

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE LABOR MARKET: OPPORTUNITIES AND CHALLENGES FOR YOUTH DECENT WORK, QUALITY EDUCATION AND HUMAN CAPITAL IN THE CONTEXT OF DIGITAL TRANSFORMATION IN KAZAKHSTAN



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ABSTRACT

The diffusion of artificial intelligence (AI), and of generative AI in particular, is reshaping the demand for labour and skills, and young people entering the labour market are the group most exposed to its opportunities and risks, with direct consequences for decent work, quality education and reduced inequalities. This study assesses the impact of AI and digital transformation on Kazakhstan's youth labour market, identifies the opportunities and risks they present, and determines directions for adapting youth human capital to changing labour market demands. The study combines a structured synthesis of empirical evidence published in 2023–2026, a content analysis of national strategic documents, and an economic-statistical analysis of national and regional employment data of the Bureau of National Statistics of Kazakhstan for 2020–2025, using growth rates, the regional differentiation coefficient, the coefficient of variation and the Gini coefficient. The results show that average employment rose from 8,966.9 thousand in 2022 to 9,298.2 thousand in 2025 (+3.69%) and the average unemployment rate fell from 4.90% to 4.60%. In contrast, the regional differentiation coefficient of employment rose from 9.89 to 11.74, the coefficient of variation from 44.31% to 49.12% and the Gini coefficient from 0.232 to 0.252. The findings suggest that the current phase of AI diffusion is accompanied by employment growth rather than contraction, that the effects of AI on youth are dual, combining the substitution of standardized cognitive tasks with the augmentation of inexperienced workers, and that these effects will unfold unevenly across regions with persistent, moderately widening disparities.

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INTRODUCTION

The diffusion of artificial intelligence (AI), and of generative AI in particular, has become one of the defining forces of the digital transformation of labour markets. According to the International Monetary Fund, about 40% of global employment is exposed to AI, rising to about 60% in advanced economies (Cazzaniga et al., 2024). Roughly 80% of the United States workforce could see at least 10% of their tasks affected by large language models, and about 19% could see at least half of their tasks affected (Eloundou et al., 2024), while a refined global index places one in four workers worldwide in occupations exposed to generative AI, with clerical work the most exposed (Gmyrek et al., 2025). Adoption has been faster than that of the personal computer: 45% of working-age adults in the United States already use generative AI, and 27% of employed adults use it at work in a given week (Bick et al., 2026). Employers expect 170 million jobs to be created and 92 million to

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be displaced by 2030, with about 39% of core skills changing and 63% of firms citing skills gaps as the main barrier to transformation (World Economic Forum, 2025).

The scientific problem addressed in this paper is that evidence on the direction of these effects is contradictory, with the contradiction most pronounced for young workers. Field and laboratory experiments show that generative AI raises productivity most for the least experienced workers: an AI assistant increased the number of customer issues resolved per hour by 15% on average, with the largest gains for novice agents (Brynjolfsson, Li, & Raymond, 2025); professional writing tasks were completed 40% faster and with 18% higher quality (Noy & Zhang, 2023); junior software developers adopted AI tools more readily and gained more from them (Cui et al., 2025); and consultants completed 12.2% more tasks 25.1% faster inside the technological frontier (Dell'Acqua et al., 2026). These results imply that AI complements the human capital of newcomers. At the same time, a growing body of evidence points to substitution. Freelancers in AI-exposed occupations lost both jobs and earnings after the release of ChatGPT (Hui et al., 2024); employment of 22–25-year-olds in the most AI-exposed occupations fell by 13% relative to less exposed groups, driven by reduced hiring rather than separations (Brynjolfsson, Chandar, & Chen, 2025). Adoption itself is unequal, concentrated among younger, already better-paid workers (Humlum & Vestergaard, 2025). Macroeconomic estimates of the productivity effect remain modest, at most 0.66% of total factor productivity over ten years (Acemoglu, 2025) or 0.25–0.6 percentage points per year (Filippucci et al., 2024), and task-level exposure reduces labour demand even when aggregate employment effects are limited (Hampole et al., 2025). The structure of skill demand is shifting toward non-routine analytical, managerial and social competencies (Green, 2024; Liang et al., 2025; Zhang & Zhang, 2026), with contested consequences for the skill premium and wage inequality (Bloom et al., 2025; Georgieff, 2024) and for the groups most at risk of exclusion (Lane, 2024).

Young people are the natural focus of this problem because they are simultaneously the most receptive to new technologies and the most dependent on entry-level positions that are being redefined. Global youth unemployment stood at 13% in 2023, yet 20.4% of young people were not in employment, education or training (NEET), with a rate of 28.1% among young women (International Labour Organization, 2024). In Kazakhstan, youth unemployment fell from 13.97% to 4.94% for young women and from 11.60% to 2.87% for young men between 2005 and 2024 (Baidalinova et al., 2026), and a 1% rise in internet penetration lowers youth unemployment by 0.27% in the short run (Barzhaksyyeva et al., 2026). However, the structure of jobs is changing more slowly than the economy requires, and youth unemployment shocks have the strongest effect on total unemployment (Beisembina et al., 2025); vertical and horizontal skill mismatches persist, with acute shortages of ICT and hybrid digital profiles and strong regional disparities (Arynova et al., 2025; Berdibekov et al., 2026); and labor productivity under AI depends more on the competency composition of graduates than on the volume of educational output (Ramazanova et al., 2026), while regional productivity growth is associated with ICT spending rather than with fixed investment (Togaibayeva et al., 2026). What is missing is a systematic assessment of how the current phase of AI diffusion relates to the national and, above all, the regional dynamics of employment, against which Kazakhstan's youth labour market will adapt. This question bears directly on the Sustainable Development Goals of decent work and economic growth (SDG 8), quality education and lifelong learning (SDG 4), industry, innovation and infrastructure (SDG 9) and reduced inequalities (SDG 10).

The study aims to assess the impact of AI and digital transformation on Kazakhstan's youth labour market by identifying the opportunities and risks they present and determining directions for adapting youth human capital to changing labour market demands. Achieving this aim required solving four intermediate tasks: systematizing the mechanisms of substitution and augmentation identified in the empirical literature of 2023–2026; analysing the priorities of national strategic documents on the labour market and AI; quantifying the dynamics and regional differentiation of employment in Kazakhstan in 2020–2025 with growth rates, the regional differentiation coefficient, the coefficient of variation, the interquartile range and the Gini coefficient; and verifying the research hypotheses. The methodological basis combines a structured evidence synthesis, a content analysis of strategic documents and an economic-statistical analysis of official data of the Bureau of National Statistics of Kazakhstan.

The remainder of the paper is organized as follows. The literature review examines the theoretical basis and empirical evidence on AI, skills, and youth employment, and concludes with the study's purpose and hypotheses. The materials and methods section describes the data, variables and analytical procedures. The results section presents the national dynamics of the labour market, the regional differentiation of employment and the verification of the hypotheses. The discussion compares the findings with previous studies and identifies unresolved problems, while the conclusions summarise the contribution, implications, limitations, and directions for future research.

LITERATURE REVIEW

The theoretical basis of the study is the task-based approach to technological change, in which the effects of AI on employment and wages depend on whether the technology substitutes for human labour in existing tasks or complements it by raising productivity and creating new tasks. Acemoglu (2025) formalizes this distinction and shows that the aggregate gains from AI are bounded by the share of tasks that can be profitably automated, yielding a total factor productivity gain of no more than 0.66% over a decade. Autor (2024) argues, by contrast, that AI can extend expert-level decision-making to a broader, non-elite workforce and thereby rebuild middle-skill jobs. The two views are not contradictory: they describe the substitution and augmentation mechanisms whose relative strength is an empirical question, and the balance between them is precisely what determines whether AI narrows or widens the entry barriers faced by young workers.

Experimental evidence on generative AI has clarified the augmentation mechanism. Noy and Zhang (2023) found that ChatGPT reduced the time needed for professional writing tasks by about 40% while raising output quality by about 18%, with the largest improvements among initially less productive participants. Brynjolfsson, Li, and Raymond (2025)

reported a 15% average increase in issues resolved per hour among 5,172 customer support agents, with the largest gains for less experienced and lower-skilled workers, an effect they attribute to the transfer of tacit knowledge from top performers to novices. Cui et al. (2025) observed a 26% increase in completed tasks across three field experiments with 4,867 software developers, with junior developers adopting and benefiting more. Dell'Acqua et al. (2026) showed that 758 consultants using GPT-4 completed 12.2% more tasks, 25.1% faster, and with higher quality within the frontier of AI capabilities, but were 19 percentage points less likely to produce correct answers on tasks outside that frontier. A meta-analysis of 106 experiments found that human–AI combinations on average underperform the better of humans or AI working alone ($g = -0.23$), with gains concentrated in content-creation tasks (Vaccaro et al., 2024). For young workers, these results imply that AI can compensate for a lack of experience, but only when users can recognize the technology's limits and critically evaluate its output.

Evidence on exposure and employment describes the substitution mechanism. Occupational exposure is high and unevenly distributed: it reaches 34% of employment in high-income countries, but 11% in low-income countries, and the most exposed group comprises 4.7% of women versus 2.4% of men (Gmyrek et al., 2025). Task-level exposure measured from 2010 to 2023 predicts lower labour demand, although adopting firms grow and aggregate effects are modest (Hampole et al., 2025). Hui et al. (2024) found that freelancers in exposed occupations experienced declines in both jobs and earnings after the release of generative AI, and that top performers were not protected. Brynjolfsson, Chandar, and Chen (2025) documented that employment of early-career workers aged 22–25 in the most AI-exposed occupations fell by 13% relative to other groups, that the decline was concentrated where AI automates rather than augments work, and that there was no economy-wide displacement. Humlum and Vestergaard (2025) showed among 18,000 Danish workers that adoption of ChatGPT was concentrated among younger, less experienced workers, that women were 16 percentage points less likely to use it at work, and that adopters already earned more before the technology appeared. Regional evidence from China indicates that AI reduces demand for low-skilled labour by 2.05 percentage points while raising demand for medium- and high-skilled labour by 1.19 and 1.17 percentage points (Liang et al., 2025), and that industrial AI raises manufacturing employment through productivity and virtual agglomeration effects (Shen & Zhang, 2024). A systematic review of fourteen studies concludes that generative AI raises efficiency and creates roles in some sectors while eroding others, so that reskilling and regulation are decisive (Salari et al., 2025), and firm-level evidence shows that AI improves employee wellbeing only indirectly, through task optimization (Valtonen et al., 2025).

A third strand concerns skills and wages. Green (2024) shows that most workers in AI-exposed occupations will not need specialized AI skills, that managerial and business skills are the most in demand in such occupations, and that the earlier rise in vacancies requiring emotional, cognitive, and digital skills is now waning. The human capital behind AI combines technical and transferable skills (Samek et al., 2021). An analysis of 67 million job postings finds that exposure to displacement reduces demand for routine cognitive skills. In contrast, augmentation exposure raises demand for non-routine analytical skills, producing a de-coring of skill portfolios that is strongest in small, low-entry firms (Zhang & Zhang, 2026). Bloom et al. (2025) demonstrate that, unlike industrial robots, AI that substitutes for high-skilled labour lowers the skill premium in their simulations, from 2.0 to 1.52, while Georgieff (2024) finds no effect of AI on between-occupation wage inequality and a reduction in inequality within occupations across nineteen OECD countries. Lane (2024) warns that less-educated, female, and older workers risk exclusion from AI-related jobs and productivity tools rather than from automation as such. Micro-level studies confirm that the returns to AI tools run through transferable skills: perceived usefulness and ease of use of AI tools raise employability, and soft skills mediate 56–77% of that effect (Alabri & Shannaq, 2025); clustering of job positions by AI exposure identifies digital aptitude, emotional capability and problem solving as durable competencies (Shannaq et al., 2025); and the benefits of ChatGPT for human-resource performance are realized mainly through user training (Shannaq & Alabri, 2025). Digital and financial literacy jointly explain about half of the variance in the adoption of digital financial services (Islam & Khan, 2024), and trust, security, and privacy, rather than perceived risk, determine the acceptance of mobile fintech services (Islam et al., 2024). In education, awareness of AI tools among students is already widespread, but its integration into curricula remains unsystematic (Pande et al., 2024).

The organizational side of the transformation matters for how young people are hired and managed. Digital leadership drives AI adoption in human resource management and sustainable performance, with managerial innovation as the key mediator (Mollah et al., 2026), and human capital, together with transformational leadership, explains about 60% of the variance in organizational performance (Islam et al., 2023). However, AI-driven recruitment tools and HR analytics can reproduce discrimination against women, minorities and persons with disabilities, and current legal frameworks leave regulatory gaps (Sony et al., 2025), which is a specific risk for young candidates with short employment histories. Platform-based and technology-driven enterprises widen access to work in the Global South but reproduce precarious employment through algorithmic control and the externalization of risk (Debnath et al., 2026), and among young people in Jordan the gains from AI-enabled digital work are positive but uneven because of language, regulatory and financial barriers (Al-Dmour et al., 2026).

A fourth strand examines the institutions that mediate the transition. AI is already used in the labour market for drafting job vacancies, sourcing candidates, screening resumes, and algorithmic matching (Broecke, 2023), and about half of public employment services in OECD countries use AI, mainly for matching jobseekers to vacancies (Brioscú et al., 2024). Statistical profiling of the unemployed raises questions of accuracy and reporting standards (Gallagher & Griffin, 2025). The digital transformation of public employment services can reshape the entire service chain from registration to outcome monitoring, but its maturity depends on channel integration, data quality and organizational adaptation (Pieterse et al., 2023); different digital solutions alter the discretion of frontline staff in distinct ways (Ball et al., 2023); and similar technologies produce different service models under different institutional conditions, as the comparison of the United Kingdom and Australia shows (Ingold et al., 2025). In the Eurasian Economic Union, digitalization makes the labour market

more transparent. Still, it requires adapting labour legislation (Makrushin, 2023). In Kazakhstan's civil service, the competence of human resource staff is the dominant driver of job satisfaction under digital governance (Dauyeshova et al., 2026).

Research on Kazakhstan itself has expanded rapidly. Kurmanov et al. (2023) find that human capital is the strongest driver of regional labour markets in the digital economy, with a 1% rise in the share of students increasing ICT employment by 0.15%, while ICT infrastructure is not yet decisive. Suieubayeva et al. (2023) show that digital platforms expand self-employment and the peer-to-peer economy, and Utebaliyeva et al. (2026) report that the number of active small and medium enterprises rose from 1.355 to 2.176 million between 2018 and 2025, as digital payments explained 91.9% of the variation in output. Beisembina et al. (2025) establish, using vector autoregression, that youth unemployment shocks have the strongest effect on total unemployment and that job structures change more slowly than the economy requires. Serikkyzy et al. (2025) show that Generation Z accounts for only 19.2% of the employed, with about half of the cohort still outside employment because of study, and that it has higher digital literacy and mobility but faces persistent gender gaps. Baidalinova et al. (2026) document a U-shaped relationship between internet penetration and the gender gap in youth unemployment, with a turning point at 49.1% internet penetration, and Barzhaksyyeva et al. (2026) find that digitalization reduces youth unemployment in the short run but only weakly in the long run. Arynova et al. (2025) and Berdibekov et al. (2026) identify persistent mismatches between the education system and employer demand. Ramazanova et al. (2026) show that gross value added per employee correlates strongly with the stock of degree holders at a given level ($r = 0.913$) but weakly with annual changes ($r = 0.297$), suggesting that productivity under AI depends on the composition of competencies rather than the volume of graduates. Togaibayeva et al. (2026) find that ICT spending, not fixed-asset investment, is associated with regional productivity growth.

Taken together, the literature establishes that AI affects youth employment through two mechanisms whose balance varies by task, sector, firm size, and region; that the returns to AI run through transferable skills and training; and that institutional mediation shapes the outcome. Three gaps remain. First, most causal evidence comes from advanced economies and online platforms, and its transferability to a resource-based, regionally heterogeneous economy such as Kazakhstan is untested. Second, studies of Kazakhstan examine either national aggregates or single determinants, without linking the current phase of AI diffusion to the spatial structure of employment against which young people will adapt. Third, the two mechanisms have not been integrated with the priorities of national strategic documents. The purpose of the study is therefore to assess the impact of AI and digital transformation on Kazakhstan's youth labour market, identify the opportunities and risks they generate, and determine directions for adapting youth human capital to changing labour market demands. In line with this purpose, the following hypotheses are proposed.

H₁: The current phase of digital transformation and AI diffusion (2022–2025) is accompanied by growth in total employment and a decline in unemployment in Kazakhstan, so that the effects of AI are structural rather than a contraction of aggregate employment.

H₂: Interregional disparities in employment in Kazakhstan are persistent and are increasing moderately, so the impact of AI on the youth labour market will be spatially heterogeneous.

H₃: The impact of AI on youth employment is twofold: the automation of routine, standardized functions creates a substitution effect, whereas the use of AI as a tool that supports professional activity creates an augmentation effect that raises the productivity of inexperienced workers.

H₄: Entry-level roles with a high share of standardized cognitive tasks are the most vulnerable to generative AI, thereby raising barriers for young people entering these segments of the labour market.

H₅: The combination of digital and AI competencies with analytical, communication, and lifelong learning skills, supported by the alignment of educational programs with employer needs, increases youth adaptability and converts technological risks into employment opportunities.

MATERIALS AND METHODS

The study follows a sequential mixed design in which a structured synthesis of empirical evidence and a content analysis of strategic documents provide the conceptual framework, and an economic-statistical analysis of official data provides the quantitative context for Kazakhstan's youth labour market. Hypotheses H₁ and H₂ are tested directly with statistical data. Hypotheses H₃, H₄ and H₅ concern mechanisms that cannot be identified from aggregate employment series; they are evaluated by confronting the results of the statistical analysis with the systematized findings of experimental and quasi-experimental studies and with the priorities of national policy documents.

The evidence synthesis covered studies published between 2023 and 2026 on the effects of AI and generative AI on productivity, employment, occupational structure, skill demand and the position of young workers. Sources were selected from peer-reviewed journals and from the analytical series of the OECD, ILO, IMF, World Economic Forum, and the National Bureau of Economic Research; each study was coded by design, sample, outcome, and the direction of the effect, distinguishing between substitution and augmentation mechanisms. The content analysis examined the Concept for Labour Market Development of the Republic of Kazakhstan for 2024–2029 and the Concept for the Development of Artificial Intelligence for 2024–2029, and coded their provisions on human capital, digital competencies, vocational training, youth employment, and the adaptation of the labour market to technological change.

The quantitative analysis relies on the official statistics of the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2026). Two data sets were used. The first consists of monthly national series for the labour force, employed, and unemployed populations for 2022–2025, from which annual averages, chain growth rates, cumulative changes, and the average unemployment rate were calculated. The second consists of annual

employment by region for 2020–2025, covering seventeen regions and the cities of Astana, Almaty and Shymkent. Because the administrative reform of 2022 created the regions of Abai, Zhetysu and Ulytau, the regional differentiation indicators are calculated for 2022–2025, when the regional grid is comparable. Indicators of the youth labour market, including youth employment, unemployment, and the NEET rate, and indicators of digitalization, including internet access, digital literacy, and the development of information and communication technologies, were drawn from the same source and the reviewed studies to interpret the results.

Territorial differentiation was measured with a set of complementary indicators. The regional differentiation coefficient is the ratio of the maximum to the minimum regional value of employment:

$$K_d = Y_{\max} / Y_{\min} \quad (1)$$

Where $Y_{\max}$ and $Y_{\min}$ are the maximum and minimum regional values of the number of employed persons.

The coefficient of variation relates the standard deviation of the regional values to their mean:

$$CV = (\sigma / \bar{x}) \times 100\% \quad (2)$$

Where σ is the standard deviation of the regional values, and $\bar{x}$ is their mean.

The Gini coefficient of the regional distribution of employment was calculated from the ordered regional values as

$$G = 2 \sum y_i / (n \sum y_i) - (n + 1) / n \quad (3)$$

Where y_i is the employment of region i ranked in ascending order, and n is the number of regions.

The compound annual growth rate of employment over the period was calculated as

$$CAGR = (Y_t / Y_0)^{1/t} - 1 \quad (4)$$

Where Y_t and Y_0 are the values of the indicator in the final and initial year, and t is the number of years.

In addition to absolute employment, a relative employment level was calculated as the ratio of the number of employed persons to the population of working age in each region, which removes the distorting effect of differences in regional population size; the range, interquartile range, coefficient of variation, Gini coefficient and differentiation coefficient were then recalculated for this relative indicator. The strength of the design lies in the combination of comprehensive official coverage of the national and regional labour market with the most recent experimental evidence on AI mechanisms. Its limitation is that the statistical analysis is descriptive: changes in employment during 2022–2025 are interpreted as the context in which AI diffusion is unfolding, not as its causal consequence, and conclusions on mechanisms rest on the transferability of evidence obtained in other economies.

RESULTS

The analysis begins with the national dynamics of the labour market in the current phase of digital transformation and the diffusion of generative AI. Table 1 reports the average annual values of the main indicators calculated from monthly data for 2022–2025.

Table 1. Indicators of labour market dynamics in the Republic of Kazakhstan, 2022–2025

Indicator	2022	2023	2024	2025	Change 2025/2022
Average labour force, thousand persons	9,425.8	9,524.7	9,647.3	9,746.9	+3.41%
Average number of employed persons, thousand persons	8,966.9	9,073.8	9,197.1	9,298.2	+3.69%
Average number of unemployed persons, thousand persons	458.9	450.9	450.2	448.6	–2.2%
Employment growth rate, % to previous year	–	1.19	1.36	1.10	CAGR 1.22%
Average unemployment rate, %	4.90	4.73	4.65	4.60	–0.30 p.p.

Note. Calculated from monthly data of the Bureau of National Statistics (2026); p.p. denotes percentage points.

The labour force grew by 3.41%, and the average number of employed persons increased from 8,966.9 thousand in 2022 to 9,298.2 thousand in 2025, an increase of 331.3 thousand or 3.69%, corresponding to a compound annual growth rate of 1.22%. The average number of unemployed persons declined by 10.3 thousand, or 2.2%, and the average unemployment rate fell from 4.90% to 4.60%. Employment growth was positive in every year, at 1.19% in 2023, 1.36% in 2024 and 1.10% in 2025. These results confirm hypothesis H1: the years in which generative AI became widely available in Kazakhstan were years of employment expansion and declining unemployment, not of contraction. The economic interpretation is that the current phase of AI diffusion affects the composition of employment rather than its volume, which is consistent with the modest aggregate effects estimated for other economies and with the concentration of adjustment in

hiring rather than in separations.

National indicators, however, conceal the territorial heterogeneity of the labour market. Differences in demographic potential, economic structure, urbanization and digital infrastructure produce different employment trajectories across regions. Table 2 presents annual employment by region for 2020–2025.

Table 2. Number of employed persons by region of the Republic of Kazakhstan, thousand persons

Region	2020	2021	2022	2023	2024	2025
Republic of Kazakhstan	8,732.0	8,807.1	8,971.5	9,081.9	9,214.2	9,320.6
Abai	–	–	287.1	292.5	292.3	295.9
Akmola	398.0	397.0	421.4	407.1	401.8	400.1
Aktobe	416.4	419.8	424.7	434.9	457.9	462.6
Almaty	974.0	973.0	697.7	704.8	722.3	738.7
Atyrau	314.5	317.7	326.7	335.1	347.8	352.0
West Kazakhstan	321.0	322.3	330.9	333.3	336.8	340.2
Zhambyl	503.8	502.7	539.5	543.7	544.8	517.1
Zhetysu	–	–	319.7	309.3	296.7	294.1
Karaganda	641.8	643.4	534.8	535.8	542.7	513.4
Kostanay	466.3	475.2	453.8	449.5	439.3	430.7
Kyzylorda	329.4	330.1	330.1	331.5	334.5	336.1
Mangistau	308.4	331.7	332.7	336.7	347.4	372.1
Pavlodar	387.1	383.7	384.2	385.2	386.1	383.1
North Kazakhstan	289.3	287.3	279.1	274.5	267.7	254.9
Turkestan	779.4	777.6	792.2	800.6	817.1	830.6
Ulytau	–	–	100.9	100.9	97.3	95.5
East Kazakhstan	669.5	668.3	366.5	368.8	367.0	364.5
Astana city	563.4	580.3	625.5	658.7	685.1	764.9
Almaty city	959.3	982.8	998.0	1,045.5	1,083.0	1,120.9
Shymkent city	410.3	414.3	426.1	433.5	446.4	453.4

Note. Data from the Bureau of National Statistics (2026). The regions of Abai, Zhetysu and Ulytau were established in 2022 from parts of East Kazakhstan, Almaty and Karaganda regions, which explains the break in those series.

Employment growth is concentrated in the three cities of republican significance and in the western and southern regions. Astana added 201.5 thousand employed persons between 2020 and 2025 (+35.8%), Almaty city 161.6 thousand (+16.8%), Mangistau 63.7 thousand (+20.7%) and Turkestan 51.2 thousand (+6.6%), whereas North Kazakhstan lost 34.4 thousand (–11.9%) and Kostanay 35.6 thousand (–7.6%). The concentration of employment in metropolitan centres, where the digital economy, higher education and AI-intensive services are also concentrated, is the spatial pattern against which the youth labour market adapts. To quantify territorial differences, the regional differentiation coefficient and the dispersion indicators defined in formulas (1)–(3) were calculated for the comparable regional grid of 2022–2025 (Table 3).

Table 3. Regional differentiation of employment in the Republic of Kazakhstan, 2022–2025

Indicator	2022	2023	2024	2025
Maximum employment, thousand persons	998.0	1,045.5	1,083.0	1,120.9
Region with the maximum	Almaty city	Almaty city	Almaty city	Almaty city
Minimum employment, thousand persons	100.9	100.9	97.3	95.5
Region with the minimum	Ulytau	Ulytau	Ulytau	Ulytau
Regional differentiation coefficient (Kd), times	9.89	10.36	11.13	11.74
Regional average, thousand persons	448.58	454.10	460.70	466.04
Standard deviation, thousand persons	198.77	208.08	217.57	228.93
Coefficient of variation, %	44.31	45.82	47.23	49.12
Range, thousand persons	897.1	944.6	985.7	1,025.4
Interquartile range, thousand persons	206.73	204.93	207.00	175.15
Gini coefficient	0.232	0.238	0.245	0.252

Note. Calculated from the data in Table 2 for twenty regional units.

All indicators of dispersion increase over the period. The differentiation coefficient rose from 9.89 in 2022 to 11.74 in 2025, the coefficient of variation from 44.31% to 49.12%, the range from 897.1 to 1,025.4 thousand persons and the Gini coefficient from 0.232 to 0.252, while the interquartile range narrowed from 206.73 to 175.15 thousand persons. The combination of a rising range and a narrowing interquartile range shows that the growth of disparity is driven by the tails of the distribution, above all by the expansion of Almaty and Astana, rather than by a general dispersion of the middle regions. This result cannot be read directly as a deterioration in the labour market, because the absolute indicator reflects the large population differences between the metropolitan cities and Ulytau. To control for population size, the same indicators were recalculated for the relative employment level (Table 4).

Table 4. Regional differentiation of the relative employment level in the Republic of Kazakhstan

Indicator	2022	2024	Change
Coefficient of variation, %	5.69	6.16	+0.47 p.p.
Range of regional values, percentage points	15.70	18.12	+2.42
Gini coefficient	0.0318	0.0341	+0.0023
Regional differentiation coefficient (Kd), times	1.275	1.320	+0.045

Note. Calculated from the data of the Bureau of National Statistics (2026); p.p. denotes percentage points.

The relative indicators confirm the direction of change while reducing its scale. The coefficient of variation of the relative employment level rose from 5.69% in 2022 to 6.16% in 2024, the range from 15.70 to 18.12 percentage points, the Gini coefficient from 0.0318 to 0.0341 and the differentiation coefficient from 1.275 to 1.320. Interregional disparity in employment intensity is therefore low but persistent and not narrowing, which confirms hypothesis H₂. The economic significance of this result for the youth labour market is that the same intensity of AI adoption will produce different outcomes across territories: in regions with a more developed digital economy, AI can expand opportunities for young people through new professional roles, remote work and entrepreneurship, whereas in regions with limited opportunities for professional and digital adaptation the automation of standardized functions may widen the gap between the qualifications of young workers and employer requirements.

The long-run trajectory of employment places these changes in context (Figure 1). The number of employed persons rose from 8,114.2 thousand in 2010 to 9,320.6 thousand in 2025, an increase of 1,206.4 thousand or 14.9%. The trend was not uniform: after rising to 8,570.6 thousand in 2013, the indicator fell to 8,433.3 thousand in 2015, then began a steady recovery. Growth has been particularly pronounced since 2020, from 8,732.0 thousand to 9,320.6 thousand, an increase of 588.6 thousand (6.7%), coinciding with the acceleration of digital transformation and the arrival of generative AI.

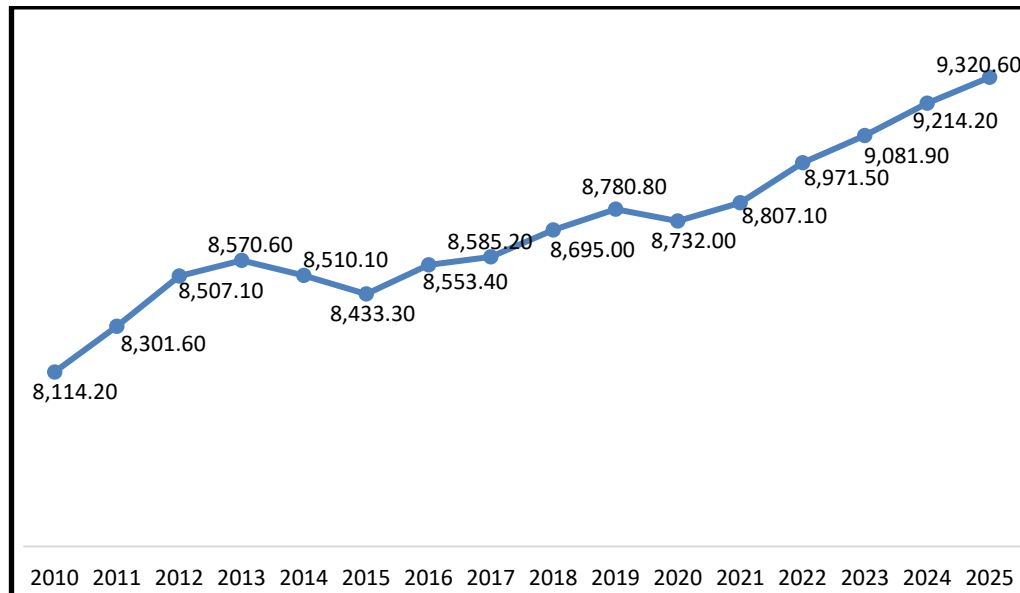


Figure 1. Number of employed persons in the Republic of Kazakhstan in 2010–2025, thousand persons (data of the Bureau of National Statistics, 2026)

Hypotheses H₃, H₄, and H₅ were evaluated by comparing these results with the coded evidence from the synthesis and the content of the strategic documents. The Concept for Labour Market Development for 2024–2029 and the Concept for the Development of Artificial Intelligence for 2024–2029 both prioritize the development of digital competencies, the alignment of vocational education with employer demand, lifelong learning and the support of youth employment, and both treat AI as an instrument of productivity rather than as a threat to employment. The coded studies were consistent in three respects. All experimental studies of generative AI found the largest productivity gains among the least experienced workers, which supports the augmentation mechanism of H₃; all studies of exposure found that adjustment is concentrated in occupations dominated by standardized cognitive and clerical tasks and in hiring rather than separations, which supports the substitution mechanism of H₃ and hypothesis H₄. All studies of skill demand found that the returns to AI tools depend on transferable analytical, managerial and social skills and on training, which supports hypothesis H₅. Table 5 summarises the verification of the hypotheses.

Table 5. Summary of hypothesis verification

Hypothesis	Evidence used	Result
H₁. Employment growth and declining unemployment during AI diffusion	Monthly national data 2022–2025 (Table 1)	Supported
H₂. Persistent and moderately increasing regional disparities	Regional data 2022–2025 (Tables 3 and 4)	Supported
H₃. Dual substitution and augmentation effect of AI on youth	Synthesis of experimental and exposure studies; Table 1	Supported
H₄. Highest vulnerability of entry-level standardized cognitive roles	Synthesis of exposure and early-career studies	Supported, requires micro-data for Kazakhstan
H₅. Adaptability through combined digital and transferable skills and lifelong learning	Synthesis of skill-demand studies; content analysis of national concepts	Supported, requires micro-data for Kazakhstan

The verification shows that the statistical evidence for Kazakhstan directly supports H₁ and H₂; that the mechanisms in H₃ are consistent with both the national data and the international evidence; and that the synthesis supports H₄ and H₅ but requires regional- or individual-level data on youth employment by occupation to be tested econometrically for Kazakhstan.

DISCUSSIONS

The results support the primary hypotheses H₁ and H₂ and are consistent with the secondary hypotheses H₃, H₄ and H₅. The finding that employment in Kazakhstan grew by 3.69% and unemployment fell by 2.2% during 2022–2025 parallels the absence of economy-wide displacement reported for the United States by Brynjolfsson, Chandar, and Chen (2025) and the modest aggregate effects estimated by Hampole et al. (2025) and Acemoglu (2025). It is also consistent with the ARDL evidence of Barzhaksyyeva et al. (2026) that digitalisation lowers youth unemployment in the short run and with the long-run decline in youth unemployment documented by Baidalinova et al. (2026). The interpretation offered here is that the Kazakhstani economy is in the phase in which AI changes the composition of tasks and the requirements for entrants faster than it changes the number of jobs, so that the burden of adjustment falls on the qualification of young workers rather than on aggregate employment.

The growth of regional disparity qualifies this optimistic aggregate picture. The rise of the differentiation coefficient from 9.89 to 11.74 and of the Gini coefficient from 0.232 to 0.252, together with the concentration of employment growth in Astana and Almaty, extends the finding of Kurmanov et al. (2023) that human capital rather than infrastructure drives regional labour markets, and the finding of Togaibayeva et al. (2026) that ICT spending explains regional productivity growth. It also resonates with the international evidence that the benefits of generative AI accrue first to those already better positioned (Humlum & Vestergaard, 2025) and that exposure differs sharply between richer and poorer contexts (Gmyrek et al., 2025). For Kazakhstan, the implication is that a single national policy for youth adaptation to AI will reproduce, rather than correct, the metropolitan concentration of opportunities unless it is differentiated by region, which is a direct concern of SDG 10.

The dual mechanism in H₃ reconciles findings that have often been presented as contradictory. The augmentation evidence of Noy and Zhang (2023), Brynjolfsson, Li, and Raymond (2025), Cui et al. (2025) and Dell’Acqua et al. (2026) and the substitution evidence of Hui et al. (2024) and Brynjolfsson, Chandar, and Chen (2025) describe the same technology acting on different tasks: generative AI raises the productivity of novices in tasks they still perform and removes the tasks that previously served as the training ground for novices. This is why entry-level roles are vulnerable even as experienced workers in the same occupation gain, and why that vulnerability is expressed in hiring rather than dismissals. The meta-analytic finding is that human–AI combinations underperform the better of the two on average (Vaccaro et al., 2024). The boundary effect identified by Dell’Acqua et al. (2026) shows that the augmentation gain is contingent on the capacity to evaluate AI output critically, a skill young workers must acquire through education rather than through experience they do not yet have. The results of Alabri and Shannaq (2025) and Shannaq et al. (2025), in which soft skills mediate most of the effect of AI tools on employability and durable competencies are analytical and emotional rather than narrowly technical, support the same conclusion, as does the finding of Green (2024) that management and business skills dominate demand in AI-exposed occupations.

The findings also explain why the volume of educational output is an insufficient policy lever. Ramazanova et al. (2026) show that the correlation between degree holders and productivity nearly vanishes in growth rates, and Arynova et al. (2025) and Berdibekov et al. (2026) document persistent mismatch between graduates and vacancies. In the terms of this study, the education system produces the quantity of human capital that H₅ requires but not yet its composition. The evidence that training is the decisive channel for the benefits of AI in organizations (Shannaq & Alabri, 2025; Mollah et al., 2026) and that digital literacy conditions the adoption of digital services (Islam & Khan, 2024) points to the same priority: the integration of AI use, data skills and critical evaluation into curricula and into workplace-based learning. At the same time, the risk that AI-based recruitment reproduces discrimination (Sony et al., 2025) and that platform work reproduces precarity (Debnath et al., 2026) indicates that the institutional mediation examined by Brioscú et al. (2024), Ball et al. (2023) and Ingold et al. (2025) will determine whether the augmentation mechanism is available to all young people or only to those in metropolitan labour markets with the relevant skills.

The theoretical significance of the results lies in specifying the task-based framework for a resource-based, regionally heterogeneous emerging economy: the balance between substitution and augmentation depends not only on the task content

of occupations but on the regional capacity of human capital to adapt, so that spatial disparity is a moderator of the effect of AI on youth employment. The practical significance is that adaptation policy should be targeted at entry-level segments and at lagging regions rather than at the labour market as a whole. Several problems remain unresolved. The analysis cannot establish AI's causal contribution to the observed changes in employment because the same period saw post-pandemic recovery, administrative reform, and strong growth in metropolitan cities. The regional data do not separate young workers from the total employed, and no comparable measure of occupational AI exposure exists for Kazakhstan to those used by Eloundou et al. (2024) or Gmyrek et al. (2025). Whether the U-shaped relationship between connectivity and the gender gap found by Baidalinova et al. (2026) also holds for AI adoption, and whether the short-run gains from digitalization identified by Barzhaksyyeva et al. (2026) persist as generative AI matures, are open questions that this study raises but cannot answer.

CONCLUSIONS

The purpose of this study was to assess the impact of artificial intelligence and digital transformation on Kazakhstan's youth labour market, identify the opportunities and risks they generate, and determine directions for adapting youth human capital to changing labour market demands. The study established that the current phase of AI diffusion in Kazakhstan is a phase of employment growth and declining unemployment, that interregional disparities in employment are persistent and moderately widening, driven by the expansion of the metropolitan cities, and that the effect of AI on young people operates through two mechanisms at once: the substitution of standardized cognitive tasks that previously formed the entry points into professions, and the augmentation of inexperienced workers whose productivity AI raises most. The main conclusion is that the challenge for youth is not displacement by technology but the widening gap between the pace at which AI transforms the content of work and the pace at which human capital, the education system and employment institutions adapt, and that this gap is larger in the regions than in the capitals.

The paper's unique contribution is threefold. It links the most recent experimental and exposure evidence on generative AI to the national and regional employment statistics of Kazakhstan for the first time; it introduces spatial disparity as a moderator of the effect of AI on the youth labour market; and it integrates the substitution and augmentation mechanisms with the priorities of the national concepts on the labour market and on AI.

Theoretically, the results indicate that the task-based framework must be extended to include a regional dimension when applied to emerging economies. For management and policy, the results imply a shift from reacting to skills shortages toward the proactive management of youth human capital: fostering AI literacy, data skills and the critical evaluation of AI output within educational programs; expanding dual education, internships and other entry pathways that replace the automated tasks through which young people formerly gained experience; developing reskilling programs differentiated by region; monitoring the professions and job functions most exposed to AI; and ensuring that AI-based recruitment and profiling in public and private employment services do not create new barriers for young applicants.

The study has limitations. Its statistical analysis is descriptive and covers a short period marked by post-pandemic recovery and administrative reform, so the observed changes cannot be attributed causally to AI. The regional data do not disaggregate by age, and no national measure of occupational AI exposure was available. The evaluation of the mechanisms rests on evidence from other economies whose transferability to Kazakhstan is assumed rather than tested. Future research should construct an occupational AI-exposure index for Kazakhstan, apply regional panel models that link youth employment and NEET rates to digitalization, digital literacy and ICT development, use individual-level data to test the vulnerability of entry-level roles and the returns to combined digital and transferable skills, and examine gender differences in the adoption of AI among young workers.

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