

Gender Pay Gap Analysis in the Indian Technology Sector Using Primary Survey Data

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Abstract

Gender pay inequality remains an important human-capital and management issue. The technology sector provides a useful context because compensation varies substantially by role, technical specialization, experience, seniority, location and company size. This paper develops a primary-survey framework for analyzing the gender pay gap in India's technology sector. It distinguishes the raw pay gap from an adjusted gap that controls for observable job-related characteristics. The proposed model includes gender, experience, seniority, education, role, location, company size and work arrangement. Recent Indian corporate reporting continues to show gender-pay disparities across major companies, reinforcing the importance of more detailed analysis. The paper proposes descriptive statistics and multiple regression and explains how AI can support compensation analytics while avoiding the reproduction of historical bias. The central argument is that responsible compensation analytics should combine statistical evidence, transparent assumptions and human review.

Keywords: gender pay gap; technology; India; HR analytics; regression; compensation; AI; diversity.

1. Introduction

The gender pay gap is generally defined as the difference in average or median earnings between men and women. Interpretation requires care because a raw gap can arise from differences in occupation, experience, seniority, location, hours or specialization.

Technology companies provide an interesting setting because compensation can vary substantially across technical and non-technical roles. They also increasingly use analytics and AI in recruitment, performance evaluation and compensation.

Recent reporting based on FY2026 annual-report data from Nifty 50 companies found that women had lower median salaries than men in five out of six companies analyzed. This reinforces the importance of examining compensation patterns in greater detail.

2. Literature Review

Gender-pay analysis commonly separates explained and unexplained components. Education, experience and occupation may explain part of a raw difference. However, occupational segregation itself can reflect organizational and social structures.

A primary survey can collect variables often missing from public reports, including promotion history, negotiation experience, career breaks and perceptions of pay transparency.

AI can support compensation auditing by identifying unusual patterns. However, if historical salary data contain bias, a model trained on those data can reproduce it. Responsible AI therefore requires auditing and human oversight.

3. Objectives and Hypotheses

The objectives are to estimate the raw pay gap, examine whether it changes after controlling for role and experience, explore promotion and negotiation differences, and assess AI-enabled compensation analytics.

H1: Average compensation differs by gender in the sample.

H2: The gap decreases after controlling for role, experience and seniority.

H3: A residual gender association remains after adjustment, requiring further organizational investigation.

4. Primary Survey Methodology

A target sample of 250–400 technology-sector employees could be collected using an anonymous questionnaire. Employer names should not be required.

Variables should include gender, education, total experience, years in current role, job family, managerial level, city, work arrangement and annual compensation band. Additional questions can cover promotion frequency, pay transparency and compensation negotiation.

Salary bands may produce higher response rates than exact salaries. Self-reported data should be acknowledged as a possible source of recall and reporting bias.

5. Analytical Framework

The first analysis should compare median and mean compensation by gender. A raw pay-gap percentage can be calculated as:

$(\text{male median compensation} - \text{female median compensation}) / \text{male median compensation} \times 100.$

The second stage can use multiple regression:

$\log(\text{compensation}) = \beta_0 + \beta_1(\text{gender}) + \beta_2(\text{experience}) + \beta_3(\text{seniority}) + \beta_4(\text{role}) + \beta_5(\text{education}) + \beta_6(\text{location}) + \varepsilon.$

The gender coefficient represents the adjusted association between gender and compensation after controlling for included variables. It should not automatically be interpreted as proof of discrimination because unobserved variables may remain.

6. Management and AI Implications

A company finding a raw gap should first conduct a structured compensation audit. If women are concentrated in lower-paying roles or have lower average tenure, these patterns require organizational attention even if the adjusted gender coefficient becomes smaller.

If an adjusted gap remains, possible explanations include starting salaries, promotion timing, negotiation outcomes, performance evaluation or access to high-value assignments.

AI can support compensation analysis by identifying unusual salary patterns and monitoring promotion outcomes. But automated recommendations should not replace human review in sensitive employment decisions.

7. Conclusion

A rigorous gender-pay study requires more than comparing average salaries. Primary survey data can combine compensation with role, experience, seniority and career history. Regression can separate observable sources of variation from residual differences, while AI can support large-scale compensation auditing. For a Management and Business AI student, this topic demonstrates how data analytics can be applied to an important management problem responsibly.

Research Figure

Proposed analytical framework; values are illustrative.

References

- International Labour Organization. (2018). Global Wage Report 2018/19: What lies behind gender pay gaps.
- World Economic Forum. (2025). Global Gender Gap Report 2025.
- Economic Times. (2026). Analysis of FY2026 annual reports of Nifty 50 firms on gender pay parity.

Appendix: Suggested Primary-Survey Variables

Paper 1

Age; education; financial knowledge; risk tolerance; investment experience; social-media exposure; AI/fintech use; investment horizon; diversification.

Paper 2

Business category; years operating; sales band; UPI adoption date; payment-mode share; transaction value; footfall; cash-handling time; perceived benefits.

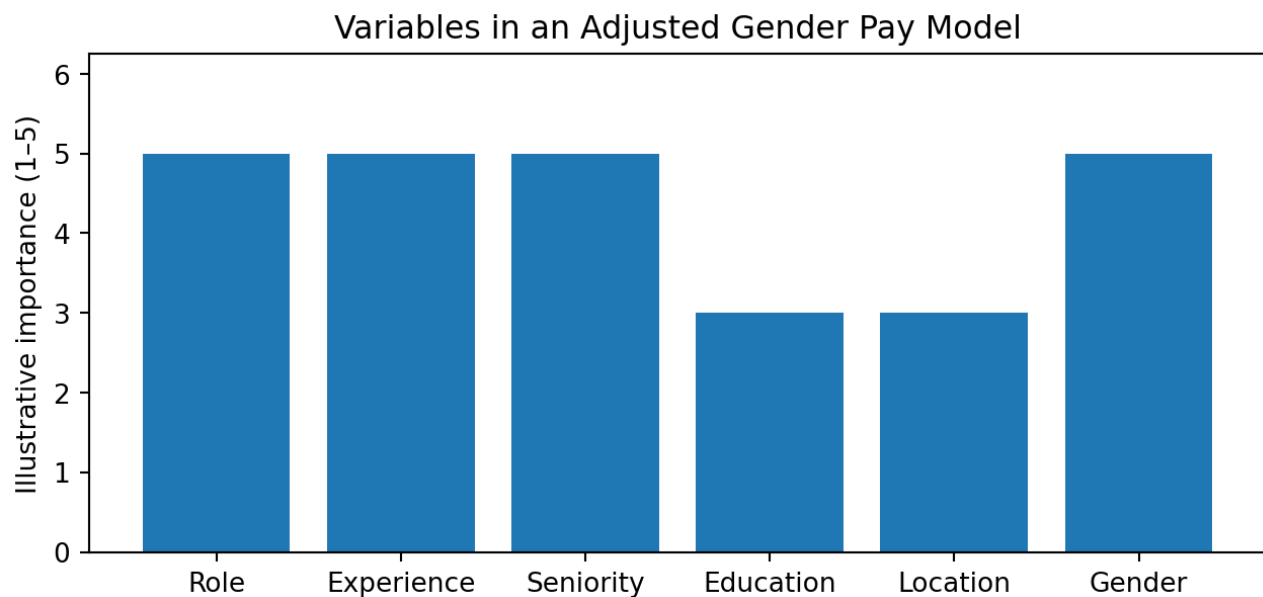
Paper 4

Age; education; platform; hours/week; gross and net earnings; expenses; platform tenure; flexibility; income stability; benefits; career plans.

Paper 5

Gender; education; experience; role; seniority; location; work arrangement; salary band; promotions; negotiation; pay transparency.

Research Figure



Proposed analytical framework; not survey findings.

Figure note: This is the figure embedded in the original research-paper document. The source describes the figures as source-based/illustrative conceptual material rather than primary-survey results.