Artificial Intelligence and Gender Equality in Global Labor Markets

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1. Introduction

The proliferation of Artificial Intelligence (AI) is precipitating a structural transformation of global labor markets, often heralded as a core component of the Fourth Industrial Revolution (Schwab, 2024). This technological wave carries a dual potential: it promises unprecedented gains in productivity and economic growth, yet it also threatens to deepen existing inequalities (Acemoglu & Restrepo, 2019). A particular dimension of this discourse is the impact of AI on gender equality. Historically, technological disruptions have unevenly reshaped opportunities for men and women, at times dismantling traditional barriers and at others erecting new ones (Goldin, 2006). The rise of AI presents a critical juncture, raising a pivotal question: will it serve as a catalyst for narrowing the persistent gender gap in labor markets, or will it entrench and widen it?

While extensive research has documented the persistent underrepresentation of women in science, technology, engineering, and mathematics (STEM) fields, the specific implications of women's participation within the nascent AI economy remain empirically underexplored. The AI sector is not merely another high-technology field; it is a foundational technology poised to redefine job roles, skill requirements, and competitive advantage across all industries (Brynjolfsson & McAfee, 2014). Consequently, women's position within this critical domain may have far-reaching "spillover" effects on their broader economic inclusion. Exclusion from the creation and deployment of AI risks relegating women to roles more susceptible to automation, while inclusion could create pathways to leadership and high-wage employment, challenging entrenched occupational segregation.

This study aims to fill a critical gap in the literature by empirically investigating the relationship between the share of women in AI-related skills and occupations and the overall gender gap in labor force participation. While previous work has often focused on the potential threats of automation to female-dominated jobs, this paper explores the alternate hypothesis: that greater representation of women in the high-growth, high-status AI sector can act as a powerful engine for broader gender parity. We argue that a higher female share in AI not only provides direct economic benefits to the women involved but also generates positive externalities by challenging stereotypes, creating role models, and influencing the design of more inclusive technologies and workplace cultures.

To test this hypothesis, this study employs a balanced panel dataset of 41 countries over the period 2016–2023. Our dependent variable is the ratio of female to male labor force participation, one measure of gender inequality in labor market access. Our key explanatory variable, the share of women in the AI talent pool, is derived from novel data that directly captures gender representation in AI skills and occupations. Using a comprehensive econometric strategy that progresses from pooled OLS to dynamic panel models (System GMM) to account for country-specific heterogeneity, temporal dynamics, and potential endogeneity, we rigorously assess this relationship.

Our findings consistently support a positive and statistically significant association between a higher share of women in AI and a more balanced female-to-male labor force participation ratio. This result is robust across numerous model specifications and control variables. Further analysis reveals a non-linear relationship, suggesting the impact is strongest at lower levels of female AI participation and diminishes as representation grows, pointing to a potential saturation effect or the influence of deeper structural barriers at higher levels of parity. This paper contributes by providing the first multi-country empirical evidence of the broader labor market benefits of gender inclusion within the AI sector, underscoring that fostering women's participation in frontier technologies is a crucial lever for achieving comprehensive gender equality.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on technological change, gender gaps, and AI. Section 3 outlines the data and empirical methodology. Section 4 presents the main regression results, while Section 5 explores non-linearity. Finally, Section 6 discusses the implications of our findings and concludes.

2. Literature Review

This study is situated at the intersection of three broad streams of literature: the economic impact of technological change, the determinants of gender inequality in labor markets, and the emerging scholarship on the societal implications of AI.

The first stream of literature establishes the transformative power of technology on labor. Foundational work by Acemoglu and Restrepo (2019, 2020) conceptualizes automation as a process of displacing labor from tasks, which can reduce wages and employment unless counteracted by the creation of new tasks where labor has a comparative advantage. This framework highlights that the net effect of technology is not pre-determined. Brynjolfsson and McAfee (2014) argue that digital technologies and AI represent a "second machine age" that favors high-skilled, cognitive labor over routine manual and cognitive tasks, leading to labor market polarization. This literature sets the stage by confirming that AI is not a neutral force but one that actively reshapes demand for skills and labor.

The second, extensive body of literature documents the persistence and evolution of gender gaps in labor markets. Scholars have identified numerous drivers, including differences in human capital, occupational segregation, discrimination, social norms, and the disproportionate burden of unpaid care work on women (Blau & Kahn, 2017; Goldin, 2014). Occupational segregation, whereby men and women are systematically concentrated in different jobs, is a particularly resilient source of the gender pay gap and career immobility (Hegewisch & Hartmann, 2014). While gender convergence in education and experience has narrowed some gaps, progress has slowed in recent decades, particularly in achieving parity in leadership and high-wage sectors (England, 2010). This context is critical, as it frames the "problem" that new forces like AI will act upon: a deeply entrenched, multi-faceted system of gender inequality.

The third and most directly relevant stream of literature examines the gendered dimensions of AI and automation. This scholarship has largely proceeded along two parallel tracks.

The first track focuses on the risks AI poses to female employment. Because women are overrepresented in routine-intensive clerical, administrative, and service roles (e.g., cashiers, receptionists, data entry clerks), several studies have warned that automation could disproportionately displace female workers (World Economic Forum, 2020; Brussevich, Dabla-Norris, & Khalid, 2019). This perspective paints a pessimistic picture where AI exacerbates existing gender disparities by devaluing skills in female-dominated occupations.

The second track highlights the persistent underrepresentation of women in the creation and governance of AI. Numerous reports document a significant gender gap in AI talent, with women constituting only a small fraction of AI researchers, developers, and engineers (UNESCO, 2019; WEF, 2018). This "supply-side" issue is often traced back to the "leaky pipeline" in STEM education and careers whreby the proportion of students who are female declines at higher levels of education. The consequences are twofold: it risks creating a new, highly paid "digital elite" that is predominantly male, and it raises concerns about algorithmic bias, where AI systems trained on biased data or designed with a narrow worldview may perpetuate or even amplify harmful gender stereotypes (O'Neil, 2016; West, Whittaker, & Crawford, 2019).

While both tracks provide crucial insights, a significant gap remains in understanding the potential positive spillover effects of improving women's representation in the AI sector. The existing literature has yet to empirically test whether closing the gender gap within AI can contribute to closing the gender gap in the broader labor market. The theoretical basis for such a link is plausible: a greater presence of women in a high-status, future-oriented field like AI could serve as a powerful signal, breaking down stereotypes about women's technical capabilities, creating visible role models to inspire the next generation, and fostering more inclusive innovations and work environments (Begeny et al., 2020). This study directly addresses this gap. By moving beyond the threat of job displacement or the problem of underrepresentation, we provide a quantitative assessment of the potential for gender inclusion in AI to act as a catalyst for wider progress in labor market equality.

3. Methods and Data

3.1 Data and Sources

This study draws on a balanced panel of 41 countries covering the period 2016–2023. The dependent variable is the ratio of female to male labor force participation in the overall economy, obtained from the World Bank's World Development Indicators (WDI) (World Bank, 2025). This variable is a widely used measure of gender inequality in labor market access: a value of 100 indicates parity in participation rates, while values closer to 0 indicate underrepresentation of women in the labor force. The choice of this dependent variable reflects the central concern of the study: whether the diffusion of AI-related skills and occupations, has the potential to narrow or widen existing gender gaps in labor markets.

The main explanatory variables, AI female share and AI male share, capture the gender distribution of AI-related skills and employment. They are based on LinkedIn data measuring the proportion of members worldwide who either possess at least two AI engineering skills or are employed in an AI occupation, disaggregated by gender (OECD, 2025) They represent a novel contribution to the literature by directly measuring how women and men are positioned within the emerging AI economy.

Several control variables are included to account for economic, demographic, and educational factors: Unemployment rate is drawn from the WDI (World Bank, 2025) as a measure of labor market slack. Higher unemployment is often associated with limited opportunities for labor market entrants, which may disproportionately affect women. Tertiary education rate, sourced from the WDI (World Bank, 2025), serves as a proxy for the supply of highly educated labor and indicates the extent to which women and men have access to advanced skills relevant for AI-related employment. It is measured as the gross enrollment ratio, defined as the total enrollment in tertiary education, regardless of age, expressed as a percentage of the population in the official age group corresponding to this level of education. . Log of GDP per capita (PPP, constant international $) comes from the WDI. This indicator measures economic development and is expected to correlate positively with technological adoption and women's participation in labor markets. Log of total population is obtained from (World Bank, 2025). This control accounts for demographic scale effects, as larger countries may face different dynamics in both labor market structures and AI adoption compared to smaller economies.

Table 1 presents the descriptive statistics for the full sample. The female-to-male labor force participation ratio averages 77.8 percent, with substantial variation across countries, highlighting significant disparities in gender inclusion (ranging from a minimum of 25.5 in Saudi Arabia in 2016 to a maximum of 90.8 in Finland in 2023). The AI employment shares reflect the gender divide in technology-intensive sectors: women account on average for 28.3 percent of AI-related skills and occupations, while men account for 71.7 percent. Considerable variation is also evident in the control variables, with unemployment ranging from 2 to 34 percent, tertiary enrollment rates spanning 19 to 167[1] percent, and log GDP per capita ranging from 8.67 to 11.88.

Tabel 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Female to Male LF	328	77.78	13.05	25.51	90.76
AI female share	328	28.31	4.92	14.02	42.27
AI male share	328	71.69	4.92	57.73	85.98
Unemployment	328	8.56	7.00	2.02	34.01
Tertiary Education	328	75.86	23.34	18.96	166.67
Log GDP pc	328	10.69	0.55	8.67	11.88
Log Population	328	16.52	1.55	13.27	21.09

Source: own calculations

Table 2 (Correlation Matrix) shows generally modest correlations among explanatory variables. GDP per capita is positively correlated with female-to-male labor force participation and negatively correlated with population size. The AI female share is positively but weakly associated with the dependent variable, suggesting that greater female involvement in AI employment may be linked to more balanced labor force participation. Importantly, correlations among the explanatory variables are low, alleviating concerns about multicollinearity.

This value was observed in Greece, where a relatively high number of older individuals are enrolled in tertiary education. To account for its potential influence as an outlier, we re-ran the regressions excluding Greece as a robustness check.

To formally assess multicollinearity, Table 3 reports the Variance Inflation Factors (VIFs). All values are well below the conventional thresholds of 5 or 10 often used to indicate problematic multicollinearity (Pan & Jackson, 2008; Rogerson, 2011), with the highest being 1.37 for log GDP. The mean VIF of 1.16 suggests a very low level of collinearity in the dataset.

Table 2. Correlation Matrix

	Female to Male LF	AI female share	GDP pc	Population	Unemployment	Tertiary Education
Female to Male LF	1.00	0.12	0.34	-0.5	0.08	0.12
AI female share	0.12	1.00	0.002	-0.04	-0.01	-0.07
GDP pc	0.34	0.0025	1.00	-0.28	-0.24	0.04
Population	-0.5	-0.0418	-0.28	1.00	-0.0D	-0.30
Unemployment	0.08	-0.0103	-0.24	-0.03	1.00	-0.02
Tertiary Education	0.12	-0.0768	0.03	-0.30	-0.02	1.00

Source: own calculations

Table 3. Variance Inflation Factors (VIF)

Variable	VIF	1/VIF
Log GDP	1.37	0.728885
Log Pop	1.25	0.800008
Unemployment rate	1.07	0.933509
Tertiary Education	1.06	0.940948
AI female share	1.02	0.978391
Mean VIF	1.16	

Source: own calculations from ***

Figures 1 and 2 present the evolution of women's representation in AI and their participation in the overall labor force between 2016 and 2023 across some Global South and Global North countries. The trends raise the question of whether progress in one domain can stimulate advances in the other. We notice that in the Global North, where female-to-male labor force participation ratios are already high, women's representation in

AI appears to reinforce equality by signaling access to high-skill and future-oriented sectors. Countries such as Finland, Sweden, and the United States combine near parity in the labor market with relatively strong AI female shares. Here, AI functions less as a driver of labor force inclusion than as a consolidator of existing equality. However, in cases such as Italy or Germany, AI female shares lag behind overall labor market equality, underscoring that barriers specific to STEM (Science, Technology, Engineering, and Mathematics) education and technology careers can constrain the spillover effect of AI inclusion on broader female employment.

In the Global South, the dynamics are more heterogeneous and suggest stronger potential for AI to act as a catalyst. Saudi Arabia and the UAE stand out: despite very low female labor force participation ratios, their AI female shares have risen rapidly in recent years. This divergence suggests that targeted entry points into AI and digital sectors may create "elite pathways" for women, which could in turn challenge cultural norms and expand broader labor market opportunities. Similarly, Singapore and South Africa, which combine relatively high labor participation with strong AI female shares, illustrate how digital inclusion can help sustain and deepen gender equality in employment. In contrast, Brazil and Chile show that high labor force participation without commensurate AI inclusion risks entrenching occupational segregation, with women concentrated in traditional rather than high-growth sectors.

Taken together, the trends indicate that AI female share has the potential to act as a lever for broader labor force participation, particularly in contexts where women's entry into technology-intensive fields carries symbolic and material weight.

Thus, while in the Global North AI female share appears to reflect and reinforce already high levels of female labor force participation, in the Global South it may function as a more transformative entry point, with the potential to accelerate gender inclusion more broadly. The policy challenge lies in ensuring that women's participation in AI does not remain isolated, but instead becomes a driver of systemic change in the labor market as a whole.

Figure 1 : Comparing Female Labor Force Participation across North and South Economies

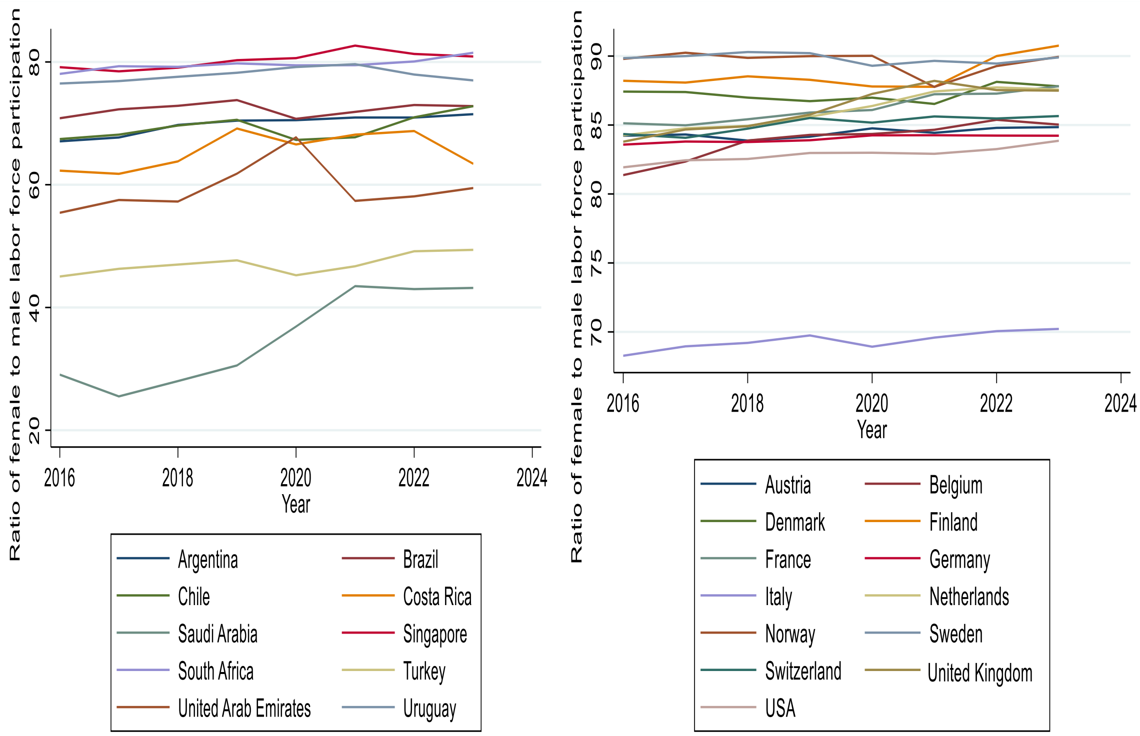
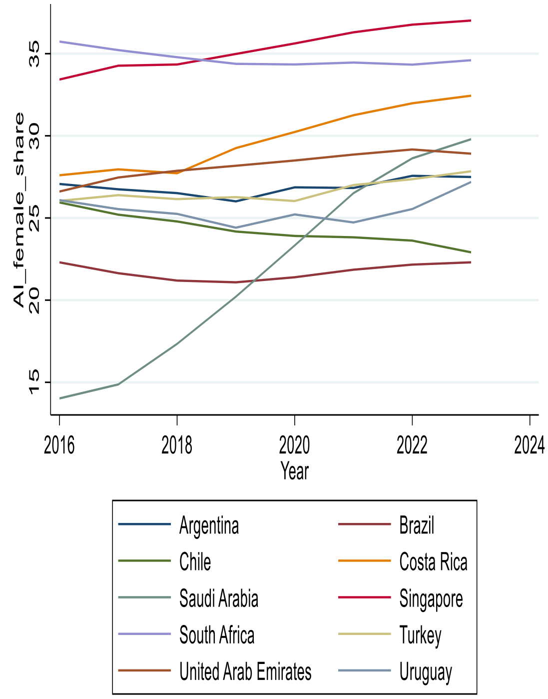
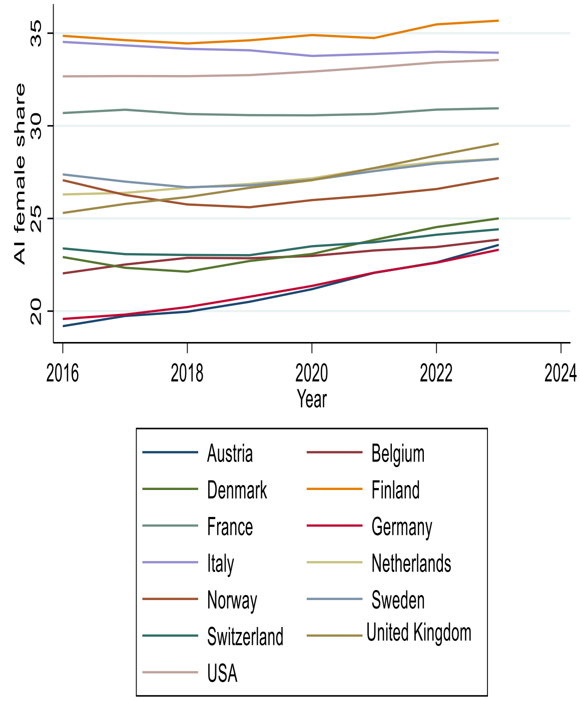


Figure 2. AI Female Share in Global North and Global South Countries





3.2. Empirical Framework

The empirical strategy of this study is designed to examine the relationship between female participation in artificial intelligence (AI) and gender inequality in labor markets, proxied by the ratio of female to male labor force participation. The underlying argument is that greater representation of women in AI-related occupations can generate broader spillover effects in terms of changing gender gaps in employment and participation.

We begin with a series of pooled OLS regressions as a baseline, where controls are progressively added in a stepwise fashion. The baseline model can be written as:

$$Fmale\ to\ male\ LF_{it} = \alpha + \beta_1 AI\ female\ share_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$
$$and\ (i = 1, \ldots n; t = 1, \ldots T)$$

$Female\ to\ male\ LF_{it}$ is the measure of relative female participation for country (i) and time (t). $AI\ female\ share_{it}$ is the measure gender distribution of AI-related skills and occupations. X_{it} is the vector set of explanatory variables that vary across time and countries. The parameter α contains a constant and country-specific variable invariant over time. The μ_i captures unobservable individual-specific effects and λ_t captures unobservable time-specific effects. ε_{it} is the error term.

However, pooled OLS does not account for unobserved heterogeneity. To address this, we estimate fixed effects (FE) and random effects (RE) models. FE estimators remove time-invariant country-specific influences, such as cultural norms, legal traditions, or institutional structures, which could bias the results if unobserved (Baltagi, 2013). By contrast, RE models exploit both within- and between-country variation but assume that unobserved heterogeneity is uncorrelated with the regressors. A Hausman test (Hausman, 1978) is employed to determine the more appropriate specification. In addition, we estimate two-way fixed effects models that control simultaneously for country- and year-specific effects, thereby accounting for global shocks and temporal dynamics affecting labor markets across all countries. These specifications provide further evidence that AI female participation remains a strong and significant predictor of the female-to-male labor force participation ratio. Recognizing the persistence of labor market participation ratios, we incorporate dynamic panel models by including a lagged dependent variable. Dynamic effects are estimated using the Generalized Method of Moments (GMM) framework. First, we apply the Arellano and Bond (1991) difference GMM estimator, which instruments the differenced lagged dependent variable with its own lagged levels. This approach corrects for simultaneity and dynamic panel bias but may suffer from weak instruments when the dependent variable is highly persistent. To overcome this limitation, we also employ the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), which augments the difference equation with an additional level equation and uses lagged differences as instruments for the levels.

Figure 3 plots the relationship between AI female share and the ratio of female to male labor force participation, with red circles marking the main patterns. The lower stretched circle shows a positive trend: as the share of women in AI increases from around 15% to 30%, the ratio of female to male participation also tends to rise. This suggests that at lower levels of AI representation, additional female participation in AI is associated with meaningful improvements in gender parity in the broader labor market. The upper circle highlights a stabilization zone, where countries with higher AI female shares (above ~30%) cluster together with ratios concentrated between 80 and 90. This indicates that once women's representation in AI reaches higher levels, labor force parity becomes more consistent, showing less variation across countries. Together, the two clusters reveal both an upward trend at lower AI female shares and a convergence effect at higher shares. Which could support the interpretation that expanding women's share in AI is most impactful at earlier stages, while broader structural and economic factors explain variations at higher levels of participation.

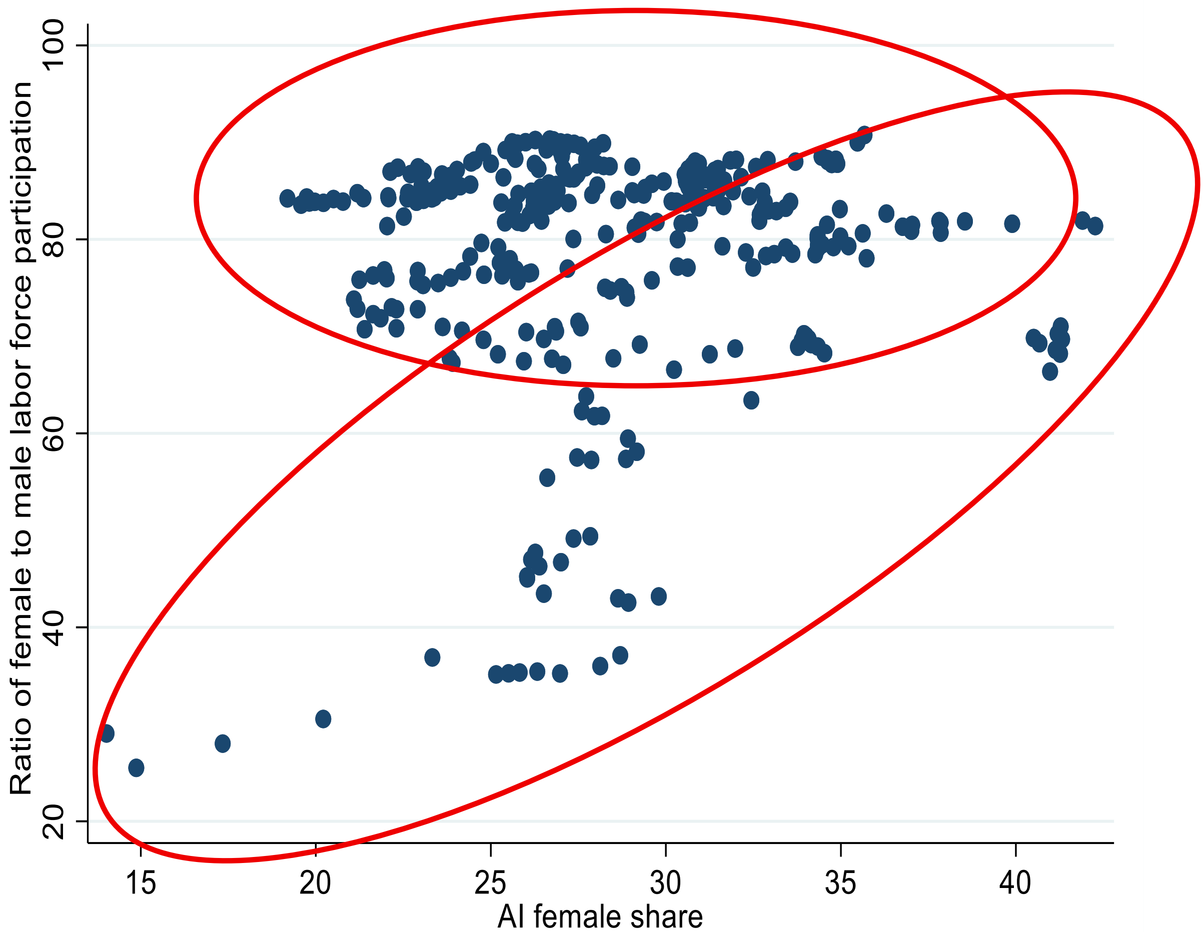


Figure 3. Scatterplot of AI Female Share and the Female-to-Male Labor Force Participation Ratio, 2016–2023

4. Results

Model specification includes the Breusch–Pagan Lagrange Multiplier test (random effects versus pooled OLS) and the Hausman test (fixed versus random effects). The results support the use of fixed effects at the country level. Table 4 reports the regression results of the effect of AI female share on the ratio of female-to-male labor force participation across 41 countries from 2016 to 2023. Model 1 includes only the main explanatory variable, while Models 2 to 5 progressively add key controls for income (log GDP per capita), population (log Population), unemployment rate, and tertiary education enrollment.

Across all specifications, the AI female share variable remains positive and statistically significant at the 5% level or better. The estimated coefficient ranges between 0.270 and 0.352, suggesting that a higher proportion of women in AI-related skills and occupations is associated with a more balanced participation of women relative to men in the overall labor force. This finding provides initial evidence that AI-related opportunities may help reduce gender gaps in labor force participation.

Adding GDP per capita in Model 2 strongly increases the explanatory power of the regression (R^2 rises from 0.016 to 0.237). GDP per capita enters with a large and highly significant positive effect, indicating that higher levels of development are closely associated with narrowing gender gaps in labor force participation. When controlling for population size in Model 3, the coefficient is negative and significant, suggesting that larger populations are associated with wider participation gaps.

Introducing the unemployment rate in Model 4 further improves the fit ($R^2 = 0.338$). Unemployment exerts a positive and statistically significant effect, suggesting that higher unemployment rates are associated with a narrowing of the female-to-male participation ratio. One possible interpretation is that economic shocks disproportionately affecting male-dominated industries may temporarily reduce gender gaps in labor force participation. However, this effect should be interpreted with caution, as the relative impacts on male and female employment during downturns can vary depending on which sectors are most affected and on how unemployment is defined and measured.

Finally, the inclusion of tertiary education enrollment in Model 5 does not produce a statistically significant effect, and the magnitude is small. This suggests that, once other macroeconomic controls are accounted for, higher enrollment in tertiary education does not directly translate into closing gender gaps in labor force participation in the short run. Overall, the progression from Model 1 to Model 5 demonstrates that the relationship between AI female share and the female-to-male participation ratio is robust to the inclusion of macroeconomic controls. The consistently positive and significant coefficients provide empirical support for the hypothesis that AI-related skills and occupations for women contribute to reducing gender inequality in labor force participation.

Table 5 presents the regression results from a range of econometric models applied to the ratio of female-to-male labor force participation. These models progressively address issues of unobserved heterogeneity, dynamics, and potential endogeneity in the panel
Across nearly all specifications, the AI female share variable remains positive and statistically significant, confirming the robustness of the earlier findings. In pooled OLS, the coefficient is 0.283 ($p < 0.05$), while under the fixed-effects (FE) model it rises to 0.739 ($p < 0.01$), suggesting that when accounting for country-specific heterogeneity, the role of AI female share in reducing gender gaps becomes even more pronounced. Random effects (RE) provide a very similar estimate (0.753, $p < 0.01$), reinforcing this conclusion. Two-way FE estimates also remain positive, although less precise, indicating some sensitivity to the inclusion of time effects. Dynamic panel models further strengthen the interpretation. In the Arellano–Bond (AB-GMM) specification, which uses lagged levels as instruments for the differenced equation, the coefficient on AI female share is 0.368 ($p < 0.05$). The lagged dependent variable is positive (0.488, $p < 0.10$), indicating moderate persistence in the participation ratio over time. The System GMM model, which combines equations in levels and differences (Arellano & Bover, 1995; Blundell & Bond, 1998), produces a smaller but still significant coefficient (0.185, $p < 0.05$) and a highly significant lagged dependent variable (0.928, $p < 0.01$). This suggests that persistence is very strong, and once dynamics are controlled for, the direct contribution of AI female share remains positive but attenuated.
Among the controls, GDP per capita is generally positive and significant, though weaker in dynamic specifications, while population size often exerts a negative influence, consistent with larger countries facing structural barriers to gender equality in labor force

participation. Unemployment shows mixed effects: it is positive and significant in OLS and RE models, but turns insignificant or even negative under GMM. This may reflect cyclical dynamics or the differential effect of unemployment shocks on male-dominated versus female-dominated sectors. Tertiary education is never significant, suggesting that higher education alone does not translate into immediate improvements in gender balance in labor force participation. The alternative estimator, FGLS, produces results consistent with the panel models. The coefficient on AI female share (0.226, $p < 0.10$) remains positive and significant, while GDP and population effects align with earlier findings.

The positive and significant effect of AI female share across multiple econometric methods confirm the robustness of the finding. Despite variation in coefficient size, the direction and significance remain stable, supporting the conclusion that higher AI female participation helps reduce gender disparities in labor force participation.

To verify that our findings are not driven by variable construction, we re-estimate the full set of models by replacing AI female share with AI male share as the key explanatory variable. The results, reported in Table 6, show negative and statistically significant coefficients for AI male share across most specifications. This mirrors the positive effect of AI female share in the baseline models and is consistent with the expectation that higher male dominance in AI participation is associated with lower relative female labor force participation. The consistency of these inverted results reinforces the robustness of our main findings and underlines the gendered dimension of AI participation.

Table 4. Regression Results: Ratio of Female to Male Labor Force Participation

	Model 1	Model 2	Model 3	Model 4	Model 5
AI female share	0.333**	0.352***	0.270**	0.279**	0.283**
	(0.146)	(0.129)	(0.125)	(0.121)	(0.122)
Log GDP pc		11.085***	8.313***	9.613***	9.489***
		(1.141)	(1.220)	(1.220)	(1.251)
Log Population			-2.281***	-2.253***	-2.257***
			(0.438)	(0.425)	(0.426)
Unemployment				0.394***	0.393***
				(0.087)	(0.088)
Tertiary Education					0.012
					(0.026)
Constant	68.359***	-50.697***	18.946	0.958	1.330
	(4.190)	(12.803)	(18.181)	(18.104)	(18.144)
F Statistic	5.20	50.51	45.42	41.20	32.92
R^2	0.0157	0.2371	0.2960	0.3379	0.3383
Observations	328	328	328	328	328
Countries	41	41	41	41	41

Note: ***p<0.01, **p<0.05, *p<0.10. The dependent variable is the ratio of female to male labor force participation — standard errors in parentheses. All models are estimated with country-level panel data (41 countries, 328 observations). Specifications progressively add controls for GDP, population, unemployment, and tertiary education.

Table 5. Regression Results : Dependent variable: Ratio of Female to Male LF Participation

	Pooled OLS	Fixed Effects (FE)	Random Effects (RE)	Two-Way FE	AB-GMM	System GMM	FGLS
Female to Male LF					0.488*	0.928***	
					(0.270)	(0.023)	
AI female share	0.283**	0.739***	0.753***	0.739***	0.368**	0.185**	0.226*
	(0.122)	(0.066)	(0.065)	(0.231)	(0.181)	(0.087)	(0.127)
Log GDP pc	9.489***	1.484*	2.972***	1.484	0.684	-0.000	2.918
	(1.251)	(0.858)	(0.796)	(1.425)	(1.452)	(0.000)	(1.903)
Log Population	-2.257***	12.273***	-1.868*	12.273**	-7.594	-0.000	-4.033***
	(0.426)	(3.948)	(1.116)	(4.684)	(7.313)	(0.000)	(1.061)
Unemployment	0.393***	0.080	0.129**	0.080	-0.097	-0.033	0.097
	(0.088)	(0.062)	(0.061)	(0.076)	(0.098)	(0.053)	(0.108)
Tertiary Education	0.012	-0.000	-0.004	-0.000	0.024	0.004	-0.023
	(0.026)	(0.021)	(0.020)	(0.021)	(0.036)	(0.010)	(0.043)
Constant	1.330	-162.448***	54.781***	-162.448**	146.720	1.809	102.721***
	(18.144)	(62.108)	(19.567)	(71.342)	(111.125)	(2.543)	(28.974)
F-statistic	32.92***	51.28***		14.99***			
Wald chi2			242.77***		108.69***	2406.15***	27.54***
R^2	0.338	0.476	0.214	0.476			
Breusch–Pagan LM test	1093.27***						
Hausman test (FE vs. RE)		45.89***					
Observations	328	328	328	328	246	287	328
Countries	41	41	41	41	41	41	41

Note: ***p<0.01, **p<0.05, *p<0.10. The dependent variable is the ratio of female to male labor force participation — standard errors in parentheses. Pooled OLS, FE, RE, and Two-Way FE are estimated with country-level data. AB-GMM (Arellano & Bond, 1991) uses the difference equation with lagged levels as instruments. System GMM (Arellano & Bover, 1995; Blundell & Bond, 1998) adds the level equation with lagged differences as instruments. FGLS is Feasible Generalized Least Squares, robust to heteroskedasticity and autocorrelation. Specification tests indicate rejection of pooled OLS in favor of panel estimators (Breusch–Pagan LM test) and rejection of random effects in favor of fixed effects (Hausman test). All specifications include controls for unemployment, tertiary enrollment, GDP, and population.

Table 6. Regression Results : Dependent variable: Ratio of Female to Male LF Participation (AI male share)

	Pooled OLS	Fixed Effects (FE)	Random Effects (RE)	Two-Way FE	AB-GMM	System GMM	FGLS
Female to Male LF					0.488* (0.270)	0.928*** (0.023)	
AI male share	-0.283** (0.122)	-0.739*** (0.066)	-0.753*** (0.065)	-0.739*** (0.231)	-0.368** (0.181)	-0.185** (0.087)	-0.226* (0.127)
Log GDP pc	9.489*** (1.251)	1.484* (0.858)	2.972*** (0.796)	1.484 (1.425)	0.684 (1.452)	-0.000 (0.000)	2.918 (1.903)
Log Population	-2.257*** (0.426)	12.273*** (3.948)	-1.868* (1.116)	12.273** (4.684)	-7.594 (7.313)	-0.000 (0.000)	-4.033*** (1.061)
Unemployment	0.393*** (0.088)	0.080 (0.062)	0.129** (0.061)	0.080 (0.076)	-0.097 (0.098)	-0.033 (0.053)	0.097 (0.108)
Tertiary Education	0.012 (0.026)	-0.000 (0.021)	-0.004 (0.020)	-0.000 (0.021)	0.024 (0.036)	0.004 (0.010)	-0.023 (0.043)
Constant	29.639 (18.728)	-88.542 (63.777)	130.052*** (21.503)	-88.542 (78.156)	183.506 (111.044)	20.340*** (7.432)	125.296*** (31.029)
F-statistic	32.92***	51.28***		14.99***			
Wald chi2			242.77***		108.69***	2406.15***	27.54***
R^2	0.338	0.476	0.214	0.476			
Observations	328	328	328	328	246	287	328
Countries	41	41	41	41	41	41	41

Note: ***p<0.01, **p<0.05, *p<0.10. The dependent variable is the ratio of female to male labor force participation — standard errors in parentheses. Pooled OLS, FE, RE, and Two-Way FE are estimated with country-level data. AB-GMM (Arellano & Bond, 1991) uses the difference equation with lagged levels as instruments. System GMM (Arellano & Bover, 1995; Blundell & Bond, 1998) adds the level equation with lagged differences as instruments. FGLS is Feasible Generalized Least Squares, robust to heteroskedasticity and autocorrelation. All specifications include controls for unemployment, tertiary enrollment, GDP, and population.

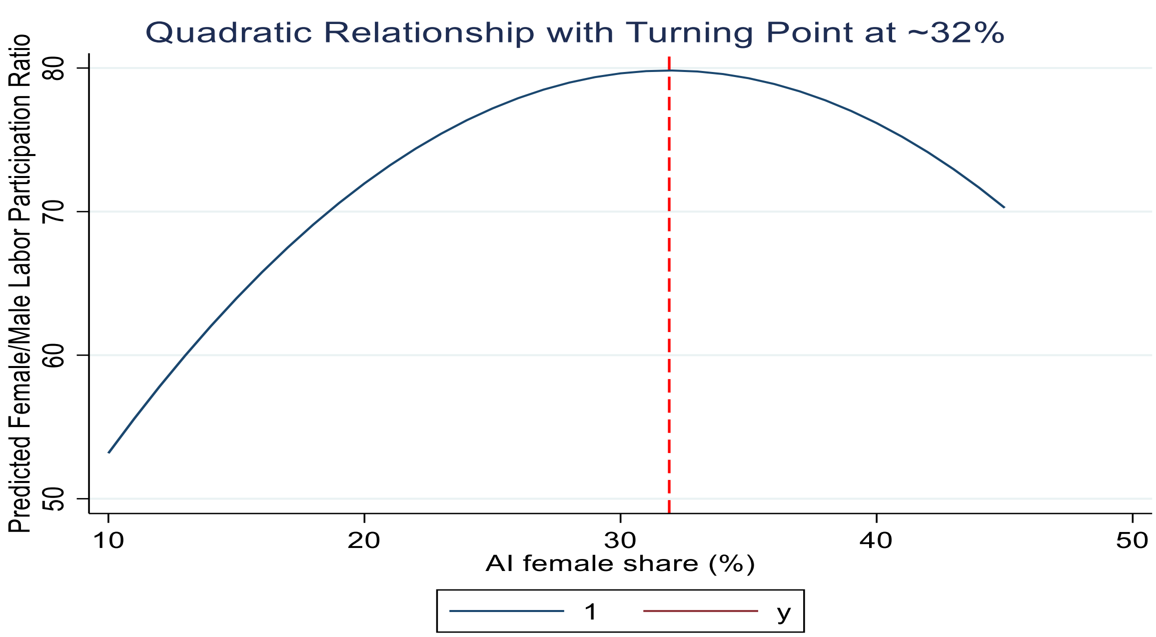
5- Testing nonlinearity

To further explore the relationship between AI female share and gender parity in labor force participation, we estimated a quadratic specification including both the linear and squared terms of AI female share. The model fit indicates strong explanatory power, with an F-statistic of 30.06 ($p < 0.001$) and an R^2 of 0.36, meaning that the extended model explains approximately 36% of the variation in female-to-male labor force participation parity. Results from the full regression (Appendix C) highlight that AI female share continues to exert a positive and statistically significant effect on labor participation parity, but with diminishing returns. The coefficient on the linear term is positive (3.55, $p < 0.001$), while the quadratic term is negative (–0.056, $p = 0.001$), indicating concavity. This implies that the impact of increasing women's share in AI is strongest at lower levels but weakens as their representation rises. The turning point of the quadratic function is obtained from the formula:

$$X = \frac{\beta_1}{2\beta_2} = \frac{3.5487}{2 \times (-0,556)} = 31,9\%$$

This value suggests that up to approximately 32% AI female share, further increases are associated with substantial improvements in parity, while beyond this threshold, the marginal effect diminishes and may eventually turn negative. Figure 4 visualizes this non-linear relationship, with the vertical dashed line marking the estimated turning point. However, this result should be interpreted with precaution, as the estimated threshold is sensitive to data limitations and country-specific structural factors. For instance, in Nordic countries where overall female labor force participation is already high and institutions are relatively inclusive, raising the AI female share further may not generate additional improvements in parity. By contrast, in countries with lower baseline participation and weaker institutional support, increasing women's representation in AI can still yield large gains. The turning point therefore highlights a possible saturation effect in some contexts, rather than a universal boundary, underscoring the importance of considering country-level dynamics when interpreting the results. Overall, the non-linear specification provides a more nuanced account of how women's representation in AI interacts with broader economic and structural conditions. It demonstrates that the benefits of AI inclusivity are most pronounced at earlier stages of female labor force participation, when new opportunities in technology can act as a catalyst for reducing gender gaps. However, these benefits diminish beyond a critical threshold, as structural barriers begin to dominate. At higher levels of participation, progress is increasingly limited by institutional and cultural constraints such as occupational segregation, unequal access to leadership and technical roles, and persistent gender biases embedded in labor markets and even in AI systems themselves. In such contexts, AI by itself cannot overcome entrenched inequalities , it may even reproduce them if left unchecked. This underscores that while AI has the potential to accelerate convergence, its effects are conditional on complementary policies that target the deeper structural and institutional obstacles that prevent women from fully benefiting from technological change.

Figure 4. Non-Linear Relationship between AI Female Share and Female Labor Force Participation



6- Conclusion

This study investigated whether women's participation in AI-related skills and occupations contributes to narrowing gender disparities in labor force participation. Drawing on a balanced panel of 41 countries from 2016 to 2023 and applying a wide range of econometric methods (pooled OLS, FE/RE, two-way FE, AB-GMM, System GMM, and FGLS), the results converge on a clear finding: greater AI female share is positively and significantly associated with a higher female-to-male labor force participation ratio. While the size of the coefficient varies with specification, the stability of the sign and significance confirms the robustness of this relationship.

Yet the analysis of non-linear effects reveals important limits. The impact of women's AI participation is strongest up to a turning point of about 32 percent, beyond which marginal gains diminish. This reflects structural realities: in contexts with already high female labor force participation and inclusive institutions (e.g., Nordic economies), additional increases in AI female share deliver smaller improvements. By contrast, in countries with lower baseline participation and weaker institutional frameworks (Global South countries), expanding women's access to AI skills continues to yield substantial benefits. Thus, AI should be understood as a tool for inclusion, capable of reducing gender inequality in the labor market, but not a substitute for broader institutional and cultural reforms.

Fiscal policies can reinforce these efforts by aligning technological change with equality goals. For example, governments could provide subsidies for AI start-ups with gender-inclusive hiring practices or use public procurement to privilege companies that demonstrate fair labor standards. Beyond incentives, active state intervention is essential: public investment in reskilling programs, the expansion of STEM education for women, and redistributive measures that reduce unpaid care burdens are all needed to correct structural imbalances in labor markets. AI is therefore not a neutral tool, its impact on gender disparities in labor force participation depends on whether businesses and governments actively design policies and workplace practices that reduce structural inequalities and foster inclusive labor markets.

Despite these findings, the study faces several limitations. First, the time coverage of the dataset is relatively short, spanning only 2016–2023, which constrains the ability to capture long-term structural dynamics in gender and technology. Second, the measure of AI-related skills and occupations used here reflects overall AI activity without distinguishing between IT-specific roles and other sectors. While it remains the only available indicator with a gender dimension, this limitation may mask important cross-sectoral differences. Addressing these issues in future research would provide a more nuanced understanding of the dynamics at play.

Appendix A - Country list

Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, India, Ireland, Israel, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Turkey, the United Arab Emirates, the United Kingdom of Great Britain and Northern Ireland, the United States of America, and Uruguay.

Appendix B- Regressions without Greece

	Pooled OLS	Fixed Effects (FE)	Random Effects (RE)	Two-Way FE	AB-GMM	FGLS
Female to Male LF					0.500*	
					(0.262)	
AI Female share	0.269**	0.760***	0.775***	0.760***	0.419**	0.227*
	(0.125)	(0.068)	(0.067)	(0.230)	(0.180)	(0.127)
Log GDP pc	9.266***	1.151	2.541***	1.151	-0.060	2.858
	(1.298)	(0.894)	(0.842)	(1.467)	(1.515)	(1.871)
Log Population	-2.299***	11.475***	-1.958*	11.475**	-9.675	-4.011***
	(0.435)	(4.033)	(1.131)	(4.743)	(7.528)	(1.049)
Unemployment	0.405***	0.041	0.084	0.041	-0.136	0.100
	(0.090)	(0.068)	(0.067)	(0.088)	(0.103)	(0.107)
Tertiary Education	0.025	0.012	0.009	0.012	0.058	-0.012
	(0.031)	(0.022)	(0.022)	(0.020)	(0.041)	(0.044)
Constant	3.841	-146.990**	59.581***	-146.990*	184.618	102.328***
	(18.655)	(63.801)	(20.041)	(72.993)	(115.443)	(28.691)
F-statistic	32.25***	50.85***		15.16***		
Wald chi2			242.20***		110.52***	27.53***

R^2	0.339	0.480	0.204	0.480		
Observations	320	320	320	320	240	320
Countries	40	40	40	40	40	40

Appendix C- Non-linear Specification

Variable	Coefficient	Std. Error	t-value	p-value
AI female share	3.549***	1.002	3.54	0.000
(AI female share)^2	–0.056***	0.017	–3.28	0.001
Unemployment	0.366***	0.087	4.23	0.000
Tertiary education	0.010	0.026	0.40	0.688
Log GDPpc	9.156***	1.236	7.41	0.000
Log Population	–2.283***	0.420	–5.44	0.000
Constant	–40.836	22.014	–1.85	0.065

Model fit: $F(6, 321) = 30.06$, $p < 0.001$; $R^2 = 0.360$; Adj. $R^2 = 0.348$; Observations = 328; Countries = 41

Note: ***p<0.01, **p<0.05, *p<0.10. Standard errors in parentheses.

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