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Gender Pay Inequality in the Digital Economy and Its Global and Regional Dimensions

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Abstract

The article examines gender pay inequality in Kazakhstan under conditions of digital transformation. The purpose of the study is to assess the scale and principal mechanisms of wage differences between men and women, with particular attention to human capital, occupational segregation, digital-sector participation, managerial status, working-time arrangements, and regional factors. The empirical analysis combines aggregated wage indicators for 2015–2024 with an analytical microdata sample of 5,000 employees for 2024. The methodology includes descriptive and comparative analysis, extended Mincer wage regressions, the Oaxaca–Blinder decomposition, and regional analysis. The results show that the gender pay gap based on aggregated national indicators declined from 22.7% in 2015 to 21.6% in 2024, although its dynamics remained unstable. In the analytical microdata sample, the gap amounted to 25.8%. Despite almost identical average levels of education and work experience, women were substantially underrepresented in STEM occupations, digital-sector employment, and managerial positions and were approximately 3.4 times more likely to work part-time. The econometric estimates indicate that women's conditional wages were approximately 17.6% lower than men's after controlling for individual, occupational, sectoral, regional, and temporal characteristics. STEM, digital-sector, and managerial employment were associated with wage premiums, whereas part-time employment reduced earnings. The Oaxaca–Blinder decomposition showed that observable characteristics explained 31.2% of the total gap, while 68.8% remained unexplained. The findings indicate that gender pay inequality is driven mainly by unequal access to high-return employment opportunities rather than by differences in formal education or work experience.

Keywords: Gender, Wage, Digitalization, Employment, Platform, Segregation, Algorithm, Employment, Inequality.

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1. INTRODUCTION

Digital transformation is reshaping employment relations, wage-setting mechanisms, and the interaction between workers and employers. The expansion of digital platforms, remote work, online freelancing, and algorithmic management has reduced some geographical and organisational barriers to labour-market participation. At the same time, technological change does not automatically eliminate existing gender inequalities. Digital tools may reproduce differences in occupational specialisation, access to highly paid jobs, career advancement, working-time arrangements, and remuneration.

The gender pay gap remains persistent across both traditional and digital labour markets. According to Payscale (2026), women in the United States earned an average of USD 0.82 for every dollar earned by men when occupational and individual characteristics were not controlled. After adjusting for comparable characteristics, the ratio increased to USD 0.99. This difference indicates that a substantial part of gender inequality is associated not only with unequal pay for identical work but also with unequal access to higher-paying occupations, managerial positions, and career opportunities. Cohn and Gould (2026) similarly found that women's hourly earnings in 2025 remained lower than men's even after differences in age, education, race, and ethnicity were considered.

The expansion of platform and project-based employment has introduced additional mechanisms through which wage inequality may be reproduced. Digital platforms formally standardise worker profiles, ratings, task allocation, and customer interactions. However, women and men may remain concentrated in different service categories and follow different pricing, project-selection, and working-time strategies. Teutloff et al. (2025), using data on more than 23,000 freelancers, found that the gender income gap in digital labour could reach 30%. Women were more frequently employed in relatively low-paid text-based and administrative services, whereas men were more strongly represented in programming, data analysis, and other high-income technological activities. Similar findings were obtained by Dong et al. (2024), who showed that women's average monthly income in China's platform economy was approximately 85% of men's income.

In Kazakhstan, the gender pay gap is shaped by the country's sectoral and regional economic structure. Men are more strongly represented in extractive industries, technical occupations, and other highly paid activities, while women are concentrated in education, healthcare, trade, social services, and administrative employment. By the end of 2024, women's average monthly wages remained substantially lower than men's wages, while significant disparities persisted in information and communications and in financial and insurance activities (Energyprom, 2025; Kapital.kz, 2026).

This inequality contrasts with women's relatively high educational attainment. Women in Kazakhstan have levels of higher and vocational education comparable to or exceeding those of men, yet this human capital is not fully translated into equal labour-market returns. Consequently, differences in formal education alone cannot explain the observed wage gap. Occupational segregation, unequal access to managerial positions, differences in working-time arrangements, family responsibilities, regional employment structures, and limited participation in highly paid digital occupations may play a more substantial role.

Existing studies have examined gender inequality, occupational segregation, digital employment, and regional labour-market differences separately. However, the relationship between digital transformation and gender wage inequality in Kazakhstan remains insufficiently investigated. In particular, limited attention has been paid to whether employment in digital activities provides equal wage returns to men and women, how occupational and vertical segregation contribute to the observed gap, and what proportion of wage inequality can be explained by observable characteristics.

This study addresses this research gap by combining aggregated wage indicators for 2015–2024 with an analytical microdata sample for 2024. The study evaluates gender differences in wages, education, work experience, STEM employment, digital-sector participation, managerial status, and part-time employment. It also estimates the conditional gender wage gap and decomposes it into explained and unexplained components.

The purpose of the study is to assess the scale and principal mechanisms of gender pay inequality in Kazakhstan under digital transformation. The study pursues the following objectives: to analyse the dynamics of the gender pay gap; to identify differences in the human-capital and employment characteristics of men and women; to estimate the conditional effect of gender on wages; to determine the contribution of occupational, digital, vertical, and working-time segregation; and to examine regional differences in gender wage inequality.

The study tests three hypotheses. First, women receive lower wages than men even after controlling for individual and employment characteristics. Second, digital-sector employment is associated with higher wages, but women have more limited access to this wage premium. Third, observable differences in education, experience, occupation, and employment arrangements explain only part of the total gender pay gap.

The contribution of the study lies in the integrated assessment of individual, occupational, sectoral, and regional mechanisms of gender wage inequality. Unlike studies based solely on aggregated indicators, the analysis combines descriptive evidence with extended wage regressions and the Oaxaca–Blinder decomposition. This approach makes it possible to distinguish between inequality associated with observable labour-market characteristics and the component arising from differences in returns to comparable characteristics and other unobserved factors.

The object of the research is the system of wage formation in Kazakhstan under the conditions of digital transformation. The subject of the research is the set of individual, occupational, sectoral, institutional, and regional factors influencing wage differences between men and women.

2. LITERATURE REVIEW

The study of gender wage inequality is based on several complementary theoretical approaches. The discrimination model developed by Becker (1957) explains wage differences through the preferences and biases of employers, employees, or consumers. In this framework, discrimination generates additional economic costs and may lead employers to offer different remuneration to workers with comparable productivity. Although competitive labour markets were expected to weaken discriminatory practices over time, the continued persistence of gender wage inequality suggests that market mechanisms alone are insufficient to eliminate it (Blau & Kahn, 2017).

Human capital theory provides another explanation for wage differences. According to Schultz (1961) and Mincer (1974), earnings are determined by investments in education, professional training, work experience, and the accumulation of labour-market skills. From this perspective, gender differences in wages may partly reflect differences in qualifications, employment continuity, and professional experience. However, empirical research consistently shows that a substantial part of the gender pay gap remains after controlling for education, experience, occupation, industry, and other observable characteristics (Blau & Kahn, 2017). This indicates that differences in human capital cannot fully explain gender wage inequality.

Occupational segregation theory emphasises the unequal distribution of women and men across industries, professions, and hierarchical positions. Women are more frequently concentrated in education, healthcare, trade, social services, and administrative occupations, whereas men are more strongly represented in engineering, information technology, finance, extractive industries, and senior management. Since these occupational groups differ considerably in wage levels and career prospects, horizontal segregation contributes directly to the gender pay gap (Polachek, 1981).

Vertical segregation further restricts women's access to managerial and decision-making positions. The "glass ceiling" describes invisible barriers that limit career progression at higher organisational levels. At the same time, the "sticky floor" refers to the concentration of women in low-paid positions with limited promotion opportunities. Arulampalam et al. (2007) demonstrated that gender wage inequality may be particularly pronounced at both the lower and upper ends of the wage distribution. Therefore, the gender pay gap reflects not only unequal remuneration within occupations but also unequal access to higher-paying professional and managerial positions.

The Oaxaca–Blinder decomposition is one of the most widely used methods for examining the structure of gender wage inequality (Blinder, 1973; Oaxaca, 1973). This method separates the total wage gap into an explained component and an unexplained component. The explained component reflects differences in observable characteristics, including education, work experience, occupation, sector, region, and working-time arrangements. The unexplained component reflects differences in the returns to these characteristics as well as the influence of omitted institutional, organisational, and behavioural factors.

The unexplained component should not automatically be interpreted as a direct measure of discrimination. It may also include differences in the quality of education, productivity, work intensity, career preferences, employment interruptions, bargaining behaviour, and other unobserved characteristics. Nevertheless, a persistently large unexplained component indicates that observable human-capital differences alone are insufficient to account for gender wage inequality (Blau & Kahn, 2017).

Digital transformation has introduced new mechanisms of employment and remuneration. Digital platforms, remote work, online freelancing, algorithmic task allocation, automated performance evaluation, and reputation systems have changed the way workers access jobs and negotiate remuneration (De Stefano, 2016; Kellogg et al., 2020). These technologies were initially expected to reduce subjective employer bias by standardising worker profiles, evaluation procedures, and customer access. However, formal technological neutrality does not necessarily produce gender-neutral outcomes.

Agrawal et al. (2013) showed that online labour markets can reduce certain geographical and informational barriers, particularly for workers from less developed countries. At the same time, digital platforms may reproduce existing inequalities through occupational categorisation, ranking systems, customer ratings, visibility algorithms, and automated order allocation. Barzilay and Ben-David (2017) argue that platform inequality is often embedded in the architecture of digital labour markets rather than arising solely from explicit customer discrimination.

Project selection, pricing strategies, risk preferences, and occupational specialisation also influence gender differences in platform earnings. Litman et al. (2020) found that women may set lower initial prices, participate in less profitable categories, and raise their rates more cautiously. These differences can accumulate over time because platform rankings and future access to orders are often linked to previous earnings, customer reviews, and completed projects.

Using data on more than 23,000 freelancers, Teutloff et al. (2025) found that the gender earnings gap in online freelancing may reach approximately 30%. Women were more frequently concentrated in writing, translation, administrative support, and other relatively low-paid services. At the same time, men were more strongly represented in programming, data analysis, and high-income technological activities. Differences in project selection and income-maximising strategies also contributed to unequal earnings.

Evidence from China indicates that platform employment may have mixed effects on gender inequality. Dong et al. (2024) found that women's average monthly income in the gig economy was approximately 85% of men's income. However, the gender gap in platform employment was smaller than in traditional employment. A considerable part of the observed difference was associated with professional specialisation, working hours, experience, and work intensity. This suggests that digital platforms may reduce some forms of direct discrimination while maintaining structural inequality in access to highly paid competencies and projects.

Algorithmic management represents another important dimension of digital labour inequality. It includes automated task distribution, worker monitoring, performance measurement, ranking, and managerial decision-making (Kellogg et al., 2020). Although standardised algorithms may reduce individual managerial bias, they can reproduce historical inequalities when training data reflect past patterns of occupational segregation or unequal promotion. Jarrahi and Sutherland (2019) emphasise that workers' ability to understand and strategically interact with algorithms has become an increasingly important labour-market competency.

The gender digital divide is not limited to access to devices and the Internet. It also includes differences in digital literacy, advanced technological competencies, and the ability to convert digital skills into employment and income. Picatoste et al. (2023) demonstrate that gender inequality in digital skills and employment quality is closely associated with wage differences. Women's limited representation in data science, artificial intelligence, programming, engineering, and other STEM occupations restricts their access to rapidly growing and highly paid labour-market segments.

Working-time arrangements also influence gender wage inequality. Women are more likely to combine paid employment with unpaid household and care responsibilities, which may increase their participation in part-time, flexible, or intermittent employment. Although digital and remote work can reduce spatial and scheduling constraints, it may also blur the boundaries between paid and unpaid labour. Reduced working hours and interrupted employment trajectories can limit access to bonuses, training, promotion, and high-value projects (Litman et al., 2020; Teutloff et al., 2025).

Gender wage inequality in Kazakhstan is characterised by pronounced sectoral and regional differentiation. Women's relatively high educational attainment coexists with their concentration in lower-paid social sectors and limited representation in highly paid technical, industrial, financial, and managerial occupations. Kireyeva and Satybaldin (2019) identify persistent regional and sectoral differences in the gender pay gap, while national statistical and analytical data indicate that substantial disparities remain in information and communications, finance, industry, and other high-income sectors (Bureau of National Statistics, 2025; Energyprom, 2025; Kapital.kz, 2026).

Women also remain underrepresented in leadership positions and technology-intensive occupations in Kazakhstan. This indicates that horizontal occupational segregation is reinforced by vertical barriers to promotion and decision-making (UN Women, 2024; UNDP, 2024). Consequently, the expansion of digital industries does not automatically ensure more equal access to high-income employment.

Existing research points to several institutional mechanisms that may reduce gender wage inequality. Wage transparency can decrease information asymmetry and strengthen employees' bargaining positions. Regular analysis of remuneration structures can help identify unjustified wage differences within organisations. The concept of "equality by design" also proposes integrating gender-equality principles into digital platforms, recruitment systems, ranking algorithms, and human-resource technologies from the initial stage of their development (Wachter-Boettcher, 2017).

The regulation of platform employment is equally important. Social protection mechanisms traditionally linked to standard employment contracts may not cover freelancers, platform workers, and other non-standard employees. Charles et al. (2022) emphasise the importance of adapting labour regulation, social insurance, and skill-development policies to digital employment. Such measures should be combined with broader access for women to STEM education, advanced digital competencies, managerial training, and highly paid occupational segments.

The reviewed literature shows that digital transformation has a dual effect on gender wage inequality. On the one hand, it can expand access to employment, reduce geographical barriers, and create new income opportunities. On the other hand, it can reproduce occupational segregation, unequal working-time patterns, limited access to managerial positions, and differences in returns to digital skills. However, these mechanisms remain insufficiently studied in Kazakhstan using an integrated empirical approach.

Based on the theoretical and empirical literature, the study advances three hypotheses:

H1. Women receive lower wages than men after controlling for education, work experience, occupation, employment status, sector, region, and other observable characteristics.

H2. Employment in the digital sector is associated with higher wages, but women have more limited access to this wage premium because of occupational and vertical segregation.

H3. Observable differences in human capital and employment structure explain only part of the total gender pay gap, while a substantial proportion remains unexplained.

3. METHODOLOGY

The empirical analysis combines aggregated statistical indicators for 2015–2024 with an analytical microdata sample for 2024. Aggregated data were used to examine the long-term dynamics and regional differentiation of the gender pay gap. In contrast, individual-level data were applied to estimate the determinants and structure of wage inequality.

The main source of aggregated information was the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan. The dataset included average monthly wages of men and women by year, region, and type of economic activity, as well as indicators of employment structure and participation in information and communication activities. International reports and studies were used for comparative interpretation of digital employment, platform work, and gender inequality.

The individual-level analysis was based on an analytical sample of 5,000 employed persons in 2024, including 2,609 men and 2,391 women. The sample contained information on wages, gender, age, education, work experience, marital status, presence of minor children, place of residence, occupation, type of economic activity, managerial status, working-time arrangement, and regional affiliation.

Observations with missing values for wages, gender, education, employment status, or regional affiliation were excluded. Wage observations with implausible or extreme values were also removed. The final analytical sample was formed after data cleaning and consistency checks. To ensure reproducibility, the final version of the study should specify the exact criteria used to identify wage outliers and clarify whether survey weights were applied.

The dependent variable in the econometric analysis was the natural logarithm of monthly wages. The logarithmic transformation was used to reduce the influence of extreme values and to interpret regression coefficients as approximate percentage changes in wages.

The gender pay gap was calculated as formula (1):

$$GPG_{\mathrm{t}} = \left(1 - \frac{\bar{W}f_t}{\bar{W}m_t}\right) \times 100\ \% \tag{1}$$

where:

GPG_{t} - the size of the gender gap in the period t;

$\bar{W}f_t$ - the average salary of women;

$\bar{W}m_t$ - the average salary of men.

A positive value indicates that women's average wages are lower than men's average wages.

At the first stage, descriptive and comparative analyses were conducted. Average and median wages, education, work experience, STEM participation, digital-sector employment, managerial status, and part-time employment were compared by gender. The dynamics of the gender pay gap between 2015 and 2024 were then analysed using aggregated statistical indicators.

At the second stage, an extended Mincer wage equation was estimated to identify the individual, occupational, and structural determinants of wages. The analysis focused on the conditional association between gender and wages after controlling for education, work experience, demographic characteristics, STEM employment, digital-sector participation, managerial status, part-time employment, industry, region, and year.

The baseline specification was expressed as formula (2):

$$\ln W_i = \beta_0 + \beta_1 Female_{\mathrm{i}} + \beta_2 Educ_i + \beta_{3Exp_i} + \gamma X_i + \varepsilon_i \tag{2}$$

where:

$ln\, W_i$ is the natural logarithm of the monthly wage of employee (i);

$Female_i$ is a binary variable equal to 1 for women and 0 for men;

$Educ_i$ represents the duration of education in years;

Exp_i denotes potential or actual work experience;

X_i is a vector of individual, occupational, sectoral, and regional characteristics;

ε_i is the stochastic error term.

Four regression specifications were estimated sequentially. Model 1 included gender, education, work experience, and demographic characteristics. Model 2 additionally included STEM employment, digital-sector participation, managerial status, and part-time employment. Model 3 introduced industry effects. Model 4 additionally controlled for regional and temporal effects. Robust standard errors were used to reduce the influence of heteroskedasticity.

The coefficient $beta_1$ represents the conditional gender wage difference after controlling for the included characteristics. Since the dependent variable is expressed in logarithmic form, the exact percentage effect of a binary variable was calculated as formula (3):

$$100 \times [\exp(\beta) - 1] \tag{3}$$

The explanatory variables included education, work experience, age, marital status, presence of minor children, urban residence, STEM employment, digital-sector employment, managerial status, and part-time employment. Industry, regional, and year effects were introduced in the extended specifications to account for structural and territorial heterogeneity.

Multicollinearity was assessed using the variance inflation factor. The absence of severe multicollinearity was assumed when VIF values remained below the selected threshold. Model quality was evaluated using the coefficient of determination, the statistical significance of individual coefficients, and the joint significance of the explanatory variables.

At the third stage, the Oaxaca–Blinder decomposition was applied to separate the total gender wage gap into explained and unexplained components as formula (4):

$$(X_m - X_f)\beta + X_m(\beta_m - \beta) + X_f(\beta * - \beta_f) = \Delta lnW \qquad (4)$$

where X_m and X_f are the mean characteristics of men and women, respectively; β_m and β_f are the estimated returns to these characteristics; and β^* is the non-discriminatory reference coefficient vector.

The explained component reflects gender differences in observable characteristics, including education, experience, STEM participation, digital-sector employment, managerial status, and part-time employment. The unexplained component captures differences in returns to comparable characteristics as well as the influence of omitted, unobserved, or imperfectly measured factors. It was therefore not interpreted exclusively as direct discrimination.

At the fourth stage, regional differences in the gender pay gap were examined. Regional indicators included the gender pay gap, the share of employment in digital activities, STEM participation, and selected indicators of digital infrastructure.

The variables used in the econometric analysis are presented in Table 1.

Table 1. Variables of the econometric model

Variable	Definition	Expected effect
Female	1 for women, 0 for men	Negative
Education	Duration of education, years	Positive
Experience	Work experience, years	Positive
$Experience^2$	Squared work experience	Negative
Age	Age of the employee, years	Ambiguous
Married	1 for registered marriage, 0 otherwise	Ambiguous
Children	1 if minor children are present, 0 otherwise	Negative for women
Urban	1 for urban residence, 0 for rural residence	Positive
STEM	1 for employment in a STEM occupation, 0 otherwise	Positive
Digital sector	1 for employment in a digital activity, 0 otherwise	Positive
Female × Digital	Interaction between gender and digital-sector employment	To be determined
Manager	1 for managerial position, 0 otherwise	Positive
Part-time	1 for part-time employment, 0 otherwise	Negative
Industry effects	Controls for type of economic activity	Control
Region effects	Controls for regional differences	Control
Year effects	Controls for common temporal changes	Control

Note: Compiled by the authors

All statistical and econometric calculations were performed using Stata 17.0. Data processing, additional statistical analysis, and regional clustering were conducted using Python 3.11 with the pandas, statsmodels, and scikit-learn libraries. Statistical significance was evaluated at the 1%, 5%, and 10% levels.

4. ANALYSIS AND RESULTS

The descriptive analysis revealed persistent gender differences in remuneration despite the broadly comparable human-capital characteristics of male and female employees. According to the analytical microdata sample for 2024, the average monthly wage of men amounted to KZT 2,560.4 thousand, whereas the corresponding figure for women was KZT 1,900.7 thousand. The gender pay gap calculated from these values reached 25.8%. Median wages also differed considerably, amounting to KZT 2,136.9 thousand for men and KZT 1,622.3 thousand for women. Thus, gender differences were observed not only among the highest-paid employees but also around the central part of the wage distribution.

The descriptive statistics presented in Table 2 indicate that men and women had almost identical average levels of formal education and work experience. More substantial differences were observed in occupational specialisation, participation in the digital sector, access to managerial positions, and working-time arrangements.

Table 2. Descriptive statistics of wages and human capital indicators by gender, 2024

Indicator	Men (N = 2,609)	Women (N = 2,391)
Average wage, KZT thousand	2,560.4	1,900.7
Median wage, KZT thousand	2,136.9	1,622.3
Average work experience, years	18.3	18.1
Average duration of education, years	14.2	14.1
Share employed in STEM, %	22.8	10.5
Share employed in the digital sector, %	5.0	1.5
Share of managers, %	19.5	14.1
Share employed part-time, %	7.4	25.2

Note: compiled by the authors

As shown in Table 2, the difference in average work experience between men and women amounted to only 0.2 years, while the difference in the duration of education was 0.1 years. These relatively small disparities indicate that the observed wage gap cannot be explained primarily by differences in formal education or accumulated work experience.

By contrast, substantial gender differences were identified in occupational and employment characteristics. The share of men employed in STEM occupations was 22.8%, compared with 10.5% among women, producing a difference of 12.3 percentage points. The proportion of men employed in the digital sector was more than three times higher than that of women: 5.0% compared with 1.5%. Men were also more frequently represented in managerial positions, with a gender difference of 5.4 percentage points.

The largest difference concerned working-time arrangements. The share of women employed part-time reached 25.2%, compared with 7.4% among men. Women were therefore approximately 3.4 times more likely to work part-time. This concentration may reduce monthly earnings directly through shorter working hours and indirectly through more limited access to bonuses, professional training, complex assignments, and promotion opportunities.

The descriptive results suggest that gender wage inequality is related less to differences in the quantity of accumulated human capital than to differences in its labour-market utilisation. Although women and men had comparable education and work experience, women had more limited access to STEM employment, digital activities, managerial positions, and full-time work. These structural differences were subsequently examined in the econometric analysis.

The analysis of aggregated indicators showed that the gender pay gap followed an uneven trajectory between 2015 and 2024. Table 3 presents the dynamics of average wages and the calculated gender pay gap over the study period.

Table 3. Dynamics of the gender pay gap in Kazakhstan, 2015–2024

Year	Average wage of men, KZT thousand	Average wage of women, KZT thousand	Gender pay gap, %
2015	2,410.4	1,864.2	22.7
2016	2,558.5	1,848.3	27.8
2017	2,411.1	1,768.9	26.6
2018	2,587.6	1,919.2	25.8
2019	2,497.0	1,745.1	30.1
2020	2,653.1	1,920.6	27.6
2021	2,600.8	1,845.8	29.0
2022	2,676.5	2,035.8	23.9
2023	2,571.8	2,002.3	22.1
2024	2,604.7	2,041.0	21.6

Note: compiled by the authors

The gender pay gap increased from 22.7% in 2015 to 27.8% in 2016 and remained above 25% during most of the period from 2016 to 2021. The highest value was recorded in 2019, when women's average wages were 30.1% lower than men's wages. After declining to 27.6% in 2020, the gap widened again to 29.0% in 2021.

A more pronounced narrowing was observed from 2022 onwards. The gender pay gap decreased to 23.9% in 2022, 22.1% in 2023, and 21.6% in 2024. Compared with 2015, the indicator declined by 1.1 percentage points. However, the fluctuations recorded during the study period do not provide sufficient evidence of a stable long-term movement towards wage equality. Periods of convergence were repeatedly followed by renewed widening.

The dynamics of the gender pay gap are presented in Figure 1.

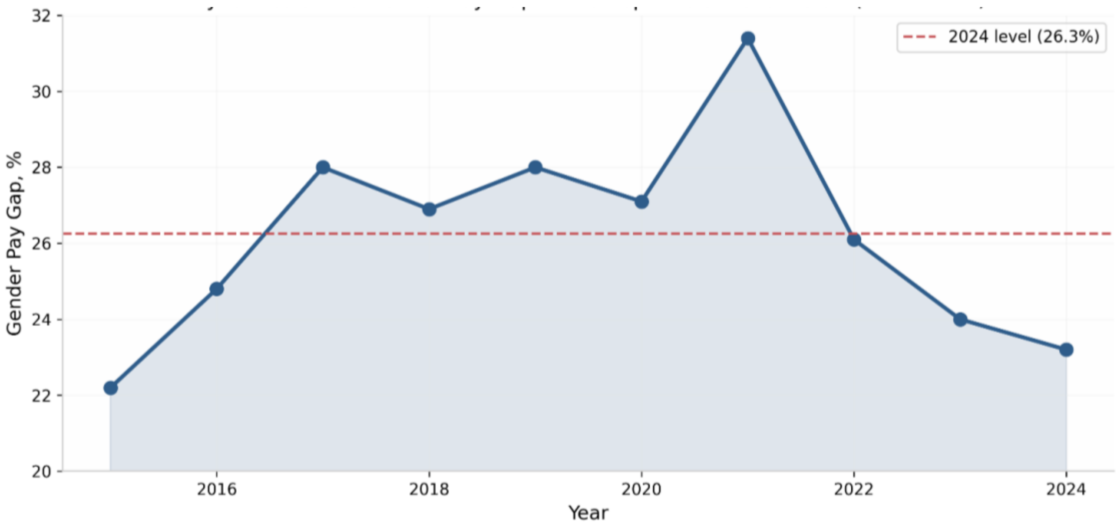

Figure 1. Dynamics of the gender pay gap in Kazakhstan, 2015–2024

Two different estimates of the gender pay gap are reported for 2024. The estimate obtained from the analytical microdata sample was 25.8%, whereas the estimate calculated from aggregated national indicators was 21.6%. The difference arises from the distinct coverage, composition, and calculation procedures of the two datasets.

The microdata-based estimate reflects wage differences within the analytical sample of 5,000 employees used in the individual-level econometric analysis. The aggregated estimate reflects the general national wage dynamics reported for men and women. Therefore, the estimate of 25.8% is used in the descriptive and econometric analysis of individual employees, while the estimate of 21.6% is used to examine long-term national trends.

This distinction is important because the composition of an analytical microdata sample may differ from the structure of the entire employed population by occupation, sector, region, working time, and other characteristics. The two estimates should therefore be treated as complementary rather than directly interchangeable measures of gender wage inequality.

The descriptive analysis identified substantial differences in the occupational and employment structure of men and women. However, these comparisons do not show whether the gender pay gap persists after controlling for differences in education, work experience, professional specialisation, managerial status, working-time arrangements, industry, and region. To address this issue, four wage-equation specifications were estimated sequentially.

Model 1 included gender, education, work experience, and demographic characteristics. Model 2 additionally controlled for STEM employment, digital-sector participation, managerial status, and part-time employment. Industry effects were introduced in Model 3, while Model 4 additionally included regional and time effects. The dependent variable in all specifications was the natural logarithm of monthly wages. The results are presented in Table 4.

Table 4. Results of econometric modelling of wages

Variable	Model 1	Model 2	Model 3	Model 4
Female	−0.2718***	−0.1965***	−0.1953***	−0.1940***
Education, years	0.0727***	0.0716***	0.0714***	0.0715***
Work experience, years	0.0364***	0.0364***	0.0359***	0.0359***
STEM employment	—	0.2284***	0.2225***	0.2237***
Digital-sector employment	—	0.2395***	0.2475***	0.2521***
Managerial position	—	0.2950***	0.2989***	0.2985***
Part-time employment	—	−0.2116***	−0.2102***	−0.2068***
Demographic controls	Yes	Yes	Yes	Yes
Industry effects	No	No	Yes	Yes
Regional effects	No	No	No	Yes
Time effects	No	No	No	Yes
Constant	12.8120	12.7224	12.4969	12.4148
Number of observations	5,000	5,000	5,000	5,000
R^2	0.457	0.523	0.626	0.631

Note: compiled by the authors

The coefficient on the female variable was negative and statistically significant in all four specifications. In Model 1, its value was −0.2718, which corresponds to an exact percentage effect of approximately −23.8%. Thus, after controlling for education, work experience, and demographic characteristics, women earned approximately 23.8% less than men.

After STEM employment, digital-sector participation, managerial status, and part-time employment were included in Model 2, the absolute value of the female coefficient decreased from −0.2718 to −0.1965. This reduction indicates that part of the initial gender wage difference was associated with occupational segregation, unequal access to digital and managerial employment, and differences in working-time arrangements.

Nevertheless, the coefficient remained negative and statistically significant. The inclusion of industry effects in Model 3 changed the estimate only slightly, from −0.1965 to −0.1953. After regional and time effects were introduced in Model 4, the coefficient declined to −0.1940, corresponding to an exact percentage difference of approximately −17.6%. Accordingly, women's conditional wages were approximately 17.6% lower than men's wages after individual, occupational, sectoral, regional, and temporal characteristics were controlled for. The limited variation in the coefficient across Models 2–4 confirms the robustness of the estimated gender wage penalty.

Education had a positive and statistically significant relationship with wages in all specifications. In Model 4, the coefficient was 0.0715, corresponding to a wage increase of approximately 7.4%. Thus, each additional year of education was associated with an increase in wages of approximately 7.4%, holding other characteristics constant.

Work experience also had a positive and statistically significant effect. In Model 4, the coefficient was 0.0359, corresponding to a wage increase of approximately 3.7%. Therefore, each additional year of work experience was associated with an increase in wages of approximately 3.7%. This result should be interpreted as the average association within the observed range of experience because the estimated model did not include a squared experience term.

Employment in a STEM occupation was associated with a substantial wage premium. In Model 4, the coefficient was 0.2237, corresponding to a wage premium of approximately 25.1%. Thus, employees in STEM occupations earned approximately 25.1% more than otherwise comparable employees outside STEM fields. Since women were substantially underrepresented in STEM employment, unequal access to this wage premium contributed to the overall gender wage gap.

Digital-sector employment was also positively and statistically significantly associated with wages. In Model 4, its coefficient was 0.2521, corresponding to a wage premium of approximately 28.7%. Employment in digital activities was therefore associated with wages approximately 28.7% higher than those of otherwise comparable employees outside the digital sector. However, only 1.5% of women in the analytical sample were employed in the digital sector, compared with 5.0% of men. The results consequently demonstrate unequal access to the digital-sector wage premium.

The estimated specifications did not contain an interaction term between gender and digital-sector employment. Therefore, they do not allow a direct conclusion as to whether men and women receive different wage returns within the digital sector. The results establish only that digital-sector employment is associated with higher wages and that women are less frequently represented in this segment.

Managerial status produced the largest positive coefficient among the included employment characteristics. In Model 4, the coefficient was 0.2985, corresponding to a wage premium of approximately 34.8%. Holding a managerial position was therefore associated with wages approximately 34.8% higher than those of comparable non-managerial employees. Women's lower representation in managerial positions indicates that vertical occupational segregation constitutes an important mechanism of gender wage inequality.

Part-time employment had a negative and statistically significant effect in all extended specifications. In Model 4, the coefficient was −0.2068, corresponding to a wage reduction of approximately 18.7%. Part-time employees earned approximately 18.7% less than otherwise comparable full-time employees. Since women were approximately 3.4 times more likely than men to work part-time, differences in working-time arrangements contributed considerably to the observed gender wage gap.

The explanatory power of the models increased as occupational and structural characteristics were added. The (R^2) value increased from 0.457 in Model 1 to 0.523 in Model 2 and reached 0.631 in Model 4. Thus, the final specification explained 63.1% of the variation in the natural logarithm of monthly wages.

Overall, the regression results support the first hypothesis: women received lower wages than men even after controlling for a broad range of observable characteristics. The results also partially support the second hypothesis. Digital-sector employment was associated with higher wages, but women had considerably less access to this wage premium. A direct test of gender differences in the returns to digital-sector employment requires a separate model containing an interaction term between gender and digital-sector employment.

To examine the internal structure of the gender pay gap, the Oaxaca–Blinder decomposition was applied. This method separates the total difference in average logarithmic wages into an explained component associated with observable characteristics and an unexplained component reflecting differences in returns to those characteristics and other unobserved factors. The results are presented in Table 5.

Table 5. Oaxaca–Blinder decomposition of the gender pay gap

Component	Value, log points	Share, %
Total gap	0.2857	100.0
Explained component	0.0891	31.2
Unexplained component	0.1965	68.8

Note: compiled by the authors

The total difference in average logarithmic wages between men and women amounted to 0.2857 log points. Of this difference, 0.0891 log points, or 31.2%, were associated with gender differences in observable characteristics. The remaining 0.1965 log points, or 68.8%, constituted the unexplained component.

The explained component reflects differences between men and women in education, work experience, occupational specialisation, digital-sector participation, managerial status, working-time arrangements, and other observed characteristics. The relatively limited share of this component indicates that differences in measured human capital and employment structure account for less than one-third of the total wage gap.

The unexplained component represents differences in the returns to comparable characteristics as well as the influence of unobserved or imperfectly measured factors. These may include differences in job quality, career trajectories, bargaining opportunities, employment interruptions, work intensity, access to professional networks, organisational practices, and other institutional factors. Therefore, the unexplained component should not be interpreted exclusively as a direct measure of discrimination.

Part-time employment was the second most important factor. Its contribution amounted to 0.0228 log points, corresponding to 25.6% of the explained component. This finding is consistent with the descriptive statistics, which showed that women were approximately 3.4 times more likely than men to work part-time. Since part-time employment was associated with lower monthly wages, gender differences in working-time arrangements contributed substantially to the observed gap.

A more detailed decomposition of the explained component is presented in Table 6.

Table 6. Contribution of individual factors to the explained component of the gender pay gap

Factor	Contribution, log points	Share of the explained component, %
Education	0.0066	7.4
Work experience	0.0062	7.0
Urban residence	0.0016	1.8
Marital status and children	–0.0002	–0.2
Segregation in STEM	0.0282	31.6
Segregation in the digital sector	0.0083	9.3
Vertical segregation	0.0158	17.8
Part-time employment	0.0228	25.6

Note: compiled by the authors based on the Oaxaca–Blinder decomposition. Vertical segregation reflects gender differences in access to managerial positions.

The largest contribution to the explained component was made by segregation in STEM occupations. This factor accounted for 0.0282 log points, or 31.6% of the explained wage gap. The result indicates that women's lower representation in STEM occupations substantially reduced their access to the wage premium associated with technological and technical employment.

Vertical segregation accounted for 0.0158 log points, or 17.8% of the explained component. Men were more frequently represented in managerial positions, which generated the largest wage premium among the occupational characteristics included in the regression models. Women's limited access to managerial employment therefore constituted another important mechanism of gender wage inequality.

Segregation in the digital sector contributed 0.0083 log points, or 9.3% of the explained component. Although employment in digital activities was associated with a substantial wage premium, women were considerably less likely to work in this sector. The contribution of digital segregation was smaller than that of STEM and managerial segregation, but it remained economically meaningful.

Education and work experience explained relatively small proportions of the observed component. Education accounted for 7.4%, while work experience contributed 7.0%. This result is consistent with the descriptive analysis, which showed only minor differences between men and women in average years of education and accumulated work experience.

Urban residence accounted for 1.8% of the explained component. The combined contribution of marital status and the presence of children was slightly negative, at −0.2%. A negative contribution means that gender differences in these characteristics marginally reduced rather than widened the observed wage gap within the selected decomposition structure.

Overall, the decomposition confirms that occupational and employment segregation played a considerably larger role than formal human-capital differences. STEM segregation, part-time employment, vertical segregation, and digital-sector segregation jointly accounted for 84.3% of the explained component:

$$31.6+25.6+17.8+9.3=84.3\%$$

By contrast, education and work experience together explained only 14.4%. These findings suggest that increasing women's educational attainment alone is unlikely to eliminate wage inequality unless it is accompanied by broader access to highly paid technological occupations, managerial positions, digital employment, and full-time work.

The results support the third research hypothesis. Observable characteristics explained only 31.2% of the total gender pay gap, while 68.8% remained unexplained. This indicates that gender wage inequality cannot be reduced solely to differences in education, experience, occupation, or working-time arrangements.

Following the individual-level analysis, the study examined regional differences in gender wage inequality. The results indicate substantial territorial variation in the gender pay gap. According to the available regional dataset, the indicator ranged from 12.5% to 33.5% in 2024. This variation suggests that gender wage inequality is associated not only with individual characteristics but also with regional economic specialisation, employment structure, and the concentration of highly paid occupations.

Table 7. Gender pay gap by region of Kazakhstan, 2024

Region	Gender pay gap, %	Average wage of men, KZT thousand	Average wage of women, KZT thousand
Almaty city	33.5	2,649.4	1,760.7
Turkestan	31.1	2,695.7	1,857.2
Aktobe	30.5	2,767.9	1,922.7
Kyzylorda	30.3	2,637.3	1,837.8
Mangystau	28.3	2,705.0	1,940.0
Astana city	27.8	2,447.4	1,767.4
Pavlodar	25.1	2,638.1	1,975.8
Karaganda	24.3	2,399.0	1,816.5
East Kazakhstan	24.2	2,597.1	1,968.0
Shymkent city	23.9	2,573.0	1,958.4
Kostanay	23.8	2,496.3	1,901.0
North Kazakhstan	23.8	2,485.3	1,893.8
Almaty	22.6	2,589.4	2,003.1
Akmola	21.4	2,538.6	1,996.5
Zhambyl	21.1	2,275.6	1,796.2
Atyrau	18.1	2,579.9	2,113.9
West Kazakhstan	12.5	2,254.8	1,972.0

Note: compiled by the authors

The highest gender pay gap was recorded in Almaty city, where women's average wages were 33.5% lower than men's wages. High values were also observed in the Turkestan, Aktobe, and Kyzylorda regions, where the gap exceeded 30%. These results indicate that substantial wage inequality is not limited to resource-intensive regions but also occurs in major urban and service-based labour markets.

The lowest values were recorded in the West Kazakhstan and Atyrau regions, where the gender pay gap amounted to 12.5% and 18.1%, respectively. However, a relatively small average wage gap should not automatically be interpreted as evidence of equal labour-market opportunities. It may also reflect a compressed wage distribution, a smaller share of women in highly paid industries, or differences in the occupational composition of male and female employment.

In regions dominated by education, healthcare, public administration, agriculture, or other activities with more compressed wage distributions, the average gender pay gap may be smaller. Nevertheless, lower wage inequality may coexist with limited access to high-income employment for both women and men. Therefore, the size of the regional gender pay gap should be assessed together with employment structure, wage levels, occupational segregation, and women's representation in managerial and technological positions.

The regional distribution of the gender pay gap is illustrated in Figure 2.

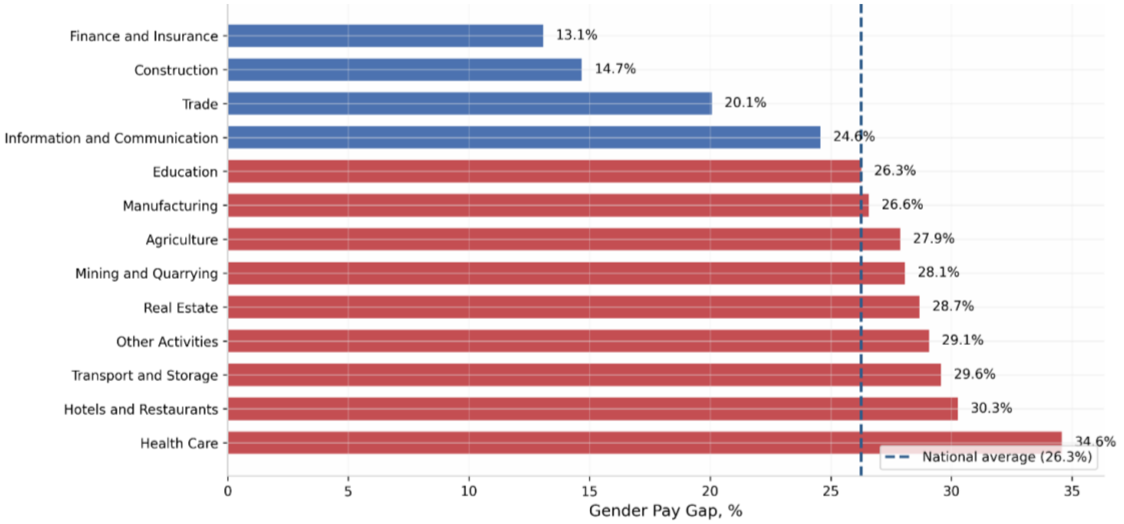

Figure 2. Gender pay gap by region of Kazakhstan, 2024

Regional differences should be interpreted in relation to the economic structure of each territory. In regions with a high concentration of financial, technological, industrial, or resource-based activities, men may be more strongly represented in the highest-paid technical and managerial occupations. This can widen the average gender pay gap even when women's employment levels are relatively high.

To identify broader territorial patterns, the regions were grouped according to the combination of gender wage inequality and selected indicators of digital and technological employment. The preliminary classification is presented in Table 8.

Table 8. Typology of regions by the level of digitalisation and the gender pay gap

Region	Gender pay gap, %	Share of the digital sector, %	Share of STEM employment, %	Type of region
Turkestan	31.1	5.1	20.5	High gap and low digitalisation
East Kazakhstan	24.2	4.5	20.7	High gap and low digitalisation
Aktobe	30.5	2.1	14.2	Medium digitalisation and high gap
Kyzylorda	30.3	2.4	13.5	Medium digitalisation and high gap
Almaty city	33.5	3.4	18.3	Medium digitalisation and high gap
Astana city	27.8	3.7	16.7	Medium digitalisation and high gap
Zhambyl	21.1	3.3	16.3	Relatively low gap
West Kazakhstan region	12.5	4.9	17.1	Relatively low gap

Note: compiled by the authors

The preliminary results indicate that a higher level of digital-sector participation does not necessarily correspond to a smaller gender pay gap. Almaty and Astana combine relatively developed digital and business activities with substantial wage inequality. This pattern may reflect the concentration of men in highly paid managerial, financial, technical, and information-technology positions.

Several regions with relatively low digital-sector employment also displayed large gender wage gaps. In the Aktobe and Kyzylorda regions, the gap exceeded 30%, while the share of digital-sector employment remained below 2.5%. In such regions, inequality may be reinforced by limited economic diversification, a narrow range of highly paid occupations, and the concentration of women in lower-paid sectors.

The Turkestan region requires cautious interpretation. According to the presented data, it had the highest share of digital-sector employment among the regions included in Table 8, at 5.1%. However, it also recorded one of the largest gender pay gaps. It should therefore not be classified as a region with low digitalisation. Instead, the result suggests that the expansion of digital employment alone does not ensure an equal distribution of its wage benefits.

The West Kazakhstan region combined a relatively high share of digital-sector employment with the lowest gender pay gap in the available dataset. This may indicate a more balanced occupational distribution, but additional information on industry structure, managerial representation, and women's employment is required before drawing a definitive conclusion.

The regional typology is illustrated in Figure 3.

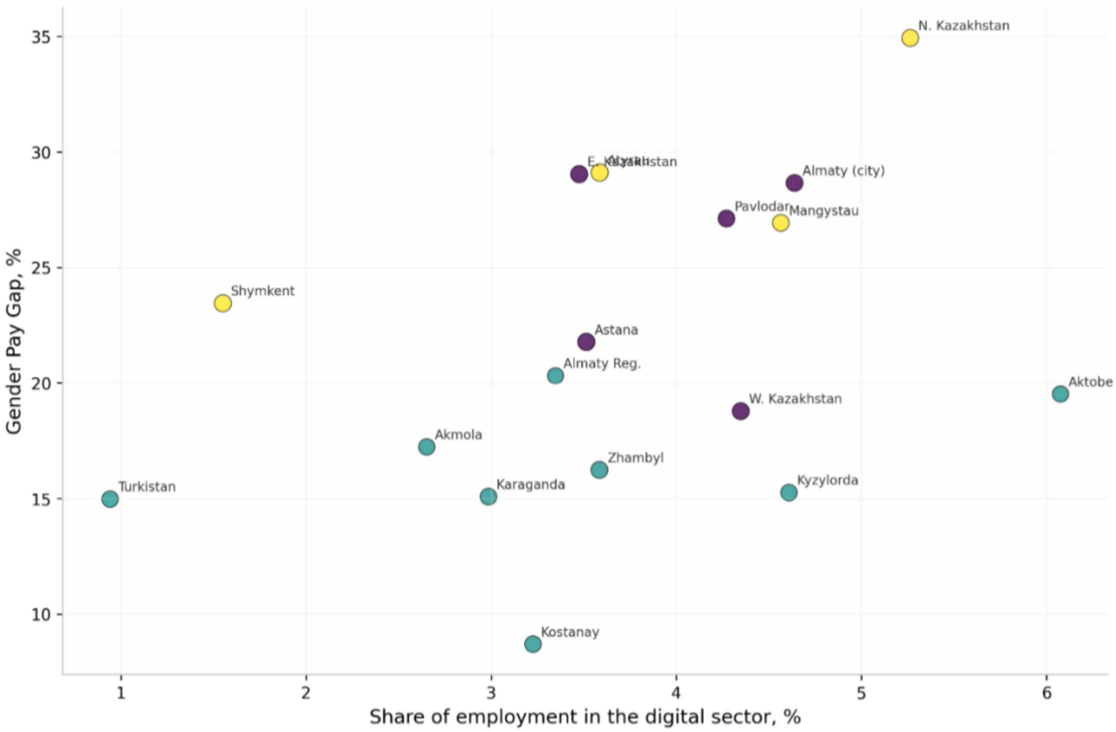

Figure 4. Typology of the regions of Kazakhstan by the level of digitalisation and the gender pay gap

Overall, the regional analysis demonstrates that the relationship between digitalisation and gender wage inequality is not linear. Digital development may generate new high-income employment opportunities, but the effect on gender equality depends on women's access to technological occupations, managerial positions, full-time work, and wage premiums.

The regional findings should be considered preliminary because the available table does not include all administrative regions of Kazakhstan. A complete cluster analysis requires a harmonised dataset covering all 17 regions and three cities of republican significance, standardisation of all indicators, and formal validation of the selected number of clusters using the elbow method or silhouette coefficient.

The combined results demonstrate that digital transformation generates substantial wage returns but does not distribute these benefits equally between men and women. Employees in STEM occupations, digital activities, and managerial positions received significant wage premiums. At the same time, women were markedly underrepresented in each of these employment categories and were substantially more likely to work part-time.

The regression estimates confirmed that the gender wage penalty persisted after controlling for differences in education, experience, occupation, employment arrangements, industry, region, and time. In the most comprehensive specification, women's conditional wages were approximately 17.6% lower than men's wages. The stability of the female coefficient across the extended models indicates that the result was not driven solely by sectoral or territorial differences.

The Oaxaca–Blinder decomposition further showed that observable characteristics explained 31.2% of the total gender wage gap, while 68.8% remained unexplained. Within the explained component, the largest contributions were associated with segregation in STEM occupations, part-time employment, limited access to managerial positions, and lower participation in the digital sector.

The regional analysis revealed substantial territorial variation in gender wage inequality. However, the relationship between digitalisation and the gender pay gap was not linear. Regions and major cities with relatively developed digital activities could still display considerable wage inequality when men were more strongly represented in highly paid technical and managerial positions.

Taken together, the results indicate that the principal problem is not simply unequal educational attainment. Men and women had almost identical average education and work experience, but their human capital was used differently in the labour market. Women had more limited access to occupations and employment arrangements associated with the highest wage returns.

5. DISCUSSION

The findings confirm that digital transformation does not automatically eliminate gender wage inequality. Instead, it changes the mechanisms through which inequality is reproduced. Digital employment, STEM occupations, and managerial positions offer substantial wage premiums, but women have more limited access to these segments of the labour market.

This conclusion is consistent with the theoretical distinction between human-capital differences and structural inequality. According to human capital theory, wage differences may reflect variations in education, training, and work experience (Schultz, 1961; Mincer, 1974). However, the descriptive results showed that men and women in the analytical sample had almost identical average education and work experience. Therefore, the observed wage gap cannot be explained primarily by differences in the amount of accumulated formal human capital.

The econometric results support this interpretation. Even after individual, occupational, sectoral, regional, and temporal characteristics were controlled, women's conditional wages remained approximately 17.6% lower than men's. This result is consistent with the broader literature showing that a substantial gender wage gap persists after observable characteristics are taken into account (Blau & Kahn, 2017).

The reduction in the female coefficient

from −0.2718 in the baseline model to −0.1940 in the final specification demonstrates that occupational and employment characteristics explain part of the initial difference. Nevertheless, the remaining statistically significant coefficient indicates that observed segregation and working-time arrangements do not fully account for gender wage inequality.

The Oaxaca–Blinder decomposition provides additional evidence. Observable characteristics explained 31.2% of the total gap, while 68.8% remained unexplained. This unexplained component was larger than the explained component, indicating that differences in education, experience, occupational position, and employment arrangements accounted for only a limited part of wage inequality.

However, the unexplained component should not be interpreted exclusively as direct discrimination. It may also reflect unobserved differences in job responsibilities, productivity, work intensity, employment interruptions, education quality, access to professional networks, bargaining behaviour, and career trajectories. Measurement error and omitted variables may also influence its magnitude. Nevertheless, the large unexplained share demonstrates that formal human-capital indicators alone are insufficient to explain wage differences.

Occupational segregation in STEM fields made the largest contribution to the explained component, accounting for 31.6%. This finding is consistent with Picatoste et al. (2023), who link gender differences in digital skills and technological employment to broader inequalities in earnings and employment quality. Since STEM occupations generated an estimated wage premium of approximately 25.1%, women's underrepresentation in these fields substantially reduced their access to higher earnings.

Part-time employment accounted for 25.6% of the explained component. Women were approximately 3.4 times more likely than men to work part-time. This difference directly reduced monthly earnings and may also have limited access to bonuses, professional development, complex assignments, and promotion. The result supports previous research showing that gender differences in paid working time and unpaid care responsibilities contribute to wage inequality (Litman et al., 2020; Teutloff et al., 2025).

Vertical segregation explained a further 17.8% of the observed component. Managerial employment was associated with the largest wage premium among the included occupational characteristics, at approximately 34.8%. However, women were less frequently represented in managerial positions. This result is consistent with the concepts of the "glass ceiling" and unequal access to organisational decision-making described in earlier studies (Arulampalam et al., 2007).

Digital-sector segregation accounted for 9.3% of the explained component. Employment in digital activities was associated with an estimated wage premium of approximately 28.7%, but women were considerably less likely to work in this sector. This finding demonstrates that digital transformation may expand high-income opportunities without ensuring equal access to them.

The results are consistent with studies of platform employment. Barzilay and Ben-David (2017) argue that gender inequality may be embedded in platform structures, including service categorisation, reputation systems, rankings, and task allocation. Litman et al. (2020) and Teutloff et al. (2025) similarly show that differences in occupational specialisation, starting rates, project selection, and pricing strategies can generate persistent income disparities in digital labour markets.

Evidence from China also suggests that platform work has mixed effects. Dong et al. (2024) found that women's platform income remained below men's, although the gap was smaller than in traditional employment. The present study similarly indicates that digitalisation can create new opportunities while preserving structural differences in access to highly paid skills and occupations.

Algorithmic management may reinforce

these inequalities when automated systems are trained on historical employment data or use performance indicators that reflect earlier labour-market disparities. Although standardisation can reduce some forms of subjective bias, algorithms may reproduce unequal promotion, ranking, and task-allocation patterns (Jarrahi & Sutherland, 2019; Kellogg et al., 2020).

The regional findings also demonstrate that digital development does not have a uniform relationship with gender wage equality. Major cities and regions with relatively developed digital and business activities may still display large wage gaps when men dominate highly paid technical, financial, and managerial occupations. Conversely, a relatively small regional wage gap may result from compressed wage structures rather than equal access to high-income employment.

These findings have several policy implications. First, policies aimed solely at increasing women's general educational attainment are unlikely to eliminate the gender pay gap. Measures should focus on women's access to STEM occupations, advanced digital skills, managerial training, and career progression.

Second, wage transparency should be strengthened. Employers can be required or encouraged to disclose salary ranges, establish clear remuneration criteria, and regularly audit pay structures by gender. Such measures can reduce information asymmetry and help identify unjustified wage differences.

Third, digital platforms and algorithmic human-resource systems should be subject to regular equality audits. Recruitment, ranking, performance evaluation, task allocation, and remuneration algorithms should be tested for systematically different outcomes for men and women.

Fourth, policies should address unequal working-time arrangements. Expanding affordable childcare, flexible but protected employment, and access to full-time work may reduce women's concentration in lower-paid part-time positions.

Fifth, regional policy should reflect differences in economic structure. Less diversified regions require wider access to digital infrastructure, retraining, and remote employment opportunities. Major cities and technologically developed regions require stronger measures against vertical segregation and unequal access to managerial and high-income technical positions.

The study has several limitations. First, the analytical microdata sample contains 5,000 observations and may not fully reproduce the structure of the entire employed population. Second, the study lacks direct measures of advanced digital skills, algorithmic exposure, bargaining behaviour, and employment interruptions. Third, the available regional dataset does not include all current administrative regions of Kazakhstan and therefore limits the completeness of the clustering analysis. Fourth, the unexplained component of the Oaxaca–Blinder decomposition includes both potential institutional inequality and unobserved individual characteristics.

Despite these limitations, the results provide consistent evidence that gender wage inequality in Kazakhstan is associated primarily with unequal access to high-return occupations, managerial positions, digital employment, and full-time work rather than with large differences in formal education or work experience.

6. CONCLUSION

The study assessed the scale, structure, and principal mechanisms of gender pay inequality in Kazakhstan under conditions of digital transformation. The results show that technological development and the expansion of digital employment do not automatically reduce wage differences between men and women. Digitalisation creates substantial wage returns, but access to these returns remains uneven.

According to the analytical microdata sample for 2024, the gender pay gap amounted to 25.8%. At the same time, the long-term analysis based on aggregated national indicators showed that the gap declined from 22.7% in 2015 to 21.6% in 2024. However, its dynamics remained unstable throughout the study period. These estimates reflect different datasets and should therefore be interpreted as complementary indicators of gender wage inequality.

The descriptive analysis demonstrated that men and women had almost identical average levels of education and work experience. However, women were substantially underrepresented in STEM occupations, digital-sector employment, and managerial positions and were considerably more likely to work part-time. This indicates that gender inequality is related not only to the accumulation of human capital but also to unequal opportunities for its labour-market utilisation.

The econometric results confirmed the persistence of a statistically significant gender wage penalty. In the most comprehensive specification, women's conditional wages were approximately 17.6% lower than men's after controlling for individual, occupational, sectoral, regional, and temporal characteristics. The stability of this coefficient across the extended specifications indicates that the observed difference cannot be explained solely by sectoral or territorial heterogeneity.

The results also showed that STEM employment, digital-sector participation, and managerial status were associated with substantial wage premiums, while part-time employment reduced monthly earnings. Since women had more limited access to the first three categories and were much more frequently employed part-time, occupational, vertical, digital, and working-time segregation contributed significantly to the overall gender pay gap.

The Oaxaca–Blinder decomposition demonstrated that observable characteristics explained 31.2% of the total wage gap, while 68.8% remained unexplained. The largest contributions to the explained component were associated with segregation in STEM occupations, part-time employment, limited access to managerial positions, and lower participation in the digital sector. By contrast, education and work experience accounted for only a relatively small proportion of the explained difference.

The regional analysis revealed substantial territorial differentiation. The relationship between digitalisation and the gender pay gap was not linear: regions and major cities with relatively developed digital and business activities could still display high wage inequality when men were more strongly represented in highly paid technical and managerial positions. Therefore, digital development should be assessed not only by the expansion of technological employment but also by the gender distribution of access to its benefits.

Reducing the gender pay gap requires a comprehensive policy approach. Priority measures include increasing women's participation in STEM and digital occupations, expanding access to managerial positions, strengthening wage transparency, conducting regular gender audits of remuneration systems, and evaluating recruitment and task-allocation algorithms for unequal outcomes. Policies aimed at reducing women's concentration in part-time employment, including improved childcare infrastructure and access to protected flexible work, are also important.

Regional policy should take into account differences in economic specialisation, employment structure, and digital development. Less diversified regions require broader access to digital infrastructure, retraining, and remote employment opportunities. Major cities and technologically developed regions require stronger measures to reduce vertical segregation and unequal access to high-income professional and managerial positions.

The study has several limitations. The analytical microdata sample may not fully reproduce the structure of the entire employed population. Direct indicators of advanced digital skills, algorithmic exposure, employment interruptions, and bargaining behaviour were not available. In addition, the regional dataset did not cover all current administrative regions of Kazakhstan, which limits the completeness of the cluster analysis.

Further research should use nationally representative longitudinal microdata, include direct measures of digital competencies and platform employment, and estimate gender differences in the returns to digital-sector employment through interaction effects. Separate analysis by occupation, wage quantile, age group, parental status, and region would also provide a more detailed understanding of the mechanisms underlying gender wage inequality.

AUTHOR CONTRIBUTION

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Software and supervision: Gakku Tansykbayeva.
Data collection, analysis, and interpretation: Zhanar Baigireyeva, Zhanna Nurgaliyeva.
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Writing – review and editing: Gakku Tansykbayeva, Zhanar Baigireyeva, Zhanna Nurgaliyeva.

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