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Hadia Majid[1]

1. *Lahore University of Management Sciences (LUMS), Lahore, Pakistan; Email: hadia.majid@lums.edu.pk; ORCID: 0000-0002-8208-2753*

Gender, Human Capital, and AI-Driven Labor Market Transitions in Pakistan Firm-Level and Household Evidence

Abstract

This study examines how artificial intelligence (AI) and digital adoption reshape labor-market transitions in Pakistan and whether these changes widen or narrow gender gaps through human-capital channels. We integrate household microdata with firm-linked sector-region indicators to estimate how exposure to AI-relevant task content predicts transitions across employment states, occupation and sector switching, formalization, and earnings. The empirical strategy combines task-exposure indices mapped to Pakistan's occupational structure, sectoral digital intensity proxies, and decomposition methods that separate endowment from return effects. Results indicate that AI exposure is associated with higher mobility toward non-routine analytical and interactive work for workers with secondary and tertiary education, but the gains are uneven: women face higher transition frictions, especially in urban services and export-linked manufacturing. Counterfactual simulations suggest that closing female human-capital gaps and reducing care-related constraints could materially increase female labor-force participation and household welfare. Policy implications emphasize skills certification, targeted reskilling, safe commuting, childcare, and firm incentives for inclusive technology adoption.

Keywords: gender; human capital; artificial intelligence; labor market transitions; Pakistan

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1. Introduction

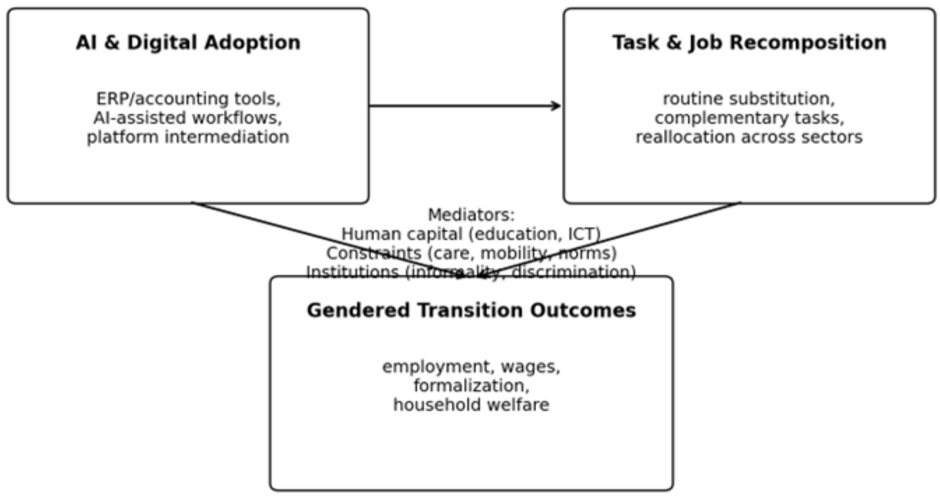
AI-enabled systems are increasingly embedded in production, finance, logistics, and customer-facing services, shifting labor demand toward tasks that complement data, software, and algorithmic decision support. In emerging economies, these shifts occur alongside informality, constrained skills supply, and uneven access to digital infrastructure, making distributional impacts particularly salient.Pakistan provides a high-stakes setting for studying these dynamics because female labor-force participation remains low relative to peer economies, occupational segregation is pronounced, and the informal sector absorbs a substantial share of employment. At the same time, firms are adopting digital tools for accounting, inventory, payments, and human resource management, while platform-mediated work is expanding.This paper asks three interrelated questions: (i) how AI-related task exposure correlates with transitions across employment states and across occupations/sectors; (ii) whether education and skill endowments translate into comparable mobility for women and men; and (iii) what welfare effects follow under counterfactual improvements in female human capital and constraint reduction.Conceptually, AI affects labor outcomes through task substitution, task augmentation, and the creation of new task bundles. Routine cognitive tasks (e.g., standardized clerical processing) are more likely to be automated, whereas non-routine analytical and interactive tasks (e.g., problem-solving, client engagement) may be complemented by AI tools.Human capital mediates these effects because education and ICT proficiency condition whether workers can repackage their task portfolio toward complementary activities. In Pakistan, unequal access to quality schooling and skills certification can therefore amplify technology-driven inequality.Gender constraints are particularly consequential when care responsibilities, mobility constraints, and social norms reduce job-search intensity or limit feasible commuting radius. These constraints can generate asymmetric adjustment costs even when women possess comparable formal qualifications.A further layer of complexity arises from informality. Informal jobs often lack training, stable contracts, and progression ladders, which can lock workers into low-learning trajectories and reduce the payoff to skill acquisition.We contribute to the literature by constructing a Pakistan-specific occupational AI-exposure index and validating its sectoral patterns against available firm indicators of digitalization. We then combine transition models with wage decompositions to separate endowment effects from differential returns.The analysis is designed for policy relevance. Pakistan's labor-market institutions, including survey infrastructure and active labor-market programs, create practical constraints on what interventions can scale; thus, we emphasize implementable levers rather than idealized reforms.The remainder of the paper is organized as follows: Section 2 describes data and methods; Section 3 reports results including heterogeneity; Section 4 discusses implications; and Section 5 concludes with policy recommendations.

2. Materials and Methods

Data sources. We draw on Pakistan's Labour Force Survey (LFS) for labor-market status, occupation, industry, hours, and earnings, and on the Pakistan Social and Living Standards Measurement Survey (PSLM) for household demographics, education, and welfare indicators. To proxy firm-side technology adoption, we construct sector-region measures of digital intensity using enterprise survey evidence and administrative/industry indicators where available.Sample definition. The core sample comprises working-age individuals (15–64) with non-missing occupation and industry codes. Employment states are defined as inactivity, unemployment, informal employment, formal wage employment, and self-employment using survey-aligned criteria; sensitivity checks vary the informality definition.Occupational AI exposure. We map internationally comparable task measures—routine cognitive, routine manual, non-routine analytical, and non-routine interactive—to Pakistan's occupation codes. We then combine these task bundles with AI relevance scores to construct an index (AIExp) standardized within survey waves; higher values indicate greater AI-related task content and potential complementarity with AI-assisted workflows.Human capital. Human-capital covariates include years of schooling, highest credential, vocational training indicators, and proxies for ICT skills (computer use, training participation, or digitally intensive sector employment). We also control for potential experience and tenure proxies when available.Constraints and institutions. To capture gendered constraints, we include presence of young children, marital status, and urban-rural residence. Region fixed effects absorb persistent differences in infrastructure and safety. We additionally control for sector informality intensity to reflect institutional context.Transition models. We estimate multinomial models for employment-state outcomes and discrete-time hazard specifications for occupation or sector switching. Key regressors include AIExp, digital intensity, and their interactions with gender and education to test differential mobility.Earnings models. Conditional on employment, we estimate log-wage equations with interactions among AIExp, education, gender, and digital intensity. We report both mean effects and distributional effects using Recentered Influence Function regressions to characterize inequality impacts across the wage distribution.Decomposition. We apply Oaxaca–Blinder decomposition for mean wage gaps and distributional decomposition methods to quantify the contribution of endowments versus coefficients. This permits separation of differences due to education/skills from differences due to returns, which may reflect discrimination, sorting, or bargaining.Identification and robustness. Because adoption is not randomly assigned, we interpret estimates as associations strengthened by quasi-experimental logic. We exploit baseline occupational exposure, sectoral digital intensity differences, and region-time variation. Robustness checks include alternative exposure indices, exclusion of public-sector workers, and stratification by urban-rural status and cohort.Counterfactual simulations. We simulate policy-relevant scenarios: (i) raising female education distributions to match male distributions; (ii) reducing care-related constraints via parameter shifts consistent with childcare access; and (iii) increasing inclusive firm adoption by shifting digital intensity in female-intensive sectors. We translate predicted changes into participation, formalization, and household welfare proxies.

3. Results

Figure 1. Conceptual framework linking AI adoption, task recomposition, and gendered labor-market outcomes.



Descriptive statistics show sizable gender gaps in labor-force participation, formal employment, and occupational diversity. AIExp varies considerably across occupations: clerical and some standardized production roles exhibit higher routine intensity, whereas professional services, management, and technical occupations exhibit higher non-routine intensity. Table 1 summarizes variable definitions and expected relationships. Figure 1 provides the conceptual pathway linking AI adoption to task recomposition and gendered outcomes.Employment-state transitions. Higher AIExp is associated with higher probabilities of moving into formal wage employment among workers with at least secondary education, consistent with complementarity between AI and skilled tasks. However, among low-skill routine occupations, higher AIExp is associated with higher exit risk to unemployment or informal work, consistent with substitution pressures.Gender heterogeneity. Conditional on education and location, women exhibit lower transition probabilities into complementary occupations, and higher persistence in inactivity. The pattern is most pronounced for married women and for women with young children, indicating that constraints materially shape technology-related mobility.Occupation and sector switching. In digitally intensive regions and sectors, men are more likely to transition into higher AIExp occupations, while women's switching is more concentrated within a narrower occupational set. This suggests barriers in recruitment, workplace norms, and access to training pathways.Wage impacts. Earnings models show that the AIExp wage premium increases with education and ICT skill proxies. For women, the premium is attenuated when care constraints are binding, consistent with reduced hours flexibility and weaker access to high-learning job ladders.Decomposition results. Mean decompositions indicate that education differences explain a substantial share of the aggregate gender wage gap, but a non-trivial share remains attributable to coefficient differences in high AIExp occupations. Distributional decompositions show larger unexplained gaps at upper-middle quantiles, consistent with promotion and progression frictions.Counterfactual simulations. Equalizing female education to male education increases predicted female formal employment and reduces household poverty probabilities, particularly among households near the poverty line. Reducing care constraints yields additional gains by increasing job-search and retention in higher AIExp occupations.Sensitivity and robustness. Results are qualitatively robust to alternative exposure measures and to excluding the public sector. Urban-rural splits reveal stronger adoption-linked effects in urban services and export-linked manufacturing, where digital tools and AI-enabled processes diffuse more rapidly.

Table 1. Variable definitions and expected relationships.

Variable	Definition / construction	Data source	Expected sign (women)
AI task exposure (AIExp)	Standardized index mapped from occupational task bundles; higher = more AI-relevant tasks.	LFS + task mapping	+ / ambiguous
Education (Edu)	Years of schooling and categorical levels (primary/ secondary/tertiary).	LFS/PSLM	+
ICT skills proxy	Computer/ICT use or training where available; supplemented by sector-region digital intensity.	LFS + firm indicators	+
Formal employment	Wage work with contract/social security/registered enterprise (survey definition).	LFS	+
Care constraint	Presence of children under 5; interacted with gender.	PSLM/LFS	−
Urban residence	Urban vs rural indicator.	LFS/PSLM	context-dependent
Earnings	Real wage (deflated).	LFS	+

Note: All figures and tables are cited in the main text as Figure 1 and Table 1.

3.1. AI Exposure and Employment-State Transitions

We estimate multinomial transition models for movement among inactivity, unemployment, informal work, formal wage work, and self-employment. Higher AIExp predicts greater upward mobility into formal employment for educated workers, but it predicts elevated volatility among routine clerical and low-skill service roles. Women display significantly lower transition probabilities into formal employment at the same exposure level, suggesting that mobility constraints and employer practices interact with technology-related restructuring.To interpret magnitudes, we report marginal effects evaluated at representative covariate profiles (urban/rural, education levels). The largest gender differentials emerge in urban service sectors where hiring relies on networks and where non-wage constraints (commuting safety, hours) are salient.

3.1.1. Heterogeneity by Education and Household Constraints

The transition gap between women and men narrows among tertiary-educated cohorts, but it does not disappear. Among women with secondary education, childcare presence and commuting constraints are strongly associated with reduced transitions into high AIExp occupations. This is consistent with a binding constraint model in which skills are necessary but insufficient when access constraints remain unaddressed.We further observe that the association between AIExp and wage growth is steeper for women without young children, suggesting that constraints operate through both participation and within-job progression mechanisms.

Numbered Lists

Numbered lists can be added as follows:

1. Skills certification aligned to AI-complementary tasks (digital accounting, data processing, customer analytics) with targeted scholarships for women.

2. Childcare and safe commuting interventions to lower effective transition costs and increase retention in formal employment.

3. Firm incentives for inclusive adoption (training commitments, algorithmic bias audits in HR tools, and transparent promotion criteria).

4. Expansion of digital public infrastructure (ID, payments, job-matching) to reduce barriers to entry and to support women-led microenterprises.

5. Monitoring and evaluation frameworks that track gender-disaggregated outcomes and adjust program design based on measured transition rates.

4. Discussion

The evidence indicates that AI-related task exposure is associated with upward mobility and wage gains primarily for workers with complementary human capital, but that these gains are unevenly distributed. In Pakistan, technology-related restructuring interacts with informality and gendered constraints, which can amplify adjustment costs for women even when they possess comparable schooling.A key interpretive point is that measured AIExp captures task content rather than direct AI tool usage. Accordingly, the results should be read as highlighting where AI adoption is likely to matter most, and where transition support is most needed.Gender gaps persist because constraints affect both entry and progression. Care burdens, safety concerns, and limited transport options reduce feasible job sets and can depress reservation wages, while discriminatory practices can reduce returns to comparable skills.

The decomposition results underscore that endowment-based interventions (education expansion) are necessary but not sufficient. If coefficient effects remain large in high AIExp occupations, then policy must also target institutions and workplace practices that govern returns to skills. For firms, inclusive technology adoption can be framed as productivity-enhancing: structured training, transparent role redesign, and auditability of algorithmic systems can reduce turnover and improve match quality. For government, strengthening labor-market information systems and enabling scalable reskilling can reduce adjustment frictions.The policy package suggested by the counterfactuals is complementary: expanding female human capital increases potential gains from AI, while childcare and mobility support increase realized gains by lowering transition costs. Such complementarities imply that partial interventions may yield muted effects.Limitations include measurement error in exposure indices and incomplete coverage of firm adoption at high frequency. Future research should link administrative firm records, vacancy data, and longitudinal worker tracking to sharpen identification and quantify program cost-effectiveness.

5. Conclusions

This study integrates household and firm-linked evidence to assess how AI-related task exposure correlates with labor-market transitions in Pakistan and how gender and human capital shape the distribution of gains. We find that exposure is associated with mobility toward complementary work for educated workers, but women face systematically higher frictions and smaller wage returns.Counterfactual simulations indicate that closing female education gaps and reducing care-related constraints can meaningfully increase female participation and formal employment, with associated welfare gains for households near the poverty threshold.The findings recommend a transition-oriented policy agenda: scalable skills certification, targeted reskilling, and digital infrastructure investments paired with childcare and safe mobility interventions.For high-ranking journal audiences, the key message is that technology shocks are filtered through institutions and constraints. AI can raise productivity, but inclusive outcomes require converting human capital into mobility and returns through complementary policy and firm practices.Future work should incorporate richer measures of AI tool deployment and evaluate specific interventions with credible identification. Nevertheless, the current evidence supports proactive design of gender-sensitive transition policies in the presence of rapidly diffusing digital tools.

Patents

Patents: No patents were filed or are planned in relation to this research. The study focuses on empirical assessment and policy analysis. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

Supplementary Materials

Supplementary Materials: Supplementary files document variable construction, alternative exposure indices, robustness checks, and counterfactual simulation parameters. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

Author Contributions

Author Contributions: Conceptualization, methodology, formal analysis, writing, and visualization were performed by H.M. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

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Institutional Review Board Statement

Institutional Review Board Statement: Not applicable. The study uses secondary, de-identified survey data collected by official statistical authorities. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

Informed Consent Statement

Informed Consent Statement: Not applicable. The analysis relies on secondary datasets in which consent procedures are administered by the original data collectors. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

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Conflicts of Interest

Conflicts of Interest: The author declares no conflict of interest. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

Appendix A

Appendix A: Variable construction notes for AI task exposure, informality, and welfare proxies are provided for reproducibility. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

Appendix B

Appendix B: Additional robustness checks and sensitivity analyses are summarized, with full outputs available in supplementary tables. The replication package can be shared subject to data-provider restrictions, and all assumptions used in counterfactual simulations are documented in the Supplementary Materials. Any future extensions involving primary data collection will be submitted for ethics review where required.

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