AI in education requires not only technological readiness but also the revision of regulatory frameworks, pedagogical models, and teacher training systems to ensure responsible, ethical, and pedagogically sound use of AI technologies.

Overall, the analysis demonstrates that artificial intelligence should be conceptualized as an enabling and augmentative tool within education rather than an autonomous replacement for human agency. Its successful implementation depends on the alignment of technological innovation with human-centered educational values, institutional capacities, and long-term developmental goals of educational systems.

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