New technological innovations and gender inequality: should we neglect artificial intelligence?

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Abstract

Gender equality has slightly improved over recent decades, but it is still a critical issue across the globe. This study uses a panel data sample of 50 countries to investigates the influence of new technological innovations on gender inequality from 2002 to 2019 and considering five dimensions: employment, health, education, and women social, political and economic rights, aiming to fill an important research gap. By applying the OLS and IV-GMM estimator to deal with potential biases like endogeneity, the results indicate that new technologies captured by artificial intelligence appears to increase employment opportunities for women, especially for those in the 15+ ratio, which results in an improvement in the number of female implications in the labor market in comparison with their male counterparts. Artificial intelligence is also found to re-balance gender inequality in health, education and women socio-politico-economic rights. Hence spotlighting AI's potential as a transformative force in mitigating gender inequalities. To enhance the credibility of our findings and contribute valuable insights into this critical area of research, our results are checked for robustness by two alternative proxies of gender inequality and technological innovations, the addition of supplementary control variables and the use of an alternative estimate strategies. Based on these findings, the governments of developing countries should focus principally on the need for investment in new technological innovations infrastructure and targeted policies that promote their diffusion as the first and most crucial policy to curb gender inequality.

Keywords: Artificial intelligence, gender inequality, panel data, sustainable development, technological innovations

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1. Introduction

The process of modernization has driven cultural change that have not only facilitated women's rise in public life but also fostered the development of democratic institutions. Consequently, the issue of gender equality has emerged as a focal point in both scientific inquiry and public discourse. Achiving gender equality and empower all women and girls on the one hand and building a resilient infrastructure, promoting inclusive and sustainable industrialization and fostering innovations are two of the major common goals of all societies and humankind nowadays. These are reflected by the UN sustainable goals 5 and 9 (SDGs5 and SDGs9), calling the concern of all nations. Achieving gender equality will require to address multiple issues: social, economic, and political empowerment and technology (Rana, 2020). Do new technological innovations matter for gender inequality? This paper tries to answer to this question.

As economies worldwide enter new phases of technological advancement and industrial transformation, the development and application of AI technology has also ignited a revolution for sustainable development and AI has emerged as a strategic driver of change (Xin and Ye, 2024). The flourishing AI industry has powered the emergence of thrilling careers in domains such as machine learning, data analytics, and data science. As societies increasingly recognize the importance of AI (Kerr, 2021) in mitigating gender biases be it at both micro (individual or company) and macro levels including: industries, health care and facilities, education (Suvarna et al., 2024; Nuseir et al., 2021; Frennert, 2021; Joshi, 2024). It becomes imperative to understand how these advancements can be harnessed to promote equity. The rapid development of Artificial Intelligence (AI) presents both socio-economic and environmental contribution on a global scale (Dong et al., 2024; Qin et al., 2024). The impact of robotics applications on inequalities has become a crucial area of research, with significant concerns for social equity on a global scale (Xin and Ye, 2024). The existing literatures on the relationship between artificial intelligence and gender inequality is generally based on micro-data from surveys, focusing primarily on the gender differences in generative AI adoption and application and its consequences.

This study investigates the implications of new technological innovations applications on gender inequalities, contributing to deeper the understanding how new technologies influence gender disparities globally. We conducted a globally oriented qualitative study to explore the potential of AI tools to enhance gender equality. By considering a global sample, our research transcends geographical boundries and holds relevance for economies around the world. Our

focus is aligned with the United Nations Sustainable Development Goals (SDGs), particularly Goal 5, which addresses gender equality. Specifically, we examine five critical areas: education, health, employment, economic empowerment, social empowerment and political empowerment. We aim to explore how AI technologies can alleviate gender inequalities and offer new perspectives and strategies to address this challenge on a broader, global level.

While the integration of industrial robotics creates new job opportunities and technologies making noteworthy contribution to green innovation (Dong et al., 2024), it simultaneously renders certain skills and traditional roles obsolete, raising concerns about its mixed impact on employment and inequalities (Qin et al., 2024; Xin and Ye, 2024). The rising AI integration of into various sectors of the economy and day-to-day activities has raised serious concerns about its potential mixed impact especially on the job market in particular and inequalities in general (Qin et al., 2024; Xin and Ye, 2024). This call for more attention on the female to male ration employment and diversified issue as well as its consequences.

Scholarly discourse has primarily focused on the quantitative aspects of AI's impact like on employment while neglecting its qualitative dimensions, particularly concerning gender (Xin and Ye, 2024). Despite extensive research on the relationship existing between artificial intelligence and gender inequality[2],' the empirical exploration of how AI can be leveraged to address gender equality challenges remains underdeveloped. Recent studies have highlighted that AI may inadvertently perpetuate discriminatory labeling of certain social groups, thereby exacerbating existing gender inequalities (Tschopp and Salam, 2023).

AI technologies hold significant potential to reduce gender discrimination across various facets of life ranging from workplaces to households by improving services and support for victims of gender-based violence and enhancing educational and heterogenous opportunities (Badarevski, 2023; Petering et al., 2018). Recent research has also concluded that the use of artificial intelligence can help in the reduction of gender inequalities in the agricultural sector (Olivier and Ibrahim, (2024); health sector and other medical therapies (Mahalakshmi and Jayanthiladevi, 2024; García-Micó and Laukyte, 2023) and various aspects of women empowerment (Shahbazi et al., 2024; Mahalakshmi and Jayanthiladevi, 2024; Ramchandani, 2024). Juhn et al. (2014) suggests that new technologies resulting from trade liberalization may contribute to reducing gender inequality in two main ways. Firstly, by diminishing the demand for physically demanding skills through computerized production processes, enhancing

[2] See Patón-Romero et al. (2022a) and Patón et al. (2022b) for more details

women's relative wages and employment opportunities in blue-collar tasks while potentially disadvantaging them in white-collar roles. Secondly, tariff reductions and foreign competition may cause new firms to enter the export market with updated their technology replacing male blue-collar workers with female blue-collar workers and the reduction of discrimination brought about by foreign competition. Thus, with effective control for misuse and a human-centered AI (HAI) evolution, AI can enhance human welfare in numerous respects, such as improved the productivity of food, health, water, education, and energy services, human rights and result in employment, racial and gender inequalities (Yang et al., 2021; Badarevski, 2023; Mahalakshmi and Jayanthiladevi, 2024; Shahbazi et al., 2024; Ramchandani, 2024; Juhn et al., 2014).

This study aims to add to a broader discussion about how developing technologies, such as artificial intelligence, can impact gender inequality worldwide. Our findings and recommendations have important implications for policymakers, industries, researchers, and stakeholders around the world, promoting inclusive economic growth and equitable distribution of opportunities across gender in the age of automation. This study is structured as follows: a review of the literature is presented in Section 2; Section 3 presents data and methodology used in this study; Section 4 is dedicated to empirical results presentation and discussion; Section 5 is the conclusions.

2. Literature review

Gender inequality still exists and has been a central topic in the economics literature for a long time (Nguyen et al., 2021). Known to have several associated political and socio-economic consequences (Nguyen, 2021), gender inequality has emerged as requiring urgent attention in recent decades, especially in developing countries (Nguyen and Su., 2021, Asongu and Odhiambo, 2020) and more outstanding in Muslim-dominated countries (Cooray and Potrafke, 2011; Lussier and Fish, 2016[3]). The substantial attention paid by economists to gender inequality can be seen through the inclusion of gender in mainstream economics theory (Radović-Marković, 2011; Perrons, 2005). This places gender inequality and its drivers among influential topics in both research and practice. It is also very important for the UN SDGs (UN, 2020). Overall, gender inequality is considered and investigated from different angles (Nguyen, 2021; Badarevski, 2023; Ramchandani, 2024; Juhn et al., 2014). Yet gender equality remains elusive. However, most studies show only that gender inequality might be derived from

[3] See Lussier and Fish (2016) for more highlight on the links between gender inequality and energy intervention

institutions, cultures, religions, and other socio-economic factors (Nguyen, 2021; Cooray and Potrafke, 2011; Nguyen and Su, 2021). The literature on gender inequality mostly focuses on specific aspects (Badarevski, 2023; García-Micó and Laukyte, 2023; Shahbazi et al., 2024; Juhn et al., 2014).

This literature highlights key determinants of gender inequality amongst which energy poverty [4] and globalization. After checking the existence of a gender Kuznets curve (GKC) on a sample of 51 developing countries from 2002 to 2017, Nguyen and Su (2021) reveal that energy poverty significantly impacts the educational and socio-economic rights of women. Additionally, globalization has been found to empower women but can also limit their access to labor markets depending on regional contexts (Akhter and Ward, 2009; Baliamoune-Lutz, 2007). Akhter and Ward (2009) used ordinary least square regression on a sample of 48-70 nation-states to highlight globalization as an important gender empowerment parameter. Their results revealed that higher commodity concentration significantly lowers women's access to the formal and informal labor force and women's decision-making power. Baliamoune-Lutz (2007) found similar results when examining the effects of globalization and growth on gender inequality in African economies using 5-year average data for the periods 1990-94 and 1995-99. They revealed that globalization and growth seemed to not affect gender equality in non-SSA developing countries while higher integration in global markets and growth increased gender inequality in SSA. Similarly, Potrafke and Ursprung, (2012) found that socio-economic globalization encouraged social institutions which lower female subjugation and promote gender equality.

The COVID-19 pandemic has further highlighted these disparities, with women disproportionately affected in terms of job loss and income inequality (Kristal and Yaish, 2020; Flor et al., 2022). Based on wave one of a longitudinal survey of 2040 adult Israeli men and women (age 18+) data collected between April 23 and May 4 by Panel4all, Kristal and Yaish (2020) found that though the coronavirus pandemic outbreak did not flatten the inequality curve, it consequences for gender equality were harsh, with women affected much more severely than men. More women lost jobs than did men, which in turn increased significantly the gender income gap. These results were similar to those obtained by Flor et al. (2022), Alon et al. (2020) and Carli (2020) highlighting the importance of the COVID-19 pandemic on gender inequality as it went along to reduce domestic and childcare responsibilities gender gap

[4] See Nguyen and Su (2021) for more insight on the relationship between gender inequality and energy intervention.

but increased overall gender equality. This crisis went along to re-balance female entrepreneurial activities (Sarfaraz et al., 2014; MEHALA, 2014).

Using the Ordinary Least Squares (OLS) with robust standard errors that are clustered by region, Cooray and Potrafke, (2011) investigate the primary determinant of gender inequality in education in a sample of 157 countries over the period spanning from 1991-2006. Their result revealed that while culture and religion are the primary determinants of inequality in education, political institutions did not significantly influence girls' education, being autocratic or democratic regimes. In accordance with existing literature, these results further highlighted the important relationship existing between gender equality and institutions (Waylen, 2014; Inglehart et al., 2003; Beer, 2009). Parallel and most noteworthy in less democratic, agriculture-dependent and lower levels of economic development states, Eastin (2018) highlighted climate change as an important determinant aggravating gender inequality, as deviations from long-term mean temperatures and increasing incidence of climatological and hydro-meteorological disasters are associated with declines in women's socio-economic rights.

The literature has equally revealed evidence indicating the existence of a relationship between gender inequality and economic complexity. Saâd and Ella (2019) analyze the effect of economic complexity on the Gender Parity Index in education (GPI) using the generalized method of moments (GMM) over the period from 1984 to 2014. The results highlight several critical insights. While economic complexity is revealed to positively impact the GPI at the primary and secondary levels taking into account the global sample, it negatively impacts the GPI at the tertiary level in the case of the sample of high-income countries and MENA. Their results also revealed a positive effect of economic complexity on the GPI taking into account the global sample, middle-income countries, low-income countries and African countries.

Furthermore, the integration of information and communication technologies (ICTs) has shown potential in promoting gender equality through improved access to education and resources (Chen, 2004; Reinen and Plomp, 1997). After employing the OLS and IV panel regressions with country fixed-effects on data for 209 countries ranging from 1960 to 2002 for their analyses, Chen (2004) revealed that higher levels of ICT infrastructure and education among the general population tend to promote gender equality. Another important global economic and cultural factor, considered to have an important non-negligible impact on all aspects of sustainable development is tourism[5]. From a sample of 36 Asian countries over the period

[5] See Zhang and Zhang (2020) for more details.

2006–2018, using a system generalized method of moments estimation approach, Zhang and Zhang (2020) highlight that tourism as a result of its cultural attributes of tourism apart from economic characteristics significantly promotes gender equality, especially in east and southeast Asian countries, less in west and central Asian countries, and least in south Asian countries.

In summary, while AI presents opportunities for advancing gender equality, it also risks entrenching existing biases. Addressing these challenges requires a multi-faceted approach that includes promoting women's participation in STEM (Science, Technology, Engineering, and Mathematics) fields and ensuring equitable AI development practices.

3. Methodology and Data

3.1. Estimation Strategy

This study evaluates the effect of artificial intelligence on gender inequality on a global sample. In view of this, we state that gender equality (GE) depends on artificial intelligence (AI) and other control covariates (Z)

$$\mathrm{GE} = \mathrm{f}(\mathrm{AI}, \mathrm{Z}) \qquad (1)$$

Transforming equation (1) into its semi-log-linear form is stated in equation (2) as below:

$$GE_{it} = \alpha_0 + \beta_1 LAI_{it} + \sum \beta_j Z_{it} + \mu_i + \gamma_t + \varepsilon_{it} \qquad (2)$$

Where:

GE_{it}: gender equality in country *i* for year *t*. LAI_{it} represent the natural logarithm of artificial intelligence.Z_{it}: is the vector for control variables (i) trade openness (Open), (ii) log of foreign direct investment (LFDI), (iii) Industrialization (Ind), (iv) Urbanization (Urb). γ_t and μ_i are country and time fixed effects; α_0 and $\beta_1 \ldots\ldots \beta_j$ are constant parameter and coefficients to be estimated. ε_{it}: error term.

We estimate equation (1) using the OLS technique. Although this method is easy to implement and provides interesting insights well all conditions are verified because it corrects correlation within the cluster, heterogeneity, endogeneity and some unobserved differences issues may alter parameter estimation (Djeunankan et al., 2024). The study's potential endogeneity issues may result from biases related to measurement error, or reverse causality and omission variables.

First, measurement errors can arise, especially in some developing countries, due to inaccuracy in measuring the level of artificial intelligence in a country captured by the total number of industrial robots. Second, the omitted variables problem, in particular, is related to the possibility that relevant confounders are excluded from the baseline model. This concern is usually addressed by incorporating several key determinants of energy poverty into the regression. Nevertheless, it is impossible to determine whether artificial intelligence is orthogonal to the disturbance term, even when we control for many key determinants of gender inequality. This concern prompts the adoption of the Oster [2019] test of coefficient stability. The third difficulty is the potential bias associated with reverse causality which could exist since previous literature shows that gender inequality may hinder artificial intelligence development (Rönnblom et al. 2023). AI development like facial recognition systems are generally built with white male faces as the norm. Also, digital tools generally replicate racial injustices and create oppressed social groups (Kerr, 2021). To address these shortcomings, we apply the instrumental variable generalized method of moments (IV-GMM), initially proposed by Baum et al. (2003).

Several reasons motivate the use of this technique. The IV-GMM technique is best suited for this study because it can address endogeneity sources such as measurement errors, reverse causality and omitted variable bias (Yasmeen and Shah, 2025). It is indicated that using a conventional estimator such as the ordinary least square (OLS) to estimate an empirical model with endogeneity issues can create attenuation bias, whereby OLS estimates are downwards-biased (Acheampong et al., 2022). In addition to addressing the endogeneity issue, the IV-GMM estimator allows consistent estimations in the presence of AR (1) autocorrelation within panels and heteroscedasticity (Baum et al., 2003). Unlike the dynamic system-GMM estimator, which estimates short-run coefficients, the IV-GMM estimator, which is a static estimator, provides long-run coefficients. In estimating equation (2) using the IV-GMM, we applied the robust option to control for heteroskedasticity. We also used the Hansen J-statistics and the Cragg-Donald/Kleibergen-Paap F-statistics to test the validity of the instruments. The Hansen J-statistics tests for instrument over-identification while the Cragg-Donald/Kleibergen-Paap F-statistics test for weak instrument identification. The IV-GMM estimator has been utilized in current applied research (Acheampong et al., 2022; Yasmeen Shah, 2025).

3.2. The Data

In this study, we use comprehensive unbalanced panel data for a total of 50 countries[6] worldwide to investigate the impact of new technological innovation variables: artificial intelligence on gender inequality outcomes from 2002 to 2019. The number of years and countries have been chosen strictly based on data availability for all the variables employed in the study. Table A1 lists these countries. We describe the variable selection and data sources below.

-The dependent variables:

Following Nguyen. (2021), this study uses a comprehensive and inclusive analysis of the four main dimensions of gender equality, this study uses 5 indicators of which a proxy for each indicator: gender equality in employment captured by the Employment to population ratio, 15+, of females (%)/Employment to population ratio, 15+, of males (%) ratio; gender equality in health proxied by the Mortality rate, adult, females (per 1000 female adults)/Mortality rate, adult, males (per 1000 male adults) ratio and gender equality in education measured by the School enrollment, primary, females (% gross)/ School enrollment, primary, males (% gross) ratio. All variables are collected and calculated from the WDI of the World Bank (version 2024), which is mostly available beginning in 1991. The empirical literature also prefers to use the CIRI database in an empirical analysis of gender inequality (e.g., see Nguyen and Su, 2021; Nguyen, 2021). We equally use three indicators collected from the CIRI Human Rights Dataset (Cingranelli and Richards, 2010)[7]. The Data on socio-conomic and political rights in the CIRI database are available until 2011 and thus are analyzed for the period 2002–2011. Following the recent literature (Sorgner, 2021), we further use the United Nation Development[8] and our world in data[9] index for gender inequality. These indexes cover three dimensions: reproductive health, empowerment, and economic status. Scores range between 0-1 and higher values indicate higher inequalities.

[6] Australia, Argentina, Austria, Bulgaria, Belgium, Brazil, Switzerland, China, Chile ,Colombia, Czechia, Egypt, Arab Rep, Germany, Morocco, Denmark, Malaysia, Spain, Peru, Estonia, Philippines, Finland, Russian Federation, France, Serbia, United Kingdom, Tunisia, Greece, Turkiye, Croatia, Ukraine, Hungary, South Africa, Ireland, Iceland, Israel, Italy, Japan, Korea Rep, Lithuania, Latvia, Netherlands, Norway, New Zealand, Poland, Portugal, Singapore, Slovak Republic, Slovenia, Sweden, United States

[7] http://www.humanrightsdata.com/p/data-documentation.html

[8] https://hdr.undp.org/data-center/documentation-and-downloads

[9] UNDP, Human Development Report (2024) – with minor processing by Our World in Data. "Gender Inequality Index" [dataset]. UNDP, Human Development Report, "Human Development Report 2023-2024" [original data]. Retrieved November 12, 2024 from https://ourworldindata.org/grapher/gender-inequality-index-from-the-human-development-report

- The independent variables of interest:

Per existing studies on artificial intelligence (Dong et al., 2024; Chen et al., 2022), we use industrial robot density (the operational stock of industrial robots per 10,000 industrial workers) as a proxy variable for the level of AI using data on industrial robots from the IFR. We equally used the extent of AI development in current AI-related research is operational stock and installation to gauge artificial intelligence for robustness analysis. On this floor, we divided the operational stock of industrial robots by the total number of industrially employed persons as our AI indicator to exclude the effects of country size and the industrial employment share. This indicator reflects the adoption and development of industrial robots in each country. Another proxy used in this study is total patent applications which measure the set of exclusive rights granted by law to applicants for inventions that are new, non-obvious and commercially applicable filed with a patent office of a given country/jurisdiction by an applicant residing in that country or another country/jurisdiction.

- The control covariates:

Following previous literature (Nguyen and Su, 2021; Chen et al., 2013), we include macro drivers of gender inequality. The control variables included in our model to prevent variable omission bias are globalization (Trade, % of GDP), urbanization (Urban population, % of total population), industrialization (industrial value added, % of GDP) and foreign direct investment (natural logarithm) (net inflows, % of GDP). Per existing literature, we further use personal remittances (Asongu and Odhiambo, 201; Asongu and Odhiambo, 2020), digitalization (Chen, 2004; Asongu and Odhiambo, 2020; Reinen and Plomp, 1997; Sandys, 2005) and income inequality (Stolzenburg et al., 2020) as additional control variables for robustness purposes. These variables are issued from the WDI of the World Bank. The descriptive statistics of our variables are provided in Table 1.

4. Results presentation and discussion

This study examined the influence of artificial intelligence on five main aspects of gender inequality (inequality in employment; inequality in health; inequality in education; and women socio-politico-economic rights). Each aspect of gender inequality is proxied by one chosen indicator. Figure 1 give a glance of the relationship that exist between artificial intelligence and each of these aspects.

Table 1: Descriptive Statistics

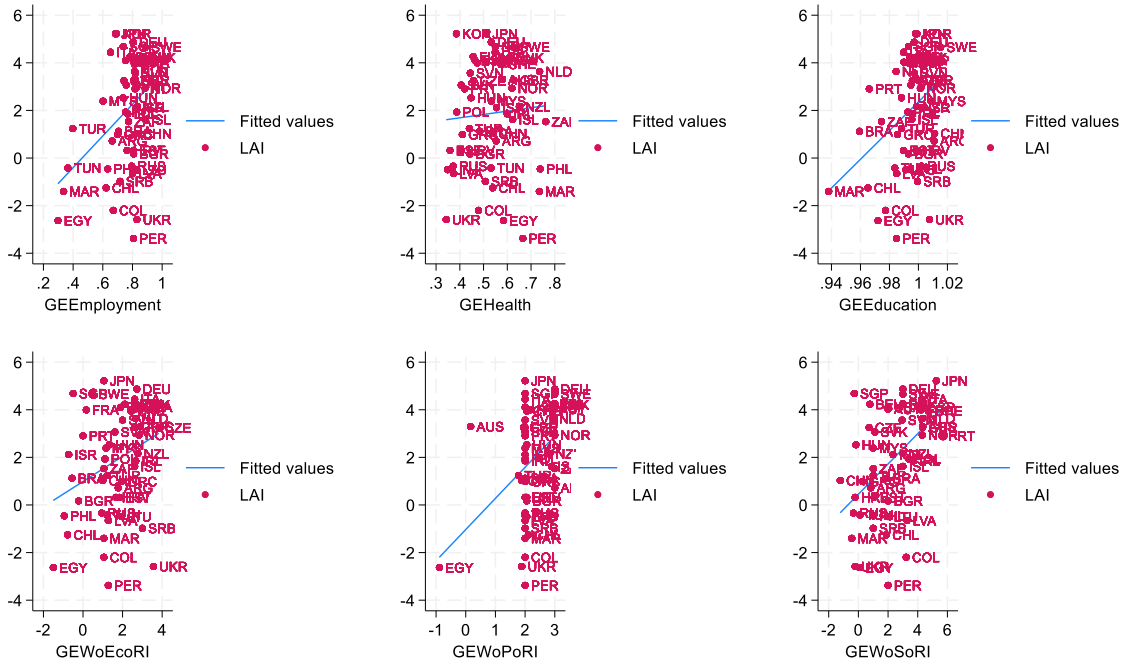
Variable	Obs	Mean	Std. Dev.	Min	Max
GEEmployment	900	0.741	0.137	0.232	0.911
GEHealth	892	0.523	0.11	0.296	0.847
GEEducation	839	0.992	0.016	0.9	1.058
GEWoEcoRI	882	1.531	2.016	-8	10
GEWoPoRI	882	2.16	0.904	-7	3
GEWoSoRI	865	2.134	2.175	-4	11
LAI	858	1.995	2.437	-6.152	6.198
LPatents	880	8.049	2.314	0	14.194
LAI install	800	0.201	2.122	-6.204	4.377
Open	900	4.348	.543	3.018	6.081
LFDI	900	1.63	1.274	-4.384	5.153
Ind	900	3.248	0.222	2.592	3.882
Urb	900	4.276	0.198	3.649	4.605
Personalremittances	894	1.589	2.378	0	12.784
LMobile	898	16.7	1.489	12.47	21.283
LGiniIndex	864	3.556	0.222	3.011	4.199

4.1. Baseline results: OLS

Table 2 presents the benchmark results from OLS. From columns (1) to (6), we progressively alter the proxy of gender equality while at each time controlling for our control variables. Per Figure 1, we find that the coefficient associated with artificial intelligence is positive and statistically significant at one percent. The literature highlights some plausible explanations for these results. As regards column 1, the statistically significant positive coefficient (0.0134 at 1% level) indicates that increased AI adoption positively influences gender equality in employment. This suggests that AI technologies might help close gender gaps in employment opportunities. The development of AI technologies and growing AI business have triggered automation and revolution in job creation in domains such as machine learning, data analytics, and data science which are high-value tasks and less physically demanding, thus encouraging women's employability (Qin et al., 2024; Agrawal et al., 2018). In the education sector also (column 3), a highly significant coefficient (0.00193 at 1% level) suggests that AI adoption positively influences gender equality in education. This could be linked to AI-enhanced access to learning resources and opportunities for women and girls. AI introduction has improved teaching outcomes for boys and girls, reduced the pre-existing gender gap (Bao et al., 2024) and overcome gender-related barriers during education and training with the use of virtual personalized learning tools and augmented reality, remote mentoring, and simulators (Mari et al., 2022), hence propelling women's rights and facilitating their engagement across different domains of the society.

Regarding the socio-economic and political aspects, AI has a positive and significant effect (0.0687 at 5% level) on women economic rights. This finding implies that AI might support women's economic empowerment, potentially by improving access to economic resources or enabling entrepreneurship (column 4). The statistically significant coefficient (0.0380at 1% level) equally suggests a modest positive relationship between AI and political rights, implying that AI might also amplify women's voices in political discourse or advocacy (column 5). Regarding women social rights, the coefficient (0.269) is significant at 1% level, indicating a strong positive impact of AI on women's social rights, highlighting that AI might play a role in awareness campaigns or social empowerment programs (column 6). These results are per existing studies highlighting that AI holds promises for advancing women's empowerment and upholding inclusivity (Ramchandani, 2024); economically by financial inclusion through AI-driven fintech platforms like mobile money platforms (Kofman and Payne, 2021), more inclusive political campaigns and policy-making through social media platforms and big data analytics (Lütz, 2023), challenging societal norms and promoting women's rights by allowing for a better work-life balance with AI-powered personal assistants and raising awareness on women's rights and gender equality (Mahalakshmi and Jayanthiladevi, 2024). In times of crisis and humanitarian circumstances, AI can equally assist with disaster response, resource allocation, and medical aid, catering to the special issues that women may experience in such situations (Mahalakshmi and Jayanthiladevi, 2024).

Figure 1. Relationship between new technological innovations and gender inequality



Regarding our control variables, they reveal mixed results for each chosen indicator of gender equality, reinforcing the need for targeted policies addressing sectoral and demographic disparities. Firstly, we look at industrialization (Ind). Industrialization may lead to the displacement of women from traditional jobs (e.g., agriculture) without offering equivalent opportunities in male-dominated industrial sectors (Tejani and Milberg, 2016). Though region-specific, these results can be explained by the fact that industrializing countries are generally at lower stages of economic development and are more likely to have higher levels of gender inequality (Sorgner, 2021), especially in employment. As industries upgrade, competition forces firms to lower costs and some women may lose their jobs to more qualified men or be pushed down the production chain to subcontractors (Braunstein, 2006). Also, industrialization is revealed to increase educational gender equality but reduces overall women's social rights. According to Asongu and Odhiambo (2018) and Sorgner (2021), this may be explained by the fact that the participation of women in the formal economic sector in some countries are considerably low, with most women specializing in small holding farming, domestic activities and petty trading lacking in new technological competencies. Industrialization may equally erode women's social rights by exploiting women's labor without offering equivalent social protections, prioritizing productivity over community welfare, particularly in patriarchal societies (Elson and Pearson, 1981). This may go a long way to reduce women political and social rights.

Associated with this is urbanization which is revealed to have a positive and significant bond with gender equality. Urbanization provids opportunities and improved working and living conditions, leading to higher living standards, a healthier environment, and better education options (Dhamija et al., 2023; Sertyesilisik, 2023; Norris and Inglehart, 2001). As a result of urbanization, women also play a key role in sustainable urban cities through their paid and unpaid labor as primary caregivers in households (UNFPA, 2017). This goes a long way to increase their socio-political and economic contributions to their society (Dhamija et al., 2023). All these contribute to promoting gender equality.

Parallelly, Foreign direct investment (FDI) appears to have a mixed bond with gender equality in cross-country and within-country contexts. Though FDI has beneficial effects on gender equality with more career-enhancing opportunities (Stolzenburg et al., 2020), globalization and foreign direct investment come along with industrial upgrading that increases the demand for skilled male labor, and the exploitation of female employees with low levels of human capital in a great need for stable employment by multinational assembly plants (Fussell, 2000;

Braunstein and Brenner, 2007; Chen et al., 2013). Also, FDI often targets industries with low female representation, such as heavy manufacturing or capital-intensive sectors, which rarely prioritize gender-sensitive reforms (Braunstein, 2012) and equity in governance or political representation, focusing instead on profitability in male-dominated sectors (Dollar and Gatti, 1999). This leads to the reduction of women empowerment and rights. However, FDI inflows in community-focused projects, such as education or healthcare infrastructure, can indirectly improve women's social rights (Kabeer, N. (2016). Also, the positive effect of foreign direct investment on women social rights can be explained by the fact that foreign-owned firms are exposed to competition from abroad, which limits their ability to discriminate in a costly manner, thus allowing for a more effective allocation of resources within the firm and more women social rights (Stolzenburg et al.,2020).

Globalization measured by trade openness (Open) is equally revealed to have mixed results on gender equality. This may be explained by the fact that industrialization has both inter-industry and intra-industry effects, increasing competitive pressure which may reduces gender discrimination in wages and employment and provides women with more employment opportunities and training, especially in developing countries (Chen et al., 2013). As many transition economies open up to international trade and foreign direct investment (FDI), cheap female labor results in a dramatic increase in the number of women employed by foreign-invested and export-oriented industries, often increasing women's access to formal employment and income. Globalization also results in the expansion of the export industry, especially textiles and electronics where women labor is preferred (Kolářová, 2006). This process of rendering labor more flexible and informal is associated with its feminization as well as women economic and political empowerment (Talam, 2017). Nevertheless, this effect depends on policies that ensure decent working conditions and wage equality (Seguino, 2000). However, this increased feminization of the labor force may lead to their exposure to the generally unhealthy industrial working environment as well as their exposure to sexual harassment and even physical punishment (Featherstone and USAS, 2002). Trade openness equally fosters dialogue on international human rights standards, which often include gender-sensitive political reforms. It can pressure governments to improve women's political representation (True, 2003). Hence, while trade openness improves economic opportunities, it may undermine women's social rights by neglecting protections against exploitation in informal sectors (Featherstone and USAS, 2002). Hence globalization often increases women’s participation in precarious work environments, limiting their access to broader social rights (Standing, 1999). In some regions,

there are changes in gender identities. Young girls become the main breadwinner in the family, suffering from over-burdened as they have to occupy two roles: breadwinner and person responsible for the household; a source of anxiety for both men and women (Kolářová, 2006). This can cause a crisis within the family; and sometimes a woman's independence produces violent reactions from men, having negative impacts on women social rights (Kolářová, 2006).

Hence, by providing flexible and affordable learning options and other opportunities, AI can empower women to acquire new skills and information, allowing them to pursue satisfying careers and leadership roles and thereby promote gender equality.

Table 2: OLS baseline results

	Dependent Variable: Gender equality (GE)					
	1	2	3	4	5	6
Part (A). OLS Baseline						
VARIABLES	GEEmployment	GEHealth	GEEducation	GEWoEcoRI	GEWoPoRI	GEWoSoRI
LAI	0.0134***	0.00274	0.00193***	0.0687**	0.0380***	0.269***
	(0.00191)	(0.00172)	(0.000226)	(0.0331)	(0.0140)	(0.0338)
Open	0.0327***	-0.0286***	0.00266**	0.435***	0.263***	-0.578***
	(0.00786)	(0.00710)	(0.00103)	(0.134)	(0.0568)	(0.136)
LFDI	0.00180	0.00221	-0.000995**	-0.129**	-0.0749***	0.127**
	(0.00334)	(0.00302)	(0.000388)	(0.0572)	(0.0242)	(0.0581)
Ind	-0.0882***	0.0122	0.0143***	0.0626	-0.113	-1.068***
	(0.0199)	(0.0180)	(0.00238)	(0.353)	(0.149)	(0.358)
Urb	0.118***	0.0429**	0.0143***	0.586	1.277***	0.905**
	(0.0240)	(0.0217)	(0.00292)	(0.412)	(0.174)	(0.421)
Constant	0.356**	0.415***	0.871***	-2.981	-4.028***	3.524
	(0.142)	(0.129)	(0.0174)	(2.478)	(1.048)	(2.530)
Part (B). Oster (2019) stability test						
Oster bounds (β^, β* (Rmax = 1, δ=1))	[0.02005, 0.01341]	[0.00262, 0.00274]	[0.00218, 0.00193]	[0.11117, 0.06867]	[0.09609, 0.03805]	[0.29413, 0.26901]
Delta (δ) statistic for β = 0	3.57110	2.42225	2.68242	1.98327	3.35444	3.11576
Observations	858	850	799	840	840	827
R-squared	0.206	0.030	0.181	0.033	0.144	0.152

Notes: *** p<0.01, ** p<0.05, * p<0.1; denotes significance at 1%, 5%, and 10%, respectively. Robust standard errors are reported in parentheses.

In our investigation of the effects of artificial intelligence on gender inequality, we initially employed Ordinary Least Squares (OLS) regression analysis. This method yielded results that supported our hypothesis; however, we recognized a significant limitation inherent in OLS: it does not adequately address endogeneity concerns. Specifically, endogeneity can arise from

omission variable bias, which may distort our findings by failing to account for relevant unobserved variables (Gylfason and Zoega, 2003). To confront these potential biases, we implemented the Oster coefficient stability test, a robust statistical tool increasingly utilized in empirical research to evaluate whether results are significantly influenced by unobserved controls (for example, see Djeunankan et al., 2024 and Dhamija et al., 2023). The rationale behind this test is grounded in the seminal work of Altonji et al. (2005) and further elaborated by Oster (2019). They posit that selection bias due to unobserved factors can be estimated by analyzing the impact of adding observable confounders to the baseline model.

The results from our implementation of these statistics, as presented in part (B) of Table 2, reveal a δ value exceeding the conventional threshold of one. This finding implies that for unobserved confounding factors to significantly alter our results, their influence would need to be substantially greater (close to twice) than that of observed confounders. Furthermore, our analysis shows that the interval between β and β* safely excludes zero, providing additional evidence that supports our baseline OLS findings. The findings indicate that the impact of AI on gender inequality is unlikely to be significantly influenced by unobserved factors, reinforcing the validity of our baseline OLS results and contributing to the broader discourse on AI's role in perpetuating or alleviating gender disparities. By rigorously addressing potential biases, we enhance the credibility of our findings and underscore the importance of considering methodological robustness in research on critical social issues like gender inequality.

4.1.1. Endogeneity concern: Baseline IV-GMM

In our investigation of the effects of artificial intelligence (AI) on gender inequality, we initially observed through Ordinary Least Squares (OLS) that AI appears to promote gender equality. To strengthen the validity of these findings, we employed Oster's (2019) coefficient stability test, which indicated that our results are not primarily influenced by omitted variable bias. However, the potential for reverse causality remains a concern, necessitating robust methodological approaches to ensure the reliability of our conclusions. To address this issue, our preferred method was the internal Instrumental Variable Generalized Method of Moments (IV-GMM). The results from the IV-GMM analysis, detailed in Table 3, revealed positive and statistically significant coefficients for AI, consistent with our initial OLS findings. Given the unobserved nature of the error term, direct empirical testing of the exclusion restriction condition is not feasible (Djeunankan et al., 2024). Instead, we relied on partial tests to validate our instrumental strategy. The Kleibergen-Paap Wald rk F statistic serves as a critical indicator of instrument validity (Kleibergen and Paap, 2006).

Table 3: IV-GMM results

	Dependent Variable: Gender equality (GE)					
	1	2	3	4	5	6
VARIABLES	GEEmployment	GEHealth	GEEducation	GEWoEcoRI	GEWoPoRI	GEWoSoRI
LAI	0.0139***	0.00332*	0.00189***	0.0759***	0.0377***	0.307***
	(0.00235)	(0.00198)	(0.000295)	(0.0292)	(0.00985)	(0.0356)
Open	0.0331***	-0.0295***	0.00250**	0.448***	0.280***	-0.636***
	(0.00738)	(0.00590)	(0.00101)	(0.152)	(0.0769)	(0.171)
LFDI	0.00147	0.00261	-0.00100***	-0.132***	-0.0754***	0.129
	(0.00215)	(0.00315)	(0.000303)	(0.0450)	(0.0177)	(0.0810)
Ind	-0.0891***	0.0122	0.0135***	0.0654	-0.126	-1.050**
	(0.0200)	(0.0175)	(0.00242)	(0.328)	(0.0955)	(0.463)
Urb	0.120***	0.0439*	0.0134***	0.576	1.346***	0.838*
	(0.0256)	(0.0224)	(0.00326)	(0.513)	(0.274)	(0.437)
Constant	0.346**	0.413***	0.879***	-3.034	-4.365***	3.901
	(0.148)	(0.129)	(0.0199)	(2.998)	(1.338)	(2.925)
Observations	808	800	754	791	791	779
R-squared	0.209	0.033	0.166	0.034	0.149	0.159
Hansen-J	0.000	0.000	0.000	0.000	0.000	0.000
No. of instruments	6	6	6	6	6	6
No. of Countries	50	50	50	50	50	50
Kleibergen-Paap rk LM P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F	2.9e+04	2.9e+04	2.7e+04	2.8e+04	2.8e+04	2.7e+04
Stock-Yogo weak ID test critical values						
10% maximal IV size	16.38	16.38	16.38	16.38	16.38	16.38
15% maximal IV size	8.96	8.96	8.96	8.96	8.96	8.96
20% maximal IV size	6.66	6.66	6.66	6.66	6.66	6.66
15% maximal IV size	5.53	5.53	5.53	5.53	5.53	5.53

Heteroscedasticity robust standard errors in parentheses. J is Hansen J-statistics. F-statistics is the Cragg-Donald/Kleibergen-Paap F-statistics for weak instrument identification. The Hansen J-statistics suggests that instruments are exactly identified. The instruments are exactly identified in the models because a single instrument was used to prevent instrument over-identification. The Cragg-Donald/Kleibergen-Paap F-statistics also suggests the instrument are not weak since the values are greater than the Stock-Yogo weak ID test critical values. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our results show that the Kleibergen-Paap rk LM test statistic is statistically significant at the one percent level, confirming the validity of our models and instruments.

Overall, our findings indicate that AI has a positive impact on gender equality, with all control variables exhibiting expected signs and statistical significance. Thus, we conclude that our results remain robust under the IV-GMM framework.

4.2. Robustness checks

To confirm our previous results, we performed some robustness tests. First, we use alternative measures of artificial intelligence in our model. Second, we use alternative measures of gender inequality. Third, we include several additional control variables representing determinants of gender inequality. Finally, we test the robustness of the results to an alternative estimation strategy.

4.2.1. Replacing the explanatory variable

Table 4: Robustness alternative interest variable

	Dependent Variable: Gender equality (GE)					
	1	2	3	4	5	6
VARIABLES	GEEmployment	GEHealth	GEEducation	GEWoEconRI	GEWoPolRI	LGEWoSocRI
Part (A)						
LAI_install	0.0231***	0.00467**	0.00197***	0.146***	0.0728***	0.478***
	(0.00312)	(0.00236)	(0.000400)	(0.0510)	(0.0136)	(0.0485)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.687***	0.526***	0.879***	-3.966	-3.736***	6.781**
	(0.142)	(0.133)	(0.0216)	(2.974)	(1.328)	(3.031)
Observations	738	730	685	721	721	720
R-squared	0.235	0.024	0.147	0.049	0.149	0.197
Kleibergen-Paap rk Wald F	3337.696	3295.361	2924.305	3092.536	3092.536	3085.661
Part (B)						
LPatents	0.0192***	0.00370**	0.00271***	0.0842***	0.0170**	0.194***
	(0.00220)	(0.00179)	(0.000271)	(0.0230)	(0.00747)	(0.0389)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.000809	0.217*	0.839***	-3.892	-4.592***	0.544
	(0.164)	(0.124)	(0.0220)	(2.840)	(1.256)	(2.832)
Observations	831	823	775	831	831	816
R-squared	0.261	0.044	0.223	0.035	0.147	0.123
Kleibergen-Paap rk Wald F	5298.966	5275.242	4569.976	5298.966	5298.966	2.1e+04
Kleibergen-Paap rk LM P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen-J	0.000	0.000	0.000	0.000	0.000	0.000
No. of instruments	6	6	6	6	6	6
No. of Countries	50	50	50	50	50	50
Stock-Yogo weak ID test critical values						
10% maximal IV size	16.38	16.38	16.38	16.38	16.38	16.38
15% maximal IV size	8.96	8.96	8.96	8.96	8.96	8.96
20% maximal IV size	6.66	6.66	6.66	6.66	6.66	6.66

15% maximal IV size	5.53	5.53	5.53	5.53	5.53	5.53

Heteroscedasticity robust standard errors in parentheses. J is Hansen J-statistics. F-statistics is the Cragg-Donald/Kleibergen-Paap F-statistics for weak instrument identification. The Hansen J-statistics suggests that instruments are exactly identified. The instruments are exactly identified in the models because a single instrument was used to prevent instrument over-identification. The Cragg-Donald/Kleibergen-Paap F-statistics also suggests the instrument are not weak since the values are greater than the Stock-Yogo weak ID test critical values. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, we test the robustness of our result by using two alternative measures of artificial intelligence and the result is presented in Table 4. According to Dong et al. (2014); Chen et al. (2022); Xin, B., & Ye, X. (2024), the installation density of industrial robots (AI_install) can also be employed to gauge AI development. Therefore, we chose AI_install to replace AI in the regression. We equally use patent (LPatents) applications as an alternative proxy to artificial intelligence. Results are presented in Table 4. We see that the coefficient of AI_install part (A) and LPatents part (B) on gender equality are significantly positive at a conventionally accepted threshold in all the columns. These results imply that artificial intelligence development, access and use increases gender equality in opportunities and contribution in the reduction of the gender gap.

4.2.2. Replacing the explanatory variable

Following Sorgner (2021), we use the UNDP[10] Human Development Report gender inequality indexes (GII) as an appropriate alternative gauge for gender inequality. This GII index reflects gender-based disadvantage in three dimensions: reproductive health, empowerment and the labor market. It shows the loss in potential human development due to inequality between female and male achievements in these dimensions. Computed using the association-sensitive inequality measure suggested by Seth (2009), the GII uses the same framework as the UNDP's inequality-adjusted human development index (IHDI). Higher GII levels suggest more discrepancies between males and females, leading to higher human development losses. While the first column presents the index built by the UNDP's inequality-adjusted human development index (IHDI) with no modifications, the second column presents the UNDP's inequality-adjusted human development index (IHDI) obtained from Our World In Data (OWID) database which is built by using the IHDI with minor modifications. Results are presented in Table 5.

[10] UNDP: United Nations Development Program. https://hdr.undp.org/sites/default/files/2023-24_HDR/hdr2023-24_technical_notes.pdf. Accessed 28 November 2024.

We see that the coefficient of AI on gender inequality is significantly negative, showing that AI has the potential to mitigate gender inequalities.

Hence, our results indicate that increased AI adoption negatively influences gender inequality. This suggests that AI technologies might help close gender gaps in overall three dimensions: reproductive health, empowerment and the labor market.

Table 5: Robustness alternative dependent variable

	Dependent Variable: Gender inequality index (GII)	
	1	2
VARIABLES	GII UNDP	GII OWID
LAI	-0.0330***	-0.0330***
	(0.00125)	(0.00131)
Open	-0.0782***	-0.0784***
	(0.00617)	(0.00617)
LFDI	0.000144	0.000136
	(0.00235)	(0.00236)
Ind	0.0754***	0.0765***
	(0.0131)	(0.0143)
Urb	-0.0770***	-0.0765***
	(0.0172)	(0.0175)
Constant	0.690***	0.685***
	(0.108)	(0.113)
Observations	808	791
R-squared	0.627	0.622
Kleibergen-Paap rk Wald F	2.9e+04	2.8e+04
Kleibergen-Paap rk LM P-value	0.0000	0.0000
Hansen-J	0.000	0.000
No. of instruments	6	6
No. of Countries	50	50
Stock-Yogo weak ID test critical values		
10% maximal IV size	16.38	16.38
15% maximal IV size	8.96	8.96
20% maximal IV size	6.66	6.66
25% maximal IV size	5.53	5.53

Heteroscedasticity robust standard errors in parentheses. J is Hansen J-statistics. F-statistics is the Cragg-Donald/Kleibergen-Paap F-statistics for weak instrument identification. The Hansen J-statistics suggests that instruments are exactly identified. The instruments are exactly identified in the models because a single instrument was used to prevent instrument over-identification. The Cragg-Donald/Kleibergen-Paap F-statistics also suggests the instrument are not weak since the values are greater than the Stock-Yogo weak ID test critical values. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3. Adding control variables

We test the robustness of our result by including a set of additional control variables cumulatively. The result is presented in Table 6. We find that the coefficients associated with artificial intelligence are positive and statistically significant at a conventionally accepted threshold in all the columns.

Table 6: Additional control variables

	Dependent Variable: Gender equality (GE)					
	1	2	3	4	5	6
VARIABLES	GEEmployment	GEHealth	GEEducation	GEWoEconRI	GEWoPolRI	GEWoSocRI
LAI	0.00593*	0.0146***	0.00186***	0.0940***	0.0927***	0.113***
	(0.00306)	(0.00255)	(0.000335)	(0.0159)	(0.0113)	(0.0400)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Personalremittances	-0.0148***	0.0111***	0.00124***	-0.0171	0.0328***	-0.00530
	(0.00291)	(0.00253)	(0.000287)	(0.0143)	(0.00870)	(0.0272)
LMobile	-0.0109***	-0.00540	0.00109**	-0.0581**	-0.0811***	-0.140**
	(0.00356)	(0.00429)	(0.000446)	(0.0281)	(0.0201)	(0.0627)
LGiniIndex	-0.118***	0.169***	-0.0157***	-0.736***	0.102	-1.331***
	(0.0331)	(0.0277)	(0.00302)	(0.168)	(0.178)	(0.319)
Constant	1.297***	-0.393**	0.868***	5.987***	-2.694***	7.175**
	(0.217)	(0.171)	(0.0248)	(1.447)	(0.940)	(3.050)
Observations	777	769	730	384	384	98
R-squared	0.305	0.114	0.236	0.380	0.354	0.445
Hansen-J	0.000	0.000	0.000	0.000	0.000	0.000
No. of instruments	9	9	9	9	9	9
No. of Countries	50	50	50	50	50	50
Kleibergen-Paap rk LM P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F	1.5e+04	1.4e+04	1.3e+04	6921.921	6921.921	725.960
Stock-Yogo weak ID test critical values						
10% maximal IV size	16.38	16.38	16.38	16.38	16.38	16.38
15% maximal IV size	8.96	8.96	8.96	8.96	8.96	8.96
20% maximal IV size	6.66	6.66	6.66	6.66	6.66	6.66
15% maximal IV size	5.53	5.53	5.53	5.53	5.53	5.53

Heteroscedasticity robust standard errors in parentheses. J is Hansen J-statistics. F-statistics is the Cragg-Donald/Kleibergen-Paap F-statistics for weak instrument identification. The Hansen J-statistics suggests that instruments are exactly identified. The instruments are exactly identified in the models because a single instrument was used to prevent instrument over-identification. The Cragg-Donald/Kleibergen-Paap F-statistics also suggests the instrument are not weak since the values are greater than the Stock-Yogo weak ID test critical values. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regarding the additional control variables, personal remittances (Personalremittances) is found to have mixed results on gender equality across our sample. While it is shown to increase gender equality in education, it is found to reduce women's economic rights. These mixed results are in line with those of Asongu and Odhiambo (2018) and Asongu and Odhiambo (2020) who found respectively that remittances could promote gender exclusion and gender equality.

Similarly, digitalization (Mobile) and income inequality (GiniIndex) have mixed and statistically significant effects on gender equality. These results are in line with those of Chen (2004), Asongu and Odhiambo (2020) and Reinen and Plomp (1997), showing that digitalization has the potential to promote gender equality through improved access to education and other resources. However, while there is recognition of the potential of ICT as a tool for the promotion of gender equality and the empowerment of women (Chen, 2004; Asongu and Odhiambo, 2020), Sandys (2005) highlights that there exists a "digital divide" more precisely a "gender divide", with women and girls enjoying less use and access to information technology than men and boys, exacerbating existing inequalities between women and men and creating new forms of inequality in capacity-building opportunities, employment and potential for empowerment. The negative effect of income inequality on gender equality can be explained by the fact that income inequality can slow economic growth by reducing the entry of women into the workforce. This result is in line with the wok of Stolzenburg et al. (2020). We can then conclude that our results are resilient to the inclusion of additional control variables.

4.2.4. Alternative estimation strategy

Baseline IV-GMM Previous results from OLS suggest that artificial intelligence reduces gender inequality. More importantly, we provide empirical evidence from Oster's (2019) coefficient stability test supporting that this result is unlikely to be mainly driven by omitted variables. Even though this provides interesting insides in support of our hypotheses, this result may still suffer from the well-known bias of reverse causality.

For robustness purposes, we further our analyses by implementing the Lewbel (2012) estimation technique. Results are presented in Table 7. Regarding our results, the Kleibergen-Paap rk LM test statistic is statistically significant at the one percent threshold and the Kleibergen-Paap rk LM wald F statistic are greater than 10 in each case. Judging from these post-estimation tests; the estimated models and corresponding instruments are valid. Looking at Table 7, results show that artificial intelligence has positive and statistically significant coefficients which are in line with our hypotheses and are consistent with the OLS results.

Globally, the empirical results from Lewbel (2012) are quite satisfactory. Regarding the control variables, they all have the expected signs and statistical significance. Thus, we can conclude that our results remain robust to the use of Lewbel (2012).

Combining the robustness test results above, we can deduce that our baseline regression results are correct, highly plausible and robust.

Table 7: Alternative estimation strategy

	Dependent Variable: Gender equality (GE)					
	1	2	3	4	5	6
VARIABLES	GEEmployment	GEHealth	GEEducation	GEWoEconRI	GEWoPolRI	LGEWoSocRI
LAI	0.0138***	0.00313	0.00190***	0.0775***	0.0371***	0.304***
	(0.00235)	(0.00197)	(0.000294)	(0.0290)	(0.00991)	(0.0356)
Open	0.0332***	-0.0293***	0.00248**	0.446***	0.281***	-0.632***
	(0.00738)	(0.00590)	(0.00101)	(0.152)	(0.0769)	(0.172)
LFDI	0.00141	0.00253	-0.000999***	-0.132***	-0.0756***	0.128
	(0.00215)	(0.00315)	(0.000303)	(0.0450)	(0.0178)	(0.0810)
Ind	-0.0893***	0.0120	0.0135***	0.0680	-0.127	-1.056**
	(0.0200)	(0.0175)	(0.00241)	(0.328)	(0.0956)	(0.463)
Urb	0.121***	0.0447**	0.0134***	0.570	1.348***	0.851*
	(0.0257)	(0.0224)	(0.00327)	(0.513)	(0.274)	(0.437)
Constant	0.344**	0.410***	0.879***	-3.014	-4.373***	3.859
	(0.148)	(0.129)	(0.0200)	(2.998)	(1.338)	(2.924)
Observations	808	800	754	791	791	779
R-squared	0.209	0.033	0.166	0.034	0.149	0.159
Number of instruments	10	10	10	10	10	10
Hansen	0.0000	0.0000	0.0000	0.0287	0.0001	0.0000
Kleibergen-Paap rk LM P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F	1.1e+04	1.1e+04	1.0e+04	1.0e+04	1.0e+04	1.0e+04
Stock-Yogo critical values: 10% max IV size	16.38	16.38	16.38	16.38	16.38	16.38

Notes: *** p<0.01, ** p<0.05, * p<0.1 denotes significance at 1%, 5%, and 10%, respectively. Heteroscedasticity robust standard errors are reported in parentheses. F-statistics is the Cragg-Donald/Kleibergen-Paap F-statistics for weak instrument identification.

5. Conclusion

Addressing high levels of inequality is a key goal for policymakers and features prominently in the Sustainable Development Goals (SDGs). An important aspect of aggregate inequality is gender inequality, whose reduction is also listed as a separate goal in the SDGs. In effectively all countries across the world important gaps remain between men and women in socio-economic and political aspects. This has led to its high level of interest by policymakers and scholars amongst others. Artificial intelligence is important to address gender inequality as it creates and raises the available opportunities. In the existing literature, the impact of Artificial intelligence on different aspects of gender inequality is less clear and gender inequality is poorly understood. Hence, it is important to understand how gender inequality is affected by Artificial intelligence, especially for a global sample.

In this paper, we study the effect of Artificial intelligence on gender inequality to shed light on this area. We used the OLS and IV-GMM estimation techniques in our baseline analyses on a panel of 50 countries worldwide with data ranging from 2002 to 2019. For this study, we had as dependent variable gender equality proxied by 5 indicators (gender equality in employment, health and education, and women economic, political and social rights) for our baseline analyses. We also used the UNDP and OWID Gender Inequality Indexes for robustness purposes. Artificial intelligence is our main independent variable of interest, captured by industrial robot density. We equally used the operational stock and installation and total patents application for robustness analyses. Our control variables were carefully selected from existing literature. Our study shows that Artificial intelligence is an important determinant of gender inequality. Comparing our results with those of other authors and using several robustness tests, we find confirmation.

Hence, policymakers who want to reduce gender inequality must pay attention to Artificial intelligence technologies and their gender structures. While the positive effect of Artificial intelligence on gender equality suggests that amplifying Artificial intelligence can benefit not only growth but also gender equality, it is important to ensure that AI integration in recruitment and workplace environments, education systems, socio-economic and political aspects should be prioritized, alongside upskilling programs for women to ensure equitable participation in AI-enabled industries, ensuring that women benefit equally from advancements in medical technology, participation in technology-intensive subjects, financial services, especially in rural areas, and AI-driven civic tech platforms and AI-driven social campaigns to promote gender

equality at the economic, political and societal level. Only in these conditions can we unconditionally conclude that artificial intelligence is a tool for gender equality.

An important avenue for future research is to understand the channels that drive our results. Although we have established how artificial intelligence affects gender inequality, our results do not speak to the underlying channels that can explain these findings. Research that sheds light on such channels would thus complement our work and allow for more targeted policy advice on how to address these established inequalities. Further research could also examine the heterogeneity of our results across individual countries with their specificities or countries' development states. One could imagine, for instance, that this may be the case only in developed economies. Future research could target these aspects and complement our work.

References

Acheampong, A. O., Opoku, E. E. O., Dzator, J., & Kufuor, N. K. (2022). Enhancing human development in developing regions: Do ICT and transport infrastructure matter?. *Technological Forecasting and Social Change*, *180*, 121725.

Agrawal, A., Gans, J., & Goldfarb, A. (2022). *Prediction Machines, Updated and Expanded: The Simple Economics of Artificial Intelligence*. Harvard Business Press.

Akhter, R., & Ward, K. B. (2009). Globalization and gender equality: A critical analysis of women's empowerment in the global economy. In *Perceiving gender locally, globally, and intersectionally* (pp. 141-173). Emerald Group Publishing Limited.

Alon, T., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). *The impact of COVID-19 on gender equality* (No. w26947). National Bureau of economic research.

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of political economy*, *113*(1), 151-184.

Asongu, S. A., & Odhiambo, N. M. (2018). ICT, financial access and gender inclusion in the formal economic sector: evidence from Africa. *African Finance Journal*, *20*(2), 45-65.

Asongu, S. A., & Odhiambo, N. M. (2020). Inequality and gender inclusion: Minimum ICT policy thresholds for promoting female employment in Sub-Saharan Africa. *Telecommunications Policy*, *44*(4), 101900.

Badarevski, B. (2023). Gender Equality and Artificial Intelligence. *Annual of the Faculty of Philosophy in Skopje*, *76*(1), 805-815.

Baliamoune-Lutz, M. (2007). Globalisation and gender inequality: Is Africa different?. *Journal of African Economies*, *16*(2), 301-348.

Bao, L., Huang, D., & Lin, C. (2024). Can artificial intelligence improve gender equality? Evidence from a natural experiment. *Management Science*.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal*, *3*(1), 1-31.

Beer, C. (2009). Democracy and gender equality. *Studies in Comparative International Development*, *44*, 212-227.

Braunstein, E. (2006). Foreign direct investment, development and gender equity: A review of research and policy.

Braunstein, E. (2012). *Neoliberal development macroeconomics: A consideration of its gendered employment effects*. Geneva, Switzerland: UNRISD.

Braunstein, E., & Brenner, M. (2007). Foreign direct investment and gendered wages in urban China. *Feminist Economics*, *13*(3-4), 213-237.

Carli, L. L. (2020). Women, gender equality and COVID-19. *Gender in management: an International Journal*, *35*(7/8), 647-655.

Chen, D. H. (2004). Gender equality and economic development: The role for information and communication technologies. *Available at SSRN 610329*.

Chen, Y., Cheng, L., & Lee, C. C. (2022). How does the use of industrial robots affect the ecological footprint? International evidence. *Ecological Economics*, *198*, 107483.

Chen, Z., Ge, Y., Lai, H., & Wan, C. (2013). Globalization and gender wage inequality in China. *World Development*, *44*, 256-266.

Cingranelli, D.L., Richards, D.L., 2010. The Cingranelli and Richards (CIRI) human rights data project. Hum. Rights Q. 32, 401–424.

Cooray, A., & Potrafke, N. (2011). Gender inequality in education: Political institutions or culture and religion?. *European Journal of Political Economy*, *27*(2), 268-280.

Dhamija, G., Roychowdhury, P., & Shankar, B. (2023). Does Urbanization Empower Women? Evidence from India. *Evidence from India (December 7, 2023)*.

Djeunankan, R., Njangang, H., Tékam, H., & Raghutla, C. (2024). Examining the effect of economic complexity on energy justice. *Journal of Environmental Management*, *370*, 122680.

Dollar, D., & Gatti, R. (1999). *Gender inequality, income, and growth: are good times good for women?* (Vol. 1). Washington, DC: Development Research Group, The World Bank.

Dong, Z., Tan, C., Ma, B., & Ning, Z. (2024). The impact of artificial intelligence on the energy transition: The role of regulatory quality as a guardrail, not a wall. *Energy Economics*, 107988.

Eastin, J. (2018). Climate change and gender equality in developing states. *World development*, *107*, 289-305.

Elson, D., & Pearson, R. (1981). ‘Nimble fingers make cheap workers’: An analysis of women's employment in third world export manufacturing. *Feminist review*, *7*(1), 87-107.

Featherstone, L. & United Students Against Sweatshops (USAS) (2002) Students Against Sweatshops, New York, Verso

Flor, L. S., Friedman, J., Spencer, C. N., Cagney, J., Arrieta, A., Herbert, M. E., ... & Gakidou, E. (2022). Quantifying the effects of the COVID-19 pandemic on gender equality on health, social, and economic indicators: a comprehensive review of data from March, 2020, to September, 2021. *The Lancet*, *399*(10344), 2381-2397.

Frennert, S. (2021). Gender blindness: On health and welfare technology, AI and gender equality in community care. *Nursing Inquiry*, *28*(4), e12419.

Fussell, E. (2000). Making labor flexible: The recomposition of Tijuana's maquiladora female labor force. *Feminist Economics*, *6*(3), 59-79.

García-Micó, T. G., & Laukyte, M. (2023). Gender, health, and AI: How using AI to empower women could positively impact the sustainable development goals. In *The Ethics of Artificial Intelligence for the Sustainable Development Goals* (pp. 291-304). Cham: Springer International Publishing.

Gylfason, T., & Zoega, G. (2003). Inequality and economic growth: Do natural resources matter?.

Inglehart, R., Norris, P., & Welzel, C. (2003). Gender equality and democracy. In *Human values and social change* (pp. 91-115). Brill.

Joshi, A. (2024). Big data and AI for gender equality in health: bias is a big challenge. *Frontiers in Big Data*, *7*, 1436019.

Juhn, C., Ujhelyi, G., & Villegas-Sanchez, C. (2014). Men, women, and machines: How trade impacts gender inequality. *Journal of Development Economics*, *106*, 179-193.

Kabeer, N. (2016). Gender equality, economic growth, and women’s agency: the “endless variety” and “monotonous similarity” of patriarchal constraints. *Feminist economics*, *22*(1), 295-321.

Kerr, A. D. (2021). Artificial Intelligence, Gender, and Oppression. In *Gender Equality* (pp. 54-64). Cham: Springer International Publishing.

Kleibergen, F., & Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of econometrics*, *133*(1), 97-126.

Kofman, P., & Payne, C. (2021). Digital financial inclusion of women: An ethical appraisal. *Handbook on ethics in finance*, 133-157.

Kolářová, M. (2006). Gender and globalisation: Labour changes in the global economy. *Sociologický časopis/Czech Sociological Review*, *42*(06), 1241-1257.

Kristal, T., & Yaish, M. (2020). Does the coronavirus pandemic level the gender inequality curve?(It doesn't). *Research in Social Stratification and Mobility*, *68*, 100520.

Leach, M. (Ed.). (2016). *Gender equality and sustainable development*. London: Routledge.

Lussier, D. N., & Fish, M. S. (2016). Men, Muslims, and attitudes toward gender inequality. *Politics and Religion*, *9*(1), 29-60.

Lütz, F. (2023). Gender Equality and Artificial Intelligence: SDG 5 and the Role of the UN in Fighting Stereotypes, Biases, and Gender Discrimination. In *Women's Empowerment and Its Limits: Interdisciplinary and Transnational Perspectives Toward Sustainable Progress* (pp. 153-180). Cham: Springer International Publishing.

Mahalakshmi, V., & Jayanthiladevi, A. (2024). Harnessing Artificial Intelligence for Women Empowerment and Work-Life Balance Enhancement in Management. *IJARSCT. Published online May*, *10*, 1-10.

Mari, V., Spolverato, G., & Ferrari, L. (2022). The potential of artificial intelligence as an equalizer of gender disparity in surgical training and education. *Artificial Intelligence Surgery*, *2*(3), 122-131.

MEHALA, M. D. (2014). The relationship between women entrepreneurship and gender equality.

Nguyen, C. P. (2021). Gender equality and economic complexity. *Economic systems*, *45*(4), 100921.

Nguyen, C. P., & Su, T. D. (2021). Does energy poverty matter for gender inequality? Global evidence. *Energy for Sustainable Development*, *64*, 35-45.

Norris, P., & Inglehart, R. (2001). Women and democracy: Cultural obstacles to equal representation. *Journal of democracy*, *12*(3), 126-140.

Nuseir, M. T., Al Kurdi, B. H., Alshurideh, M. T., & Alzoubi, H. M. (2021, May). Gender discrimination at workplace: Do artificial intelligence (AI) and machine learning (ML) have opinions about it. In *The international conference on artificial intelligence and computer vision* (pp. 301-316). Cham: Springer International Publishing.

Olivier, D., & Ibrahim, N. (2024). Is artificial intelligence helping to empower women in agriculture in Africa?. *GeoJournal*, *89*(4), 142.

Oniyangi, S. (2013). *The Effects of Natural Resources on Gender Inequality: An Explanation for the Resource Curse?* (Doctoral dissertation, Amherst College).

Patón-Romero, J. D., Vinuesa, R., Jaccheri, L., & Baldassarre, M. T. (2022a). State of Gender Equality in and by Artificial Intelligence. *IADIS International Journal on Computer Science and Information Systems*, *17*(2), 31-48.

Patón-Romero, J. D., Vinuesa, R., Jaccheri, M. L., & Baldassarre, M. T. (2022b). Artificial Intelligence and Gender Equality: A Systematic Mapping Study. In *MCCSIS 2022-IADIS International Conferences on: ICT, Society and Human Beings 2022 (ICT 2022); Web Based Communities and Social Media 2022 (WBC 2022); e-Health 2022 (EH 2022)*. IADIS Press.

Perrons, D. (2005). Gender mainstreaming and gender equality in the new (market) economy: An analysis of contradictions. *Social Politics: International Studies in Gender, State & Society*, *12*(3), 389-411.

Petering, R., Um, M. Y., Fard, N. A., Tavabi, N., Kumari, R., & Gilani, S. N. (2018). Artificial intelligence to predict intimate partner violence perpetration. *Artificial intelligence and social work*, *195*.

Potrafke, N., & Ursprung, H. W. (2012). Globalization and gender equality in the course of development. *European Journal of Political Economy*, *28*(4), 399-413.

Qin, M., Wan, Y., Dou, J., & Su, C. W. (2024). Artificial Intelligence: Intensifying or Mitigating Unemployment?. *Technology in Society*, 102755.

Radović-Marković, M. (2011). Critical employment analysis: theory, methodology and research. *Journal of Security and Sustainability Issues*, *1*(2), 113-121.

Ramchandani, P. (2024). THE INFLUENCE OF ARTIFICIAL INTELLIGENCE ON WOMEN'S EMPOWERMENT.

Rana, A. N. (2020). Leveraging big data to advance gender equality. *EMCompass (86)*.

Reinen, I. J., & Plomp, T. (1997). Information technology and gender equality: a contradiction in terminis?. *Computers & Education*, *28*(2), 65-78.

Rönnblom, M., Carlsson, V., & Öjehag-Pettersson, A. (2023). Gender equality in Swedish AI policies. What's the problem represented to be?. *Review of Policy Research*, *40*(5), 688-704.

Saâd, M. B., & Ella, G. A. (2019). Economic complexity and gender inequality in education: An empirical study. *Economics Bulletin*.

Sandys, E. (2005). Gender equality and empowerment of women through ICT. *Women 2000 and beyond*, 60-76.

Sarfaraz, L., Faghih, N., & Majd, A. A. (2014). The relationship between women entrepreneurship and gender equality. *Journal of Global Entrepreneurship Research*, *4*, 1-11.

Seguino, S. (2000). Gender inequality and economic growth: A cross-country analysis. *World development*, *28*(7), 1211-1230.

Sertyesilisik, E. (2023). Sustainable Environment and Urbanization Policies to Enhance Gender Equality and Women Empowerment. In *Gender Inequality and its Implications on Education and Health: A Global Perspective* (pp. 203-212). Emerald Publishing Limited.

Seth, S. (2009). Inequality, interactions, and human development. *Journal of Human Development and Capabilities*, *10*(3), 375-396.

Shahbazi, H., Hakimi, M., Ulusi, H., Rahimi, B., & Quraishi, T. (2024). Exploring the Impact of Artificial Intelligence on Women's Empowerment: A Comprehensive Survey. *EDUTREND: Journal of Emerging Issues and Trends in Education*, *1*(2), 108-120.

Sorgner, A. (2021). Gender and industrialization: developments and trends in the context of developing countries.

Standing, G. (1999). Global feminization through flexible labor: A theme revisited. *World development*, *27*(3), 583-602.

Stolzenburg, V., Matthee, M., Janse van Rensburg, C., & Bezuidenhout, C. (2020). Foreign direct investment and gender inequality: evidence from South Africa. *Transnational Corporations Journal*, *27*(3).

Suvarna, S., Aranha, R., Sathiyaseelan, & Basavaraj, S. (2024). Empowering Gender Equality in Business Sustainability: A STARA (Smart Technologies, Artificial Intelligence, Robotics, and Algorithms)-Centric Exploration of Socio-Technological Innovation for Modern Business Environments. In *Business Development via AI and Digitalization: Volume 2* (pp. 1093-1102). Cham: Springer Nature Switzerland.

Talam, E. (2017). The link between globalisation and gender equality. *International Journal on Rule of Law, Transitional Justice and Human Rights*, *8*(8), 120-128.

Tejani, S., & Milberg, W. (2016). Global defeminization? Industrial upgrading and manufacturing employment in developing countries. *Feminist Economics*, *22*(2), 24-54.

True, J. (2003). *Gender, globalization, and postsocialism: The Czech Republic after communism*. Columbia University Press.

Tschopp, M., & Salam, H. (2023). Spot on SDG 5: Addressing Gender (In-) equality Within and With AI. In *Technology and Sustainable Development* (pp. 109-126). Routledge.

UN (2020). Goal 5: Achieve gender equality and empower all women and girls. accessed May 30 United Nationshttps://www.un.org/sustainabledevelopment/gender-equa lity/

UNFPA. (2017). Urbanization | UNFPA - United Nations Population Fund. United Nations Population Fund. Retrieved November 11, 2020, from https://www.unfpa.org/urbanization#:%7E:text=And%20in%20partnership%20with%20UN,d ata %2Dgathering%20about%20their%20needs

Waylen, G. (2014). Informal institutions, institutional change, and gender equality. *Political Research Quarterly*, *67*(1), 212-223.

Xin, B., & Ye, X. (2024). Robotics Applications, Inclusive Employment and Income Disparity. *Technology in Society*, 102621.

Yang, S. J., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Computers and Education: Artificial Intelligence*, *2*, 100008.

Yasmeen, R., & Shah, W. U. H. (2025). Impact of business cycles on energy poverty: Exploring the significance with sustainable development goals in newly industrialized economies. *Applied Energy*, *378*, 124777.

Zhang, J., & Zhang, Y. (2020). Tourism and gender equality: An Asian perspective. *Annals of Tourism Research*, *85*, 103067.