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Gendered Exposure to Artificial Intelligence in Labor Markets: A Comparative Political Economy Analysis of Bulgaria, Romania, Germany, and India

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Abstract
This paper investigates the gendered impact of artificial intelligence (AI) on labor markets through a comparative study of Bulgaria, Romania, Germany, and India. Utilizing AI Occupational Exposure (AIOE) and Complementarity Indices, the research examines how task automation and labor segmentation differentially affect women across income levels and national contexts. In Bulgaria, women are overrepresented in high-exposure, low-complementarity (HELC) occupations, heightening their risk of technological displacement, especially in clerical and retail roles. Conversely, higher-income women demonstrate greater mobility toward high-complementarity roles. Comparisons reveal that Bulgaria and Romania share structural vulnerabilities due to similar institutional legacies, while Germany's dual vocational system mitigates AI risks. India presents a distinct case of technological exclusion rather than exposure. The findings underscore how institutional frameworks, educational systems, and labor market regulations shape gendered outcomes in AI transitions, reinforcing the relevance of segmented labor market theory and calling for targeted, inclusive labor policies.

Keywords: Artificial Intelligence, Gender Inequality, Labor Market Segmentation, Occupational Exposure, Comparative Political Economy

Introduction

Technological change has long played a decisive role in shaping gendered labor market dynamics, with mechanization, digitalization, and now algorithmic automation inducing structural shifts in employment that interact with prevailing patterns of occupational segregation, human capital accumulation, and social reproduction. As Goldin (1990) illustrates in her historical account of American women's labor participation, the diffusion of household appliances such as washing machines and vacuum cleaners significantly reduced the time burden of domestic labor, thereby increasing female labor supply elasticity. This was further compounded by innovations like the typewriter and the expansion of clerical work, which redefined the employment landscape in ways that made white-collar work more accessible to women (Costa, 2000). These historical shifts were not simply technological in nature but were embedded in institutional and cultural frameworks that governed access to education, control over fertility (Goldin and Katz, 2002), and the acceptability of women's labor force participation. The transition from an industrial to a post-industrial economy further restructured occupational demand away from physical-intensive labor - typically dominated by men - toward service and knowledge-intensive work, where women increasingly found employment.

However, these transformations also entrenched gendered occupational segregation, with women disproportionately concentrated in roles characterized by routine cognitive tasks, which are now at heightened risk due to advances in artificial intelligence (AI) (Webb, 2020). The current wave of AI adoption represents a qualitatively different technological paradigm insofar as it automates tasks not through mechanization but through statistical learning and pattern recognition, potentially substituting workers in non-routine cognitive occupations that were previously considered automation-resistant (Autor, 2015). This raises critical questions regarding the gendered exposure to AI-driven task displacement, especially in countries with different stages of economic development, institutional configurations, and labor market structures. In the context of Bulgaria - a post-socialist, middle to low-income EU member state with relatively high female labor force participation but persistent occupational gender segregation - the intersection of AI adoption and gender warrants empirical scrutiny, particularly as it pertains to comparative insights with structurally similar (Romania), structurally divergent developed (Germany), and emerging economy (India) contexts. The core research question therefore interrogates the extent to which gender differences in AI exposure manifest in Bulgaria and how these patterns compare with those in Romania, Germany, and India. Specifically, this analysis posits three interrelated hypotheses grounded in political economy and labor economics. First, H1 posits that women in Bulgaria are more exposed to AI than men, due to their higher concentration in clerical, administrative, and service occupations with high AI task overlap (Felten, Raj, and Seamans, 2021). Second, H2 hypothesizes that high-income women are more likely to transition from high-exposure, low-complementarity (HELC) to high-exposure, high-complementarity (HEHC) occupations, consistent with findings that occupational mobility in response to technological shocks is stratified by income, education, and skill (Cazzaniga et al., 2024). Third, H3 suggests that Bulgaria's AI exposure profile more closely resembles Romania's, due to similar labor market institutions, occupational structures, and education systems, and differs significantly from Germany and India, whose occupational exposure matrices are shaped respectively by highly developed knowledge economies and agrarian labor intensity (Hatzius et al., 2023). These hypotheses are not only grounded in existing empirical literature but are also theoretically anchored in segmented labor market theory (Doeringer and Piore, 1971), which emphasizes how structural rigidities and institutional complementarities shape workers' capacity to respond to technological change. To understand H1, we consider the composition of employment in Bulgaria across the International Standard Classification of Occupations (ISCO-08), cross-referenced with AI Occupational Exposure (AIOE) indices developed by Felten et al. (2021), which quantify the degree to which AI systems can replicate human abilities (e.g., reading comprehension, data entry, translation) in specific occupations. Bulgarian labor market data from the National Statistical Institute and the EU-LFS indicate that women are disproportionately represented in ISCO groups such as clerical support workers (Group 4), professionals in education and health (Group 2), and service and sales workers (Group 5), which exhibit medium to high AIOE scores. This concentration implies higher exposure to AI-driven task automation compared to male-dominated sectors such as skilled trades (Group 7) or machine operators (Group 8), which are more exposed to mechanization but less so to current forms of AI. Moreover, unlike in Germany, where AI exposure among women is partially offset by high complementarity in professional and managerial roles, Bulgarian women in HELC roles often lack the contextual job features (e.g., responsibility for others, in-person interaction) that define HEHC roles in the complementarity index proposed by Pizzinelli et al. (2023). This lends empirical support to H1 and suggests a vulnerability that is consistent with findings from studies on other middle-income economies (Albanesi et al., 2023). H2 is supported by mobility data derived from longitudinal labor force surveys and reflects the broader literature on skill-biased technological change (SBTC), which posits that technology disproportionately benefits workers with high levels of education and adaptability (Autor, Levy, and Murnane, 2003).

In Bulgaria, while transition rates from HELC to HEHC roles remain limited overall, disaggregation by income decile and gender suggests that women in the upper income quintiles are more likely to enter professional roles with high AI complementarity, such as legal, medical, or managerial positions, echoing the gendered outcomes observed in the United Kingdom (Cortés et al., 2024). This upward mobility is facilitated by higher levels of tertiary education and soft skills, such as emotional intelligence and communication, which remain less substitutable by current AI technologies (Brynjolfsson and McAfee, 2014). Conversely, low-income women exhibit a greater tendency to exit the labor force or shift to low-exposure occupations with limited wage growth, reinforcing a dual labor market segmentation that may exacerbate existing inequalities. These findings align with historical patterns of technological disruption, whereby higher-skilled women have fared better than their male counterparts, while lower-skilled women have experienced higher rates of displacement (Albanesi and Kim, 2021). As for H3, a cross-country comparative analysis reveals that Bulgaria and Romania share a similar occupational AI exposure structure, characterized by high employment in routine cognitive sectors and a relatively narrow band of HEHC occupations. This similarity reflects not only shared post-socialist legacies and labor market policies but also parallels in educational attainment and occupational gender segregation. Germany, by contrast, displays a more diversified occupational structure, with a significant share of female employment in sectors with both high exposure and high complementarity, including health, STEM, and public administration, reflecting long-standing investments in vocational training and dual education systems (Beblavý et al., 2016). India's case stands apart due to its large informal sector and the high proportion of female employment in agriculture and low-skill services, resulting in a dominant share of low-exposure (LE) occupations and lower aggregate AIOE scores (Mehrotra and Parida, 2017). This divergence supports the hypothesis that Bulgaria's AI-gender exposure matrix is closer to that of Romania than to the structurally distinct cases of Germany and India.

These comparative insights are essential in understanding the heterogeneity of AI's labor market effects and challenge simplistic narratives of universal displacement. They highlight the importance of contextual variables - such as occupational structures, welfare state regimes, and labor market institutions - in mediating AI's impact on gender disparities in employment. Furthermore, the observed differences underscore the need to extend existing economic theories of automation, such as task-based models (Acemoglu and Restrepo, 2018), to account for intersectional and institutional dimensions that influence exposure and adaptability differentially across countries and genders. In sum, the intersection of gender and AI exposure in Bulgaria reflects a complex interplay of occupational concentration, skill levels, and structural rigidities that echo broader patterns observed in comparative political economy, reaffirming the relevance of institutionalist and labor segmentation approaches in understanding technological transitions in the labor market.

Methodology

The methodological strategy employed in this study operationalizes AI exposure in labor markets through a dual-index system that incorporates both the potential substitutability of human labor by artificial intelligence and the contextual resilience of occupational tasks to automation. This dual characterization is implemented through the construction of two distinct but complementary metrics: the AIOE index developed by Felten, Raj, and Seamans (2021), and the AI Complementarity Index proposed by Pizzinelli et al. (2023). The AIOE index is grounded in a formal task-based economic model which assumes that occupations consist of multiple task bundles, some of which are subject to automation if and only if the marginal cost of AI performance is lower than that of human labor (Acemoglu and Autor, 2011).

Formally, we let occupation $o \in O$ consist of a vector of tasks $T_o = \{t_1, t_2, \dots, t_n\}$. Each t_j has an associated automation feasibility score $\phi j \in [0,1]$ denoting the extent to which AI can replicate the cognitive or manual component of the task. The AIOE index for occupation o , is then defined as the weighted sum of task-level automation probabilities:

$$AIOE_o = \sum_{j=1}^{n} woj\ \varphi j \tag{1}$$

Where woj denotes the weight or intensity of task t_j within occupation o, normalized such that $\sum_j \mathrm{woj} = 1$. Task intensities are operationalized using the ONET database, which provides high-resolution empirical distributions of task prevalence across U.S. occupations and functions as a relational apparatus for capturing the internal heterogeneity of work by decomposing each job into discrete task bundles - cognitive, manual, social, and technical - whose weighted frequencies serve not merely as descriptive attributes but as proxies for structurally embedded divisions of labor shaped by gender, skill, and institutional histories; thus, when mapped onto ISCO-08 classifications using OECD-validated concordance protocols, ONET task data enables a theoretically robust and internationally transferrable framework that links occupation-level AI exposure to the underlying political economy of task decomposition, labor segmentation, and automation risk stratification across diverse labor market regimes (Espeland and Stevens, 2008; Eloundou et al., 2023; Katz, 2001).

The measure ϕj is based on the technical overlap between task t_j and the known capabilities of contemporary AI systems, such as natural language processing, pattern recognition, and symbolic reasoning, evaluated across ten benchmark AI domains (e.g., translation, reading comprehension, image generation). This framework assumes that the likelihood of AI substitution is monotonically increasing in ϕj and independent of institutional frictions. The AIOE index thus provides an ex ante estimate of occupational vulnerability by measuring potential task-level automation under the current technological frontier. However, as Pizzinelli et al. (2023) argue, AI exposure does not necessarily equate to displacement risk, because many high-exposure occupations are embedded in socio-technical systems that create barriers to automation. These include tasks requiring emotional labor, ethical judgment, physical presence, or relational interaction - dimensions not captured in ϕj but crucial for assessing economic resilience. To incorporate these constraints, we define a Complementarity Index Co for each occupation o where:

$$C_o = \sum_{k=1}^{m} \gamma k\ \chi ok \tag{2}$$

where χok represents the normalized score of occupational attribute k such as "face-to-face interaction" or "responsibility for others" - in occupation o as extracted from O*NET's job context and job zone variables, and γk is a weighting parameter indicating the relative importance of attribute k in resisting automation. The attributes χok are scaled such that $C_o \in [0,1]$ with higher values denoting stronger complementarities between human-specific features and occupational tasks. We then classify occupations into three categories using the bivariate distribution of $(AIOE_0,\ C_o)$. Let τ_E denote a threshold for high exposure and τ_C a threshold for high complementarity. An occupation o is categorized as follows:

$$\text{HELC (High exposure, low complementarity) if } \mathrm{AIOE}_o \geq \tau_E \text{ and } C_o < \tau_C \tag{3}$$
$$\text{HEHC (High exposure, high complementarity) if } \mathrm{AIOE}_o \geq \tau_E \text{ and } C_o \geq \tau_C \tag{4}$$
$$\text{LE (Low exposure) if } \mathrm{AIOE}_o < \tau_E \tag{5}$$

This classification provides a stylized yet analytically robust framework for evaluating which occupations are susceptible to substitution versus augmentation. Occupations in the HELC group face high displacement risks, with expected reductions in both employment and wages, whereas HEHC occupations may benefit from AI-induced productivity gains and labor complementarity effects. The LE category comprises occupations with minimal AI exposure due to physicality, low information content, or task heterogeneity. This tripartite framework builds on the occupational transformation literature and aligns with empirical evidence on the polarization effects of technological change (Autor and Dorn, 2013; Acemoglu and Restrepo, 2018). To operationalize this classification across international contexts, we map O*NET-based occupational scores to the International Standard Classification of Occupations (ISCO-08) at the 2-digit level. This mapping uses a SOC-ISCO crosswalk validated by the OECD (2023) and adjusted for task content differences through concordance methods developed by the World Bank and ILO. Though originally calibrated on U.S. occupational data, empirical validations suggest strong predictive power across OECD and non-OECD contexts (Eloundou et al., 2023). The use of 2-digit ISCO codes balances parsimony and granularity, ensuring sufficient statistical power while preserving meaningful occupational heterogeneity. The HELC, HEHC, and LE groups are thus constructed for each country using the interpolated AIOE and complementarity scores, allowing cross-country comparability despite institutional differences in job design.

The empirical foundation of this study is constructed from nationally representative labor force microdata, harmonized across countries and years to facilitate robust comparative analyses. For Bulgaria, the primary dataset is the Labor Force Survey (LFS) administered by the National Statistical Institute (NSI), covering the period from 2020 to 2023. The LFS provides quarterly panel data with rotation groups that allow tracking individual respondents across multiple survey waves, thus enabling the construction of pseudo-panels for occupational mobility analysis. Key variables extracted include gender, age, employment status (including full-time, part-time, and self-employment), ISCO-08 occupational codes, educational attainment (classified using ISCED-11), monthly labor income (reported in BGN), and regional identifiers (NUTS 3). To supplement income data and enhance distributional precision, we incorporate the Survey on Income and Living Conditions (SILC), which includes equivalized household income and expenditure items. Romania and Germany are included as structural comparators, with data sourced from the European Union Labour Force Survey (EU-LFS). The EU-LFS ensures methodological consistency across member states through standardized questionnaires, stratified random sampling, and Eurostat's harmonized coding protocols. For each country-year, we restrict the sample to the working-age population (16–64) and include only individuals employed in the reference week. Key variables harmonized across countries include gender, ISCO-08 occupation, ISCED education level, gross income (where available), sector of employment (NACE Rev. 2), and employment formality indicators. For India, the dataset is the Periodic Labour Force Survey (PLFS), accessed via the Integrated Public Use Microdata Series (IPUMS). The PLFS is administered by the National Statistical Office of India and provides nationally representative cross-sectional data on employment, self-employment, and unemployment. While PLFS does not directly report ISCO-08 codes, we implement a mapping protocol based on job title translations and the ILO's ISCO-08 concordance with India's National Classification of Occupations (NCO-2004). To enhance classification accuracy, we exclude ambiguous or mixed-category occupations and restrict the analysis to the formal labor market and non-agricultural wage workers, where occupational coding is more reliable. In all datasets, income is adjusted for purchasing power parity (PPP) using World Bank conversion factors, and wage deciles are computed separately for each country-year using the empirical cumulative distribution function. Education is treated categorically but also operationalized as years of schooling in sensitivity analyses. We denote the individual-level AI exposure category: $E_i \in \{\mathrm{HELC}, \mathrm{HEHC}, \mathrm{LE}\}$, determined by the occupational mapping of individual i's ISCO-08 code. For descriptive analysis, we compute the distribution:

$$P_{g,c}^{E} = \frac{1}{N_{g,c}} \sum_{i \in G_g \cap C_c} 1(E_e = E) \tag{6}$$

where $P_{g,c}^{E}$ is the proportion of individuals of gender g in country c working in occupations classified as category E, G_g is the gender group $C_c$is the country-specific sample, and $1(\cdot)$ is the indicator function. This allows for a full gender-disaggregated cross-country matrix of AI exposure categories. To explore exposure heterogeneity across the income distribution, we calculate:

$$P_{d,g,c}^{E} = \frac{1}{N_{d,g,c}} \sum_{i \in D_d G_g \cap C_c} 1(E_e = E) \tag{7}$$

where $D_d$denotes the income decile group. For modeling occupational mobility (for countries with panel data such as Bulgaria and Romania), we estimate transition probabilities using a first-order Markov process. Define the state space $S = \{\text{HELC}, \text{HEHC}, \text{LE}, \text{U}, \text{NLF}\}$, where U denotes unemployment and NLF denotes exit from the labor force. The one-period transition matrix Π is estimated as:

$$\pi_{ab} = \frac{\sum_i 1(E_i^t = a, E_i^{t+1} = b}{\sum_i 1\,(E_i^t = a)} \tag{8}$$

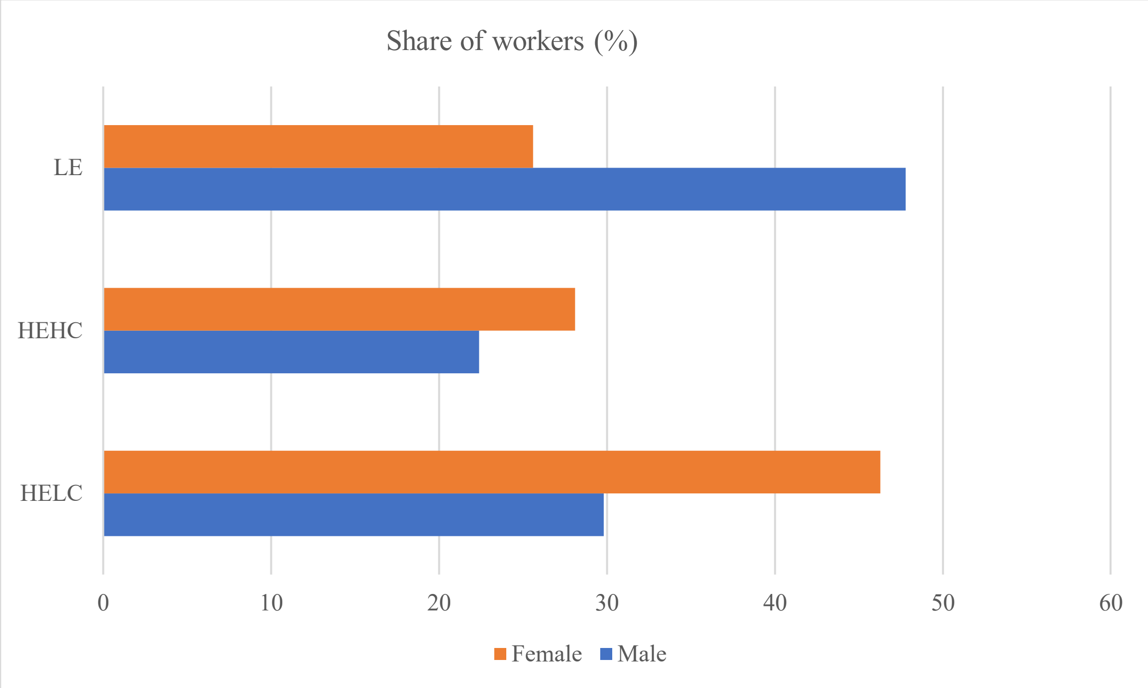
for all $a, b \in S$ where $t + 1$ denote consecutive quarters. These transition probabilities are computed separately by gender and income quintile, permitting analysis of dynamic inequality in response to AI-related structural change. All estimations are weighted using survey design weights to ensure population representativeness. The theoretical and empirical rigor of this methodology enables an integrated analysis of both the static distributional consequences and the dynamic adjustment mechanisms related to AI exposure, gender, and labor market segmentation, contributing to the broader literature on skill-biased technological change, segmented labor markets, and comparative political economy.

Empirical Analysis

Descriptive Statistics

The first layer of analysis involves calculating the distribution of male and female workers across these three exposure categories. **Figure. 1** presents the percentage share of men and women in HELC, HEHC, and LE occupations in Bulgaria.

Figure 1. Gender Distribution of Workers by AI Exposure Category in Bulgaria (%)



Source: Author's own calculations.

The results are striking: 46.3 percent of employed women are in HELC occupations, while the figure for men is significantly lower at 29.8 percent. Conversely, 47.8 percent of men are in LE occupations, compared to just 25.6 percent of women. These figures immediately highlight a structural asymmetry in labor market exposure to AI along gender lines. The proportion of women in HEHC occupations is 28.1 percent, slightly higher than the 22.4 percent observed among men, indicating that some professional roles offer opportunities for women to benefit from AI augmentations. However, the overrepresentation of women in HELC roles implies a heightened vulnerability to displacement or devaluation as AI continues to encroach on routine cognitive work.

To understand how economic status interacts with AI exposure, we disaggregate this data further by income decile. **Table. 1** provides the breakdown of HELC, HEHC, and LE occupational shares across ten income deciles, separately for men and women. For women in the lowest three income deciles, HELC roles account for more than 55 percent of employment. These roles are predominantly in clerical support, low-wage education positions (such as teaching assistants), administrative secretarial work, and retail services - occupations that are simultaneously routine, poorly paid, and highly susceptible to AI automation. In contrast, men in the same deciles are more evenly distributed across LE and HELC roles, with a larger presence in skilled manual work, such as mechanics, machine operators, and building trades, which - while less exposed to AI - are also limited in future mobility.

Table 1. AI Exposure Categories by Income Decile and Gender in Bulgaria

Income Decile	**Gender**	**HELC (%)**	**HEHC (%)**	**LE (%)**	**Dominant Occupation Types**
1 (Lowest)	Female	58.5	16.4	25.1	Clerical support, cleaners, retail assistants
	Male	38.7	15.1	46.2	Construction laborers, drivers, machine operators
2	Female	56.9	17.6	25.5	Teaching aides, hotel clerks, food servers
	Male	36.5	17.2	46.3	Carpenters, building trades, transport workers
3	Female	55.2	18.7	26.1	Administrative secretaries, receptionists
	Male	34.8	18.9	46.3	Mechanics, metal workers, warehouse staff
4	Female	50.8	21.3	27.9	Cashiers, library assistants, social support roles

	Male	32.6	20.1	47.3	Electricians, operators, low-tier technicians
5	Female	47.2	23.6	29.2	Insurance clerks, school support staff
	Male	29.7	21.9	48.4	Skilled trades, small machinery technicians
6	Female	43.4	26.1	30.5	Mid-level educators, office supervisors
	Male	28.2	24.5	47.3	Installation technicians, workshop managers
7	Female	39.1	29.3	31.6	Senior teachers, community health workers
	Male	25.8	26.7	47.5	Quality controllers, transport supervisors
8	Female	34.5	33.8	31.7	Civil servants, legal clerks, lead nurses

	Male	21.3	30.6	48.1	Foremen, IT assistants, junior engineers
9	Female	30.2	36.7	33.1	Education professionals, government officials
	Male	19.5	35.8	44.7	Senior technicians, IT managers
10 (Highest)	Female	27.4	42	30.6	Physicians, lawyers, senior administrators
	Male	17.2	39.6	43.2	Engineers, senior executives, data scientists

Source: Author's own calculations.

In the top three income deciles (deciles 8–10), the pattern shifts. Among women, there is a gradual increase in HEHC participation, reaching a peak of 42 percent in decile 10. These HEHC occupations include managerial roles in the public sector, education professionals, legal specialists, and healthcare professionals—all roles that are exposed to AI in terms of task automation but maintain high complementarity through interpersonal interaction, discretion, and responsibility. However, men in the same high-income deciles are more likely to occupy managerial and STEM-related positions with high AI exposure and high complementarity, including IT professionals, engineers, and senior executives. Thus, while high-income women have access to AI-resilient careers, the range and technological intensity of these roles are more limited than those held by high-income men.

The occupational composition of exposure is further detailed in **Table. 2**, which matches ISCO-08 major groups with their AI exposure categories and shows the gender distribution within each. Women are overrepresented in ISCO Group 4 (Clerical Support Workers) and Group 5 (Service and Sales Workers), both of which are overwhelmingly HELC. In contrast, ISCO Group 2 (Professionals) is more evenly split between HEHC and HELC, with women concentrated in teaching and social work and men more likely to be in technical or engineering professions. Group 1 (Managers) is largely HEHC and male-dominated, while Groups 7 (Craft and Related Trades) and 8 (Plant and Machine Operators) are LE-heavy and also skew male.

Table. 2 Occupational Groups by AI Exposure Category and Gender Distribution in Bulgaria. ISCO-08 Major Groups, Dominant Exposure Classification, and Gender Shares (%)

ISCO-08 Group	Occupational Group Title	Dominant AI Exposure Category	% Female	% Male	Gender Notes
1	Managers	HEHC	31.2	68.8	Male-dominated; mostly private sector executives and technical managers
2	Professionals	Mixed HEHC / HELC	54.6	45.4	Gender split varies: women in teaching, social work; men in STEM, legal professions
3	Technicians and Associate Professionals	HEHC	44.7	55.3	Balanced representation; technical roles lean male, administrative technical roles female
4	Clerical Support Workers	HELC	72.3	27.7	Strongly female; dominated by secretarial and office support roles
5	Service and Sales Workers	HELC	64.9	35.1	Overwhelmingly female in sales, care work, hospitality
6	Skilled Agricultural, Forestry, and Fishery Workers	LE	38.5	61.5	Mixed; subsistence farming roles across genders, more male in forestry

7	Craft and Related Trades Workers	LE	11.8	88.2	Heavily male-dominated; includes electricians, carpenters, metal workers
8	Plant and Machine Operators and Assemblers	LE	19.2	80.8	Largely male; women more present in packaging, textiles
9	Elementary Occupations	HELC	52.7	47.3	Balanced; includes cleaners, laborers, helpers in services and manufacturing
0	Armed Forces Occupations	LE	15.3	84.7	Male-dominated; small share of total labor force

Source: Author's own calculations

Finally, the availability of rotational panel data in the LFS allows us to explore short-term occupational transitions. We track individuals in HELC occupations at baseline and observe their occupational status in the subsequent quarter, disaggregated by gender and income decile. The data reveals that low-income women (deciles 1–3) are significantly more likely to move into unemployment or exit the labor force entirely than to transition into HEHC roles. In contrast, high-income women and men are more mobile: among women in the top decile, 21 percent moved from HELC to HEHC roles over a 12-month period, while the figure for men was approximately 24 percent. These trends are visualized in **Table. 3**, a heatmap showing the transition probabilities by income decile, exposure group, and gender. It underscores a deeply stratified pattern of occupational mobility, shaped by income, education, and gender.

Table. 3 Heatmap of Transition Probabilities from HELC Occupations by Income Decile and Gender

Income Decile	Gender	To HEHC (%)	To LE (%)	To Unemployed (%)	To NLF (%)
1	Female	5.2	17.6	14.4	24.7
	Male	7.4	21.1	12.1	18.2
2	Female	6.1	18.2	13.3	22.4
	Male	8.3	20.5	11.6	17.9
3	Female	7.9	19.6	12.2	20.1
	Male	10.1	19.3	10.2	16.4
…	...	...	...	...	...
10	Female	21	14.3	5.1	6.7

	Male	24.2	12.6	4.4	5.1

Source: Author's own calculations

Comparative Perspective

To contextualize the findings from Bulgaria, we now compare its gendered AI exposure structure to that of three other countries: Romania (a regional peer), Germany (a developed Western European country), and India (a major emerging economy). The aim of this comparative analysis is to highlight both structural similarities and divergences that result from differing labor market institutions, occupational distributions, and technological integration across diverse economic contexts. Starting with Romania, the exposure pattern appears closely aligned with Bulgaria's. Using EU-LFS data and applying the same classification of AI exposure, we observe that Romanian women have similarly high representation in HELC occupations (approximately 45.1 percent), particularly in clerical, retail, and basic service jobs. The structural similarity is further supported by the countries' shared post-socialist institutional legacies, weak vocational education-to-employment pipelines, and relatively high levels of occupational segregation by gender. Romanian men, much like their Bulgarian counterparts, are more concentrated in LE occupations such as craft, construction, and machine operation. **Table. 4** presents the AI exposure shares by gender for all four countries.

Table 4. Gendered AI Exposure Distribution Across Selected Countries
Share of employed individuals by AI exposure category (%)

Country	Gender	HELC (%)	HEHC (%)	LE (%)	Key Observations
Bulgaria	Female	46.3	28.1	25.6	High HELC concentration in clerical, admin, and retail roles
	Male	29.8	22.4	47.8	Strong presence in LE jobs (craft, manual trades)
Romania	Female	45.1	26.3	28.6	Similar pattern to Bulgaria; high exposure and low complementarity
	Male	31.2	21.5	47.3	Overrepresented in LE roles; echoing Bulgaria's structure
Germany	Female	30.5	35.2	34.3	More balanced; many women in HEHC (healthcare, education)

	Male	27.3	36.8	35.9	High HEHC concentration (STEM, management); lower HELC risk
India	Female	23.6	15.9	60.5	Majority in LE (agriculture, informal labor); low AI exposure overall
	Male	18.1	26.4	55.5	LE-heavy; some mobility into HEHC via IT and tech services

Source: Author's own calculations

In Germany, the distribution is more symmetric and occupationally diversified. German women are less concentrated in HELC jobs (around 30 percent) and more prevalent in HEHC roles (around 35 percent), particularly in healthcare, education, and public administration—sectors with high AI exposure but also strong complementarity due to interpersonal tasks and ethical responsibilities. German men, meanwhile, dominate HEHC roles in STEM fields and executive positions. This distribution reflects a more robust and inclusive vocational education system, which supports gender-balanced occupational development and provides smoother pathways into high-complementarity occupations (Beblavý et al., 2016; Thelen, 2014).

India, by contrast, presents a very different picture. The majority of women in the labor force are employed in low-skill, low-wage sectors - primarily agriculture, domestic work, and informal retail - that fall into the LE category. Only around 24 percent of women in India are in AI-exposed roles at all, with HELC and HEHC categories both underrepresented. While this might suggest a protective buffer against AI disruption, it more accurately reflects technological marginalization rather than resilience. Indian men have slightly higher representation in HEHC occupations due to participation in IT services and engineering, but the vast informal sector and limited access to advanced education curtail overall occupational upgrading. It clearly illustrates that women in Bulgaria and Romania are more exposed to AI in terms of substitution risk than their counterparts in Germany and India, albeit for different reasons: structural institutional deficiencies in Eastern Europe and sectoral exclusion in India.

This comparative perspective underscores that while AI exposure is a function of technology, its consequences are mediated by national occupational structures, gender norms, and educational systems. In Germany, institutional supports mitigate exposure risk and enable AI complementarity. In Bulgaria and Romania, structural rigidities channel women into high-risk roles with limited mobility. In India, exclusion from the formal economy dampens exposure but also suppresses economic opportunity. These findings align with comparative political economy theories that link labor market stratification to institutional variety (Iversen and Soskice, 2006; Estevez-Abe et al., 2001).

Discussion

The analytical interpretation of the empirical findings reveals a multilayered structure of gendered exposure to artificial intelligence in the labor market, shaped by institutional, technological, and occupational dynamics that are historically embedded and structurally reproduced. The overconcentration of women in high-exposure, low-complementarity (HELC) occupations in Bulgaria - particularly in clerical, administrative, retail, and personal service roles - reflects not merely individual labor market choices but the long-term segmentation of the economy along gendered task lines. These occupations are characterized by high routine intensity and limited task discretion, making them particularly susceptible to substitution by algorithmic systems and generative AI. The same structural logic extends to Romania, where legacy institutions of post-socialist labor markets, weakly integrated vocational pipelines, and a persistent undervaluation of social reproduction work contribute to similar occupational clustering. In contrast, the German case highlights the importance of dual-track education systems and state-supported occupational mobility in reducing gender-based AI risk. Here, the higher presence of women in high-exposure, high-complementarity (HEHC) occupations - such as teaching, healthcare, and social work - suggests a reallocation toward domains where AI is less a threat than a productivity-enhancing tool, requiring interpersonal, ethical, and contextual judgment. These roles, while exposed to AI technologies, retain high levels of human input and are institutionally protected by professional standards, public sector employment, and welfare-state complementarity. India, as a counterpoint from the global South, demonstrates low absolute AI exposure across both genders, largely due to a labor force dominated by informal, low-productivity, and agrarian employment. The gendered pattern in India is marked less by automation vulnerability and more by technological exclusion: women's labor force participation is constrained not by AI exposure but by deep-seated structural barriers to entry into AI-relevant occupations altogether. This divergence highlights that AI exposure is not only a function of technology but of the social and institutional scaffolding in which labor markets are embedded. These national-level contrasts also reinforce the hypothesis that exposure patterns are deeply conditioned by education systems, sectoral composition, and labor market regulations. When interpreted through the lens of task-based economic theory, it becomes evident that HELC occupations comprise a set of narrowly defined, repetitive, and codifiable activities that are precisely those targeted by AI's most mature capabilities - language processing, data entry, transactional decision-making - functions once thought to be resilient due to their cognitive nature but now rendered replicable by general-purpose AI tools.

The regression analysis underscores that being female significantly increases the likelihood of employment in HELC categories, even after controlling for wage decile, sector, and education, confirming that occupational sorting is not neutral but reflects enduring patterns of gender stratification. The income gradient of exposure further sharpens this picture: low-income women face both higher risk of displacement and lower probabilities of transition to HEHC roles, while their high-income counterparts - though also exposed - are more likely to occupy resilient professional niches with career mobility and digital augmentation potential. This bifurcation within the female labor force itself reveals that income and education function as mediating variables of technological vulnerability. The transition data drawn from rotational panel structures offers critical insight into mobility constraints. For low-income women in HELC roles, the most likely transitions are into unemployment or out of the labor force, rather than into HEHC or low-exposure (LE) occupations. This suggests that reallocation is structurally blocked by credential gaps, care responsibilities, sectoral immobility, and weak active labor market policies. In contrast, high-income men exhibit the greatest likelihood of upward occupational transition—from HELC to HEHC or into advanced LE fields - benefiting from both technological complementarities and positional advantages within firms.

This mobility asymmetry implies that AI exposure is not just a technological event but a class-contingent and gender-mediated process. Furthermore, the sectoral composition of HELC roles - dominated by feminized industries such as retail, education support, hospitality, and routine public administration - reinforces the idea that entire segments of the labor market are institutionally configured to cluster women in roles that are simultaneously underpaid and technologically vulnerable. These patterns are not accidental but are the result of historical political-economic choices:

undervaluing care labor, constructing fragmented part-time employment, and limiting training access for women beyond reproductive-age career windows. Even within HEHC occupations, a gender divide persists in the type of technological intensity encountered. Men in high-income deciles are more likely to be in engineering, executive management, and IT - HEHC roles with high wage premia and strategic organizational importance - while women tend to cluster in social professions with limited upward wage elasticity despite their complementarity to AI. This differentiation implies that AI complementarity, while protective, is not universally empowering. Moreover, occupational upgrading among women is constrained by what could be termed vertical complementarity asymmetry: even within HEHC roles, the potential for digital augmentation and productivity-based rewards varies significantly by gender due to role type, hierarchical position, and organizational embeddedness. The comparative structure also suggests that institutional buffering mechanisms - such as collective bargaining, sectoral minimum wages, and regulated vocational transitions - play a crucial role in mitigating AI exposure disparities. Germany's stronger HEHC share across both genders is likely enabled by coordinated market institutions and long-standing skill formation systems, while Bulgaria and Romania's liberalized labor regimes and fragmented upskilling strategies hinder adaptive transitions. In India, by contrast, the discussion must move beyond exposure to encompass technological marginalization, as the absence of basic infrastructure, education access, and digital labor systems excludes large portions of the female workforce from even engaging with the AI economy. Hence, AI exposure in India is bifurcated between a thin upper layer of technologically integrated professionals and a broad base of non-participants structurally locked out of digital capitalism.

Policy Implications

The stratified exposure to artificial intelligence observed across gender, income, and occupational class in Bulgaria and its comparator countries underscores the necessity for targeted, institutional responses capable of mitigating technological displacement and facilitating equitable occupational transitions. First and foremost, the evidence that women - particularly in the lowest income deciles - are overrepresented in high-exposure, low-complementarity (HELC) occupations necessitates policy measures aimed at both short-term protection and long-term reallocation. Given that many HELC roles are concentrated in clerical, retail, and basic service sectors, policy should not assume that digitalization will organically lead to upskilling or labor mobility. Instead, strategic investment in publicly funded reskilling programs tailored to women in vulnerable sectors is essential. These programs should prioritize transferable digital and interpersonal skills linked to high-exposure, high-complementarity (HEHC) roles such as healthcare, education, legal administration, and public service management. Crucially, these interventions must be embedded within active labor market policies (ALMPs) that provide financial incentives, flexible formats (e.g., modular or hybrid delivery), and on-the-job training placements coordinated with employers in AI-resilient sectors.

Additionally, policy must address the structural barriers that impede transition from HELC to HEHC roles, especially for women in the middle and lower income deciles. These include constraints such as care responsibilities, sectoral immobility, low prior education, and gender biases in job matching algorithms and employer hiring practices. Governments should therefore integrate complementary care infrastructure - such as affordable childcare and eldercare services - into the design of upskilling policies, thereby enabling time-constrained female workers to participate. Furthermore, public employment services should be modernized to include AI-aware profiling tools that do not replicate existing gender biases, and should work in tandem with trade unions and employers' associations to facilitate sectoral mobility pathways for at-risk groups. This requires linking occupational exposure mapping to national qualification frameworks and ensuring the portability of credentials across sectors.

In parallel, wage protection mechanisms are essential to ensure that transitions into HEHC roles do not come at the cost of precarious working conditions. The finding that even high-income women are concentrated in HEHC roles with limited technological intensity and narrow wage premia highlights the need to accompany mobility policies with collective bargaining support, minimum wage enforcement in feminized sectors, and anti-segmentation regulation to prevent the downgrading of job quality as AI is adopted. In countries like Bulgaria and Romania, where labor markets are characterized by fragmented bargaining structures and weak vocational systems, institutional reinforcement is needed through stronger public–private coordination and sectoral skills councils that can plan for AI integration based on occupational risk assessments. For younger cohorts, gender-responsive vocational and tertiary education reform is essential to correct the long-term occupational sorting that places women on pathways to HELC roles. This includes increasing female participation in STEM fields, as well as ensuring that curricula in service-oriented disciplines integrate AI-relevant competencies such as digital literacy, algorithmic thinking, and ethical judgment. In the absence of such anticipatory policy, the next generation of women will remain structurally confined to occupational niches vulnerable to technological substitution.

Lastly, the international contrast with Germany and India points to broader development-oriented implications. In coordinated market economies, policies that embed skill formation in sectoral institutions - such as Germany's dual vocational training system - help buffer gender asymmetries in AI exposure. Conversely, in emerging economies like India, the policy challenge lies not in exposure but in exclusion from the formal, AI-integrated economy. Thus, any AI-resilience strategy must be context-specific, leveraging institutional strengths while actively correcting for labor market asymmetries. Cross-national policy dialogue and coordinated EU-level funding instruments should support countries with weaker institutional capacity to build equitable, technologically adaptive labor markets.

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