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Analysis of Gender Discrimination in Employee Salary Payments in Iranian Governmental Organizations Using Simultaneous Equations Modeling, Weighted Least Squares (WLS), and Stepwise Regression

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ABSTRACT

Gender discrimination in wage and salary payments remains one of the persistent challenges of the Iranian labor market. Despite the expansion of higher education among women and their increasing participation in professional occupations, income disparities between men and women remain substantial. The present study was conducted with the aim of examining the relationship between educational attainment and gender-based discrimination in salary payments among employees of Iranian governmental organizations. This applied research adopted a descriptive–analytical approach and employed simultaneous equations modeling, Stepwise Regression, and the Weighted Least Squares (WLS) estimation method. Research data were collected from 420 employees working in executive governmental agencies during the year 2024. The principal variables included the logarithm of monthly salary, gender, level of education, marital status, job tenure, and age. Data analysis was performed using EViews 8 and Microsoft Excel software. The findings indicated that the average rate of vulnerable employment among women was higher than that of men, and according to reports by the International Labour Organization (ILO), women's unemployment rates were significantly higher than those of men. Educational attainment demonstrated a positive and statistically significant effect on wage levels; however, the interaction effect between gender and education showed a negative relationship with salary levels. This result indicates that increases in educational attainment lead to greater income growth for men compared to women. Furthermore, gender as an independent variable exerted a positive effect on wages, reflecting the existence of a gender pay gap in favor of men. The findings suggest that although education plays a significant role in improving income levels, it is not sufficient on its own to eliminate gender inequalities in compensation. The model's coefficient of determination ($R^2 = 0.915$) indicates a high explanatory power in accounting for variations in the dependent variable. Finally, the study recommends the implementation of transparent pay policies, gender-sensitivity retraining workshops, and strengthened employment support mechanisms—such as parental leave policies and remote working opportunities—as practical strategies for reducing the wage gap between men and women.

Keywords: *Gender discrimination, wages and salaries, education, WLS model, stepwise regression.*

1. Introduction

Gender-based wage discrimination remains one of the most persistent and policy-relevant forms of inequality in contemporary labor markets, with consequences that extend beyond individual earnings to organizational effectiveness, social welfare, and long-run economic development. Even as women's educational attainment and labor-force participation have risen in many countries, wage gaps frequently endure, indicating that differences in observed human capital alone cannot fully explain compensation disparities (Blau & Kahn, 2017; Shah et al., 2023). In management research, the gender pay gap is not merely a macroeconomic statistic; it is an organizational outcome shaped by how jobs are designed, how performance is evaluated, how promotions are allocated, and how compensation systems absorb—and sometimes reproduce—structural inequities. Accordingly, studying pay discrimination in governmental organizations is especially important, because public-sector employment is often assumed to be more rule-based and transparent; if meaningful gaps persist even in such settings, this signals deeper institutional mechanisms that warrant careful empirical examination (Bennedsen et al., 2023; Morgan, 2019).

A key reason gender pay gaps persist is that discrimination operates through multiple channels that can be direct or indirect. Direct discrimination occurs when individuals are paid differently for comparable work, while indirect discrimination can arise when gendered patterns of job assignment, promotion, or evaluation lead to unequal access to higher-paying positions or wage progression trajectories. The broader workplace environment matters as well: perceived gender discrimination can undermine motivation and productivity, and discriminatory climates can affect retention, well-being, and performance outcomes (Tang & Xu, 2023). Moreover, inequities are not limited to pay alone; they often coexist with workplace harassment and mental-health burdens that disproportionately affect women, compounding inequality through both economic and psychosocial pathways (Mercado-Aravena, 2025). These organizational dynamics make gender wage inequality a core management issue, tightly linked to governance, fairness, and human resource systems rather than only individual-level characteristics.

Within the economics of gender inequality, extensive evidence shows that a substantial portion of the pay gap emerges or widens around parenthood, through what is often termed the "child penalty." This mechanism reflects the career costs associated with children, including disruptions in labor supply, slower wage growth, and reduced promotion probabilities, with penalties typically borne disproportionately by women (Adda et al., 2017; Angelov et al., 2016). Cross-national research further suggests that child penalties vary widely across institutional contexts, implying that policy design, labor-market structure, and organizational practices jointly shape the magnitude of gender inequality (Kleven, Landais, Posch, et al., 2019; Kleven, Landais, & Søgaard, 2019). Importantly, evidence from policy reforms and comparisons using same-sex couples underscores that penalties are not purely biological or preference-driven; rather, they are partly driven by gendered norms and institutional arrangements, which can be altered through targeted interventions and system-level reforms (Andresen & Nix, 2019). For managerial and organizational settings—especially in public administration—this line of research implies that wage inequality may reflect not only current pay-setting practices but also accumulated differences in career progression and job histories shaped by family-related constraints.

Human capital theory traditionally highlights education as a key determinant of wages, yet the education–income relationship can itself be gendered. Returns to schooling are shaped by field of study, occupational sorting, and differential access to high-paying job ladders (Kim et al., 2015). Even when women attain comparable or higher levels of education, wage gaps may persist due to evaluation biases, limited advancement opportunities, or differences in how credentials translate into seniority and leadership roles. In addition, the net return to higher education can vary depending on major choice, debt burden, and labor-market conditions, underscoring that education is necessary but not sufficient to ensure equitable wage outcomes (Webber, 2016). For management research, this indicates that education should be analyzed not only as an independent predictor of wages but also as a potential site where gendered processes shape how human capital is rewarded.

From a theoretical perspective, several strands explain why gender pay gaps can persist even under competitive conditions. Equilibrium models of discrimination emphasize that wage and employment discrimination can be sustained through labor-market frictions, employer preferences, or informational asymmetries, producing systematic differences in outcomes between men and women (Xiao, 2021). Quantitative macro-labor frameworks similarly show how differences in labor supply, occupational choice, and productivity-related factors interact with institutional constraints to generate gender wage gaps in equilibrium (Erosa et al., 2016). Yet management scholars also emphasize organizational structures—such as hierarchical promotion systems, internal labor markets, and cultural norms—that can generate persistent differences even when formal rules appear gender-neutral. Barriers to senior management, often described through "glass ceiling" dynamics, can restrict women's upward mobility and reduce access to high-compensation roles, reinforcing pay disparities across the career ladder (Ayub et al., 2019). In this sense, pay inequality is frequently the observable outcome of cumulative processes in hiring, task assignment, evaluation, promotion, and leadership inclusion.

A crucial policy and governance question is whether transparency and accountability mechanisms can reduce gender pay gaps. Compensation transparency is widely discussed as a lever to limit discretionary bias, enable detection of inequities, and shift organizational norms toward fairness (Morgan, 2019). In the broader literature, pay transparency reforms and wage reporting requirements are increasingly examined for their capacity to reduce information asymmetries and constrain discriminatory pay-setting, while also generating organizational learning about compensation structures (Bennedsen et al., 2023). For public-sector organizations, which often rely on pay scales and formal classification systems, transparency should in theory be higher than in many private-sector settings; nevertheless, gaps may remain due to differential grade placement, promotion speed, allowance allocation, or interaction effects between gender and credentials. Therefore, empirical studies that isolate these mechanisms—especially using robust econometric methods—are necessary to inform both administrative reform and managerial practice.

Beyond compensation systems, gender inequality intersects with organizational justice, inclusion, and the broader institutional environment. Gender-based disparities can emerge in a variety of sectors, including public services such as healthcare, where evidence documents systematic differences in access and outcomes across demographic lines, indicating that inequities can manifest not only in labor-market pay but also in institutional service delivery and resource allocation (Dickens et al., 2023). This aligns with distributive justice perspectives in organizational and spatial planning research, which emphasize that fairness is not simply a normative ideal but an operational criterion for evaluating how resources and opportunities are distributed across groups (Magidimisha & Chipungu, 2019). Within organizations, perceived discrimination can shape how employees evaluate organizational democracy, procedural fairness, and voice, affecting engagement and legitimacy perceptions (Troncoso et al., 2023). These considerations are central to management research, because organizational climate and governance quality influence both performance and the sustainability of workforce development.

The Iranian context adds further importance and specificity to the study of gender wage discrimination. Gender norms, labor-market segmentation, and institutional constraints may shape how education translates into pay and advancement. Evidence on gender representation and discrimination in socialization institutions, such as educational materials, suggests that gendered expectations can be reproduced early and later reflected in occupational choices and organizational role allocation (Peyvandi, 2024). At the organizational level, perceived discrimination can directly affect job performance and may also shape turnover and commitment patterns, making gender equity a strategic issue for public-sector human resource management (Tang & Xu, 2023). At the same time, the policy environment increasingly emphasizes inclusive development and equitable participation, with local economic development frameworks recognizing that sustainable progress is strengthened when institutions widen access to opportunities and address structural disadvantages (Adegbite & Machethe, 2020; Venter et al., 2022). For public administration, narrowing gender pay gaps is thus not only a fairness objective but also a governance and development imperative.

Recent management and organizational research also suggests that gender shapes how employees interact with organizational systems and technologies, with implications for administrative capacity and performance. For example, studies on information system acceptance show that gender and cultural orientations can influence usage patterns and organizational identification, implying that gender inequality may have indirect productivity effects through differential engagement with core administrative infrastructures (Arshad et al., 2025). Moreover, gender diversity in top management teams has been linked to organizational resilience under varying environmental conditions, suggesting that gender inclusion can have strategic value beyond individual equity outcomes (Zhou & Lan, 2025). These strands broaden the rationale for studying gender inequality in governmental organizations: unequal pay and opportunity structures may not only disadvantage individuals but also undermine institutional learning, adaptability, and long-term performance.

Despite the extensive literature on gender wage gaps, important empirical challenges remain in identifying the pathways through which education and other determinants produce differential wage outcomes by gender. Standard single-equation wage regressions can be limited when key explanatory variables are jointly determined—such as education, work history, and wages—creating endogeneity and simultaneity that may bias estimates. Simultaneous relationships are particularly plausible in public-sector labor markets where educational credentials influence job assignment and wage grade, while job tenure and organizational position shape both wage progression and incentives for further education. Methodologically, this motivates the use of simultaneous equation systems and estimators that can address heteroskedasticity and correlated disturbances, thereby improving inference about gendered effects in compensation structures. In parallel, complementary approaches such as stepwise modeling can help explore the incremental explanatory contribution of predictors and interactions in settings where multicollinearity and overlapping determinants are plausible.

Overall, the literature indicates that gender pay gaps reflect a combination of human capital processes, family-related career penalties, organizational barriers to advancement, institutional norms, and governance features such as transparency and accountability (Adda et al., 2017; Angelov et al., 2016; Ayub et al., 2019; Bennedsen et al., 2023; Blau & Kahn, 2017; Morgan, 2019). These mechanisms are especially salient for governmental organizations, where the legitimacy of administrative systems depends on perceived fairness and equal opportunity, and where policy levers for reform—such as transparent pay rules, family-supportive employment practices, and anti-harassment safeguards—can be operationalized through public governance.

Accordingly, the aim of this study is to examine the relationship between educational attainment and gender-based wage discrimination among employees of Iranian governmental organizations by estimating a simultaneous equations model using Weighted Least Squares and stepwise regression to identify the magnitude and structure of gendered effects on wages.

2. Methods and Materials

Research methodologies can be classified into four categories based on research objectives: applied research, research and development, basic research, and evaluation research. The present study is categorized as applied research in terms of its objective. In addition, considering the method of data acquisition, the study falls within descriptive (non-experimental) research, aiming to describe the phenomenon under investigation. This research employed a simultaneous equations system to examine the relationships among the study variables in accordance with the research objectives. The hypothesis testing period corresponds to the year 2024. The study population consisted of personnel working in governmental administrative organizations. A population refers to the largest set of elements of interest at a specific time, while a statistical population includes elements sharing at least one defining characteristic that distinguishes them from other populations. The statistical population included employees of governmental offices. The research sample was determined using simple random sampling based on Cochran's sampling formula.

For data analysis, the model parameters were estimated using a simultaneous equations system. To compute all internal relationships among endogenous variables, all equations were solved simultaneously. The estimation method used for a single equation or a system of equations typically depends on the research objective. Since all endogenous variables in the system were not independent of disturbance components and the objective of this study was to calculate the simultaneous total effects of predetermined variables on endogenous variables, system estimation methods were applied. Therefore, the model was estimated using a simultaneous equations framework.

The research model was formulated as follows:

LNWAGE = C(1)×AGE02 + C(2)×DEGREE + C(3)×GENDER + C(4)×MARIAGE + C(5)×WORKHISTORY + C(6)×GENDER×DEGREE + C(7)

DEGREE = C(8)×AGE02 + C(9)×GENDER + C(10)×MARIAGE + C(11)

WORKHISTORY = C(12)×AGE02 + C(13)×DEGREE + C(14)×GENDER×DEGREE + C(15)×GENDER×WORKHISTORY + C(16)

Where:

LNWAGE = Logarithm of wages and salaries

AGE02 = Age

DEGREE = Educational attainment

MARIAGE = Marital status

WORKHISTORY = Job tenure

Model estimation and statistical analyses were conducted using EViews 8 and Microsoft Excel software.

3. Findings and Results

Descriptive statistics refer to a set of concepts and techniques used to organize, summarize, tabulate, visualize, and describe collected data, providing an overall representation of observed quantitative indicators.

Table 1

Descriptive Statistics of Labor Market Indicators for Women and Men in Iran (1991–2023)

Statistic	Vulnerable Employment (Women %)	Vulnerable Employment (Men %)	Wage & Salary Workers (Women %)	Wage & Salary Workers (Men %)	Male Labor Force (%)	Female Labor Force (%)	Female Youth Unemployment (15–24 %)	Male Youth Unemployment (15–24 %)	Female Unemployment (%)	Male Unemployment (%)
Mean	45.73114	40.69812	53.26954	54.65592	71.90800	15.90787	35.57836	20.89673	18.47491	9.653273
Median	45.40858	40.49337	53.71723	54.14889	70.64700	16.44199	35.66100	20.44500	18.73800	9.453000
Maximum	53.44006	43.29591	62.65564	57.70191	81.71100	19.86528	43.61300	25.60700	24.59800	12.15400
Minimum	36.10954	37.93459	45.77309	52.63973	66.70300	10.13897	23.90200	17.48900	13.43400	7.703000
Standard Deviation	4.593746	1.624341	4.515939	1.628716	4.158326	2.931947	5.179072	2.094159	2.488199	1.019339
Skewness	−0.121603	0.129522	0.106026	0.379605	0.793773	−0.676970	−0.260691	0.588151	0.222038	0.107551
Kurtosis	2.422221	1.772641	2.418302	1.655514	2.728302	2.284492	2.267874	2.675197	2.573022	2.738541
Jarque–Bera	0.540345	2.163580	0.527090	3.278057	3.566918	3.224523	1.110790	2.047630	0.521832	0.157616
Probability	0.763248	0.338988	0.768323	0.194169	0.168056	0.199436	0.573845	0.359222	0.770346	0.924217
Sum of Squared Errors	675.2800	84.43150	652.5987	84.88686	553.3335	275.0819	858.3292	140.3360	198.1164	33.24969
Observations	33	33	33	33	33	33	33	33	33	33

As presented in Table 1, measures of central tendency and dispersion for labor market indicators of Iranian women and men during the period 1991–2023 are reported. During the examined period, the average proportion of female wage and salary workers reached 53.269%, whereas the corresponding value for men was 54.655%. The mean rate of vulnerable employment among women was 45.73%, compared with 40.69% among men.

Furthermore, the average unemployment rate among young women aged 15–24 was 35.57%, significantly higher than the corresponding rate for young men (20.89%). In the next stage of analysis, Student's t-test was employed to examine differences between male and female group means across the studied variables.

As shown in the previous table, the measures of central tendency and dispersion for labor market variables related to female and male workers in Iran during the period 1991–2023 are presented. During the examined period, the mean proportion of female wage and salary workers (percentage of female employment) was 53.269%, while the mean proportion of male wage and salary workers (percentage of male employment) was 54.655%. The average rate of vulnerable employment among women was 45.73%, compared with 40.69% among men. Furthermore, the average unemployment rate among young women aged 15–24 reached 35.57%, whereas the corresponding unemployment rate among young men was 20.89%. Subsequently, differences between male and female group means were examined using the Student's t-test.

Table 2

Student's t-Test Results for Comparing Mean Vulnerable Employment Between Men and Women

Method	df	Value	Probability
t-test	64	-5.933843	0.0000
Satterthwaite–Welch t-test*	39.87887	-5.933843	0.0000
ANOVA F-test	(1, 64)	35.21050	0.0000
Welch F-test*	(1, 39.8789)	35.21050	0.0000

Test allows for unequal cell variances.

Analysis of Variance

Source of Variation	df	Sum of Squares	Mean Square
Between Groups	1	417.9659	417.9659
Within Groups	64	759.7115	11.87049
Total	65	1177.677	18.11811

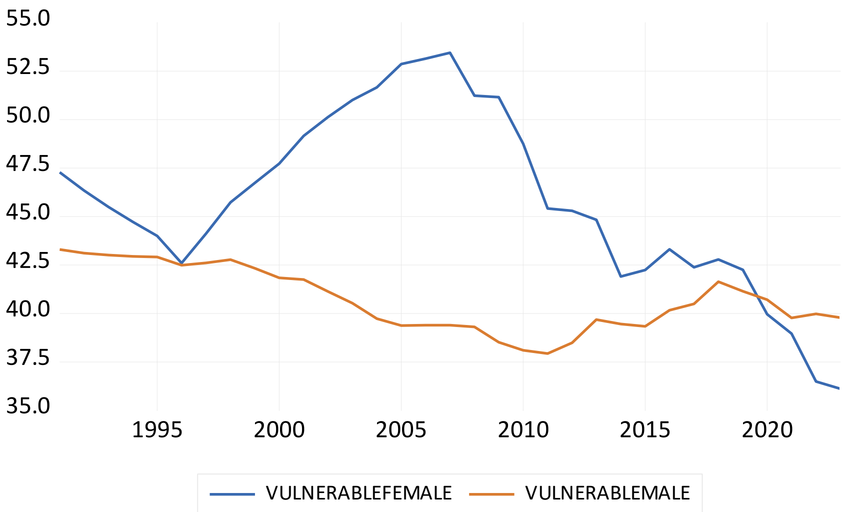
Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Error of Mean
VULNERABLEMALE	33	40.69812	1.624341	0.282762
VULNERABLEFEMALE	33	45.73114	4.593746	0.799668
All	66	43.21463	4.256538	0.523944

As observed, the Student's t-test results indicate a statistically significant difference between the mean vulnerable employment rates of men and women during 1991–2023, with male vulnerable employment averaging 5.93 percentage points lower than that of women.

Figure 1

Comparison of Vulnerable Employment Between Men and Women (ILO Modeled Estimates)



As illustrated in the figure, female vulnerable employment exceeded male vulnerable employment from 1991 to 2019. However, from 2019 to 2023, vulnerable employment among men increased and surpassed that of women.

Table 3

Student's t-Test Results for Comparing Mean Wage and Salary Workers Between Women and Men

Method	df	Value	Probability
t-test	64	1.658963	0.1020
Satterthwaite–Welch t-test*	40.18630	1.658963	0.1049
ANOVA F-test	(1, 64)	2.752157	0.1020
Welch F-test*	(1, 40.1863)	2.752157	0.1049

Test allows for unequal cell variances.

Analysis of Variance

Source of Variation	df	Sum of Squares	Mean Square
Between Groups	1	31.71369	31.71369
Within Groups	64	737.4856	11.52321
Total	65	769.1992	11.83383

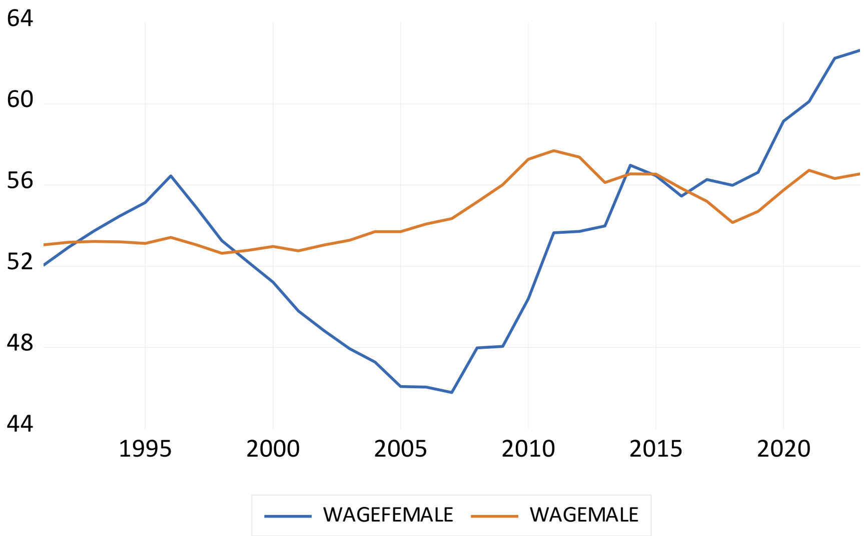
Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Error of Mean
WAGEMALE	33	54.65592	1.628716	0.283523
WAGEFEMALE	33	53.26954	4.515939	0.786124
All	66	53.96273	3.440034	0.423439

The Student’s t-test results indicate no statistically significant difference between the mean number of male and female wage and salary workers during 1991–2023, although the male average exceeds the female average by approximately 1.65 percentage points.

Figure 2

Comparison of Wage and Salary Workers Between Women and Men (ILO Modeled Estimates)



As shown in the figure, the number of male wage and salary workers was higher than that of women from 1999 to 2015. However, from approximately 2015 to 2023, the number of female wage and salary workers gradually increased and approached or exceeded male levels.

Table 4

Student’s t-Test Results for Comparing Mean Youth Unemployment Between Women and Men (Aged 15–24)

Method	df	Value	Probability
t-test	64	-15.09720	0.0000
Satterthwaite–Welch t-test*	42.19150	-15.09720	0.0000
ANOVA F-test	(1, 64)	227.9255	0.0000
Welch F-test*	(1, 42.1915)	227.9255	0.0000

Test allows for unequal cell variances.

Analysis of Variance

Source of Variation	df	Sum of Squares	Mean Square
Between Groups	1	3556.582	3556.582
Within Groups	64	998.6652	15.60414
Total	65	4555.248	70.08073

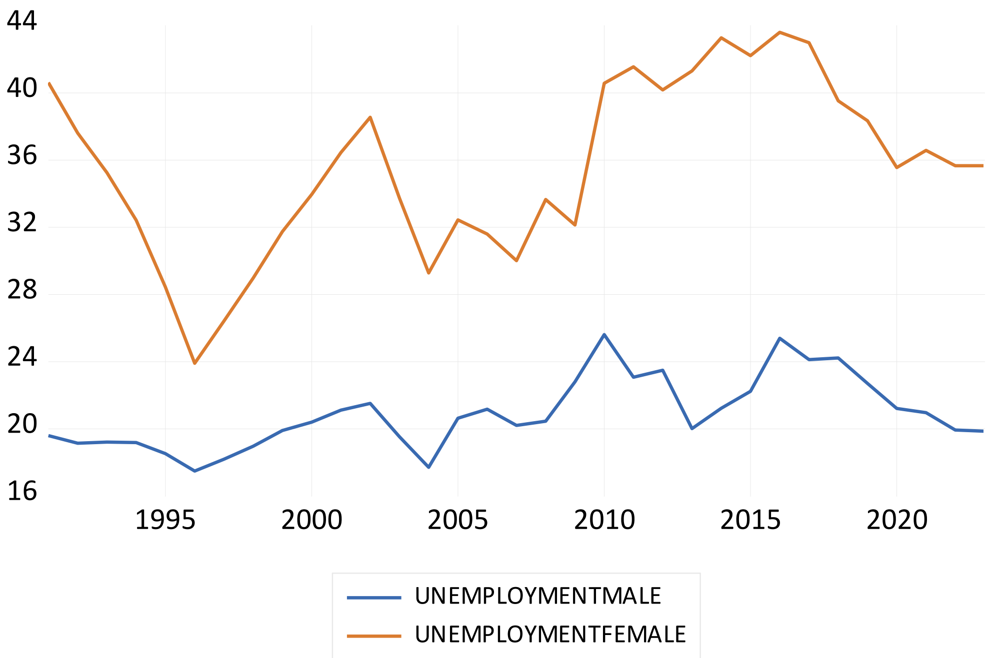
Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Error of Mean
UNEMPLOYMENTMALE	33	20.89673	2.094159	0.364546
UNEMPLOYMENTFEMALE	33	35.57836	5.179072	0.901561
All	66	28.23755	8.371424	1.030451

The Student's t-test results reveal a statistically significant difference between male and female youth unemployment rates during 1991–2023, indicating that male youth unemployment was approximately 15.09 percentage points lower than female youth unemployment.

Figure 3

Comparison of Youth Unemployment Between Women and Men (Aged 15–24) (ILO Modeled Estimates)



As illustrated in the figure, male youth unemployment remained consistently lower than female youth unemployment from 1999 to 2023.

Table 5

Student's t-Test Results for Comparing Mean Unemployment Between Women and Men (Percentage of the Labor Force)

Method	df	Value	Probability
t-test	64	-18.84653	0.0000
Satterthwaite–Welch t-test*	42.44681	-18.84653	0.0000
ANOVA F-test	(1, 64)	355.1915	0.0000
Welch F-test*	(1, 42.4468)	355.1915	0.0000

*Test allows for unequal cell variances.

Analysis of Variance

Source of Variation	df	Sum of Squares	Mean Square
Between Groups	1	1284.051	1284.051
Within Groups	64	231.3660	3.615094
Total	65	1515.417	23.31411

Category Statistics

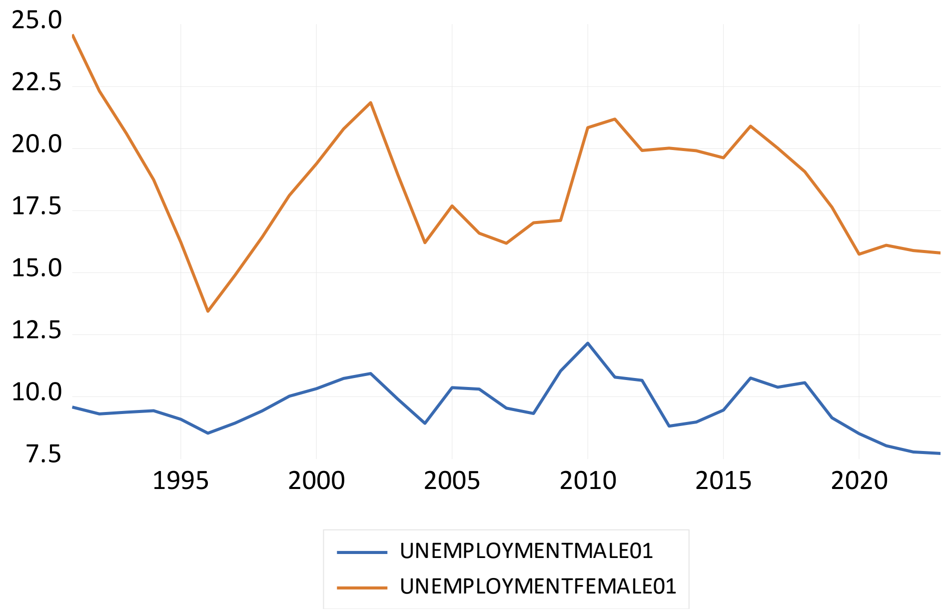
Variable	Count	Mean	Std. Dev.	Std. Error of Mean
UNEMPLOYMENTMALE01	33	9.653273	1.019339	0.177444
UNEMPLOYMENTFEMALE01	33	18.47491	2.488199	0.433140
All	66	14.06409	4.828468	0.594343

As shown, the Student's t-test results indicate that during 1991–2023 there is a statistically significant difference between the mean unemployment rates of women and men, and the mean unemployment rate for men is 18.84

percentage points lower than the mean unemployment rate for women.

Figure 4

Comparison of Unemployment Between Women and Men (Percentage of the Labor Force) (ILO Modeled Estimates)



As indicated by the figure, male unemployment from 1999 to 2023 remained lower than female unemployment.

Table 6

Student's t-Test Results for Comparing Mean Labor Force Participation Between Women and Men

Method	df	Value	Probability
t-test	64	63.22618	0.0000
Satterthwaite–Welch t-test*	57.51164	63.22618	0.0000
ANOVA F-test	(1, 64)	3997.550	0.0000
Welch F-test*	(1, 57.5116)	3997.550	0.0000

*Test allows for unequal cell variances.

Analysis of Variance

Source of Variation	df	Sum of Squares	Mean Square
Between Groups	1	51744.25	51744.25
Within Groups	64	828.4155	12.94399
Total	65	52572.66	808.8102

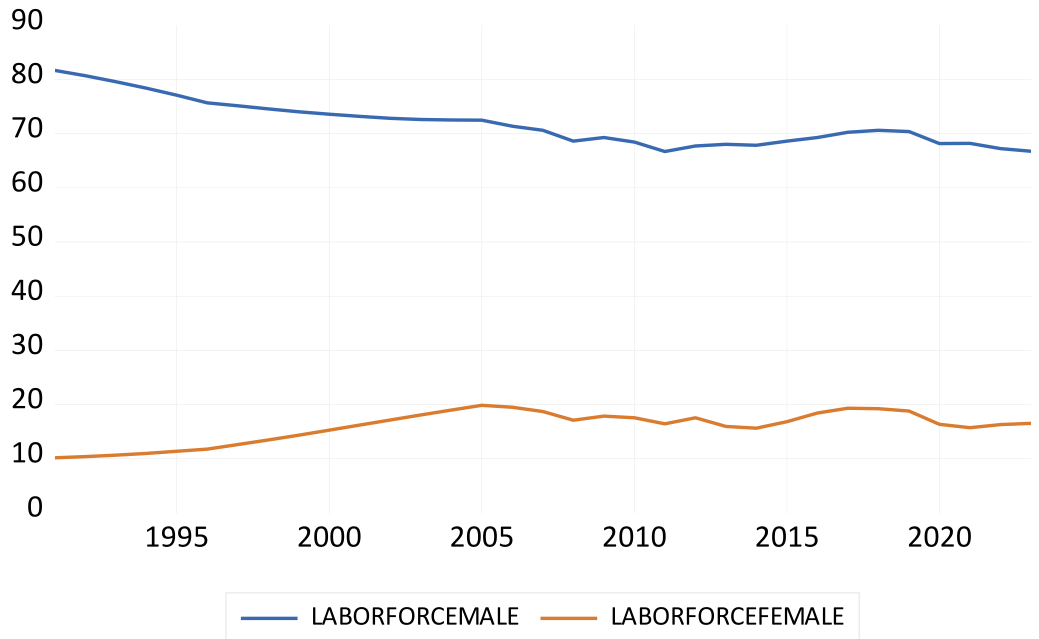
Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Error of Mean
LABORFORCEMALE	33	71.90800	4.158326	0.723872
LABORFORCEFEMALE	33	15.90787	2.931947	0.510386
All	66	43.90793	28.43959	3.500671

As shown, the Student's t-test results indicate that during 1991–2023 there is a statistically significant difference between mean labor force participation of women and men, and the mean male labor force participation rate is 63.22 percentage points higher than the mean female labor force participation rate.

Figure 5

Comparison of Labor Force Participation Between Women and Men (ILO Modeled Estimates)



The research data were collected from 420 employees of governmental organizations in 2024. The purpose of this section is to analyze the reciprocal relationships between endogenous and exogenous variables and to estimate, simultaneously, the equations related to wages, education, and work history. Because endogenous variables may be correlated with the error term, single-equation estimation approaches are not appropriate. Therefore, to obtain unbiased and efficient estimates, a Simultaneous Equation System (SES) was employed.

The research model was specified as follows:

LNWAGE = C(1)×AGE02 + C(2)×DEGREE + C(3)×GENDER + C(4)×MARIAGE + C(5)×WORKHISTORY + C(6)×(GENDER×DEGREE) + C(7)

DEGREE = C(8)×AGE02 + C(9)×GENDER + C(10)×MARIAGE + C(11)

WORKHISTORY = C(12)×AGE02 + C(13)×DEGREE + C(14)×(GENDER×DEGREE) + C(15)×(GENDER×WORKHISTORY) + C(16)

Where LNWAGE denotes the logarithm of wages; AGE02 denotes age; DEGREE denotes educational attainment; MARIAGE denotes marital status; and WORKHISTORY denotes job tenure.

Table 7

Descriptive Statistics for Log Wage, Age, and Work History

Statistic	Log Wage (LNWAGE)	Age	Work History
Mean	10.95500	34.6127	13.243
Median	10.93939	35.00000	14.00000
Maximum	11.60628	51.00000	24.00000
Minimum	9.978502	28.00000	5.000000
Std. Dev.	0.324442	2.962694	4.141242
Skewness	-0.485131	0.037847	-0.291888
Kurtosis	2.523334	2.392051	2.129996
Jarque–Bera	16.50675	5.301554	15.50503
Probability	0.000260	0.070596	0.000430

Table 8

Frequency Distribution of Gender

Value	Count	Percent	Cumulative Count	Cumulative Percent
Female	195	46.42	195	46.42
Male	225	53.58	420	100.00
Total	420	100.00	420	100.00

Table 9

Frequency Distribution of Educational Attainment

Value	Count	Percent	Cumulative Count	Cumulative Percent
PhD	47	11.19	47	11.19
Master’s	111	26.42	158	37.61
Bachelor’s	262	62.38	420	100.00
Total	420	100.00	420	100.00

Table 10

Frequency Distribution of Marital Status

Value	Count	Percent	Cumulative Count	Cumulative Percent
Married	213	50.71	213	50.71
Single	207	49.28	420	100.00
Total	420	100.00	420	100.00

When the dispersion of the data is substantial, the Ordinary Least Squares (OLS) estimator can no longer provide the best and most efficient estimates. Put differently, if heteroskedasticity exists in the data, OLS treats all observations with equal weight, whereas this assumption is statistically inappropriate.

To address this issue, estimation methods that explicitly account for differences in variance must be used. Among the most important corrective methods are Weighted Least Squares (WLS) and, more generally, Generalized Least Squares (GLS). These approaches assign greater weight to observations with lower variance and smaller weight to observations with higher dispersion, thereby producing estimates that are unbiased and more efficient.

In this study, heteroskedasticity was diagnosed using the variance–covariance matrix. In such a matrix, if the diagonal elements differ across sections, this indicates the presence of heteroskedasticity among observations. Based on the computed and examined matrix elements, the variances were not equal across different cross-sections; therefore, WLS was employed to estimate the model in order to enhance estimation precision and prevent bias in the coefficients.

Table 11

Variance–Covariance Matrix

	LNWAGE	AGE02	DEGREE	WORKHISTORY	GENDER	MARIAGE
LNWAGE	0.118	0.402	0.162	0.767	0.101	0.142
AGE01	0.751	7.045	2.401	15.503	-0.171	0.738
AGE02	0.382	8.713	1.162	7.085	-0.063	0.381
DEGREE	0.153	1.162	0.482	2.472	-0.026	0.150
WORKHISTORY	0.741	7.085	2.472	17.122	-0.209	0.739
GENDER	0.096	-0.063	-0.026	-0.209	0.244	0.149
MARIAGE	0.135	0.381	0.150	0.739	0.149	0.250
WORKHISTORY02	0.098	1.014	0.338	2.481	-0.046	0.098

As shown in the table, the values on the main diagonal of the matrix are not equal to one another, indicating the presence of heteroskedasticity across different cross-sections. To address this problem and prevent bias in the estimated coefficients, the model was estimated using the Weighted Least Squares (WLS) method.

The Wald test was used to test the hypothesis regarding the existence or absence of the intercept in the model. In this test, the null hypothesis assumes that the intercept does not exist in the model, whereas the alternative hypothesis assumes that the intercept exists in the regression model.

$$H_0: \alpha_0 = 0 H_1: \alpha_0 \neq 0$$

The results of the Wald test are reported in Table 12.

Table 12

Wald Test Results

Test Statistic	Value	P-Value
t-statistic	-8.508862	0.0000
F-statistic	72.40073	0.0000
Chi-square	72.40073	0.0000

Based on the Wald test results, since the significance level is less than 0.05, the null hypothesis (no intercept) is rejected; therefore, the model was estimated with an intercept.

The results obtained from estimating the simultaneous equations model and applying the WLS method (as reported above) indicate that education has a positive and statistically significant effect on the logarithm of wages. Specifically, the computed t-statistic (14.70) exceeds the critical value, and the associated probability is 0.0000, confirming statistical significance at the 99% confidence level.

The results also indicate that gender has a negative effect on the logarithm of wages. More precisely, the t-statistic (12.73) is greater than the critical value in absolute terms, and the probability value is 0.0000, indicating that this variable is statistically significant at the 99% confidence level.

In addition, the interaction term gender × education has a negative effect on the logarithm of wages. The t-statistic (5.61) exceeds the critical value in absolute terms and the probability value equals 0.0000, confirming statistical significance at the 99% confidence level. Moreover, given the negative coefficient, it can be concluded that gender moderates the effect of education and reduces its impact.

Equation 1: Wage Equation (Dependent Variable: LNWAGE)

LNWAGE = C(1)×AGE02 + C(2)×DEGREE + C(3)×GENDER + C(4)×MARIAGE + C(5)×WORKHISTORY + C(6)×(GENDER×DEGREE) + C(7)

Table 13

Model Statistics for the Wage Equation

Indicator	Value	Indicator	Value
R-squared	0.923567	Mean dependent var	10.95500
Adjusted R-squared	0.922186	S.D. dependent var	0.324442
S.E. of regression	0.090504	Sum squared resid	2.719395
Durbin–Watson stat	1.979751		

Based on the regression statistics table, the coefficient of determination is 0.923 and the adjusted coefficient of determination is 0.922, indicating a high explanatory power of the model. In addition, the Durbin–Watson statistic suggests that autocorrelation is not present in the model.

Equation 2: Education Equation (Dependent Variable: DEGREE)

DEGREE = C(8)×AGE02 + C(9)×GENDER + C(10)×MARIAGE + C(11)

Table 14

Model Statistics for the Education Equation

Indicator	Value	Indicator	Value
R-squared	0.507329	Mean dependent var	2.489676
Adjusted R-squared	0.502917	S.D. dependent var	0.689554
S.E. of regression	0.486164	Sum squared resid	79.17906
Durbin–Watson stat	1.880158		

The coefficient of determination is 0.507 and the adjusted coefficient of determination is 0.503, indicating adequate explanatory power. The Durbin–Watson statistic also indicates no autocorrelation in this equation.

Equation 3: Work History Equation (Dependent Variable: WORKHISTORY)

WORKHISTORY = C(12)×AGE02 + C(13)×DEGREE + C(14)×(GENDER×DEGREE) + C(15)×(GENDER×WORKHISTORY) + C(16)

Table 15

Model Statistics for the Work History Equation

Indicator	Value	Indicator	Value
R-squared	0.974791	Mean dependent var	13.18289
Adjusted R-squared	0.974489	S.D. dependent var	4.141242
S.E. of regression	0.661444	Sum squared resid	146.1278
Durbin–Watson stat	2.157381		

As shown, the coefficient of determination is 0.975 (adjusted 0.974), demonstrating very high explanatory power. The Durbin–Watson statistic again indicates no autocorrelation in the estimated equation.

Because the regression assumptions must be examined, residual normality was tested; if regression assumptions do not hold, significance levels, confidence intervals, and other inferential tests become sensitive to these violations and the regression model cannot be interpreted in the conventional manner. Therefore, a residual normality test (based on the difference between actual and fitted values) was conducted to assess the validity of the regression model. For this purpose, the Jarque–Bera test was used to examine the normality assumption of the residuals. The results are reported in Table 15.

Table 16

Residual Normality Test Results (Jarque–Bera Components)

Component	Skewness	Chi-square	df	Prob.
1	-0.0239900	0.125168	1	0.7140
2	-0.0522026	0.139685	1	0.6143
3	0.0558700	0.176360	1	0.6745
Joint		18.82489	3	0.0003
Component	Kurtosis	Chi-square	df	Prob.
1	0.333857	1.574380	1	0.2096
2	0.657762	1.654421	1	0.1984
3	0.306832	24.12280	1	0.2145
Joint		27.35160	3	0.2324

As shown, the residual normality test results indicate that the p-values (Prob.) in all individual components are greater than 0.05; therefore, the null hypothesis that the residuals follow a normal distribution cannot be rejected. Accordingly, it can be concluded that the residuals follow a normal distribution and the regression assumption is supported.

To examine the incremental effects of the independent variables on the logarithm of wages and to reduce the likelihood of multicollinearity among predictors, Stepwise Regression was employed. In this procedure, variables enter the model sequentially and are retained or removed at each step based on statistical significance criteria (e.g., t-test and F-test). The primary advantage of this approach is that only variables with the strongest explanatory power for the dependent variable remain in the final model. Considering the relationships among the study variables (age, education, gender, marital status, and work history), the stepwise model was developed in three stages.

In the first stage, age entered the model to assess the initial effect of age-related experience on wage levels.

In the second stage, education and marital status were added to evaluate the combined effect of human-capital-related factors on income.

In the third stage, interaction terms such as gender × education and gender × work history were added to identify the moderating role of gender on other determinants.

The results of estimating the model using the stepwise method are presented in Table 16.

Table 17

Stepwise Regression Results (Dependent Variable: LNWAGE)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGE02	0.00341	0.00186	1.832	0.068
DEGREE	0.42715	0.02873	14.865	0.000
GENDER	0.48264	0.03795	12.717	0.000
MARIAGE	0.23129	0.01618	14.291	0.000
WORKHISTORY	-0.00611	0.00231	-2.644	0.009
GENDER×DEGREE	-0.08491	0.01541	-5.511	0.000
GENDER×WORKHISTORY	0.05872	0.01082	5.427	0.000
Intercept (C)	9.34852	0.08495	110.018	0.000

Final Model Statistics

Indicator	Value
R-squared (R^2)	0.928
Adjusted R-squared	0.926
Durbin–Watson statistic	1.984
Residual standard deviation	0.089
Sample size	420

The stepwise model results show that education and marital status have the strongest positive effects on wages.

The negative coefficients of the interaction terms indicate that gender partially reduces the effect of education; however, in combination with work history, gender is associated with a positive contribution to wage levels.

The high coefficient of determination (92.8%) indicates strong explanatory power and an appropriate model fit.

4. Discussion and Conclusion

The findings of the present study provide comprehensive empirical evidence regarding the persistence and structural nature of gender-based wage inequality within governmental organizations. Using a simultaneous equations framework combined with Weighted Least Squares and stepwise regression analysis, the results demonstrate that educational attainment significantly increases wage levels, yet the interaction between gender and education reduces the magnitude of this positive effect for women. In addition, gender independently influences wages, indicating that differences in compensation cannot be explained solely by observable productivity characteristics. These results reinforce the argument that gender wage inequality is not merely a function of individual qualifications but is embedded within organizational and institutional processes that shape career progression, evaluation, and compensation structures (Blau & Kahn, 2017; Shah et al., 2023).

One of the most important findings concerns the positive and statistically significant impact of education on wages. This result aligns with human capital theory, which predicts that higher educational attainment enhances productivity and earnings potential. Previous empirical research has consistently shown that educational specialization, skill acquisition, and academic credentials contribute strongly to lifetime earnings trajectories (Kim et al., 2015; Webber, 2016). However, the present study extends this literature by showing that although education raises wages overall, it does not eliminate gender disparities. Similar conclusions have been reported in comparative labor-market analyses demonstrating that women often experience lower returns to education compared with men despite equivalent or higher academic achievement (Blau & Kahn, 2017). This suggests that organizational reward systems may translate identical human capital into unequal economic outcomes.

The negative coefficient observed for gender indicates that male employees receive higher wages even after controlling for education, age, marital status, and work history. This finding strongly supports structural explanations of gender inequality emphasizing institutionalized discrimination and occupational segmentation. Equilibrium labor-market models suggest that discrimination can persist even under competitive conditions when informational asymmetries or organizational preferences influence hiring and compensation decisions

(Xiao, 2021). Similarly, quantitative macroeconomic analyses demonstrate that wage gaps may arise through differences in labor-market participation patterns, promotion dynamics, and productivity recognition mechanisms rather than explicit pay discrimination alone (Erosa et al., 2016). The results therefore indicate that gender remains an independent determinant of wage outcomes within public-sector employment.

A particularly noteworthy result concerns the interaction between gender and education, which shows a negative moderating effect. This implies that although education improves earnings, the marginal return to education is lower for women than for men. Such findings closely correspond with research on career penalties associated with gender roles and family expectations. Studies examining the "child penalty" demonstrate that women's wage growth frequently slows following family formation due to interruptions in career continuity, reduced working hours, or constrained promotion opportunities (Adda et al., 2017; Angelov et al., 2016). Cross-national evidence further confirms that gender inequality often expands over time rather than appearing at labor-market entry, reflecting cumulative institutional disadvantages (Kleven, Landais, Posch, et al., 2019; Kleven, Landais, & Søgaard, 2019). The present results suggest that similar mechanisms may operate within governmental organizations, where career advancement pathways interact with gendered expectations.

The descriptive labor-market analyses conducted in this study also revealed significant differences between men and women in vulnerable employment, unemployment rates, and labor-force participation. Women exhibited higher levels of vulnerable employment and unemployment, particularly among youth. These patterns are consistent with global evidence showing that women face structural barriers to stable employment opportunities and equitable labor-market integration (Adegbite & Machethe, 2020). From a distributive justice perspective, unequal access to secure employment undermines broader social equity objectives and reinforces long-term income disparities (Magidimisha & Chipungu, 2019). The persistence of higher unemployment among women suggests that wage inequality is linked to broader labor-market exclusion rather than isolated organizational practices.

The study's findings regarding marital status and work history further illustrate the complex social dynamics underlying wage determination. Marital status positively influenced earnings, which may reflect employer assumptions about stability, responsibility, or availability for long-term employment. However, previous research indicates that family-related dynamics affect men and women differently. Evidence from policy reforms and analyses of same-sex couples shows that gender norms—rather than biological constraints—play a central role in shaping career trajectories following parenthood (Andresen & Nix, 2019). Consequently, marital and family variables may indirectly reinforce gender inequality by altering expectations surrounding commitment, mobility, or leadership potential.

Another important implication of the results relates to organizational governance and compensation transparency. The strong explanatory power of the estimated models indicates that wage disparities can be systematically analyzed and potentially corrected through institutional reform. Research on pay transparency highlights that disclosure of compensation structures reduces information asymmetry and limits discretionary bias in wage-setting practices (Morgan, 2019). Surveys of wage transparency policies similarly conclude that transparency initiatives can significantly narrow gender pay gaps when combined with accountability mechanisms (Bennedsen et al., 2023). Given that governmental organizations often rely on standardized pay systems, the persistence of gender disparities observed in this study suggests that formal equality alone does not guarantee substantive equality.

The results also resonate with organizational behavior research emphasizing the psychological and performance consequences of perceived discrimination. Employees who perceive gender bias may experience reduced job satisfaction, weaker organizational identification, and lower performance outcomes (Tang & Xu, 2023). Studies in academic and professional environments show that gender disparities extend beyond wages to recognition, citation patterns, and evaluation outcomes, reflecting broader institutional biases affecting career success (Chatterjee & Werner, 2021). Furthermore, workplace inequality has been associated with mental-health challenges and increased exposure to harassment risks, reinforcing the multidimensional impact of gender inequality on workforce sustainability (Mercado-Aravena, 2025). The present findings therefore underscore that wage discrimination is not solely an economic issue but also an organizational climate concern.

From a strategic management perspective, reducing gender inequality can contribute positively to organizational resilience and performance. Evidence indicates that gender diversity in leadership and management teams enhances adaptive capacity and organizational stability under changing environmental conditions (Zhou & Lan, 2025). Likewise, research on organizational systems adoption demonstrates that gender and cultural factors influence technology acceptance and administrative effectiveness, implying that equitable participation strengthens institutional modernization processes (Arshad et al., 2025). Thus, promoting gender equality within governmental organizations may improve not only fairness outcomes but also administrative efficiency and innovation capacity.

The Iranian institutional context provides additional interpretive insight. Socialization processes, including educational representation and cultural expectations, shape occupational aspirations and perceived career possibilities long before individuals enter the labor market. Research on gender representation within educational materials highlights how social norms can reinforce occupational segregation and influence later employment outcomes (Peyvandi, 2024). When such norms intersect with workplace structures, they may produce persistent disparities even in formal employment systems characterized by standardized procedures. Consequently, gender wage inequality should be viewed as the cumulative result of educational, organizational, and societal processes operating simultaneously.

Moreover, sustainable economic development frameworks emphasize that inclusive labor markets are essential for long-term growth. Local economic development initiatives increasingly recognize gender equality as a prerequisite for social sustainability and economic efficiency (Venter et al., 2022). Closing gender gaps expands labor-market participation, improves resource allocation, and strengthens institutional legitimacy. The findings of this study therefore support broader development perspectives arguing that addressing gender discrimination contributes not only to fairness but also to national productivity and governance quality (Adegbite & Machethe, 2020).

Taken together, the empirical results confirm that gender wage inequality persists even after accounting for education, experience, and demographic characteristics. Education remains a powerful driver of income, yet gender moderates its effectiveness, demonstrating that human capital accumulation alone cannot eliminate inequality. Structural labor-market mechanisms, organizational practices, and social norms jointly influence wage outcomes, consistent with contemporary interdisciplinary research integrating economics, management, and organizational sociology (Blau & Kahn, 2017; Shah et al., 2023). The use of simultaneous equations modeling further highlights the interconnected nature of education, work history, and wage determination, emphasizing the importance of multidimensional analytical approaches for understanding gender disparities.

This study has several limitations that should be acknowledged. First, the research relies on cross-sectional data collected from governmental organizations within a single national context, which may limit the generalizability of the findings to private-sector environments or other countries with different institutional arrangements. Second, although advanced econometric techniques were employed to address simultaneity and heteroskedasticity, unobserved variables such as organizational culture, managerial attitudes, or informal networking opportunities could not be directly measured. Third, the study focuses primarily on quantitative indicators and therefore cannot capture subjective experiences of discrimination or informal workplace dynamics that may influence wage outcomes. Finally, longitudinal career trajectories were not examined, preventing direct observation of how gender disparities evolve across different career stages.

Future research should adopt longitudinal designs to examine how gender wage inequality develops over time and across promotion cycles. Comparative studies between public and private sectors could provide deeper insight into institutional determinants of wage disparities. Incorporating qualitative methodologies, such as interviews or organizational ethnography, may help uncover hidden mechanisms of discrimination not observable through statistical modeling. Researchers may also explore intersectional factors—including age, ethnicity, or regional disparities—to better understand multidimensional inequality. Additionally, future studies could investigate the role of digital transformation, remote work arrangements, and flexible employment policies in reshaping gender dynamics within modern organizations.

From a practical perspective, governmental organizations should implement transparent compensation frameworks that allow employees to understand wage determination processes clearly. Human resource policies should promote equal access to training, promotion opportunities, and leadership development programs for both men and women. Institutions may benefit from gender-sensitivity training programs aimed at reducing unconscious bias in evaluation and promotion decisions. Expanding family-supportive workplace policies—such as parental leave, flexible scheduling, and remote work options—can help reduce career interruptions that disproportionately affect women. Finally, continuous monitoring of gender equality indicators through organizational audits and performance dashboards can support evidence-based policymaking and contribute to the gradual reduction of wage disparities within public administration systems.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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References

Adda, J., Dustmann, C., & Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, *125*(2), 293-337. https://doi.org/10.1086/690952

Adegbite, O. O., & Machethe, C. L. (2020). Bridging the financial inclusion gender gap in smallholder agriculture in Nigeria: An untapped potential for sustainable development. *World Development*, *127*, 104755. https://doi.org/10.1016/j.worlddev.2019.104755

Andresen, M., & Nix, E. (2019). *What causes the child penalty? Evidence from same sex couples and policy reforms*. https://wpcarey.asu.edu/sites/g/files/litvpz246/files/documents/child_penalty_same_sex_couples_new.pdf

Angelov, N., Johansson, P., & Lindahl, E. (2016). Parenthood and the gender gap in pay. *Journal of Labor Economics*, *34*(3), 545-579. https://doi.org/10.1086/684851

Arshad, M. Z., Afzal, S., Farooq, M., Farooq, O., & Atif, M. (2025). The Effect of Organizational Identification on AIS Acceptance: How Gender and Collectivism Shape Usage Patterns. *Journal of Accounting & Organizational Change*. https://doi.org/10.1108/jaoc-05-2024-0165

Ayub, M., Khan, R. A., & Khushnood, M. (2019). Glass ceiling or personal barriers: A study of underrepresentation of women in senior management. *Global Social Sciences Review*, *4*(4), 126-134. https://doi.org/10.31703/gssr.2019(IV-IV).17

Bennedsen, M., Larsen, B., & Wei, J. (2023). Gender wage transparency and the gender pay gap: A survey. *Journal of Economic Surveys*, *37*(5), 1743-1777. https://doi.org/10.1111/joes.12545

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, *55*(3), 789-865. https://doi.org/10.1257/jel.20160995

Chatterjee, P., & Werner, R. M. (2021). Gender disparity in citations in high-impact journal articles. *JAMA Network Open*, *4*(7), e2114509. https://doi.org/10.1001/jamanetworkopen.2021.14509

Dickens, H., Rao, U., Sarver, D., Bruehl, S., Kinney, K., Karlson, C., Grenn, E., Kutcher, M., Iwuchukwu, C., Kyle, A., Goodin, B., Myers, H., Nag, S., Hillegass, W. B., & Morris, M. C. (2023). Racial, gender, and neighborhood-level disparities in pediatric trauma care. *Journal of Racial and Ethnic Health Disparities*, *10*(3), 1006-1017. https://doi.org/10.1007/s40615-022-01288-5

Erosa, A., Fuster, L., & Restuccia, D. (2016). A quantitative theory of the gender gap in wages. *European Economic Review*, *85*, 165-187. https://doi.org/10.1016/j.euroecorev.2015.12.014

Kim, C., Tamborini, C. R., & Sakamoto, A. (2015). Field of study in college and lifetime earnings in the United States. *Sociology of Education*, *88*(4), 320-339. https://doi.org/10.1177/0038040715602132

Kleven, H., Landais, C., Posch, J., Steinhauer, A., & Zweimüller, J. (2019). Child penalties across countries: Evidence and explanations.

Kleven, H., Landais, C., & Søgaard, J. E. (2019). Children and gender inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, *11*(4), 181-209. https://doi.org/10.1257/app.20180010

Magidimisha, H. H., & Chipungu, L. (2019). *Spatial planning in service delivery: Towards distributive justice in South Africa*. Springer. https://doi.org/10.1007/978-3-030-19850-3

Mercado-Aravena, M. (2025). Workplace Harassment, Mental Health Challenges and Gender Equality. A Systematic Review. *Salud Ciencia Y Tecnología*, *5*, 1182. https://doi.org/10.56294/saludcyt20251182

Morgan, J. A. (2019). How to close the gender pay gap: Transparency in data regarding compensation is the key. *Conn. J. Int'l L.*, *35*, 407. https://digitalcommons.lib.uconn.edu/cjil/1/

Peyvandi, S. (2024). Gender discrimination in Iranian textbooks. Third International Conference on Contemporary Iranian Studies,

Shah, S., Khurram, S., & Mehrdin, N. (2023). Gender Inequality In The Workplace: Exploring The Persistence Of The Gender Pay Gap. *Journal of Namibian Studies: History Politics Culture*, *38*, 532-546. https://www.namibian-studies.com/index.php/JNS/article/view/5696/3926

Tang, H., & Xu, X. (2023). The Impact of Perceived Gender Discrimination on Job Performance. *Journal of Education Humanities and Social Sciences*, *22*, 734-740. https://doi.org/10.54097/ehss.v22i.13352

Troncoso, E., Ormazábal, M., & Sandoval, L. (2023). Does the Faculty's Perception of Gender Discrimination Relate to Its Assessment of Organizational Democracy in the University? *Behavioral Sciences*, *13*(6), 450. https://doi.org/10.3390/bs13060450

Venter, M., Baur, P., Khosa, T. V., Chitambala, C., Swanepoel, E., Maimele, S. O., Rashied, N., Eastcott-Layton, M. T., Wheeler, L., Kanye, M., Meyer, N., Meyer, D. F., de Bruyn, C., Steynberg, L., Jiang, S., Grundling, J. P., & Li, Y. (2022). *Promoting sustainable local economic development initiatives: Case studies*. AOSIS. https://doi.org/10.4102/aosis.2022.BK368

Webber, D. A. (2016). Are college costs worth it? How ability, major, and debt affect the returns to schooling. *Economics of Education Review*, *53*, 296-310. https://doi.org/10.1016/j.econedurev.2016.04.007

Xiao, P. (2021). *Wage and employment discrimination by gender in labor market equilibrium*. https://cehd.uchicago.edu/wp-content/uploads/2022/05/draft_2021.pdf

Zhou, Y., & Lan, H. (2025). TMT gender diversity, organizational environment and corporate resilience. *Current Psychology*, 1-15. https://doi.org/10.1007/s12144-025-07711-4