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STRATEGIC MANAGEMENT OF THE EDUCATIONAL PROCESS UNDER ARTIFICIAL INTELLIGENCE IMPLEMENTATION: QUALITY EDUCATION, DECENT WORK, AND HUMAN CAPITAL FOR THE TRANSFORMING LABOR MARKET OF KAZAKHSTAN

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ABSTRACT

The accelerated diffusion of generative artificial intelligence in higher education has outpaced the institutional rules that define where machine assistance should end and academic judgement should begin, leaving universities without clear boundaries for substituting for teaching labour and placing the quality education and decent work agendas at risk. This study examines how Kazakhstan's educational potential relates to labour productivity and develops a strategic model that allocates functions between the instructor and artificial intelligence. The study employs annual time-series data from the Bureau of National Statistics of the Republic of Kazakhstan for 2018-2025, covering eleven labour market and human capital indicators. It applies Pearson correlation analysis to indicator levels, first differences, and growth rates, and is complemented by functional-systemic classification and expert-analytical generalisation. The results reveal that gross value added per employee correlates strongly with wage employees ($r = 0.995$, $p < 0.001$), with employees holding higher and postgraduate qualifications ($r = 0.913$, $p = 0.002$), and with technical and vocational graduates ($r = 0.931$, $p = 0.001$), and inversely with total ($r = -0.857$, $p = 0.007$) and youth unemployment ($r = -0.886$, $p = 0.003$). In first differences, the education-productivity association falls to $r = 0.297$ ($p = 0.518$) and to $r = 0.074$ ($p = 0.876$) in growth rates, while wage employment retains $r = 0.797$ ($p = 0.032$). The findings suggest that level associations reflect a shared trend rather than an annual return in graduate numbers, and that productivity responds to the composition of competencies rather than to the volume of educational output.

INTRODUCTION

Generative artificial intelligence has entered university teaching faster than any educational technology that preceded it, and the speed of that entry is itself the source of the managerial difficulty. A systematic review of applications in education identifies generative tools as the dominant technology in current practice, with ChatGPT alone accounting for roughly 30 per cent of the reviewed applications, followed by GPT-4, machine learning systems, and augmented and virtual reality, and with the highest research intensity recorded in Canada, the United States, and China (Matos et al., 2025). Curriculum design in higher education institutions worldwide is being reworked around these tools rather than merely supplemented by them (Abbasi et al., 2025), and the arrival of general-purpose modelling technology has unsettled established assumptions about how knowledge is created, transmitted, and assessed (Dong, 2024). Integration with the Internet of Things and immersive environments is producing intelligent educational ecosystems that combine digital platforms, analytical instruments, and

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adaptive resources within a single architecture (Papadakis, 2024), while empirical evidence from student populations shows uneven awareness of these tools and heavy reliance on informal online sources for learning about them (Pande et al., 2024).

The same technology is simultaneously reshaping the labour market for which universities train specialists. Employers and employees confront a redefinition of professional roles, a redistribution of responsibilities, and new foundations for the sustainability of business systems (Nyberg et al., 2025; Huang & Rust, 2024). Machine learning analysis of occupational structures shows measurable differences across sectors in exposure to automation and in the resulting skill requirements, with direct consequences for how education systems and workforce development should be planned (Shannaq et al., 2025). Indices of job substitution possibility have been constructed to quantify these shifts (Koo et al., 2024), and socioeconomic assessments of the intelligent information society point in the same direction. Generative systems are altering the operating models of entire service industries (Dubey et al., 2025; Grewal et al., 2025), and their broader social consequences extend well beyond productivity accounting (Xie & Avila, 2025). Where digitalization was once a supporting process, it now determines competitiveness.

For Kazakhstan, these pressures coincide with an unfinished national programme of educational digitalization. Studies of the role of digital technologies in Kazakhstani universities record substantial investment accompanied by uneven institutional readiness (Nurtayeva et al., 2024; Gulmira et al., 2024), persistent implementation obstacles (Dzhanegizova, 2024), and a marketing-driven rather than pedagogy-driven approach to digital service promotion (Zarubina et al., 2024). Strategic assessments of digital transformation and labour market development across the Eurasian Economic Union place Kazakhstan in an intermediate position, with scientific literacy and workforce adaptation lagging behind infrastructure deployment (Ospanova et al., 2025). At the same time, cross-country evidence confirms that educational development remains a principal determinant of competitiveness in the knowledge economy (Mazur et al., 2025). The country therefore faces a specific version of a general problem: how to convert a growing stock of formally qualified graduates into measurable productivity gains under conditions of rapid technological substitution.

The scientific problem addressed here is not whether the teaching profession will disappear. It is the absence of a strategically justified boundary between the operations that artificial intelligence may legitimately perform, those it may support, and those that must remain under human authority. Without such a boundary, institutions oscillate between defensive prohibition and uncontrolled adoption. Both extremes carry costs: the first forfeits the efficiency gains that automation of routine work makes available, while the second transfers pedagogical and ethical accountability to systems that cannot bear it. Audits of generative tools reveal a hidden curriculum embedded in their default behaviour that reproduces particular epistemic assumptions (Warr & Heath, 2025); academic integrity is simultaneously threatened and potentially strengthened depending on how implementation is governed (Artyukhov et al., 2024); and language-teaching scholarship has documented the coexistence of genuine gains and serious hazards within the same toolset (Hockly, 2023).

This study aims to substantiate a differentiated allocation of teaching functions between the instructor and artificial intelligence that preserves pedagogical oversight, academic accountability, and educational quality, and to ground this allocation empirically in the observed relationship between Kazakhstan's educational potential and labour productivity. Achieving this aim requires solving three intermediate tasks: establishing the statistical association between the educational structure of the employed population and gross value added per employee at the level of indicators; testing whether that association survives when the common time trend is removed through first differences and growth rates; and translating the resulting evidence into a functional classification of teaching operations with an accompanying monitoring framework. Methodologically, the study combines Pearson correlation analysis of official national statistics for 2018-2025 with functional-systemic classification and expert-analytical generalization.

The article proceeds as follows. The literature review examines governance and quality policy in higher education; absorptive capacity and skills; knowledge management in universities; evidence on artificial intelligence in teaching; the transformation of the academic role; and Kazakhstani digital competence research, and concludes with unresolved issues, the purpose of the study, and the research hypotheses. The materials and methods section specifies the data, variables, and analytical procedures. The results section reports the descriptive statistics, the correlation matrix, the dynamic analysis, the outcome of hypothesis testing, the proposed allocation model, and the monitoring indicators to 2030. The discussion interprets these findings in light of prior research, and the conclusions summarise the contribution, implications, limitations, and directions for further work.

LITERATURE REVIEW

Research on the strategic management of educational institutions under technological change draws on three partly independent literatures: the governance and quality assessment of higher education, the formation of absorptive capacity through skills, and the pedagogical evidence on artificial intelligence itself. Their convergence defines the theoretical basis for the present study.

European scholarship on higher education policy has focused on instruments to improve academic performance and institutional effectiveness. Work on the transition from scientific to research excellence traces how evaluation criteria migrated from disciplinary peer judgement toward measurable output (Sorensen et al., 2016), while case analysis of the German Excellence Initiative demonstrates that concentration of resources produces stratification as well as quality gains (Menter et al., 2018). Proposals for reforming university evaluation in the era of large-scale data emphasize that ranking systems capture only a narrow slice of institutional contribution (Daraio et al., 2019), and evidence on performance-based funding of university spinoffs in Italy shows that policy incentives shape entrepreneurial output but do so unevenly across regions (Meoli et al., 2018). The provision of finance to science-based entrepreneurship follows a comparable logic, in which universities occupy a central position in the creation, transfer, and practical use of knowledge (Civera et al., 2017). The common implication is that institutional effectiveness cannot be inferred from resource inputs alone.

The literature on absorptive capacity establishes why the qualification structure of the workforce matters economically. The ability of an organisation to recognise the value of new knowledge, assimilate it, and apply it in practice depends on the composition of its existing skills. Analysis of vocational training centres shows that these institutions contribute to innovation in ways that conventional research and development metrics fail to capture (Porto Gomez et al., 2018). Comparative evidence from the United States and Western Europe identifies which specific skills contribute most to absorptive capacity, innovation, and productivity, and finds that intermediate technical competencies are disproportionately important (Mason et al., 2020). Firm participation in apprenticeship training has been shown to foster knowledge diffusion and subsequent innovation (Rupietta & Backes-Gellner, 2019). Taken together, these findings indicate that the economic return to education depends on the alignment between the competencies produced and the tasks actually performed, rather than on the volume of credentials issued.

Within universities, the mechanism through which this alignment is achieved is knowledge management. A reactive perspective alone is insufficient; institutions must incorporate the creation, dissemination, and application of knowledge into strategy (Nawaz, 2015). Knowledge management is best understood as an organised process through which individuals, professional groups, and organisations jointly create, preserve, and apply information to achieve educational and strategic goals (Sarjono & Firdaus, 2020). Readiness for such systems varies substantially across institutional contexts (Prahiawan et al., 2021). Evidence from a South African university documents internal barriers that obstruct implementation even where formal commitment exists (Masete & Mafini, 2018). Knowledge in educational organizations accumulates from prior information, professional experience, and research results, which together create the preconditions for new concepts (Ahmad et al., 2020), and improvements in workforce skills and knowledge feed directly into sectoral competitiveness (Kimeto, 2021). Self-assessment of competences by graduates further shapes their perceived and actual transition into employment (Pirog et al., 2021).

The pedagogical evidence on artificial intelligence has expanded rapidly and is now sufficiently large to support systematic synthesis. Reviews of applications in Latin American higher education identify administrative automation, predictive analytics, and adaptive tutoring as the dominant categories of use (Salas-Pilco & Yang, 2022). Early conceptual treatments questioned whether the technology represented genuine innovation or the repackaging of established practice (Pence, 2019), and applications in professional domains such as surgical and healthcare education have required deliberate interdisciplinary design (Bilgic et al., 2021; Randhawa & Jackson, 2020). Systems capable of generating varied and internally consistent training material were demonstrated well before the generative turn (Henriet, 2017). More recent work emphasizes the conditions under which willingness to communicate is preserved in online and hybrid environments, an issue that becomes acute when algorithmic mediation displaces direct interaction (Hoang, 2024). Studies of critical thinking in school populations show that its development depends on instructional design rather than on technological availability (Babu et al., 2025), and evidence on private tutoring indicates that supplementary provision can compensate for, but also entrench, differences in institutional quality (Al Hunaini et al., 2025).

A distinct strand addresses the transformation of the academic role. Teachers are simultaneously bearers of professional knowledge, organizers of the educational process, and participants in the creation of new knowledge. Contemporary algorithms generate texts and teaching materials, develop individual course elements, check assignments, and deliver personalized feedback, prompting debate about the displacement of specific teaching functions. Technological automation does not entail replacement, however, because critical interpretation, ethical responsibility, pedagogical interaction, and the formation of student character retain a predominantly human character. Systematic reviews of teacher digital competence confirm that professional development is the binding constraint on effective integration (Joya et al., 2025; Lopez-Nunez et al., 2024), and micro-course formats have been proposed as a scalable response (Trujillo-Juarez et al., 2025). Modelling work on the development of pedagogical competence under digitization identifies faculty capability as the principal mediating variable between technological investment and learning outcomes (Kapasheva et al., 2024). Occupational research warns that misalignment between institutional demands and individual capacity produces burnout and disengagement in vocational education settings (Zhou et al., 2025).

Kazakhstani scholarship provides the immediate empirical context. Experimental evidence shows that targeted digital interventions produce significant gains in the digital competence of future teachers across all measured domains, with the largest effects among students starting from lower baselines (Kazbekovna et al., 2025). Digital educational interventions have likewise been shown to enhance the professional abilities of university students (Kurakbayeva & Xembayeva, 2025), and pedagogical approaches to competence formation differ measurably in effectiveness (Medeshova et al., 2025). Studies of digital literacy among teachers document the practical difficulty of integrating computer science and design education without sustained institutional support (Temirkhanova et al., 2024), while dual education models offer one route to embedding digital technologies in teacher preparation (Seitaliyeva et al., 2025). International cooperation in professional training has been advanced as a mechanism to accelerate institutional learning (Jakubakynov et al., 2026), and disciplinary applications, such as integrating digital competencies into legal education, illustrate the breadth of the curricular revisions required (Ergasheva et al., 2025).

Three unresolved issues emerge from this body of work. First, the literature documents the effects of artificial intelligence on individual teaching tasks in considerable detail but rarely specifies, at the level of institutional strategy, which functions should be transferred, which shared, and which retained; the boundary is asserted rather than derived. Second, the empirical link between educational expansion and economic return is generally examined at the level, where a shared upward trend inflates the apparent association, and studies that remove the trend are scarce. Hence, it remains unclear whether the relationship reflects a genuine annual return or a statistical artefact. Third, monitoring frameworks for artificial intelligence in higher education continue to privilege resource indicators such as equipment counts and platform licences over pedagogical, ethical, and labour market outcomes, leaving institutions without instruments to detect whether implementation is improving quality or merely increasing throughput. These gaps justify continued research and define the direction adopted here.

The purpose of this study is to determine the statistical relationship between the educational potential of the employed population of Kazakhstan and labour productivity over 2018-2025, and to derive from it a strategic model for the differentiated allocation of teaching functions between the instructor and artificial intelligence, together with a system of indicators for monitoring its implementation through 2030. Accordingly, the following hypotheses are advanced:

H_1: The number of employed persons holding higher and postgraduate qualifications is positively and significantly associated with labour productivity, measured as gross value added per employee, at the level of indicators.

H_2: The association between educational potential and labour productivity weakens substantially and loses statistical significance when the common time trend is removed through first differences and growth rates.

H_3: Labour productivity is inversely and significantly associated with total and youth unemployment at the level of indicators.

H_4: The expansion of wage employment is more strongly associated with the dynamics of labour productivity than the expansion of self-employment.

H_5: The effectiveness of artificial intelligence implementation in the educational process is higher under a differentiated allocation of functions, in which artificial intelligence substitutes standardized operations and complements analytical and project-based functions, while the instructor retains pedagogical, evaluative, and ethical responsibility.

MATERIALS AND METHODS

Research Design: The study follows a non-experimental, quantitative-descriptive design combined with a functional-systemic classification procedure. No participants were assigned to conditions, and no experimental manipulation or intervention was administered; the labour market and educational indicators were observed naturalistically as published national aggregates. The design is therefore observational at the country level, with the year as the unit of analysis. Selection of the scientific publications underpinning the theoretical basis followed PRISMA guidelines to ensure transparency and reproducibility of the search, inclusion, and exclusion procedures.

Data Sources and Study Period: The empirical basis is official statistics of the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2025) for the period 2018-2025, giving eight annual observations for level analysis and seven for dynamic analysis. The period was selected because it is the longest interval over which all eleven indicators are published on a consistent methodological basis following the revision of national labour force accounting. No sampling of units was performed, since the data are population-level administrative aggregates rather than survey responses; consequently, there is no response rate, no attrition, and no self-selection into the sample. Because the data are aggregated, anonymous, and publicly available, the study involves no human participants and required no institutional review board approval or informed consent procedures.

Variables and Operational Definitions: Eleven indicators were used. The labour force is the sum of the employed and unemployed population aged 15 years and older, in thousands. The employed population is the total number of persons in employment, in thousands. Wage employees are persons working under an employment contract, in thousands, and their share is expressed as a percentage of the employed population. Self-employed persons are those generating income through independent activity, in thousands, with the corresponding share in per cent. Educational potential is captured by two variables: the number of employed persons with higher and postgraduate education, and the number with technical and vocational education, both in thousands. The unemployment rate is the share of unemployed persons in the labour force, and youth unemployment is the corresponding rate for the population aged 15-28 years. Labour productivity is operationalized as gross value added per employee, in thousands of tenge at current prices. Gross value added per employee serves as the dependent construct throughout, as it is the only published indicator that measures economic return per unit of labour input and is therefore the appropriate outcome against which educational potential is assessed.

Analytical Procedures: Three transformations of each series were analyzed. Levels were used directly. Absolute annual increments were computed as

$$\Delta X_t = X_t - X_{t-1} \tag{1}$$

and growth rates as

$$g_t = X_t / X_{t-1} \tag{2}$$

Where X_t is the value of the indicator in year t. The Pearson product-moment correlation coefficient measures pairwise linear association,

$$r = \Sigma(x_i - \bar{x})(y_i - \bar{y}) / \sqrt{[\Sigma(x_i - \bar{x})^2 \cdot \Sigma(y_i - \bar{y})^2]} \tag{3}$$

Where x_i and y_i denote the paired observations of two indicators and $\bar{x}$ and $\bar{y}$ their arithmetic means. The statistical significance of each coefficient was assessed using the t-statistic

$$t = r\sqrt{(n - 2)} / \sqrt{(1 - r^2)} \tag{4}$$

Evaluated against the t-distribution with n - 2 degrees of freedom. For the level analysis, n = 8, giving six degrees of freedom and critical values of r = 0.707 at the five per cent level and r = 0.834 at the one per cent level. For the dynamic analysis, n

= 7, giving five degrees of freedom and critical values of r = 0.754 and r = 0.875 respectively. Reporting the association in all three forms is deliberate: level correlations between two series can be inflated by a shared trend, whereas first differences and growth rates remove it, thereby providing a more conservative test of whether year-to-year movements are genuinely related. All computations were performed in Python using the NumPy and SciPy libraries.

Model Development Procedure: Functional and systemic approaches were applied to construct the allocation model. Teaching operations were first inventoried and then classified according to three criteria: the degree of standardization of the operation, its pedagogical complexity, and the necessity of human oversight of its outcome. Operations scoring high on standardisation and low on both pedagogical complexity and oversight requirement were assigned to substitution; operations of intermediate standardisation requiring analytical judgement were assigned to complementarity; and operations demanding evaluative discretion, ethical responsibility, or accountability for a student trajectory were assigned to retention. The expert-analytical generalization method was then used to derive monitoring indicators and indicative target values for 2030, drawing on the classification results and the empirical relationships identified in the correlation analysis.

Strengths and Limitations of the Method: The principal strength of the approach is the use of complete, officially validated population data rather than sample estimates, which eliminates sampling error and permits exact computation of the association structure. Reporting levels, increments, and growth rates in parallel is a further strength, since divergence between the three forms is itself informative and guards against the overstatement that single-form reporting invites. The principal weakness is the short series: eight annual observations provide low statistical power, so coefficients are interpreted as statistical associations rather than as evidence of causality, and moderate correlations may fail to reach conventional significance thresholds even where a relationship exists. A second weakness is that national aggregates conceal substantial regional and institutional heterogeneity in Kazakhstan. A third is the absence of a direct measure of the intensity of artificial intelligence use in universities, so the allocation model is grounded in macroeconomic conditions for implementation rather than in observed implementation itself. Conclusions are accordingly confined to what data of this structure can support.

RESULTS

At the macro level, the conditions for strategic management of the educational process in the context of the implementation of artificial intelligence are set by employment dynamics, the professional and qualification structure of the labour market, access to higher and vocational education, and the economic return per unit of labour. These parameters reflect the capacity of the national education system to adapt programmes to technological change and to supply the economy with qualified personnel. Table 1 presents the underlying series for 2018-2025.

Table 1. Labour market and educational potential indicators of the Republic of Kazakhstan, 2018-2025

Year	Labour force, thousand persons	Employed population, thousand persons	Wage employees, thousand persons	Self-employed, thousand persons	Share of wage employees, %	Employed with higher and postgraduate education, thousand persons
2018	9,138.6	8,695.0	6,612.5	2,082.5	76.0	3,360.2
2019	9,221.5	8,780.8	6,681.6	2,099.2	76.1	3,308.1
2020	9,180.8	8,732.0	6,686.6	2,045.4	76.6	3,709.2
2021	9,256.7	8,807.1	6,710.2	2,096.9	76.2	3,565.4
2022	9,429.8	8,971.5	6,847.3	2,124.2	76.3	4,017.4
2023	9,534.1	9,081.9	6,893.4	2,188.5	75.9	3,982.7
2024	9,664.0	9,214.2	7,015.1	2,199.1	76.1	3,927.3
2025	9,769.5	9,320.6	7,169.1	2,151.5	76.9	4,367.3
Year	**Share of self-employed, %**	**Unemployment rate, %**	**Youth unemployment rate, %**	**Gross value added per employee, thousand tenge**	**Employed with technical and vocational education, thousand persons**	
2018	24.0	4.9	3.8	6,173.2	3,466.4	
2019	23.9	4.8	3.7	6,869.8	3,701.9	
2020	23.4	4.9	3.8	7,111.9	3,431.0	
2021	23.8	4.9	3.8	8,423.4	3,786.9	
2022	23.7	4.9	3.8	10,083.2	3,999.4	
2023	24.1	4.7	3.5	11,354.2	4,157.8	
2024	23.9	4.7	3.1	12,886.0	4,561.3	
2025	23.1	4.6	3.1	15,905.0	4,440.0	

Note. Compiled from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (https://stat.gov.kz/). The share of wage employees and the share of self-employed are expressed as percentages of the employed population; the unemployment rate is expressed as a percentage of the labour force; youth unemployment refers to the population aged 15-28 years; gross value added per employee is measured at current prices.

Over the eight years, the labour force expanded by 6.9 per cent, from 9,138.6 to 9,769.5 thousand persons, and the employed population by 7.2 per cent, reaching 9,320.6 thousand in 2025. Wage employment grew faster, by 8.4 per cent to 7,169.1 thousand, lifting its share from 76.0 to 76.9 per cent, while self-employment rose more slowly and its share contracted from 24.0 to 23.1 per cent. Total unemployment declined from 4.9 to 4.6 per cent and youth unemployment from 3.8 to 3.1 per cent. Educational potential increased on both tracks: employed persons with higher and postgraduate education rose from 3,360.2 to 4,367.3 thousand, and those with technical and vocational education from 3,466.4 to 4,440.0 thousand. The share of the employed population holding higher or postgraduate qualifications consequently rose from 38.6 to 46.9 per cent.

Gross value added per employee grew from 6,173.2 to 15,905.0 thousand tenge, an increase of 157.6 per cent at current prices, equivalent to a compound annual rate of 14.5 per cent. The corresponding compound annual growth of higher-educated employment was 3.8 per cent. The divergence between these two rates is the first indication that productivity growth over the period was not driven primarily by the expansion of graduate numbers. Table 2 reports the full correlation matrix of the eleven indicators in level form.

Table 2. Pearson correlation matrix of labour market and educational potential indicators of the Republic of Kazakhstan in level form, 2018-2025 (n = 8)

Indicator	**1**	**2**	**3**	**4**	**5**	**6**
1. Labour force	1.000	1.000	0.989	0.850	0.321	0.884
2. Employed population	1.000	1.000	0.989	0.850	0.321	0.877
3. Wage employees	0.989	0.989	1.000	0.763	0.455	0.908
4. Self-employed	0.850	0.850	0.763	1.000	−0.225	0.601
5. Share of wage employees	0.321	0.321	0.455	−0.225	1.000	0.548
6. Employed with higher education	0.884	0.877	0.908	0.601	0.548	1.000
7. Share of self-employed	−0.321	−0.321	−0.455	0.225	−1.000	−0.548
8. Unemployment rate	−0.872	−0.881	−0.866	−0.768	−0.251	−0.659
9. Youth unemployment rate	−0.906	−0.913	−0.903	−0.776	−0.286	−0.673
10. GVA per employee	0.987	0.987	0.995	0.772	0.436	0.913
11. Employed with vocational education	0.968	0.968	0.932	0.916	0.144	0.770
Indicator	**7**	**8**	**9**	**10**	**11**	
1. Labour force	−0.321	−0.872	−0.906	0.987	0.968	
2. Employed population	−0.321	−0.881	−0.913	0.987	0.968	
3. Wage employees	−0.455	−0.866	−0.903	0.995	0.932	
4. Self-employed	0.225	−0.768	−0.776	0.772	0.916	
5. Share of wage employees	−1.000	−0.251	−0.286	0.436	0.144	
6. Employed with higher education	−0.548	−0.659	−0.673	0.913	0.770	
7. Share of self-employed	1.000	0.251	0.286	−0.436	−0.144	
8. Unemployment rate	0.251	1.000	0.924	−0.857	−0.824	
9. Youth unemployment rate	0.286	0.924	1.000	−0.886	−0.894	
10. GVA per employee	−0.436	−0.857	−0.886	1.000	0.931	
11. Employed with vocational education	−0.144	−0.824	−0.894	0.931	1.000	

Note. Column numbers correspond to the numbered indicators in the first column. Critical values of the coefficient for six degrees of freedom are 0.707 at the five per cent level and 0.834 at the one per cent level. GVA denotes gross value added. The coefficient of −1.000 between the share of wage employees and the share of self-employed is arithmetic, since the two shares sum to 100 per cent.

The strongest positive level associations with gross value added per employee are recorded for the number of wage employees ($r = 0.995$, $p < 0.001$), the labour force and the employed population ($r = 0.987$, $p < 0.001$ in both cases), employees with technical and vocational education ($r = 0.931$, $p = 0.001$), and employees with higher and postgraduate education ($r = 0.913$, $p = 0.002$). All four exceed the 1% critical value of 0.834 and are therefore significant at that level. Self-employment shows a weaker but still significant association ($r = 0.772$, $p = 0.025$), whereas the share of wage employees is not significantly related to productivity ($r = 0.436$, $p = 0.280$).

Negative associations with productivity are recorded for total unemployment ($r = -0.857$, $p = 0.007$) and youth unemployment ($r = -0.886$, $p = 0.003$), both significant at the one per cent level. Total and youth unemployment are themselves strongly co-moving ($r = 0.924$), and both decline as the educational stock rises. However, the associations with higher education ($r = -0.659$ and $r = -0.673$, respectively) are not significant. The perfect negative correlation between the share of wage employees and the share of self-employed ($r = -1.000$) is arithmetic rather than substantive, since the two shares sum to 100 per cent by construction.

Read in isolation, this matrix would support a straightforward interpretation: expanding graduate output raises productivity. That interpretation is unsafe, because ten of the eleven series trend monotonically over the observation window and a common trend inflates level correlations irrespective of any underlying relationship. Table 3 therefore reproduces the analysis after removing the trend through first differences and growth rates.

Table 3. Association between the dynamics of gross value added per employee and the dynamics of labour market and educational potential indicators of the Republic of Kazakhstan, 2018-2025 (n = 7)

Factor indicator	Increments, r	p	Growth rates, r	p	Nature of the association
Labor force	0.600	0.155	0.727	0.064	Moderate positive, not significant
Employed population	0.603	0.152	0.720	0.068	Moderate positive, not significant
Wage employees	0.797	0.032	0.699	0.081	Strong positive, significant at 5%
Self-employed	−0.127	0.786	0.192	0.680	Practically absent
Share of wage employees	0.346	0.447	0.041	0.930	Weak positive, not significant
Employed with higher and postgraduate education	0.297	0.518	0.074	0.876	Weak positive, not significant
Share of self-employed	−0.346	0.447	−0.040	0.933	Weak negative, not significant
Unemployment rate	−0.361	0.426	−0.338	0.459	Weak negative, not significant
Youth unemployment rate	−0.069	0.883	0.040	0.932	Practically absent
Employed with technical and vocational education	0.014	0.977	0.327	0.475	Practically absent

Note. Increments denote first differences and growth rates denote the ratio of consecutive annual values, as defined in Equations 1 and 2. Critical values of the coefficient for five degrees of freedom are 0.754 at the five per cent level and 0.875 at the one per cent level. The characterization in the final column refers to the association measured in increments.

The dynamic analysis substantially alters the picture. In absolute increments, only wage employment retains a significant association with the change in productivity ($r = 0.797$, $p = 0.032$), exceeding the five per cent critical value of 0.754. The labour force ($r = 0.600$, $p = 0.155$) and the employed population ($r = 0.603$, $p = 0.152$) show moderate positive but non-significant associations. Critically, the increment in employees with higher and postgraduate education correlates with the increment in productivity at only $r = 0.297$ ($p = 0.518$), and the corresponding technical and vocational figure collapses to $r = 0.014$ ($p = 0.977$). In growth-rate form, the education-productivity association falls further, to $r = 0.074$ ($p = 0.876$). In contrast, the labour force ($r = 0.727$, $p = 0.064$) and the employed population ($r = 0.720$, $p = 0.068$) approach, but do not reach, conventional significance.

The inverse association between productivity and unemployment also weakens once the trend is removed, to $r = -0.361$ ($p = 0.426$) in increments and $r = -0.338$ ($p = 0.459$) in growth rates. In contrast, the youth unemployment relationship disappears entirely ($r = -0.069$ and $r = 0.040$ respectively). Self-employment increments remain weakly negative ($r = -0.127$, $p = 0.786$). The overall pattern is that year-to-year movements in productivity track the formal employment margin and almost nothing else in the dataset. Table 4 summarises the outcome of hypothesis testing against these results.

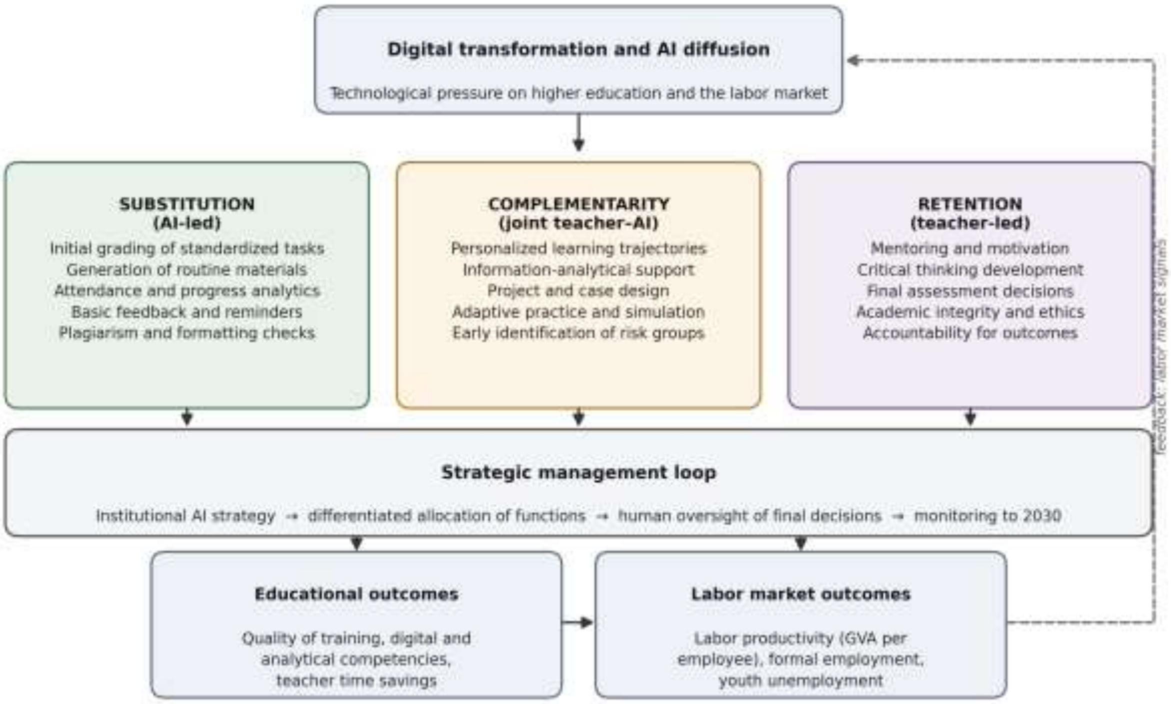
Table 4. Outcome of hypothesis testing

Hypothesis	Statement	Empirical evidence	Decision
H_1	Higher and postgraduate education is positively associated with labour productivity in level form	$r = 0.913$, $p = 0.002$, above the one per cent critical value of 0.834	Supported
H_2	The education-productivity association weakens and loses significance under detrending	r falls from 0.913 to 0.297 ($p = 0.518$) in increments and to 0.074 ($p = 0.876$) in growth rates	Supported
H_3	Labour productivity is inversely associated with total and youth unemployment in level form	$r = −0.857$ ($p = 0.007$) and $r = −0.886$ ($p = 0.003$), both above the one per cent critical value	Supported
H_4	Wage employment is more strongly associated with productivity than self-employment.	Levels: 0.995 against 0.772. Increments: 0.797 ($p = 0.032$) against −0.127 ($p = 0.786$)	Supported
H_5	Differentiated allocation of functions raises the effectiveness of AI implementation.	No published indicator of AI use intensity in universities; derived from the classification procedure and from the outcome of H_2	Not testable on the available data; advanced as a design principle

Note. AI denotes artificial intelligence. Decisions refer to the association structure observed in Tables 2 and 3 and are statistical rather than causal.

Hypotheses H_1, H_2, H_3, and H_4 are supported by the data. H_1 holds in level form, with the education-productivity association significant at the one per cent level. H_2 is decisively confirmed: the same association declines by a factor of three in increments and by a factor of twelve in growth rates, losing significance in both. H_3 holds in level form for both total and youth unemployment. H_4 is supported in both level and dynamic form, with wage employment consistently outperforming self-employment as a correlate of productivity. H_5 is not testable against the statistical series, since no published indicator measures the intensity of artificial intelligence use in Kazakhstani universities; it is therefore advanced as a design principle derived from the classification procedure and the empirical finding that quantitative expansion of educational output does not, by itself, generate productivity gains.

The economic interpretation of this configuration is specific. A country can raise its stock of graduates steadily, as Kazakhstan did at 3.8 per cent annually, while the year-to-year variation in productivity remains unrelated to that expansion. Two mechanisms are consistent with the observed pattern. The first is a lag structure in which educational investment affects productivity only after graduates have accumulated workplace experience, so annual co-movement is not expected. The second is a composition effect, in which the marginal graduate enters occupations with low technological content, so that additional credentials do not translate into additional value added. Both mechanisms point to the same managerial conclusion: the binding constraint is the composition and quality of competencies applied, not the number of diplomas awarded. This is precisely the domain in which the allocation of teaching functions between instructor and artificial intelligence becomes an economic, not merely a pedagogical, question. Figure 1 presents the resulting conceptual framework.



Note. The degree of operational standardization, the pedagogical complexity, and the necessity of human oversight of the outcome define the three regimes. The dashed line denotes the feedback of labour market signals into the allocation of functions.

Figure 1. Conceptual framework for the differentiated allocation of teaching functions between the instructor and artificial intelligence

The framework distinguishes three regimes. Substitution covers operations that are highly standardised, pedagogically simple, and amenable to automated execution: initial grading of standardised assignments, generation of routine materials, attendance and progress analytics, basic feedback, and formatting and originality checks. Complementarity encompasses intermediate standardisation operations that require analytical judgement that neither party can perform optimally alone: construction of personalised learning trajectories, information-analytical support, project and case design, adaptive practice, and early identification of students at academic risk. Retention covers operations that presuppose evaluative discretion and accountability: mentoring, development of critical thinking, final assessment decisions, enforcement of academic integrity, and responsibility for learning outcomes. The three regimes are bound together by a strategic management loop that runs from institutional policy through allocation and human oversight to monitoring, with labour market signals feeding back into allocation itself.

The empirical results shape this framework in a specific way. Because productivity responds to the composition of competencies rather than to graduate volume, the complementarity regime yields the greatest expected economic return: it is the regime in which analytical, digital, and project competencies are formed. Substitution is justified on efficiency grounds, releasing instructor time, but should not be expected to improve learning outcomes directly. Retention is justified on accountability grounds and is a precondition for the legitimacy of the other two. Table 5 operationalizes the framework as a monitoring system with baseline values for 2025 and indicative targets for 2030.

Table 5. System of indicators for monitoring the implementation of artificial intelligence in the educational process through 2030

Monitoring indicator	Regime	Baseline, 2025	Indicative target, 2030
Faculty certified in the pedagogical application of artificial intelligence, %	Retention	Not systematically recorded	80
Educational programmes containing an artificial intelligence literacy module, %	Complementarity	Fragmentary	100
Standardized assessment operations executed with automated support, %	Substitution	Fragmentary	60
Instructor time released from routine operations, hours per semester	Substitution	Not recorded	60
Courses offering personalized learning trajectories, %	Complementarity	Fragmentary	50
Assessment tasks with declared and verifiable artificial intelligence use, %	Retention	Not recorded	100
Final assessment decisions confirmed by an instructor, %	Retention	Not recorded	100
Regional universities with access to licensed artificial intelligence tools, %	Substitution	Concentrated in Astana and Almaty	90

Employer-assessed digital competence of graduates, index points	Complementarity	Not measured	Established in the first monitoring cycle
Documented incidents of algorithmic bias or data breach per academic year	Retention	Not recorded	Zero tolerance with mandatory disclosure

Note. Regime refers to the allocation categories defined in Figure 1. Baseline values describe the state of national reporting in 2025; entries recorded as fragmentary or not recorded indicate the absence of a unified official statistical basis. Target values are normative and indicative rather than forecast estimates and require empirical validation.

The indicator system deliberately combines resource, process, and outcome measures. Resource indicators, such as platform coverage, establish whether implementation is technically feasible; process indicators, such as the share of assessment tasks with declared use of artificial intelligence, establish whether it is governed; and outcome indicators, such as employer-assessed digital competence, establish whether it works. Targets are indicative and normative rather than forecast values, since no observational basis currently exists for projecting them.

DISCUSSIONS

The results support the position that artificial intelligence in the educational process should be treated as a managed redistribution of professional functions rather than a replacement for teaching labour. Support for H_1 and H_3 confirms that educational potential and labour market performance move together over the medium term, which is consistent with the absorptive capacity literature and with the finding that intermediate technical competencies contribute disproportionately to innovation and productivity (Mason et al., 2020). The near-identical level correlations obtained here for technical and vocational education (r = 0.931) and for higher and postgraduate education (r = 0.913) reinforce that argument: the vocational track is not economically subordinate, a conclusion also reached in work on the neglected innovation role of vocational training centres (Porto Gomez et al., 2018) and on apprenticeship-driven knowledge diffusion (Rupietta & Backes-Gellner, 2019).

The confirmation of H_2 is the more consequential finding, and it qualifies a substantial part of the existing literature. Studies that examine the education-productivity relationship in level form routinely report strong associations and interpret them as evidence of educational return. The present analysis reproduces exactly such a result and then demonstrates that it does not survive detrending: an association of r = 0.913 becomes r = 0.297 in increments and r = 0.074 in growth rates. This does not imply that education is economically inert. It implies that a shared trend carries the level result and cannot be read as an annual return on graduate numbers. The practical corollary aligns with cross-country evidence that educational development influences competitiveness through the quality of knowledge rather than its volume (Mazur et al., 2025), and with Kazakhstani findings that investment in digital infrastructure has outpaced institutional capacity to convert it into capability (Nurtayeva et al., 2024; Dzhanegizova, 2024).

Support for H_4 situates the finding within the structure of the national labour market. Wage employment is the only variable whose year-to-year movement tracks productivity, suggesting that the formal sector is where technological and organizational upgrading is concentrated. Self-employment, by contrast, shows no such association, and its declining share over the period is consistent with gradual formalization. This has a direct bearing on educational strategy: competencies formed in universities generate measurable return principally when graduates enter formal employment where those competencies are used. Research on job substitution possibility indices points in the same direction by showing that exposure to automation and skill requirements vary sharply by sector rather than uniformly across the economy (Koo et al., 2024; Shannaq et al., 2025).

The allocation model advanced under H5 is consistent with the pedagogical evidence. Systematic review findings that generative tools are used most extensively for transmitting theoretical knowledge and supporting personalized learning, while immersive technologies prove more effective for practical competencies (Matos et al., 2025), correspond to the boundary between the substitution and complementarity regimes: the choice of technology should follow from the educational task rather than from tool availability. The observation that generative systems are reshaping conceptions of how knowledge is created, transmitted, and assessed (Dong, 2024) supports the retention regime, since the legitimacy of assessment depends on a human author of the final judgement. Evidence that faculty capability mediates between technological investment and learning outcomes (Kapasheva et al., 2024) explains why the complementarity regime, which places the highest demands on instructor competence, is also the one with the greatest expected return. Experimental results showing that targeted digital interventions raise teacher digital competence most among those starting from lower baselines (Kazbekovna et al., 2025) indicate where professional development resources should be concentrated, a conclusion reinforced by parallel Kazakhstani findings (Kurakbayeva & Xembayeva, 2025; Medeshova et al., 2025; Temirkhanova et al., 2024).

Several results run counter to expectation and should not be obscured. The association between the increase in technical and vocational graduates and the increase in productivity is effectively zero (r = 0.014), which is difficult to reconcile with the strong result for the same variable. The most plausible explanation is a lag longer than the observation window permits detecting. Similarly, the disappearance of the youth unemployment association under detrending (r = -0.069) suggests that the level result reflects a secular decline in youth unemployment coinciding with productivity growth rather than a year-to-year relationship. Both findings are reported here because their omission would materially overstate the strength of the evidence.

The proposed indicator system extends existing monitoring approaches, which typically privilege equipment counts and platform licences. Counts of computers, platforms, and interactive systems characterize resource conditions but do not, in themselves, indicate improvement in educational quality. Monitoring, therefore, incorporates faculty artificial-intelligence competence, the degree of personalization, changes in academic performance, freed-up instructor time, and the preservation of human oversight over consequential decisions. Risks accompany implementation: algorithmic bias, unreliability of generated material, breaches of data confidentiality, growing student dependence on pre-formed answers, and erosion of independent reasoning. Audit work on the hidden curriculum embedded in generative systems demonstrates that these risks are structural rather than incidental (Warr & Heath, 2025), and the coexistence of genuine benefit and serious hazard within a single toolset has been documented in language education (Hockly, 2023). Academic integrity may be strengthened or undermined depending entirely on how implementation is governed (Artyukhov et al., 2024).

An additional constraint specific to Kazakhstan is the spatial inequality of university digital infrastructure. Concentration of financial and technological resources in Astana and Almaty risks widening the gap between metropolitan and regional institutions, a pattern already visible in studies of digital transformation across Kazakhstani universities (Gulmira et al., 2024; Zarubina et al., 2024) and in comparative assessment across the Eurasian Economic Union (Ospanova et al., 2025). Unresolved problems remain. The 2030 target values are normative and require empirical validation through pilot implementation, faculty and student surveys, expert assessment, and before-and-after comparison. No unified official statistics currently characterize the intensity or effectiveness of artificial intelligence use in Kazakhstani universities, which is itself a constraint on evidence-based policy. Whether the complementarity regime delivers the expected return, and over what horizon, cannot be established from macroeconomic aggregates and requires institution-level panel data.

CONCLUSIONS

The purpose of this study was to determine the statistical relationship between the educational potential of Kazakhstan's employed population and labour productivity over 2018-2025, and to derive a strategic model for the differentiated allocation of teaching functions between instructors and artificial intelligence from it.

The analysis established that, in level form, gross value added per employee is strongly associated with wage employment, the employed population, and both educational tracks, and is inversely associated with total and youth unemployment. When the common time trend was removed, only wage employment retained a significant association, and the education-productivity link fell from 0.913 to 0.297 in increments and to 0.074 in growth rates. The conclusion that follows is that expanding the number of graduates does not by itself raise productivity within the observation horizon; what varies with productivity is the formal employment margin, and what plausibly explains the level association is the joint upward movement of educational stock and economic output rather than an annual return on educational volume.

The unique contribution of this work is threefold. It applies a three-form correlation procedure to Kazakhstani labour market and education data, demonstrating that a widely reported level relationship does not survive detrending. It derives an allocation model for teaching functions from explicit classification criteria rather than asserting the boundary between human and machine work. It proposes a monitoring system that measures pedagogical, ethical, and labour market outcomes alongside resource provision, closing a gap in existing frameworks.

Theoretically, the findings caution against inferring educational return from trending aggregates and support a competency-composition account of how education affects productivity rather than a credential-volume account. For management practice, several implications follow. Universities should adopt institutional strategies that define permissible areas for artificial intelligence applications, participants' responsibilities, and quality-control procedures for algorithmically generated decisions. Routine and standardized operations should be transferred to automated systems, while programme design, mentoring, development of critical thinking, final assessment, and ethically consequential decisions remain with the instructor. Curricula should incorporate modules on artificial intelligence literacy, data analysis, verification of generated information, digital ethics, and academic integrity, and be revised in step with labour market requirements. Faculty development should address assignment design and control of algorithmic bias, not technical operation alone. Assessment should shift toward project-based, research-based, and oral formats in which the use of artificial intelligence is declared and verifiable. Final decisions affecting a student trajectory should never rest with an algorithm alone. State support should target the digital infrastructure of regional universities to prevent the metropolitan concentration of capability, and requirements for the storage, processing, and transfer of educational data should be established and audited. Pilot testing in individual disciplines, with comparison against control groups, should precede any large-scale rollout, and the development of digital modules should be conducted jointly with employers, with emphasis on competencies that complement rather than compete with automation.

The study has clear limitations. Eight annual observations provide low statistical power, so associations are reported as statistical relationships rather than causal effects, and moderate coefficients may fail to meet significance thresholds even when a relationship exists. National aggregates conceal substantial regional and institutional heterogeneity in Kazakhstan. No indicator of the intensity of artificial intelligence use in universities has been published, so the allocation model rests on macroeconomic conditions for implementation rather than on observed implementation. The 2030 targets are normative rather than forecast values.

Future research should extend the series as longer consistent data become available, assemble panel data across regions and individual universities, and construct a direct measure of artificial intelligence use intensity in the educational process. Quasi-experimental evaluation comparing programmes that adopt the differentiated allocation model against those that do not would permit causal identification. Disaggregation by field of study and by occupation would test the composition-effect explanation advanced here, and lag-structured analysis would test the alternative timing explanation. Finally, cross-country replication in comparable middle-income economies would establish whether the divergence between level and detrended results is a general feature of the education-productivity relationship or specific to the Kazakhstani case.

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REFERENCES

Abbasi, B. N., Wu, Y., & Luo, Z. (2025). Exploring the impact of artificial intelligence on curriculum development in global higher education institutions. *Education and Information Technologies, 30*, 547–581. https://doi.org/10.1007/s10639-024-13113-z

Ahmad, A. R., Segaran, V. A., & Sapry, H. R. M. (2020). Academic Staff and Industry Revolution 4.0: Knowledge, Innovation and Learning Factor. *Journal of Education and E-Learning Research*, *7*(2), 190–194. https://doi.org/10.20448/journal.509.2020.72.190.194

Al Hunaini, H. A., Al Hajri, R. M., & Chinnathambi, K. (2025). Omani students' perceptions of the impact of private tutoring on academic performance. *Bangladesh Journal of Multidisciplinary Scientific Research, 11*(1), 35-42. https://doi.org/10.46281/bjmsr.v11i1.2752

Artyukhov, A., Wolowiec, T., Artyukhova, N., Bogacki, S., & Vasylieva, T. (2024). SDG 4, academic integrity and artificial intelligence: Clash or win-win cooperation? *Sustainability, 16*(19), 8483. https://doi.org/10.3390/su16198483

Babu, M. R. N., Atokali, Lahon, A., & Padmanaban, S. (2025). SCIENTIFIC ATTITUDE AND CRITICAL THINKING SKILLS IN SECONDARY SCHOOL STUDENTS: THE IMPACT OF GENDER AND MANAGEMENT. *Bangladesh Journal of Multidisciplinary Scientific Research*, *10*(3), 49–56. https://doi.org/10.46281/w5crnb28

Bilgic, E., Gorgy, A., Young, M., Abbasgholizadeh-Rahimi, S., & Harley, J. M. (2021). Artificial intelligence in surgical education: Considerations for interdisciplinary collaborations. *Surgical Innovation, 29*(2), 137–138. https://doi.org/10.1177/15533506211059269

Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. (2025). Labour market and employment statistics. Retrieved from https://stat.gov.kz

Civera, A., Meoli, M., & Vismara, S. (2017). Policies for the provision of finance to science-based entrepreneurship. *Annals of Science and Technology Policy, 1*(4), 317–469. https://doi.org/10.1561/110.00000004

Daraio, C., Heitor, M., Meoli, M., & Paleari, S. (2019). Policy turnaround: Towards a new deal for research and higher education. Governance, evaluation and rankings in the big data era. *Higher Education Quarterly, 73*(1), 3-9. https://doi.org/10.1111/hequ.12196

Dong, C. (2024). Educational concepts and methodologies in the AI era: Challenges and responses. *Frontiers of Digital Education, 1*(1), 69–77. https://doi.org/10.1007/s44366-024-0022-y

Dubey, S. S., Astvansh, V., & Kopalle, P. K. (2025). Generative AI solutions to empower financial firms. *Journal of Public Policy & Marketing, 44*(3), 411–435. https://doi.org/10.1177/07439156241311300

Dzhanegizova, A. (2024). Digital transformation of higher education in Kazakhstan: Challenges and solutions. Economic Annals-XXI, 209(5-6), 42–55. https://doi.org/10.21003/ea.V209-05

Ergasheva, G., Khursanov, R., Bazarova, D., Altiyev, R., Tadjibaeva, A., Yusupdzhanova, G., & Madatova, Z. (2025). Integrating digital competencies into legal education: A pedagogical framework for the future. *Qubahan Academic Journal, 5*(2), 446–478. https://doi.org/10.48161/qaj.v5n2a1709

Grewal, D., Okazaki, S., Guha, A., & Liu-Thompkins, Y. (2025). Generative AI: Delivering on the promises and understanding the perils. *Journal of Public Policy & Marketing, 44*(3), 299–308. https://doi.org/10.1177/07439156251338200

Gulmira, B., Gulmira, M., Assel, O., Aigerim, O., Altanbek, Z., & Beibarys, S. (2024, July). Aspects of digital transformation of higher education in the Republic of Kazakhstan. In *International Conference on Computational Science and Its Applications* (pp. 111–123). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-65282-0_7

Henriet, J. (2017). Artificial intelligence-virtual trainer: An educative system based on artificial intelligence and designed to produce varied and consistent training lessons. Proceedings of the Institution of Mechanical Engineers, Part P: *Journal of Sports Engineering and Technology, 231*(2), 110–124. https://doi.org/10.1177/1754337116651013

Hoang, V. Q. (2024). Fostering willingness to communicate in online educational environments: Opportunities and challenges. In The 2nd international conference: Resiliency by technology and design (RTD, 2024) (pp. 272-286). Atlantis Press. https://doi.org/10.2991/978-94-6463-583-6_13

Hockly, N. (2023). Artificial intelligence in English language teaching: The good, the bad and the ugly. *RELC Journal*, *54*(2), 445–451. https://doi.org/10.1177/00336882231168504

Huang, M.-H., & Rust, R. T. (2024). The caring machine: Feeling AI for customer care. *Journal of Marketing*, *88*(5), 1–23. https://doi.org/10.1177/00222429231224748

Jakubakynov, B., Tolegenuly, N., Naribai, R., Nurzhanova, Z., Shcherban, T., & Nebelenchuk, I. (2026). Innovative technologies in higher education: developing international cooperation in professional training. *Globalization, Societies and Education*, *24*(4), 1331-1344. https://doi.org/10.1080/14767724.2024.2339309

Joya, L. G., Merchán, M. A. M., & Barrera, E. A. L. (2025). Development and strengthening of teachers' digital competence: Systematic review. *Contemporary Educational Technology*, *17*(1), ep555. https://doi.org/10.30935/cedtech/15744

Kapasheva, Z., Mirza, N., Shastsitka, I., Gelmanova, Z., Makouchyk, A., & Umbetova, A. (2024). Modeling the development of pedagogical competence in higher education educators amid the digitization of the contemporary world. *Frontiers in Education*, *9*, 1360712. https://doi.org/10.3389/feduc.2024.1360712

Kazbekovna, Z. K., Tumarbek, Z. Z., Sabyrkul, S., Kenesovna, K. G., & Aiym, Y. (2025). Formation of digital competences of students in the system of higher pedagogical education. *Bangladesh Journal of Multidisciplinary Scientific Research*, *11*(1), 43–54. https://doi.org/10.46281/bjmsr.v11i1.2760

Kimeto, J. C. (2021). Tertiary tourism graduate employees and tourism employers' perceptions on tourism skills and competencies relevant for providing quality tourism services in Kenya. *Tourism Critiques*, *2*(1), 20-37. https://doi.org/10.1108/TRC-07-2020-0013

Koo, G. J., Kim, J. W., Choi, Y. B., Kim, G. H., & Hong, J. E. (2024). Development of a job substitution possibility index for analyzing the labor market impact of artificial intelligence and robotics. *Korean Journal of Public Administration*, *62*(3), 37–74. Retrieved from https://www.dbpia.co.kr/journal/articleDetail?nodeId=NODE11936270

Kurakbayeva, A., & Xembayeva, S. (2025). Enhancing professional abilities of university students through digital educational interventions: A study in Kazakhstani universities. *Frontiers in Education*, *9*, 1478622. https://doi.org/10.3389/feduc.2024.1478622

Lopez-Nunez, J.-A., Alonso-Garcia, S., Berral-Ortiz, B., & Victoria-Maldonado, J.-J. (2024). A systematic review of digital competence evaluation in higher education. *Education Sciences*, *14*(11), 1181. https://doi.org/10.3390/educsci14111181

Masete, M. Z., & Mafini, C. (2018). Internal barriers to supply chain management implementation in a South African traditional university. *Journal of Transport and Supply Chain Management*, *12*(1), 1–12. https://doi.org/10.4102/jtscm.v12i0.389

Mason, G., Rincon-Aznar, A., & Venturini, F. (2020). Which skills contribute most to absorptive capacity, innovation and productivity performance? Evidence from the US and Western Europe. Economics of Innovation and New Technology, 29(3), 223–241. https://doi.org/10.1080/10438599.2019.1610547

Matos, T., Santos, W., Zdravevski, E., Coelho, P. J., Pires, I. M., & Madeira, F. (2025). A systematic review of artificial intelligence applications in education: Emerging trends and challenges. *Decision Analytics Journal*, *15*, 100571. https://doi.org/10.1016/j.dajour.2025.100571

Mazur, H., Bolhov, V., Akhnovska, I., Dluhopolskyi, O., & Kozlovskyi, S. (2025). The impact of educational development on the countries' competitiveness in the knowledge economy. *Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu*, (1), 140-146. https://doi.org/10.33271/nvngu/2025-1/140

Medeshova, A., Adelbaeva, N., Kushekkaliev, A., Akimova, S., Khazhgaliyeva, G., Ramazanova, L., & Kassymova, A. (2025). The impact of pedagogical approaches for forming digital competence in students. *Qubahan Academic Journal*, *4*(4), 374–382. https://doi.org/10.48161/qaj.v4n4a1023

Menter, M., Lehmann, E. E., & Klarl, T. (2018). In search of excellence: A case study of the first excellence initiative of Germany. *Journal of Business Economics*, *88*(9), 1105-1132. https://doi.org/10.1007/s11573-018-0909-5

Meoli, M., Pierucci, E., & Vismara, S. (2018). The effects of public policies in fostering university spinoffs in Italy. Economics of Innovation and New Technology, 27(5-6), 479–492. https://doi.org/10.1080/10438599.2017.1374048

Nawaz, N. (2015). A review of knowledge management in higher education. *International Journal of Science and Research*, *4*(11), 2062-2065. https://doi.org/10.21275/v4i11.nov151609

Nurtayeva, D., Kredina, A., Kireyeva, A., Satybaldin, A., & Ainakul, N. (2024). The role of digital technologies in higher education institutions: The case of Kazakhstan. *Problems and Perspectives in Management*, *22*(1), 562–577. https://doi.org/10.21511/ppm.22(1).2024.45

Nyberg, A. J., Schleicher, D. J., Bell, B. S., Boon, C., Cappelli, P., Collings, D. G., Dalle Molle, J. E., Feuerriegel, S., Gerhart, B., & Jeong, Y. (2025). A brave new world of human resources research: Navigating perils and identifying grand challenges of the GenAI revolution. *Journal of Management*, *51*(6), 2677-2718. https://doi.org/10.1177/01492063251325188

Ospanova, A., Mukhametzhan, A., Nurbayev, Z., Mukanov, M., & Baigabylov, N. (2025). Strategic reflections on digital transformation, scientific literacy, and labor market development in the Eurasian Economic Union: Insights from the case of Kazakhstan. *Iberoamerican Journal of Science Measurement and Communication*, *5*(3), 1–13. https://doi.org/10.47909/ijsmc.256

Pande, S., Moon, J. S., & Haque, M. F. (2024). Education in the era of artificial intelligence: An evidence from Dhaka International University (DIU). *Bangladesh Journal of Multidisciplinary Scientific Research*, *9*(1), 7-14. https://doi.org/10.46281/bjmsr.v9i1.2186

Papadakis, S. (2024). IoT, AI, and ICT for educational applications: Technologies to enable education for all. Springer Nature. https://doi.org/10.1007/978-3-031-50139-5

Pence, H. E. (2019). Artificial intelligence in higher education: New wine in old wineskins?. *Journal of Educational Technology Systems*, *48*(1), 5–13. https://doi.org/10.1177/0047239519865577

Pirog, D., Kilar, W., & Rettinger, R. (2021). Self-assessment of competences and their impact on the perceived chances for a successful university-to-work transition: The example of tourism degree students in Poland. *Tertiary Education and Management*, *27*, 367–384. https://doi.org/10.1007/s11233-021-09081-5

Porto Gomez, I., Zabala-Iturriagagoitia, J. M., & Aguirre Larrakoetxea, U. (2018). Old wine in new bottles: The neglected role of vocational training centres in innovation. *Vocations and Learning*, *11*, 205-221. https://doi.org/10.1007/s12186-017-9187-6

Prahiawan, W., Fahlevi, M., Juliana, J., Purba, J. T., & Tarigan, S. A. (2021). The role of e-satisfaction, e-word of mouth and e-trust in online shop repurchase intention. *International Journal of Data and Network Science*, *5*(4), 593–600. https://doi.org/10.5267/j.ijdns.2021.8.008

Randhawa, G. K., & Jackson, M. (2020). The role of artificial intelligence in learning and professional development for healthcare professionals. *Healthcare Management Forum*, *33*(1), 19–24. https://doi.org/10.1177/0840470419869032

Rupietta, C., & Backes-Gellner, U. (2019). How firms' participation in apprenticeship training fosters knowledge diffusion and innovation. *Journal of Business Economics*, *89*(5), 569–597. https://doi.org/10.1007/s11573-018-0924-6

Salas-Pilco, S. Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: A systematic review. *International Journal of Educational Technology in Higher Education*, *19*, 21. https://doi.org/10.1186/s41239-022-00326-w

Sarjono, V., & Firdaus, F. (2020). A readiness model for implementing knowledge management systems in higher education. *ICIC Express Letters*, *14*(5), 477-487. https://doi.org/10.24507/icicel.14.05.477

Seitaliyeva, A., Shyndaliyev, N., Altynbekova, Z., Yermanova, G., & Caliskan, E. (2025). Integration of digital technologies into the methodology of teacher training in the system of dual education. Periodicals of Engineering and Natural Sciences, 13(3), 695–710. https://doi.org/10.21533/pen.v13.i3.472

Shannaq, B., Alabri, A., Sriram, V. P., & Ali, O. B. (2025). Investigating the impact of AI on the workforce and the future of work in the region: A machine learning perspective. *Bangladesh Journal of Multidisciplinary Scientific Research*, *10*(4), 1–10. https://doi.org/10.46281/a7zcns96

Sorensen, M. P., Bloch, C., & Young, M. (2016). Excellence in the knowledge-based economy: From scientific to research excellence. *European Journal of Higher Education*, *6*(3), 217–236. https://doi.org/10.1080/21568235.2015.1015106

Temirkhanova, M., Abildinova, G., & Karaca, C. (2024). Enhancing digital literacy skills among teachers for effective integration of computer science and design education: A case study at Astana International School, Kazakhstan. *Frontiers in Education*, *9*, 1408512. https://doi.org/10.3389/feduc.2024.1408512

Trujillo-Juarez, S.-I., Chaparro-Sanchez, R., Morita-Alexander, A., Escudero-Nahon, A., & Delgado-Gonzalez, A. (2025). Strengthening teacher digital competence in higher education through micro-courses: A systematic literature review. *Discover Education*, *4*, 247. https://doi.org/10.1007/s44217-025-00687-0

Warr, M., & Heath, M. K. (2025). Uncovering the hidden curriculum in generative AI: A reflective technology audit for teacher educators. Journal of Teacher Education, 76(3), 245–261. https://doi.org/10.1177/00224871251325073

Xie, Y., & Avila, S. (2025). The social impact of generative LLM-based AI. *Chinese Journal of Sociology*, *11*(1), 31-57. https://doi.org/10.1177/2057150X251315997

Zarubina, V., Zarubin, M., Yessenkulova, Z., Salimbayeva, R., & Satbaeva, G. (2024). Digital transformation of the promotion of educational services of Kazakhstani universities. *Journal of Innovation and Entrepreneurship*, *13*, 3. https://doi.org/10.1186/s13731-023-00355-3

Zhou, J., Soo, H. S., & Aziz, A. B. (2025). Person-organization fit and job burnout as predictors of quiet quitting in vocational education. *Bangladesh Journal of Multidisciplinary Scientific Research*, *10*(4), 30–41. https://doi.org/10.46281/c9d2ab72

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