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DIGITAL TRANSFORMATION AND THE GENDER GAP IN YOUTH EMPLOYMENT: FEMALE LABOUR FORCE PARTICIPATION, HUMAN CAPITAL AND DECENT WORK IN KAZAKHSTAN, 2005–2024

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ABSTRACT

Digital transformation has altered the structure of labour demand and the conditions under which young people enter employment. Yet its gains are not shared equally between young men and young women, and gender inequality continues to limit the realization of youth human capital. This study examines how digitalization and human capital jointly shape youth employment outcomes and the gender gap in youth unemployment in the Republic of Kazakhstan, and constructs a composite measure of youth labour market readiness for the digital economy. The study employs annual time-series data for Kazakhstan spanning twenty years, from 2005 to 2024, drawn from the World Bank World Development Indicators, modelled International Labour Organisation estimates and the Bureau of National Statistics, and applies comparative and economic-statistical analysis, Pearson correlation, ordinary least squares regression with Newey–West standard errors, min–max normalization with linear aggregation, and trend extrapolation to 2030. The results show that female unemployment among young people exceeded male unemployment in every year of the period, declining from 13.97 to 4.94 percent for young women and from 11.60 to 2.87 percent for young men; the gender gap narrowed from 2.37 to 0.35 percentage points by 2017 and then widened again to 2.07 points by 2024. Internet penetration enters the gender-gap equation with negative linear and positive quadratic coefficients, implying a U-shaped relationship with a turning point at 49.1 percent . The composite index rose from 0.109 to 0.844, while the male–female index gap widened from −0.077 to 0.125.

INTRODUCTION

The reorganization of work around digital technologies has become one of the defining structural processes of the present decade, and its consequences fall with particular force on those entering the labour market for the first time. The World Economic Forum (2025a) estimates that structural labour-market churn will affect 22% of formal jobs by 2030, with 170 million positions created and 92 million displaced, and that 39% of the skills required of workers will be transformed over the same horizon. For young people, who possess neither seniority nor accumulated firm-specific experience to cushion such transitions, these projections translate directly into altered entry conditions. The International Labour Organisation 2026) reports that the global youth unemployment rate rose to 12.4 percent in 2025, equivalent to 67 million unemployed young people, reversing the fifteen-year low of 13.0 percent recorded two years earlier (International Labour Organisation, 2024), while the share of young people not in education, employment or training climbed to twenty percent , affecting more than 257 million individuals.

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What makes this reversal a scientific problem rather than a cyclical curiosity is its uneven incidence by sex. Young women are twice as likely as young men to be outside education, employment and training (International Labour Organisation, 2026). The global gender gap across economic participation, education, health and political empowerment remains at 31.2 percent , with full parity in economic participation projected to require 135 years on current trajectories (World Economic Forum, 2025b). Digitalization is frequently presented as a corrective to such disparities, on the argument that remote and platform-mediated work loosens the geographic and temporal constraints that have historically suppressed female labour force participation. Yet the evidence assembled by the OECD (2021) shows women consistently underrepresented among information and communication technology specialists, among holders of technology-related patents, and among founders of technology firms, while Singh et al. (2025) demonstrate across ninety-three empirical studies that the constraints on women's digital inclusion differ qualitatively at the levels of access, usage and outcome. Whether digitalization narrows or widens gender disparities in youth employment is therefore an open empirical question rather than a settled one, and one whose answer plausibly depends on how far the diffusion of digital technology has already progressed.

For the Republic of Kazakhstan, this question carries particular weight. The country has undergone one of the most rapid digital transitions in the Eurasian region, and it has done so alongside a sustained programme of economic diversification in which human capital is treated as the principal instrument of long-run competitiveness (World Bank, 2026). The World Bank (2024a) documents a persistent shortfall in the share of employment that meets the criteria of quality work. The World Bank (2024b) reports that Kazakhstani children attain only 53-64 percent of their potential productivity. This shortfall carries directly into the labour market outcomes of the cohorts now entering employment. Arynova et al. (2025) identify acute vertical and horizontal skills mismatches in the country, concentrated in information technology-related and hybrid digital occupations, and marked by pronounced regional disparities. Torebekov (2026), examining youth labour market transitions in Kazakhstan, finds that unemployment among young women remains higher than among young men and that women are overrepresented in the category of those neither working nor studying, despite an aggregate improvement in labour market conditions.

The scientific problem addressed here can accordingly be stated as follows. The literature on digitalization and employment, and on gender inequality in the labour market, has largely developed in parallel. Where they intersect, they do so predominantly through cross-sectional or short-panel evidence drawn from advanced economies. There is, in consequence, no established account of how the relationship between digital diffusion and gender disparity in youth employment evolves over the full course of a national digital transition, and no quantitative instrument capable of registering, in a single comparable measure, whether improvements in the aggregate quality of a youth labour force are being shared between young men and young women. In an upper-middle-income economy that has moved from three percent to ninety-three percent internet penetration within two decades, this is a question that can be posed directly against the data, and the answer bears on whether digitalization should be understood as an instrument of gender equality or as a mechanism that reproduces existing inequality in a new register.

The study is conducted on annual time-series data for Kazakhstan covering the period from 2005 to 2024, assembled from the World Bank's World Development Indicators, modelled estimates from the International Labour Organisation, and the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. The analytical apparatus combines economic-statistical and comparative analyses; Pearson correlation; ordinary least squares regression estimated with heteroskedasticity- and autocorrelation-consistent standard errors; min–max normalization with linear aggregation to construct a composite index; and linear trend extrapolation to 2030. Recent contributions to the same journal provide the immediate methodological setting: Togaibayeva et al. (2026) regress gross value added per employee on measures of digital investment in a Kazakhstani region, and Utebaliyeva et al. (2026) analyze the transformation of regional entrepreneurship and employment through the platform economy. Dauyeshova et al. (2026) examine the conditions under which digital governance generates decent jobs in the Kazakhstani public sector.

This study aims to establish the direction and functional form of the relationship between digital diffusion, human capital and the gender gap in youth unemployment in the Republic of Kazakhstan over a twenty-year horizon, and to express the resulting gender-differentiated outcomes through a composite index of youth labour market readiness for the digital economy.

The remainder of the paper is organized as follows. The next section reviews the theoretical and empirical literature on human capital, digital transformation and gendered labour market outcomes, identifies the unresolved questions that motivate the present analysis, and states the research hypotheses. The subsequent section describes the data, variable construction, index methodology and estimation procedures. The section that follows reports the descriptive, correlation, regression, index and forecasting results. The penultimate section interprets these results in light of previous research and assesses the empirical standing of each hypothesis. The final section summarises the contribution, sets out its theoretical and managerial implications, acknowledges the limitations of the analysis and indicates directions for further work.

LITERATURE REVIEW

The literature relevant to this study converges from three directions: the theory of human capital and its returns, the analysis of technological change and labour demand, and the study of gender differentiation in labour market outcomes. Each has an established tradition, and the value of reviewing them together lies in identifying the point at which they diverge.

The theoretical foundation was laid by Vaizey and Schultz (1972), who argued that expenditure on education and health should be understood as investment yielding measurable returns rather than as consumption, thereby making the productive capacity embodied in people an object of economic analysis. Pyatt and Becker (1966) formalized the argument by distinguishing between general and firm-specific human capital and deriving the implications of that distinction for who bears the cost of training and who captures its return. Mincer (1974) provided the empirical specification linking earnings to schooling and experience, which continues to underpin applied work on returns to education. The relevance of this tradition to the present study lies in its central prediction: where human capital is accumulated but not equally deployed, the aggregate return to educational investment falls below its potential, and the shortfall is attributable to the allocation mechanism rather than to the stock itself.

The second strand concerns how technological change alters the composition of labour demand. Autor (2015) argued that automation displaces specific tasks rather than whole occupations, and that the complementarity between machines and human judgement sustains employment even as the content of work shifts, a position that reframes the policy question from job loss to skill adjustment. Acemoglu and Restrepo (2020) provided countervailing evidence from United States local labour markets, showing that industrial robot adoption had measurable negative effects on employment and wages, thereby establishing that displacement and complementarity coexist, with incidence varying by context. The tension between these positions is unresolved in the literature, and it matters here because the two accounts imply different distributional consequences for workers with weak bargaining power, a category into which labour market entrants fall by construction.

Institutional analysis has extended these arguments specifically to youth. The International Labour Organisation (2024) documented that the recovery in youth employment following the pandemic was concentrated in a limited set of regions and did not reach low-income economies, and that the share of young people outside education, employment and training stood at 20.4 percent , of whom two in three were young women. The subsequent edition (International Labour Organisation, 2026) recorded a deterioration, with youth unemployment rising to 12.4 percent and the share outside education and employment reaching 20 percent . The broader labour market assessment in the World Employment and Social Outlook (International Labour Organisation, 2026) situates these movements within a wider stagnation in job quality, noting that informality and working poverty have returned to their pre-pandemic levels. Read together, these reports establish that the aggregate improvement in youth labour market indicators recorded during the 2010s has not proved durable.

The third strand addresses gender. Goldin (2014) identified the residual gender earnings gap as arising principally from the disproportionate rewards that many occupations attach to long and inflexible hours, rather than from differences in human capital endowments, and argued that occupational restructuring toward greater temporal flexibility would more effectively compress the gap than further educational investment. This argument bears directly on digitalization, which is often expected to deliver precisely such flexibility. Ivandić and Lassen (2023), using Danish administrative data on plant closures, found that women face a risk of unemployment forty to forty-five percent greater than men following an identical displacement shock, that human capital differences account for only half of the residual gap, and that mothers experience an increase in unemployment risk approaching eighty percent greater than fathers. Their finding is important for the present study because it demonstrates that gender differentials arise from responses to structural shocks rather than solely from pre-existing endowment differences.

The intersection of gender and digitalization has generated a rapidly expanding body of empirical literature. Singh et al. (2025), synthesizing ninety-three empirical studies published between 2011 and 2025, established that economic constraints dominate the access dimension of the digital divide, that literacy gaps dominate the usage dimension, and that male domination of information technology and science fields constrains the outcome dimension, a stratification that implies interventions effective at one level will not necessarily transmit to the others. The OECD (2024) documented the resulting pattern across member economies, showing women consistently underrepresented among information and communication technology specialists and among originators of technology-related innovation. The OECD (2025) refined the diagnosis by locating the difference between men and women less in the development of skills than in how skills are sorted by field of study and rewarded through occupational concentration. Kurti et al. (2024) traced the mechanism to its origin, showing that stereotyped perceptions of information technology work deter women from entering the relevant educational pipeline in the first instance.

Research on platform work has examined whether new forms of digital employment reproduce these patterns. Urzì Brancati et al. (2020) established the scale of platform participation across European economies and its concentration among younger workers. Kim (2021) documented comparable dynamics in the Republic of Korea. Munoz et al. (2024) analyzed the mechanisms by which digital labour platforms generate new forms of inequality, showing that women are disproportionately assigned to lower-paid online tasks and face constrained progression. This finding qualifies the expectation that platform-mediated work is intrinsically levelling. Petreski et al. (2025), studying gendered labour market dynamics in developing economies, found female employment to be more responsive than male employment to macroeconomic and technological disturbances, and concluded that targeted support mechanisms are required if women are not to bear a disproportionate share of adjustment costs.

Research on Kazakhstan and comparable transition economies has developed along parallel lines. Tulegenova and Tuleibayeva (2019) offered an early conceptual treatment of labour market transformation amid digitalization, highlighting the risk of skilled labour outflow. The factors shaping the development of regional labour markets in the digital economy were identified, and digital infrastructure was found to be a determinant of regional employment resilience. Insebayeva and Beyssembayev (2023) analyzed platform employment in Kazakhstan within the framework of precarious labour and capitalist transformation, noting that the expansion of self-employment through digital platforms lowers entry barriers while leaving social protection unresolved. Kuttybayeva et al. (2024) identified platform employment as the principal trend reshaping the Kazakhstani labour market, with effects concentrated in the small- and medium-enterprise sector. Suieubayeva et al. (2023) examined digital entrepreneurship as an outcome of labour market transformation, emphasizing the expansion of self-employment opportunities.

Khussainova et al. (2023) addressed the generation of productive youth employment in Kazakhstan and the reduction of the population outside education and employment, demonstrating that the youth labour market is markedly heterogeneous and strongly conditioned by educational attainment. Beisembina et al. (2025) found that the structure of employment in Kazakhstan is adjusting more slowly than the pace of economic transformation requires, implying a widening gap between the competencies supplied and those demanded. Serikkyzy et al. (2025), analyzing intergenerational dynamics, found that the youngest cohort exhibits higher digital literacy and mobility than its predecessors, while continuing to show differences between young men and young women in income, access to digital occupations, and career progression. Arynova et al. (2025) quantified the resulting mismatch, identifying its most acute expression in information technology-related and hybrid digital roles.

Evidence published in this journal bears directly on the present analysis. Togaibayeva et al. (2026) regressed the growth of gross value added per employee on digital and fixed-asset investment for a Kazakhstani region. They established a positive association between digitalization and labour productivity, providing the closest available methodological precedent for the productivity specification estimated below. Utebaliyeva et al. (2026) analyzed the platform economy as an instrument for regional entrepreneurship and employment transformation that aligns with sustainable development objectives. Dauyeshova et al. (2026) examined the conditions under which digital governance produces decent jobs in the civil service. Aitzhanova et al. (2026) traced comparable dynamics in the tourism sector, and Islam et al. (2026) reviewed the macroeconomic environment within which such sectoral adjustments occur. Shannaq et al. (2025) applied machine-learning classification to assess occupational exposure to automation, and Alabri and Shannaq (2025) established that artificial intelligence tools improve employability outcomes through the mediating channel of soft skills. Laskar et al. (2024) demonstrated that women entrepreneurs' engagement with digital marketing varies systematically with education and business tenure, and Ara (2021) examined the financing strategies that women entrepreneurs use to pursue growth in a developing economy. Uddin (2023) analyzed the managerial competencies underpinning entrepreneurial success among young founders.

Three observations follow from this body of work. First, the relationship between digitalisation and labour productivity is well established, and the relationship between digitalisation and aggregate youth employment is documented in several national settings. Still, the two are rarely estimated jointly, with the gender composition of outcomes treated as the dependent variable rather than as a control. Second, where gender differentials in the digital economy have been examined, the evidence is overwhelmingly cross-sectional or drawn from short panels, which precludes any assessment of whether the relationship is stable in form across the course of a digital transition; the possibility that the effect of digital diffusion on gender disparity changes sign as penetration deepens has not, to the knowledge of the authors, been tested. Third, composite indicators of human capital and labour market readiness are typically constructed at the aggregate level, so that a divergence between male and female outcomes occurring beneath an improving headline figure remains invisible to the measure itself.

These considerations define the purpose of the present study, which is to determine the direction, magnitude and functional form of the relationship between digital diffusion, human capital and the gender gap in youth unemployment in the Republic of Kazakhstan across the twenty years from 2005 to 2024, and to construct a gender-differentiated composite index capable of registering whether aggregate improvements in youth labour market quality are shared between young men and young women. Based on the theoretical arguments and empirical findings reviewed above, the following hypotheses are advanced:

H_1: Digital diffusion is associated with reductions in youth unemployment and increases in labour productivity in Kazakhstan over the period 2005–2024.

H_2: Female youth unemployment exceeds male youth unemployment in every year of the period, so that the gender disadvantage in youth labour market entry is persistent rather than episodic.

H_3: The relationship between digital diffusion and the gender gap in youth unemployment is non-linear and U-shaped: the gap narrows during the early phase of digital adoption and widens once penetration crosses a threshold.

H_4: The marginal association between digital diffusion and youth unemployment varies by sex, so the returns to digitalization in the youth labour market are not gender-neutral.

H_5: The composite index of youth labour market readiness improves over the period in aggregate while the male–female differential within the index widens, indicating that gains in human capital utilization are unequally distributed by sex.

MATERIALS AND METHODS

The study is based on an annual national time series for the Republic of Kazakhstan, covering the 20 years from 2005 to 2024, inclusive. The observation unit is the country-year, and the series is balanced, with no missing values for any variable included in the estimated models. The principal source is the World Bank's World Development Indicators, which harmonizes modelled estimates of labour force variables from the International Labour Organisation and telecommunications data from the International Telecommunication Union for digital diffusion. National-account and labour-force aggregates published by the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan are used to cross-check the reported figures below and to interpret the estimates at the institutional level.

One definitional matter requires explicit statement, because it governs the comparability of every figure reported in this paper. The national statistical definition of youth in Kazakhstan covers persons aged fifteen to thirty-four, following the amendment that took effect on the first of January 2023 and raised the upper bound from twenty-eight years. The international definition used by the International Labour Organisation and reproduced in the World Development Indicators covers persons aged 15 to 24. The two definitions yield materially different unemployment rates for the same year, of the order of three percent under the national definition against approximately 3.8 percent under the international definition for 2024. All estimation in this study uses the international fifteen-to-twenty-four definition because only that definition is consistently available across the full twenty-year window; national figures are reported separately and are not included in the estimation sample.

The dependent variables are, in the first specification, a real labour productivity index; in the second, the youth unemployment rate; in the third, the gender gap in youth unemployment; and in the fourth pair of specifications, the female and male youth unemployment rates estimated separately. The explanatory variables are the rate of digital diffusion, measured by the share of individuals using the internet; labour force participation, entered in aggregate and sex-specific forms; and the labour productivity index, which is not the dependent variable. Table 1 sets out the definition, construction and source of each variable.

Table 1. Variable definitions, and construction

Symbol	Variable	Definition and Construction
YU	Youth unemployment rate	Unemployed persons aged 15–24 as a percentage of the youth labour force
YUF	Female youth unemployment	Unemployed women aged 15–24 as a percentage of the female youth labour force
YUM	Male youth unemployment	Unemployed men aged 15–24 as a percentage of the male youth labour force
GGAP	Gender gap in youth unemployment	YUF minus YUM, in percentage points
RATIO	Relative gender disadvantage	YUF divided by YUM
U	Total unemployment rate	Unemployed as a percentage of the total labour force
LFPR	Labour force participation	Labour force as a percentage of population aged 15 and over
FLFP	Female labour force participation	Female labour force as a percentage of female population aged 15 and over
MLFP	Male labour force participation	Male labour force as a percentage of male population aged 15 and over
GPI	Participation parity index	FLFP divided by MLFP
DIG	Digital diffusion	Individuals using the internet, percentage of population
LP	Labour productivity index	Real GDP index (2005 = 100) divided by the employment index (2005 = 100), multiplied by 100
HCTI	Human Capital and Talent Index	Weighted linear aggregation of five min–max normalized components

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The labour productivity index requires comment, since it is the one substantive derivation in the dataset. Gross value added per employed person is not published for Kazakhstan consistently over the full twenty-year window, and the series expressed in current United States dollars is severely distorted by the tenge devaluations of 2015 and 2016, which reduce the dollar value of output without any corresponding change in physical productivity. A real index is therefore constructed. Real gross domestic product is cumulated from the annual real growth rate with 2005 set to 100; employment is obtained as the labour force multiplied by one minus the unemployment rate and is likewise indexed to 2005; and labour productivity is the ratio of the two indices, expressed in index points. The resulting series is invariant to exchange-rate movements and price-level changes, and it measures the growth of output per worker relative to the base year.

The composite Human Capital and Talent Index is constructed in three steps. Each component is first normalized using a min–max transformation, so that all components are scaled to the interval [0, 1] and rendered comparable despite their differing units. For components that contribute positively to labour market quality, the transformation is

$$X_{i,\text{ norm}} = \frac{X_i - X_{\min}}{/(X_{\max} - X_{\min}}) \ (1)$$

and for components that contribute negatively, that is, for disincentive indicators, the transformation is

$$X_{i,\text{ norm}} = \frac{(X_{\max} - X_i}{)/(X_{\max} - X_{\min}}) \ (2)$$

The normalized components are then combined by linear aggregation with expert weights, giving.

$$\text{HCTI} = 0.25 \cdot \text{LP}_{\text{norm}} + 0.25 \cdot \text{DIG}_{\text{norm}} + 0.20 \cdot \text{LFPR}_{\text{norm}} + 0.15 \cdot \text{YU}_{\text{norm}} + 0.15 \cdot \text{GPI}_{\text{norm}}$$

where LP is the labour productivity index, DIG is digital diffusion, LFPR is labour force participation, YU is youth unemployment entered as a disincentive, and GPI is the participation parity index. The weighting scheme assigns the largest shares to productivity and digital capability, on the argument that these two determine the level of labour market performance attainable; a lower weight to aggregate participation, which registers the extent to which that potential is mobilized; and equal residual weights to youth unemployment and to gender parity, which register the efficiency and the equity of that mobilization respectively. Table 2 sets out the weights and their justification.

Two sex-specific variants of the index are constructed in parallel. In each case, the gender-parity component is removed because it is not defined for a single sex, and the participation and youth unemployment components are replaced with their male or female counterparts; the four remaining weights are rescaled to sum to unity. The male–female difference between these variants, denoted HGAP, is the measure used to assess the distribution of index gains between the sexes.

Table 2. Composite index components, weights and justification

Component	Weight	Justification
Labour productivity index	0.25	Determines the level of output per worker attainable by the labour force
Digital diffusion	0.25	Registers the technological capability on which digital-economy employment depends
Labour force participation	0.20	Registers the extent to which available human capital is mobilized
Youth unemployment (disincentive)	0.15	Registers the efficiency with which entrants are absorbed into employment
Participation parity index	0.15	Registers the equity with which human capital is mobilized across the sexes

Note. Weights sum to unity. In the sex-specific variants, the parity component is omitted, and the remaining four weights are rescaled proportionally to 0.294, 0.294, 0.235 and 0.176.

Estimation proceeds by ordinary least squares. Given a sample of twenty annual observations, the specifications are deliberately parsimonious, admitting at most three regressors, and the results are subjected to four diagnostic checks. The coefficient of determination and the F statistic assess overall explanatory adequacy. The Durbin–Watson statistic assesses residual autocorrelation, which is expected in annual macroeconomic series and which, where present, biases conventional standard errors downward. Newey–West heteroskedasticity- and autocorrelation-consistent standard errors are therefore reported alongside the conventional errors, computed with a Bartlett kernel and a truncation lag of two, and inference is conducted on the robust errors. Variance inflation factors assess multicollinearity. In the quadratic specification, the digital diffusion term is centred on its sample mean before forming the square, which reduces the inflation induced by the algebraic dependence between a variable and its square without altering the fitted values, the turning point, or the coefficient on the quadratic term. First-differenced specifications are estimated as a robustness check against spurious association arising from common trends.

The forecasting procedure employs linear trend extrapolation to 2030. Two estimation windows are used, and the distinction between them is consequential. For the composite index and the labour productivity series, which display approximately monotone behaviour, the trend is fitted over the full twenty-year window. For the sex-specific youth unemployment series and the gender gap, the trend is fitted only over the sub-period from 2013 to 2024. The reason is that the full-sample trend for these variables is dominated by the steep convergence of the years 2005 to 2012 and extrapolates to negative unemployment rates before 2030, which is not an admissible projection; the post-2012 window corresponds to the structurally stable regime identified in the descriptive analysis and yields projections within the feasible range. Projections of digital diffusion are capped at 100% to respect the saturation bound. All projections are conditional on the continuation of the estimated trend and are presented as such rather than as forecasts incorporating behavioural response.

All computations were performed in Python using the NumPy and pandas libraries, with regression estimated via least-squares decomposition and the Newey–West covariance matrix computed directly from the residuals. The complete dataset accompanies this paper as a supplementary spreadsheet.

RESULTS

The descriptive characteristics of the twenty-year series are reported in Table 3. Youth unemployment averaged 5.36 percent over the period with a standard deviation of 2.72 percentage points, a dispersion that reflects the steep decline of the first eight years rather than volatility around a stable mean. The mean gender gap of 1.32 percentage points, with a range from 0.35 to 2.67 points, indicates that the disadvantage faced by young women varied by more than a factor of 7 over the period, while never reversing in sign. Digital diffusion spanned almost the entire feasible range, from 2.96 to 93.39 percent , which makes the functional form of its relationship with the gender gap identifiable in this sample. Female labour force participation, by contrast, moved within a band of barely three percentage points, from 63.61 to 66.72 percent , and the participation parity index remained between 0.844 and 0.876 throughout, indicating that the aggregate structure of female participation proved highly resistant to change over two decades of otherwise rapid transformation.

Table 3. Descriptive statistics, Republic of Kazakhstan, 2005–2024

Variable	Mean	Std. dev.	Minimum	Maximum	Obs.
Youth unemployment, total (%)	5.358	2.715	3.760	12.710	20
Youth unemployment, female (%)	6.062	2.958	3.980	13.970	20
Youth unemployment, male (%)	4.746	2.534	2.860	11.600	20
Gender gap in youth unemployment (pp)	1.316	0.804	0.350	2.670	20
Labour force participation, total (%)	70.312	0.543	69.200	71.120	20
Female labour force participation (%)	65.339	0.816	63.610	66.720	20
Participation parity index	0.860	0.009	0.844	0.876	20
Digital diffusion (%)	57.546	33.153	2.960	93.390	20
Labour productivity index (2005 = 100)	142.791	22.941	100.000	176.852	20
Human Capital and Talent Index	0.607	0.187	0.109	0.844	20

Note. Percentage points are abbreviated as pp. All series are annual and cover twenty consecutive years without interruption.

Table 4 reports the sex-disaggregated youth unemployment series in full, along with the gap and the ratio, and on this table rests the study's central descriptive finding. Female youth unemployment exceeded male youth unemployment in every one of the twenty years, without a single exception. The disadvantage is therefore structural rather than cyclical, and it survived a period in which both rates fell by approximately nine percentage points.

Table 4. Youth unemployment by sex, gender gap and relative disadvantage, 2005–2024

Year	Total (%)	Male (%)	Female (%)	Gap (pp)	Ratio (F/M)
2005	12.71	11.60	13.97	2.37	1.204
2006	11.18	10.19	12.30	2.11	1.207
2007	9.35	8.50	10.30	1.80	1.212
2008	7.39	6.71	8.15	1.44	1.215
2009	6.68	5.42	8.09	2.67	1.493
2010	5.22	4.77	5.71	0.94	1.197
2011	4.58	4.17	5.04	0.87	1.209
2012	3.94	2.90	5.11	2.21	1.762
2013	3.92	3.63	4.26	0.63	1.174
2014	3.84	3.58	4.13	0.55	1.154
2015	3.76	3.54	4.02	0.48	1.136
2016	3.81	3.61	4.03	0.42	1.116
2017	3.79	3.63	3.98	0.35	1.096
2018	3.78	3.59	3.99	0.40	1.111
2019	3.77	3.56	4.01	0.45	1.126
2020	3.78	3.45	4.17	0.72	1.209
2021	4.22	3.46	5.12	1.66	1.480
2022	3.82	2.87	4.96	2.09	1.728
2023	3.81	2.86	4.95	2.09	1.731
2024	3.82	2.87	4.94	2.07	1.721

Note. Ages 15 to 24, modelled estimates of the International Labour Organisation as harmonized in the World Bank World Development Indicators. The gap is the female rate minus the male rate, expressed in percentage points; the ratio is the female rate divided by the male rate.

The trajectory of the gap divides into three regimes. Across 2005 to 2012, it averaged 1.80 percentage points; across 2013 to 2019, it averaged 0.469 percentage points, reaching a minimum of 0.35 percentage points in 2017; and across 2020 to 2024, it averaged 1.73 percentage points, peaking at 2.07 percentage points in the final year. The relative measure is more striking still. In 2017 young women were 1.10 times as likely as young men to be unemployed; by 2024 they were 1.72 times as likely. The convergence achieved over the first twelve years of the period was thus not merely halted but substantially reversed within four years, and the reversal occurred while the aggregate youth unemployment rate remained essentially unchanged at approximately 3.8 percent . Figure 1 displays the two series with the gap shaded between them.

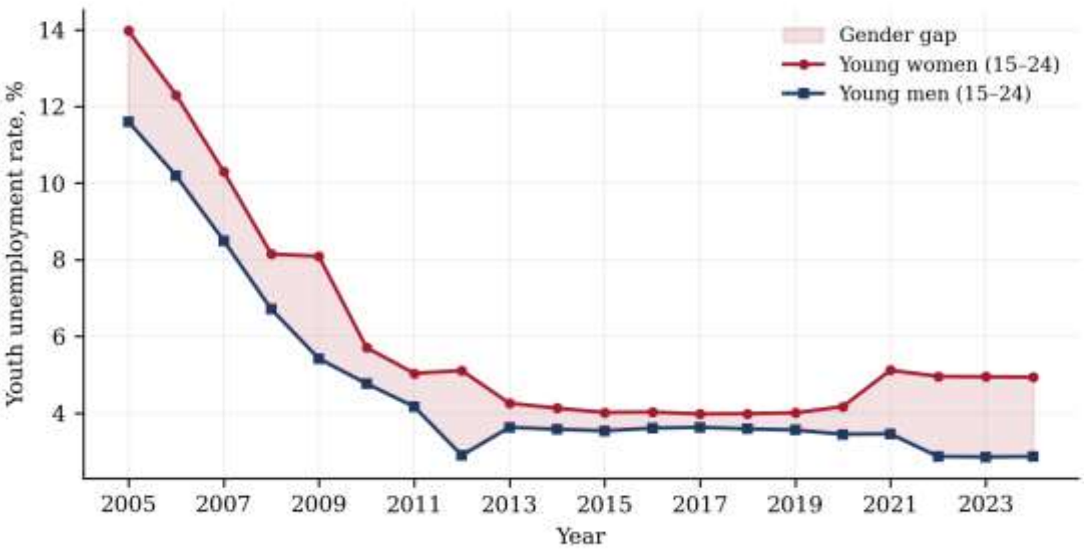

Figure 1. Youth unemployment by sex, Republic of Kazakhstan, 2005–2024

The correlation matrix is reported in Table 5. Labour productivity and digital diffusion are strongly associated, with a coefficient of 0.975, reflecting the common upward trend in both series and signalling in advance that the two cannot be entered as separate regressors without inflating the variance of their coefficients. Both are strongly negatively associated with youth unemployment, at −0.829 and −0.872 respectively. The correlation between digital diffusion and the gender gap is, however, only −0.372, which is weak relative to the other associations in the matrix and which, taken at face value, would suggest that digital diffusion bears little relation to gender disparity. The regression results demonstrate that this inference would be mistaken and that the weak linear correlation is a consequence of the underlying relationship's non-monotonicity.

Table 5. Pearson correlation matrix, 2005–2024

Variable	LP	DIG	LFPR	FLFP	YU	YUF	YUM	GGAP
Labour productivity (LP)	1.000							
Digital diffusion (DIG)	0.975	1.000						
Participation (LFPR)	−0.182	−0.191	1.000					
Female participation (FLFP)	−0.511	−0.510	0.928	1.000				
Youth unemployment (YU)	−0.829	−0.872	−0.213	0.100	1.000			
Female youth unemp. (YUF)	−0.804	−0.852	−0.196	0.106	0.992	1.000		
Male youth unemp. (YUM)	−0.837	−0.876	−0.231	0.088	0.992	0.969	1.000	
Gender gap (GGAP)	−0.321	−0.372	0.009	0.112	0.523	0.625	0.412	1.000
Parity index (GPI)	−0.798	−0.793	0.658	0.890	0.466	0.464	0.456	0.268

Note. Coefficients are Pearson product-moment correlations computed on twenty annual observations. The matrix is symmetric, and the upper triangle is omitted.

The regression results are reported in Table 6. Model 1 explains the labour productivity index and accounts for 95.45 percent of its variance, with an F statistic of 111.87. Digital diffusion carries a coefficient of 0.818, significant at the one percent level under robust standard errors, indicating that each additional percentage point of internet penetration is associated with an increase of approximately 0.82 index points in output per worker; across the observed range of ninety percentage points, this corresponds to the greater part of the seventy-seven percent cumulative productivity gain recorded over the period. Neither female participation nor youth unemployment is significant in this specification, and the variance inflation factor of 17.00 for digital diffusion indicates that the estimate should be interpreted as the association between the general process of digital transformation and productivity, rather than as the isolated effect of internet access alone.

Model 2 explains youth unemployment and accounts for 92.17 percent of its variance. Digital diffusion enters with a coefficient of −0.116, significant at the one percent level, so that each additional 10-percentage-point increase in penetration is associated with a reduction of approximately 1.16 percentage points in the youth unemployment rate. Aggregate participation enters with a coefficient of −1.983, which is also significant at the one percent level. The productivity index is not significant once digital diffusion is controlled, which is consistent with the two variables capturing a common underlying process.

Model 3 is the central specification of the study. The gender gap in youth unemployment is regressed on digital diffusion, its square and female participation, with the diffusion term centred on its sample mean. The linear term carries a coefficient of −0.0869 and the quadratic term a coefficient of 0.00088, both significant at the one percent level under robust standard errors, and the variance inflation factors of 4.08 and 3.03 confirm that the centring has removed the collinearity that would otherwise attend a quadratic specification. The signs are those of a convex function with an interior minimum, and the implied turning point lies at 49.12 percent internet penetration, a level Kazakhstan attained in 2011. The specification explains 54.42 percent of the variance in the gender gap, a figure that is modest in absolute terms but substantial for a differenced outcome variable of this kind, and the Durbin–Watson statistic of 1.721 indicates that the residuals of this specification are, unlike those of the level regressions, close to serially independent. Figure 2 plots the observed pairs against the fitted quadratic.

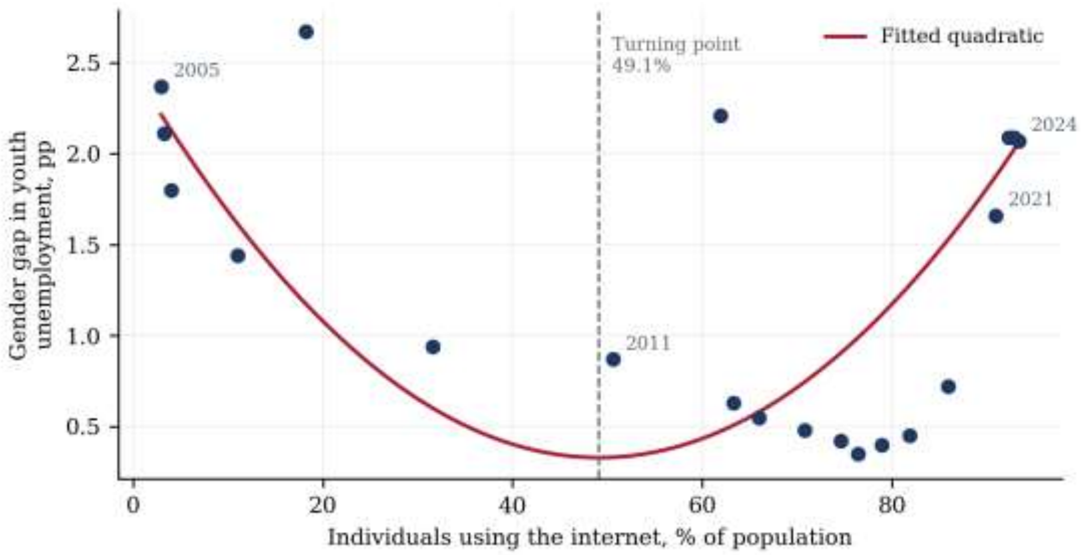

Figure 2. Digital diffusion and the gender gap in youth unemployment, with fitted quadratic and estimated turning point

Models 4a and 4b estimate the female and male youth unemployment rates separately on digital diffusion and the corresponding sex-specific participation rate. Digital diffusion carries coefficients of −0.0962 in the female equation and −0.0548 in the male equation, both significant at the 1% level. The difference between them is substantial in proportional terms: the marginal association for young women is 1.76 times that for young men. This asymmetry is the mechanism generating the U-shaped relationship. Because the female rate began the period 2.37 percentage points above the male rate, a larger marginal association was required merely to close the gap; the convergence observed to 2017 is the consequence of that larger association operating on a higher base. Once the female rate approached the male rate, however, the same asymmetry could not sustain further convergence, and the subsequent divergence indicates that the mechanism through which digitalization reduced female youth unemployment during the diffusion phase ceased to operate as penetration approached saturation.

Table 6. Ordinary least squares regression results, 2005–2024

Model and regressor	Coefficient	Std. error	Newey–West t	VIF
Model 1. Dependent variable: labour productivity index				
Constant	−46.564	213.518	−0.231	—
Digital diffusion	0.818	0.152	5.096***	17.00
Female participation	2.042	3.041	0.712	4.11
Youth unemployment	1.649	1.606	0.980	12.70
R^2 = 0.9545; adjusted R^2 = 0.9460; F = 111.87; DW = 0.875; n = 20				
Model 2. Dependent variable: youth unemployment rate				
Constant	143.321	25.339	3.623***	—
Digital diffusion	−0.116	0.026	−5.169***	20.59
Labour force participation	−1.983	0.356	−3.806***	1.04
Labour productivity index	0.057	0.038	1.358	20.52
R^2 = 0.9217; adjusted R^2 = 0.9070; F = 62.76; DW = 0.801; n = 20				
Model 3. Dependent variable: gender gap in youth unemployment				
Constant	−30.695	16.218	−2.451**	—
Digital diffusion (centred)	−0.087	0.021	−4.499***	4.08
Digital diffusion squared	0.00088	0.00024	4.408***	3.03
Female participation	0.476	0.248	2.643***	2.22
R^2 = 0.5442; adjusted R^2 = 0.4587; F = 6.37; DW = 1.721; turning point = 49.12%; n = 20				
Model 4a. Dependent variable: female youth unemployment rate				
Constant	116.826	24.215	4.118***	—
Digital diffusion	−0.096	0.009	−7.829***	1.35
Female participation	−1.610	0.366	−3.778***	1.35
R^2 = 0.8714; adjusted R^2 = 0.8563; F = 57.61; DW = 0.629; n = 20				
Model 4b. Dependent variable: male youth unemployment rate				
Constant	181.045	38.261	3.002***	—
Digital diffusion	−0.055	0.007	−7.304***	1.20
Male participation	−2.280	0.506	−2.865***	1.20
R^2 = 0.8940; adjusted R^2 = 0.8815; F = 71.65; DW = 0.771; n = 20				

Note. Standard errors reported are conventional; t-statistics are computed using Newey–West heteroskedasticity- and autocorrelation-consistent standard errors with a Bartlett kernel and a truncation lag of 2. Significance: *** p < 0.01, ** p < 0.05, * p < 0.10. VIF denotes the variance inflation factor. DW denotes the Durbin–Watson statistic. In Model 3, the digital diffusion term is centred on its sample mean before squaring.

Two robustness considerations qualify these estimates. The Durbin–Watson statistics for the level specifications, ranging from 0.629 to 0.875, indicate substantial positive residual autocorrelation, so inference is conducted throughout using autocorrelation-consistent standard errors rather than conventional ones. In first-differenced form, the association between digital diffusion and youth unemployment retains significance under robust errors, with a coefficient of −0.054 and a robust t-statistic of −2.424, as does the association with participation. In contrast, the differenced productivity specification is not statistically distinguishable from a constant drift of 3.47 index points per year. The interpretation is that the productivity relationship in Model 1 reflects shared long-run trends rather than year-to-year covariation, and it is presented as a description of the joint trajectory rather than as evidence of short-run causation. The gender-gap specification of Model 3, whose residuals are close to serially independent, does not carry this qualification.

Table 7 reports the composite index and its sex-specific variants. The aggregate index rose from 0.109 in 2005 to 0.844 in 2024, a multiple of 7.73, and traversed four of the five interpretive bands, moving from a very low level through low and medium to a high level by the end of the period. The trajectory is not monotone: the index fell from 0.713 in 2014 to 0.681 in 2017 as the currency adjustment suppressed measured productivity growth, and fell sharply again to 0.575 in 2020 before recovering. The sex-specific variants are more informative than the aggregate. The male–female differential was negative in the early years, reaching −0.101 in 2006, indicating that the composite position of young women was then marginally more favourable than that of young men on these dimensions. It crossed zero in 2014 and rose thereafter to 0.125 in 2024. The aggregate index and the differential thus moved in the same direction over the final decade, which is precisely the configuration that an undifferentiated composite measure would conceal.

Table 7. Human Capital and Talent Index, aggregate and by sex, 2005–2024

Year	HCTI, total	HCTI, men	HCTI, women	Male–female gap	Level
2005	0.109	0.000	0.077	−0.077	Very low
2006	0.210	0.070	0.171	−0.101	Low
2007	0.362	0.224	0.298	−0.074	Low
2008	0.515	0.382	0.427	−0.045	Medium
2009	0.519	0.444	0.434	0.009	Medium
2010	0.586	0.517	0.534	−0.017	Medium
2011	0.660	0.610	0.628	−0.018	High
2012	0.699	0.691	0.671	0.020	High
2013	0.709	0.701	0.706	−0.005	High
2014	0.713	0.727	0.722	0.005	High
2015	0.700	0.758	0.723	0.035	High
2016	0.682	0.785	0.719	0.066	High
2017	0.681	0.806	0.729	0.078	High
2018	0.682	0.830	0.740	0.090	High
2019	0.692	0.860	0.757	0.103	High
2020	0.575	0.731	0.674	0.057	Medium
2021	0.657	0.735	0.731	0.004	High
2022	0.743	0.922	0.789	0.133	High
2023	0.795	0.961	0.833	0.128	High
2024	0.844	1.000	0.875	0.125	Very high

Note. Interpretive bands for the aggregate index: 0.00–0.20 very low; 0.21–0.40 low; 0.41–0.60 medium; 0.61–0.80 high; 0.81–1.00 very high. The male–female gap is the male variant less the female variant. Sex-specific variants exclude the parity component and are normalized within their own range, so that the level of each variant is meaningful relative to its own trajectory rather than to the other.

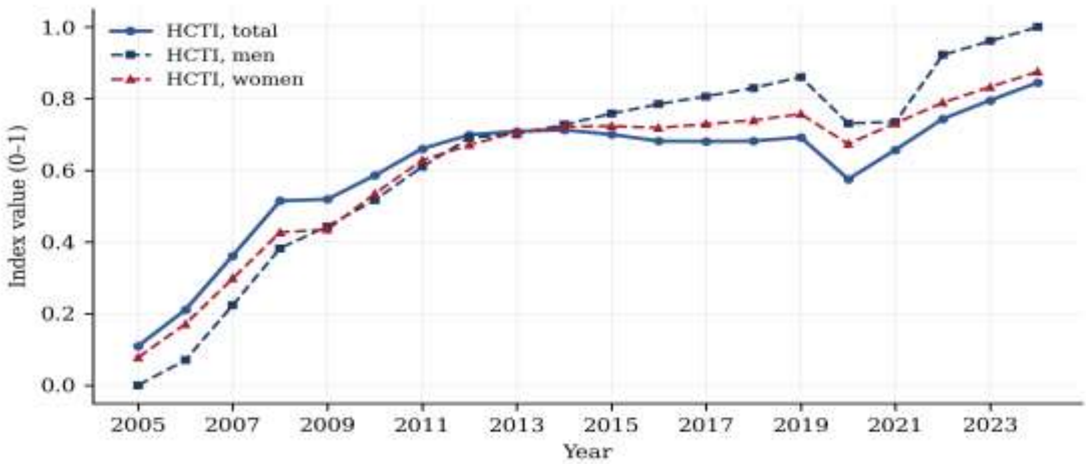

Figure 3. Human Capital and Talent Index, aggregate and by sex, 2005–2024

Table 8 reports the trend projections to 2030. The aggregate composite index is projected to reach 0.992 by 2030, and the labour productivity index 202.0 points, corresponding to a doubling of output per worker relative to 2005. Projections on the sex-disaggregated series, fitted over the structurally stable window from 2013, point in the opposite direction as regards equity: female youth unemployment is projected to rise to 5.49 percent by 2030 while male youth unemployment falls to 2.55 percent , so that the gap widens to 2.94 percentage points and the relative disadvantage ratio reaches 2.02. The male–female index differential is projected to widen from 0.125 to 0.184 over the same horizon. Figure 4 presents the observed and projected sex-specific series.

Table 8. Trend projections to 2030

Indicator	2024 actual	2026	2028	2030	Trend slope
Human Capital and Talent Index	0.844	0.892	0.942	0.992	+0.0248/yr
Labour productivity index (2005 = 100)	176.85	186.74	194.39	202.03	+3.822/yr
Female youth unemployment (%)	4.94	5.10	5.29	5.49	+0.096/yr
Male youth unemployment (%)	2.87	2.84	2.70	2.55	−0.073/yr
Gender gap in youth unemployment (pp)	2.07	2.26	2.60	2.94	+0.169/yr
Relative disadvantage ratio (F/M)	1.72	1.78	1.90	2.02	+0.061/yr
Male–female index differential	0.125	0.143	0.163	0.184	+0.0100/yr
Female labour force participation (%)	65.29	64.23	64.03	63.84	−0.097/yr

Note. Projections for the composite index and the labour productivity index are fitted over 2005–2024. Projections for the sex-disaggregated series and the participation rate are fitted over 2013–2024, the structurally stable regime identified in the descriptive analysis, because the full-sample trend for these variables extrapolates outside the feasible range before 2030. All projections are conditional on continuation of the estimated trend and incorporate no behavioural or policy response.

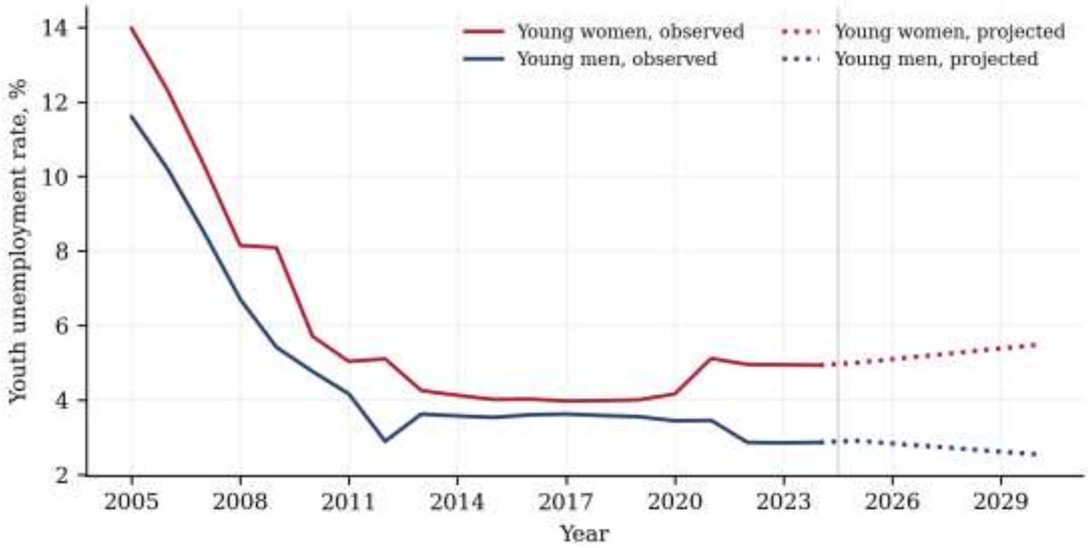

Figure 4. Observed and projected youth unemployment by sex, 2005–2030

A cross-check against national statistics is reported in Table 9 for the years for which both sources are available. The national series confirms the direction of the aggregate movements estimated on the international data: employment rose from 8.70 million in 2018 to 9.35 million in 2025, the share of employees in total employment remained close to seventy-six percent throughout, gross value added per employed person increased from 6.17 to 14.59 million tenge in nominal terms, and the count of employed persons holding higher or technical and vocational qualifications rose by 20.7 and 35.5 percent respectively. The national series also confirms the persistence of the gender differential from a different angle of measurement. The employment rate of the population aged 15 and over stood at 69.8 percent for men and 60.0 percent for women in 2025, compared with 72.1 percent and 60.3 percent in 2020, indicating that the male rate declined by 2.3 percentage points, while the female rate was essentially unchanged. The convergence recorded on this measure therefore arises from deterioration in male outcomes rather than from improvement in female outcomes, a distinction that the aggregate figure alone does not reveal.

Table 9. National statistical series, Republic of Kazakhstan, 2018–2025

Year	Labour force (000)	Employed (000)	Employees (%)	Higher education (000)	TVET (000)	GVA per employee (000 KZT)
2018	9138.6	8695.0	76.0	3360.2	3466.4	6173.2
2019	9221.5	8780.8	76.1	3308.1	3701.9	6869.8
2020	9180.8	8732.0	76.6	3709.2	3431.0	7111.9
2021	9256.7	8807.1	76.2	3565.4	3786.9	8423.4
2022	9429.8	8971.5	76.3	4017.4	3999.4	10083.2
2023	9534.1	9081.9	75.9	3982.7	4157.8	11354.2
2024	9664.0	9214.2	76.1	3927.3	4561.3	12886.0
2025	9786.5	9345.8	76.4	4056.8	4698.5	14592.4

Note. TVET denotes technical and vocational education and training; KZT denotes Kazakhstani tenge; GVA denotes gross value added. Figures for 2025 are preliminary. Source: Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. These series are reported for comparison only and are not included in the estimation sample, which uses internationally harmonized definitions throughout.

DISCUSSIONS

The results support the first hypothesis without qualification. Digital diffusion is associated with a reduction in youth unemployment of approximately 0.116 percentage points for each additional percentage point of internet penetration, significant at the one percent level under autocorrelation-consistent inference, and with an increase of 0.818 index points in output per worker. The productivity association is consistent with Togaibayeva et al. (2026), who established a positive relationship between digital investment and gross value added per employee for a Kazakhstani region using national statistical data, and the present estimates extend that finding from a single region over seven years to the national economy over twenty. The qualification introduced by the first-differenced specification is nonetheless material: the productivity relationship does not survive differencing, indicating that it operates through shared long-run trajectories rather than year-to-year covariation, and should accordingly be read as a description of joint development rather than an identified causal effect. The employment relationship does survive differencing and is the more robust of the two.

The descriptive record confirms the second hypothesis. Female youth unemployment exceeded male youth unemployment in each of the twenty years examined, a result that places the finding of Torebekov (2026) for the period 2020 to 2025 within a substantially longer frame and demonstrates that the disadvantage documented there is not a feature of the post-pandemic recovery but a structural characteristic of the Kazakhstani youth labour market that has persisted through two decades of otherwise rapid transformation. This persistence is consistent with the argument of Ivandić and

Lassen (2023), whose Danish administrative evidence shows women facing an unemployment risk forty to forty-five percent greater than men following identical displacement, with human capital differences accounting for only half of the residual. The Kazakhstani record indicates that the same asymmetry persists in an economy with a very different institutional structure, supporting their conclusion that the mechanism operates through responses to labour market shocks rather than through endowment differences alone.

The third hypothesis is confirmed and constitutes the principal original contribution of the study. The gender gap in youth unemployment is a convex function of digital diffusion, with a linear coefficient of −0.087 and a quadratic coefficient of 0.00088, both significant at the 1 percent level, and a turning point at 49.12 percent penetration. The interpretation is that the early phase of a digital transition and its mature phase have opposite distributional consequences. During diffusion, the extension of connectivity relaxes the geographic and temporal constraints that bear disproportionately on young women's participation, and the gap narrows; the observed minimum of 0.35 percentage points in 2017 followed six years of penetration above the estimated threshold. Once connectivity approaches saturation, access ceases to be the binding constraint, and the determinants of outcomes shift to the dimensions identified by Singh et al. (2025) as usage and outcome, where the constraints on women are qualitatively different and are not alleviated by further connectivity. The OECD (2025) locates the same mechanism in the sorting of women by field of study and their concentration in particular occupations rather than in skill formation itself, and Kurti et al. (2024) trace it upstream to the stereotyped perceptions that deter women from entering information technology education. The present estimates are consistent with this account and add to it a quantitative threshold at which the transition between regimes occurs.

This finding qualifies an expectation prominent in the policy literature. Digitalization is frequently advanced as an instrument of gender equality on the argument that flexible and remotely mediated work loosens historical constraints on female participation, and the results reported here confirm that this argument holds during the diffusion phase. They also establish that it ceases to hold thereafter. The evidence from Munoz et al. (2024) on the allocation of women to lower-paid tasks within digital labour platforms and their constrained progression precisely describes the configuration that emerges once access is universal. The divergence recorded in Kazakhstan after 2017 is consistent with a labour market in which connectivity is no longer scarce, but its returns remain differentiated by occupation and field.

The fourth hypothesis is confirmed. The marginal association between digital diffusion and youth unemployment is −0.096 for young women and −0.055 for young men, a ratio of 1.76 to 1, and both coefficients are significant at the 1% level in specifications free of serious collinearity. The asymmetry is the mechanism generating the U-shape. Because the female rate began 2.37 percentage points above the male rate, the larger female coefficient produced convergence while a substantial gap remained; once the rates approached one another, the same coefficient structure could no longer sustain that convergence, and the residual divergence reflects factors that connectivity does not address. This result also indicates that the aggregate elasticities reported in single-equation studies of digitalization and youth employment conceal a substantial difference in incidence, with implications for how such estimates are used in policy design.

The fifth hypothesis is confirmed in both of its components. The aggregate composite index rose from 0.109 to 0.844, traversing four interpretive bands, while the male–female differential within the index moved from −0.077 in 2005 to 0.125 in 2024, crossing zero in 2014 and widening thereafter. The two movements are simultaneous and of the same sign over the final decade. This is the configuration that motivated the construction of the sex-specific variants, and it demonstrates that a composite indicator reported only in aggregate would have recorded uninterrupted improvement over a period in which the distribution of that improvement was becoming steadily less equal. The finding aligns with Serikkyzy et al. (2025), who report that the youngest Kazakhstani cohort combines the highest digital literacy with persistent differences between young men and young women in income and access to digital occupations, and with Arynova et al. (2025), whose diagnosis of mismatch concentrated in information-technology and hybrid roles identifies the occupational locus in which the divergence is most likely to be generated.

The projections extend this divergence to 2030, assuming an unchanged trend. The aggregate index approaches 0.992, and output per worker doubles relative to 2005, while the gender gap widens to 2.94 percentage points and the relative disadvantage ratio reaches 2.02, meaning that a young woman is twice as likely as a young man to be unemployed. These projections are conditional and incorporate no behavioural or policy response; their function is to establish what the continuation of present trends implies, not to predict what will occur. The projection of a declining female participation rate warrants particular attention, since it indicates that the divergence is not confined to unemployment among participants but extends to the decision to participate at all. This is consistent with the pattern visible in the national statistics, where the narrowing of the employment-rate differential between 2020 and 2025 arises from a 2.3-percentage-point decline in the male rate against an essentially unchanged female rate, so that measured convergence on that indicator reflects deterioration among men rather than improvement among women.

CONCLUSIONS

The purpose of this study was to establish the direction and functional form of the relationship between digital diffusion, human capital and the gender gap in youth unemployment in the Republic of Kazakhstan over the twenty years from 2005 to 2024, and to express the resulting gender-differentiated outcomes through a composite index of youth labour market readiness for the digital economy.

The analysis establishes four principal results. Digital diffusion is associated with a substantial reduction in youth unemployment and a 77% cumulative increase in output per worker over the period. Female youth unemployment exceeded male youth unemployment in every year, falling from 13.97 to 4.94 percent for young women, compared with a decline from 11.60 to 2.87 percent for young men. The relationship between digital diffusion and the gender gap is not monotone but U-shaped, with a turning point at 49.12 percent penetration, so that the gap narrowed from 2.37 percentage points in

2005 to 0.35 points in 2017 and then widened to 2.07 points by 2024, while the relative disadvantage ratio rose from 1.10 to 1.72. The composite index rose from 0.109 to 0.844 while the male–female differential within it moved from −0.077 to 0.125, so that aggregate improvement and distributional deterioration occurred simultaneously.

The contribution of the study is threefold. It establishes, on a twenty-year national series spanning almost the entire feasible range of internet penetration, that the distributional consequences of digitalization for gender equality reverse in sign as diffusion deepens, and it identifies the threshold at which that reversal occurs. It demonstrates that the marginal association between digital diffusion and youth unemployment is 1.76 times larger for young women than for young men, which supplies the mechanism generating the reversal. It also develops a gender-differentiated composite index which registers a divergence in outcomes that an aggregate measure of the same construction would conceal.

The theoretical implication is that the expectation of a monotone relationship between technological diffusion and gender convergence, which underlies much of the policy literature, is not supported once the full course of a digital transition is observed. The account of Goldin (2014), which locates the residual gender gap in the reward structure of occupations rather than in human capital endowment, is consistent with the pattern reported here: connectivity relaxes the constraint that binds during diffusion, but the occupational and field-of-study sorting identified by the OECD (2025) becomes the binding constraint thereafter. It is not relieved by further connectivity. The managerial and policy implication follows directly. In an economy that has reached saturation in access, measures aimed at extending connectivity will not further narrow gender disparities in youth employment; instead, instruments must address the composition of educational choices, the occupational allocation of young women within digitally intensive sectors, and the conditions governing progression within them. Monitoring frameworks should report human capital indicators in sex-disaggregated form as a matter of routine, since the aggregate index constructed here would have signalled uninterrupted improvement across a decade in which the distribution of that improvement was deteriorating.

The study is subject to several limitations. The sample of twenty annual observations constrains specification complexity and estimation precision. The labour force series are internationally harmonized, modelled estimates that differ from national statistics, most notably in the definition of the youth age band—Internet penetration proxies for digital transformation without capturing the intensity or composition of technology use. The composite index rests on expert weights, and although the direction of the sex differential is not sensitive to moderate reweighting, its levels are. The analysis identifies association rather than causation.

Four directions for further research follow. The U-shaped relationship should be tested on a cross-country panel of economies at differing stages of digital diffusion, which would establish whether the threshold identified here is specific to Kazakhstan or general. The mechanism should be examined at the occupational level, using data on employment composition in digitally intensive sectors, to determine whether the post-threshold divergence originates in entry, allocation, or progression. The relationship between field-of-study choice and subsequent labour market outcomes should be traced through longitudinal data on Kazakhstani graduates. The composite index should be extended to the regional level, where the disparities documented by Arynova et al. (2025) suggest that the national aggregate conceals substantial internal variation.

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