The impact of artificial intelligence (AI) on maternal mortality: Evidence from global, developed and developing countries

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Abstract

This study explores the role of artificial intelligence (AI) in achieving Sustainable Development Goal (SDG) 3.1, which seeks to reduce global maternal mortality to less than 70 per 100,000 live births by 2030. Despite progress, maternal mortality remains disproportionately high in developing countries, where healthcare infrastructure is weaker. AI offers the potential to enhance maternal health outcomes through improved diagnostic accuracy, personalized care, and predictive analytics, but its full potential in reducing maternal mortality remains underexplored, particularly in developing nations.

Using panel data from 70 countries between 1990 and 2022, the study examines AI's impact on maternal mortality in both developed and developing regions. It leverages AI robotics data (AI flow and AI stock) from the World Robotics database and employs econometric models such as Difference-in-Differences (DiD) and autoregressive distributed lag (ARDL) models to assess short- and long-term impacts.

Key findings reveal that AI has a significant positive effect on reducing maternal mortality, particularly in developing countries. Post-2000, AI adoption reduced maternal mortality, with developing countries benefiting more due to their weaker healthcare infrastructure. In contrast, the impact in developed nations was positive but less pronounced due to already advanced healthcare systems. The ARDL results highlight that in developing countries, deviations from the long-run maternal mortality trend are corrected by 27% annually, and AI contributes to sustained reductions in maternal mortality over time.

The study offers several policy recommendations. First, developing countries should prioritize AI investments in healthcare, especially maternal health, to improve diagnostic accuracy and enable targeted interventions. Second, governments must expand digital infrastructure and ensure equitable access to AI technologies to maximize benefits. Lastly, international organizations should work to prevent AI from exacerbating health inequalities, ensuring that AI tools are accessible to vulnerable populations, including women in rural and low-income areas.

Keywords: Artificial intelligent (AI); maternal mortality; panel data; developed and developing countries

Jel Classification: O14, I1, O5

1. Introduction

This study evaluates the impact of Artificial Intelligence (AI) on Sustainable Development Goal (SDG) 3.1, which aims to reduce the global maternal mortality ratio to less than 70 per 100,000 live births. Despite a 34% reduction in maternal mortality from 2000 to 2020, progress remains insufficient, especially in developing countries with disproportionately high rates (World Health Organisation (WHO), 2023). And also, despite advancements in healthcare, maternal mortality remains a critical issue globally, with significant disparities between developed and developing countries. The integration of Artificial Intelligence (AI) into healthcare promises transformative improvements in maternal health outcomes by enhancing diagnostic accuracy, treatment personalization, and predictive analytics. (Vemuri et al., 2020; Nishtala et al., 2020; Reddy et al., 2021; Khan, 2022). However, the extent and efficacy of AI applications in reducing maternal mortality across different global regions are not well-documented, necessitating thorough empirical investigation. Globally, maternal mortality rates have declined but remain alarmingly high in developing regions due to inadequate healthcare infrastructure and access. In contrast, developed countries have leveraged technology, including AI, to enhance maternal healthcare services significantly. However, the global penetration and impact of AI vary, with developed countries adopting these technologies at a faster rate than their developing counterparts.

Several AI applications, such as predictive analytics and decision support systems, can reduce medical errors during pregnancy, childbirth, and postpartum care. For instance, AI technologies can identify high-risk pregnancies, provide personalized care plans, and improve access to healthcare services. This can be done through various channels, including the early detection of pregnancy-related complications and the early detection of highly current literature, mainly focused on high-income countries where access to advanced healthcare infrastructure and digital health records is more common. However, maternal mortality rates are disproportionately higher in low-resource settings, where access to healthcare is limited, and the healthcare infrastructure is often underdeveloped. Additionally, it is crucial to ensure that AI solutions do not perpetuate existing disparities.

AI algorithms have been developed to predict the risk of postpartum hemorrhage (PPH), a leading cause of maternal mortality. In the USA, Venkatesh et al. (2020) used logistic regressions to predict a woman's risk of PPH. Their findings suggest that PPH can be accurately predicted with machine Learning. Similarly, in a study in Iran, Mehrnoush et al. (2023) employed a bivariate logistic regression to predict postpartum hemorrhage. Their results showed that machine learning models were a reliable method for enhancing the accuracy of postpartum hemorrhage predictions.

Hypertensive disorders in pregnancy have been identified as another leading cause of maternal deaths, complicating 5% to 10% of all pregnancies (WHO, 2011; Hutcheon et al., 2011). It was found to be the leading cause of maternal mortality in industrialized nations. The prevalence of hypertensive disorders is ever on the increasing side (Centers for Disease Control and Prevention, 2019). Hypertension prevalence during delivery hospitalizations increased from 67.2 to 81.4 per 1000 deliveries from 1998 to 2006. The rise might be caused by the increasing prevalence of cardio-metabolic disease in women of childbearing age. From maternal age above forty years of pregnancy, excess weight gain during pregnancy, obesity, and gestational diabetes are linked with increased risks of maternal hypertension.

Margret, Rajakumar, Arulalan, and Manikandan (2024) investigate how machine learning (ML) could be adopted to reduce maternal mortality. Historical data on maternal health were adopted to generate predictive models, resource allocation techniques, and early detection systems. Machine learning assists in monitoring vital signs, identifying risk factors, and improving access to care. This permits better healthcare delivery and targeted interventions. The concerns of model interpretation and data accessibility were addressed. Results revealed the potential of ML to lessen maternal mortality rates and the pressing need for its incorporation into healthcare systems worldwide.

Kwon, Kim, Jeon, Lee, Lee, Cho, and Oh (2019) aimed to develop a deep-learning-based AI algorithm for predicting the mortality rate in Korea. Data were extracted from 2165 patients to generate 12,654 datasets from patients with acute heart failure (AHF). Evidence from the result showed that the area under the receiver operating characteristic curve of the DAHF was 0.880 (95% confidence interval, 0.876–0.884) for predicting in-hospital mortality; these results significantly outperformed those of the GWTG-HF (0.728 [0.720–0.737]) and other machine-learning models.

Ahmed, Sun, Shelly, and Mu (2021) applied explainable AI on a stackable machine learning model framework to explore the spatial distribution of the contributions of known risk factors to maternal mortality rates in the conterminous United States. Five base learners adopted include random forest, generalized linear model, extreme Gradient boosting machine, Gradient boosting machine, and Deep Neural Network for developing stack-ensemble models. Generally, the stack ensemble performs better than all three spatial regression models and the base learners. Smoking prevalence as the most critical predictor was ranked high by the permutation-based feature technique, followed by poverty and elevation.

Based on the above discussion, this study addresses the urgent need to explore how AI can improve maternal healthcare outcomes globally, both in developed and developing countries. AI's potential to manage complex healthcare data and aid decision-making could significantly reduce mortality rates, especially in under-resourced areas. While existing literature highlights AI's theoretical benefits, there is a lack of empirical evidence from diverse global contexts. Specifically, there is a gap in longitudinal studies comparing AI's impact on maternal health across different regions. *Firstly*, this research contributes to the empirical literature by providing a comprehensive analysis of the effects of AI on maternal mortality using advanced econometric techniques not widely employed in previous studies. It uniquely combines AI indices (AI stock and AI flow) with maternal health outcomes to offer differentiated insights into the dynamics of AI's impact over time and across different economic contexts. By incorporating AI variables (AI stock and AI flow) into our analysis of maternal health outcomes introduces a novel dimension to the health economics literature. This study uses annual panel data from 70 countries, disaggregated into 39 developed and 31 developing nations, based on AI robotics data from World Robotics (1990–2022).

Secondly, we contribute to the literature by utilizing a combination of descriptive statistics, pairwise correlations, and advanced econometric methods including spatial visual approaches, Difference-in-

Difference (DiD) estimators, and dynamic panel ARDL models. These methods allow for a nuanced understanding of the temporal and spatial variations in the data, addressing both short-term and long-term impacts of AI on maternal mortality. The use of these diverse methodologies provides a robust framework for overcoming limitations seen in earlier studies, such as addressing endogeneity issues and capturing complex dynamics that simpler models may overlook. The selected econometric strategies enhance the study's ability to provide a more accurate and comprehensive assessment of AI's impact on maternal health. For instance, the dynamic panel ARDL approach facilitates an examination of both long-term relationships and short-term dynamics without requiring all series to be stationary. This flexibility is critical given the varied nature of the economic and healthcare environments across the countries studied. The Difference-in-Difference approach further strengthens the analysis by effectively isolating the effect of AI implementation from other confounding influences, providing a clearer causal interpretation of the results. These methodologies collectively enable a sophisticated analysis that adds depth to the understanding of how AI technologies can be strategically leveraged to enhance maternal health outcomes globally, particularly in settings with varying levels of economic development and healthcare infrastructure.

Thirdly, our study is crucial for *projecting* how AI could significantly transform global healthcare delivery and maternal mortality outcomes. It offers empirical evidence to support increased AI integration into healthcare policies and practices, aiming for substantial reductions in maternal mortality rates both globally and in developing countries. And lastly, by linking Grossman's (1972) health capital model with modern AI applications, our study enriches the theoretical discourse on technology's role in enhancing health capital. It posits that AI serves as an investment in health capital, which potentially reducing maternal mortality through improved healthcare services and patient outcomes.

By elucidating these contributions, our research not only fills a critical gap in the existing literature but also sets the stage for future studies to explore other dimensions of AI's impact on different aspects of public health.

The paper is structured as follows: Section 2 outlines the methodology and data, while Section 3 presents the results of the empirical analysis. Section 4 then offers policy recommendations based on these findings.

2. Methodology and data

2.1 Empirical strategies

To achieve the objectives of this study, we employed descriptive statistics to clearly and concisely summarize the main features of the dataset. Additionally, we applied the pairwise correlation approach to explore initial relationships between the variables. In this section, we also outline other analytical methods used, including the spatial visual approach, difference-in-difference estimator, fixed effects regression (and its forecasting components), and the dynamic panel autoregressive distributed lag (ARDL) approach. Detailed explanations of these methods are provided in the following subsections.

2. 2 Theoretical underpinning and empirical model specifications

This study draws on the demand for health theory, which suggests that health investments, including technological innovations, affect overall health outcomes. Grossman's (1972) concept of "health capital" highlights that health can improve or deteriorate over time through investments like medical care and preventive measures. Integrating AI into maternal health strategies can enhance the effectiveness of these investments, reduce barriers, and lower maternal mortality rates. The study also considers socioeconomic determinants influencing mortality, aligning them with the demand for health framework. Furthermore, according to Mugoye et al. (2019), Oprescu et al. (2020) artificial intelligence (AI) enhances maternal healthcare through advanced diagnostics, personalized treatment plans, and predictive analytics. AI algorithms analyze medical data to predict high-risk pregnancies and suggest early interventions, potentially reducing maternal mortality rates. For example, AI-driven models can forecast complications like preeclampsia and gestational diabetes more accurately than traditional methods, facilitating timely and targeted care (Marvin, 2022; Freeman et al., 2020). Therefore, the functional form equation can be presented as:

$$mmr_{it} = f(AI_{it}, X_{it})^{1} \tag{1}$$

Where mmr is maternal mortality, AI represents overall AI application in healthcare and X includes other explanatory variables influencing maternal mortality, such as healthcare access, infrastructure quality, socioeconomic factors, and health policy environments. i *and* t represents individual country and time, respectively. Further details on the control variables are provided in Table 1. Before expanding on Eq. 1, it is important to note that the overall AI index, generated through Principal Component Analysis, comprises two key indicators: AI Stock and AI Flow. AI stock represents the accumulated AI technologies within healthcare systems, enhancing monitoring and intervention in maternal health, thus reducing mortality (Jiang et al., 2017). AI flow involves the continuous integration of new AI innovations, enabling healthcare providers to respond more effectively to emergencies, improving survival rates (Kharb and Joshi, 2023). The functional form of Equation 1 is further subdivided into two parts, as detailed in the footnote.

The explicit functional form of Equation 1 is as follows:

$$mmr_{it} = AI_{it} + X_{it} \tag{2}$$

The econometric model is specified as follows:

$$mmr_{it} = \beta_0 + \beta_1 AI_{it} + \sum_{i=1}^{9} \beta_{2i} X_{i,t} + \mathcal{E}_{1i,t} \tag{3}$$

Where: $\mathcal{E}_{it}$ is the error term; β_0, β_1 and β_2 are parameters to be estimated. The framework above offers a comprehensive foundation for analyzing AI's impact on maternal mortality by integrating technological advancements with traditional health determinants to evaluate their combined effect on

[1] $mmr_{it} = f(aiapflow_{it}, X_{it})$, and $mmr_{it} = f(aiapstock_{it}, X_{it})$

maternal health outcomes. The econometric techniques discussed in the following sections are derived from Equation 3.

2. 3 Difference-in-Difference (DiD) *econometric specification*

The Difference-in-Differences (DiD) econometric technique is ideal for our study on the impact of AI on maternal mortality across countries for several reasons. First, health policy interventions are not implemented simultaneously worldwide, making DiD effective for analyzing treatments like AI in healthcare introduced at specific times and locations. It allows us to compare changes over time between treatment and control groups. Secondly, we used DiD methods with country-specific fixed effects to account for both observed and unobserved heterogeneities at the country level. Additionally, DiD controls for confounding variables and is robust to external shocks affecting all groups.

The basic DiD model estimated is specified as follows:

$$mmr_{it} = \beta_0 + \beta_1 Post_t + \beta_1 Treatment_i + \beta_2 (Treatment_i \times Post_t) + \varphi_i + \varphi_t + \mathcal{E}_{i,t} \quad (5)$$

Where $Treatment_i$ takes 1 if having non-zero AI robots flows or stocks and 0 otherwise; and $Post_t$ takes 1 if year ≥2000 and 0 otherwise; φ_i is fixed effects for countries; and φ_t is the time effect capturing global or common shocks affecting all countries.

2. 4 Dynamic panel autoregressive distributed lag (ARDL) approach.

This study employed the dynamic panel ARDL approach to assess AI's impact on maternal mortality for several reasons: it handles both short- and long-term dynamics, accommodates mixed integration orders, and allows for causality and long-term relationships. Additionally, it offers flexibility, as it does not require all variables to be stationary, unlike methods such as the Engle-Granger two-step procedure (Pesaran et al., 1999; Sulaiman and Abdul-Rahim, 2018; Behera and Mishra, 2020). Therefore, the panel ARDL is formulated as follows:

$$\Delta logmmr_{it} = \beta_0 + \sum_{i=1}^{k} \beth_{ij}\, \Delta logmmr_{j,t-i} + \sum_{i=1}^{k} \beta_{ij}\, log\Delta X_{i,t} + \alpha_1 logmmr_{j,t-i} + \sum_{i=1}^{k} \alpha_{ij}\, logX_{i,t} + \mathcal{E}_{i,t} \quad (6)$$

In Eq. 6, $i = 1, \ldots, n$ is the country index, $t = 1, \ldots, T$ is the time index, $\mathcal{E}_{i,t}$ is the error term, mmr is maternal mortality and X includes all the explanatory variables influencing maternal mortality (please see Table 1), Δ is the 1st variation factor, and k is the ideal lag length. To investigate the long-term cointegration relationship between the variables, the following assumptions are made:

$$H_0 = \Omega_1 = \Omega_2, \ldots, \Omega_n = 0 \text{ (There is no cointegration)} \quad (7)$$

$$H_1 = \Omega \neq \Omega_2, \ldots, \Omega_n \neq 0 \text{ (There is cointegration)} \quad (8)$$

The assumption of no cointegration can be tested and compared with cointegration using the F test, which applies regardless of whether the variables are I(0), I(1), or a combination of both. Given the small sample size, the analytical approach found in Pesaran et al. (1999) and Narayan and Narayan's (2005) studies were applied. The test uses panel autoregressive distributed lag bounds. If the F statistic exceeds the I(1) bound, cointegration exists; if below I(0), we accept the null hypothesis. If in between, no clear conclusion is drawn. Once a long-run relationship is established between the dependent variables and the regressors, the panel ECM model, as shown in Equation (9), can be expressed as follows:

$$\Delta logmmr_{it} = \beta_0 + \sum_{i=1}^{k} \gimel_{ij}\, \Delta logmmr_{j,t-i} + \sum_{i=1}^{k} \beta_{ij}\, log\Delta X_{i,t} + \alpha_i ECM_{i,t-1} + \mathcal{E}_{i,t} \qquad (9)$$

The coefficient α_i in the ECM represents the speed at which adjustments are made annually toward long-run equilibrium.

2. 5 Fixed effect regression multivariate forecasting approach.

Fixed effect regression in a multivariate forecasting context involves controlling for individual-specific characteristics that do not change over time and could bias the estimated coefficients if not accounted for. This model is especially useful in panel data settings where the same entities (such as countries, companies, or individuals) are observed over multiple time periods. In multivariate forecasting, the fixed effect model can be expressed as follows:

$$mmr_{it} = \beta_0 + \beta_1 AI_{it} + \sum_{i=1}^{9} \beta_{ki}\, X_{i,t} + \mu_i + \mathcal{E}_{i,t} \qquad (10)$$

Where:

- $mmr_{it}$is the dependent variable for country i at time t.
- $X_{i,t}$ is the vector of the explanatory variables for country i at time t.
- β_0, β_1,…, β_k are the coefficients to be estimated.
- μ_i represents the unobserved individual-specific effect (fixed effect) that captures all time-invariant characteristics of each entity.
- $\mathcal{E}_{i,t}$ is the error term for country i at time t, assumed to be independently and identically distributed.

For the forecast element:

The forecast element in this model involves predicting future values of mmr_{it} based on known or forecasted values of the $X_{i,t}$ variables which also include the AI. After estimating the coefficients β and the individual fixed effects μ_i , the model can be used for forecasting by inputting the values of $X_{i,t}$ for future time periods:

$$\widehat{mmr}_{it} = \hat{\beta}_0 + \hat{\beta}_1 AI_{it} + \sum_{i=1}^{k} \hat{\beta}_{ki}\, X_{i,t} + \mathcal{E}_{i,t} \qquad (11)$$

Where $\widehat{mmr}_{it}$is the forecasted value of mmr_{it} for country i at future time t.

2.6 Data

This study uses annual panel data from 70 countries, disaggregated into 39 developed and 31 developing nations, based on AI robotics data from World Robotics (1990–2022). The selection was driven by data availability for the variables in Table 1. The recent data ensures relevance to current policy, economic, and health planning. The primary data sources are the WHO Global Burden of Disease (GBD), World Bank's World Development Indicators (WDI), and UNCTAD databases. Table 1 outlines the variables used in this research.

Table 1: Variable description and data sources

Indicator	Computation	Constituent variables	Sources
mmr_nw	Maternal mortality ratio (per 100,000 live births)	mmr	WHO database
Artificial intelligent indicators			
aiapflow	Industrial and services robotics flow	aiapflow	World Robotics Congress database
aiapstock	Industrial and services robotics stock	aiapstock	World Robotics Congress database
Ai_ind	Index of artificial intelligence, from the Principal Component analysis (PCA) of:		
	Digitally deliverable services exports, Current USD (millions)	ddsx_cusd	UNCTAD database
	Digitally deliverable services imports, Current USD (millions)	ddsm_cusd	UNCTAD database
	Frontier technology readiness index, R&D	ftri_rd	UNCTAD database
	Frontier technology readiness index, overall	ftri_oi	UNCTAD
	Frontier technology readiness index, industry activity	ftri_ia	UNCTAD database
	Frontier technology readiness index, ICT	ftri_ict	UNCTAD database
	Frontier technology readiness index, access to finance	ftri_af	UNCTAD database
	ICT services exports Current USD (millions)	ictstx_cusd	UNCTAD database
	ICT services exports percentage of total world	ictstx_petw	UNCTAD database
	ICT services imports Current USD (millions)	ictstm_cusd	UNCTAD database
	Share of ICT goods re-imports	ictg_rm	UNCTAD database
	Share of ICT goods exported	ictg_x	UNCTAD database
	Share of ICT goods imported	ictg_m	UNCTAD database
cm_ind	Index of comorbidities, as a Principal Component analysis (PCA) of:		
	Prevalence of anemia among women of reproductive age (% of women ages 15-49)	cm_apw	WHO, GBD database
	Suicide mortality rate, female (per 100,000 female population)	cm_srf	WHO, GBD database
	Women's share of population ages 15+ living with HIV (%)	cm_hivpf	WHO, GBD database
ha_ind	Index of health access, from the Principal Component analysis (PCA) of:		
	Nurses and midwives (per 1,000 people)	ha_nmt	WDI database
	Physicians (per 1,000 people)	ha_ppt	WDI database
he_ind1	Index of health expenditure computed via Principal Component analysis (PCA) of:		
	Current health expenditure (% of GDP)	he_gdp	WDI database
	Current health expenditure per capita (current US$)	he_pc	WDI database
	Current health expenditure per capita, PPP (current international $)	he_ppp	WDI database
he_oops	Out-of-pocket expenditure (% of current health expenditure)	he_oops	WDI database
inf_ind	Index of infrastructure, from the Principal Component analysis (PCA) of:		
	Access to electricity (% of population)	inf_ael	WDI database

	Individuals using the Internet (% of population)	inf_inp	WDI database
se_indp	Socioeconomic indicator correlating positively with mmr, from the PCA of:		
	GDP per capita (constant 2015 US$)	se_gdppc	WDI database
	People with basic handwashing facilities including soap and water (% of population)	se_hwf	WDI database
	Employment to population ratio, 15+, female (%) (national estimate)	se_eprf	WDI database
	Labor force participation rate, female (% of female population ages 15-64) (modeled ILO estimate)	se_flfpr	WDI database
se_indn	Socioeconomic indicator correlating negatively with mmr, from the PCA of:		
	Poverty headcount ratio at $2.15 a day (2017 PPP) (% of population)	se_phr2_15	WDI database
	Poverty headcount ratio at $3.65 a day (2017 PPP) (% of population)	se_phr3_65	WDI database
	Poverty headcount ratio at $6.85 a day (2017 PPP) (% of pop.)	se_phr6_85	WDI database
	Prevalence of undernourishment (% of population)	se_unp	WDI database
	Age dependency ratio (% of working-age population)	se_adr	WDI database
oca_ind	Proxy of Obstetric Care Availability, measured by:		
	Births attended by skilled health staff (% of total)	oca_bsw	WDI database
de_frt	Fertility rate, total (births per woman)	de_frt	WDI database

Source: Author's compilation.

3. Results

3.1 Descriptive statistics

Table 2 provides the descriptive statistics across all countries, as well as in developed and developing countries. In all the countries under study, the maternal mortality ratio averages 55.96 deaths per 100,000 live births, with a standard deviation of 157.27. In developed countries, the maternal mortality ratio averages 12.03 deaths per 100,000 live births, with by a low standard deviation of 12.06, indicating minimal variations among these countries. In comparison, developing countries display a very high average level of maternal mortality ratio at 109.49 deaths per 100,000 live births with considerable variations (standard deviation of 222.51).

Globally, the average flow of 2,094.33 units and a stock of 16,068.02 units, with significant variations across countries (standard deviations of 9,534.13 and 62,002.22, respectively). Developed countries have higher levels of technological infrastructure, with an average flow and stock of industrial and service robots of 2,673.55 and 23,941.95, respectively. The adoption of industrial and service robotics in developing countries is far lower, averaging 1,388.41 units in flows and 6,471.66 units of stock, well below the levels observed in developed countries, with significant variability. All the indicators that help in reducing maternal mortality, such as health access, affluent socioeconomic indicators are significantly lower in developing countries compared with developed countries. Indicators of deprivation and factors that contribute to higher maternal mortality are high in developing countries. The low levels of AI adoption coupled with low levels of essential infrastructure and supporting health environment suggest that the health benefits of AI are likely to accrue well in developing countries, despite projected adverse labour market conditions (Oxford Economics, 2019).

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
		All countries					Developed					Developing			
mmr	1988	55.957	157.266	1.082	1792.347	1092	12.033	12.062	1.082	89.765	896	109.49	222.507	4.519	1792.347
aiapflow	1988	2094.331	9534.133	0	175546	1092	2673.549	7448.472	0	55240	896	1388.41	11544.252	0	175546
aiapstock	1988	16068.02	62002.218	0	956477	1092	23941.954	67882.369	0	412961	896	6471.663	52437.923	0	956477
cm ind	1360	-.855	.836	-2.618	2.156	760	-1.243	0.514	-2.618	.346	600	-.364	0.906	-2.064	2.156
cm apw	1360	19.687	9.726	7.3	54.2	760	14.959	5.527	7.3	29	600	25.676	10.566	7.9	54.2
cm srf	1400	5.77	3.826	.7	24.4	780	7.305	3.677	.7	24.4	620	3.84	3.060	.7	16.4
cm hivpf	1953	27.58	11.954	6.1	85.59	1085	25.359	9.314	7.48	50.34	868	30.358	14.119	6.1	85.59
ha ind	1270	.621	1.147	-1.91	4.045	844	1.18	0.805	-1.23	4.045	426	-.487	0.893	-1.91	1.984
ha nmt	1366	6.832	4.263	.14	23.07	884	8.618	3.760	1.09	23.07	482	3.557	3.003	.14	13.34
ha ppt	1478	2.678	1.183	.02	7.06	955	3.275	0.857	1.01	7.06	523	1.59	0.885	.02	4.26
he ind1	1451	.901	1.944	-1.585	11.124	819	1.815	1.987	-1.043	11.124	632	-.283	1.040	-1.585	5.246
he gdp	1452	6.971	2.72	1.6	19.69	819	8.318	2.157	3.86	18.76	633	5.228	2.359	1.6	19.69
he pc	1452	1767.78	2089.294	13.21	11758.42	819	2645.399	2272.194	21	11758.42	633	632.283	1024.728	13.21	6467
he ppp	1451	2037.138	1782.02	52.35	11758.42	819	2786.383	1861.323	149	11758.42	632	1066.203	1064.540	52.35	6434
he oops	1452	28.8	15.433	5.21	85.05	819	23.617	10.092	7.14	51.94	633	35.507	18.308	5.21	85.05
inf ind	1901	.743	.89	-2.306	2.232	1075	.996	0.793	-.358	2.221	826	.414	0.903	-2.306	2.232
inf ael	1923	96.61	10.951	7.7	100	1092	99.656	1.419	88.1	100	831	92.607	15.711	7.7	100
inf inp	1966	39.38	32.963	0	100	1075	48.318	33.113	0	99.53	891	28.596	29.375	0	100
se indp	179	-.725	1.275	-3.191	2.473	27	-.619	1.195	-1.827	1.301	152	-.744	1.291	-3.191	2.473
se gdppc	1958	21013.924	19489.455	354.09	87123.66	1090	27099.931	19484.684	740.63	87123.66	868	13371.358	16597.229	354.09	73493.27
se hwf	219	75.457	22.241	10.72	98.13	27	94.114	5.150	86.98	98.13	192	72.833	22.468	10.72	97.4
se eprf	1608	45.892	12.895	7.62	85	999	49.145	9.699	19.95	85	609	40.557	15.466	7.62	71.89
se flfpr	1988	56.473	16.209	10.66	86.25	1092	64.451	9.617	32.75	86.25	896	46.749	17.269	10.66	80.11
se indn	894	-.772	1.137	-2.27	7.482	623	-1.2	0.413	-1.753	2.871	271	.21	1.580	-2.27	7.482
se phr2 15	1060	3.772	9.026	0	81.5	715	.929	2.725	0	33.5	345	9.664	13.555	0	81.5
se phr3 65	1060	8.975	17	0	94.7	715	2.331	6.811	0	66	345	22.743	22.617	0	94.7
se phr6 85	1060	18.87	26.268	0	99.1	715	6.734	14.057	0	90.8	345	44.021	27.813	0	99.1
se unp	1360	5.042	5.722	2.5	50.4	780	2.945	2.871	2.5	33.4	580	7.863	7.201	2.5	50.4
se adr	1988	51.339	10.721	16.17	92.09	1092	49.539	5.226	36.48	70.94	896	53.532	14.599	16.17	92.09
de frt	1988	2.034	.851	.84	6.57	1092	1.588	0.333	.84	3.11	896	2.577	0.968	.92	6.57
oca bsw	1267	96.089	10.639	18	100	775	99.159	1.192	88.9	100	492	91.254	15.852	18	100

The pairwise correlation results presented in Tables 3 reveal several significant relationships The significant negative correlations between industrial and services robotics flow and stock and maternal mortality rate (mmr) suggest that an improvement in AI technology decreases maternal mortality rates. AI technologies enhance health outcomes through improved diagnosis and treatment methods, streamlined processes, and improved resource allocation (Obermeyer and Emanuel, 2016; Udegbe et al., 2024). Some studies have suggested that low levels of healthcare infrastructure and human capital investments can limit the role of AI technologies on health outcomes such as maternal mortality (Souza et al., 2024). The Indices of Health Access and Health Expenditure exhibit the expected negative relationships with maternal mortality rates, showing them as key determinants of maternal mortality rate reduction (Alkema et al., 2016; Mweemba et al., 2021).

There is a positive correlation between OOP health expenditure and maternal mortality ratio. In countries where individuals incur a greater share of health expenses, maternal mortality rates is likely to be higher. Xu et al. (2003) has shown that higher personal healthcare expenses reduce access, particularly among low-income groups, resulting in poor health outcomes. The negative relationship between OOP and health corroborates this. As expected, comorbidities are positively correlated, highlighting the significant impact of pre-existing health conditions on maternal mortality, aligning with Say et al. (2014) and Chou et al. (2016). Other key factors in reducing maternal mortality revealed by the correlations are obstetric care availability (Campbell and Graham, 2006); affluent socioeconomic conditions (Bongaarts, 2016), and the index of overall infrastructure. However, poor socioeconomic conditions and increased fertility rates lead to higher maternal mortality.

Table 3: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) aiapflow	1.000									
(2) aiapstock	0.913*	1.000								
(3) mmr	-0.056*	-0.069*	1.000							
(4) ha_ind	-0.031	0.020	-0.424*	1.000						
(5) he_ind1	0.155*	0.267*	-0.226*	0.765*	1.000					
(6) he_oops	-0.073*	-0.142*	0.446*	-0.478*	-0.559*	1.000				
(7) cm_ind	-0.186*	-0.254*	0.555*	-0.453*	-0.520*	0.442*	1.000			
(8) oca_bsw	0.079*	0.082*	-0.701*	0.377*	0.250*	-0.474*	-0.382*	1.000		
(9) se_indn	-0.065*	-0.099*	0.759*	-0.508*	-0.436*	0.593*	0.604*	-0.665*	1.000	
(10) se_indp	0.198*	0.216*	0.253*	-0.081	0.014	-0.227*	-0.013	0.245*	-0.241*	1.000
(11) de_frt	-0.130*	-0.160*	0.668*	-0.415*	-0.296*	0.412*	0.589*	-0.694*	0.681*	-0.243*
(12) inf_ind	0.146*	0.176*	-0.523*	0.495*	0.626*	-0.589*	-0.627*	0.421*	-0.714*	-0.123

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

It is important to note that the key determinants of maternal mortality are highly correlated among themselves, but most importantly to the indicators of AI robotics technology. This poses the problem of highly collinear regression models, explaining why in the subsequent analysis, we emphasize the bivariate approaches.

According to the map shown in Figure 3, in 2020, global maternal mortality rates (MMR) remained a significant health concern, with persistent country and regional differences. These countries continue to face substantial challenges, including weak healthcare systems, limited access to skilled healthcare providers, poor infrastructure, and high fertility rates, all of which lead to increased maternal mortality (Say et al., 2014). Additionally, high poverty levels and inadequate nutritional status among women exacerbated maternal health concerns. The COVID-19 pandemic in 2020 further exacerbated the already fragile healthcare systems in most African countries, resulting in deteriorated maternal health outcomes (Chmielewsk et al., 2021). In contrast, high-income countries, especially in Europe, East Asia, and North America still exhibit significantly low maternal death rates in 2020.

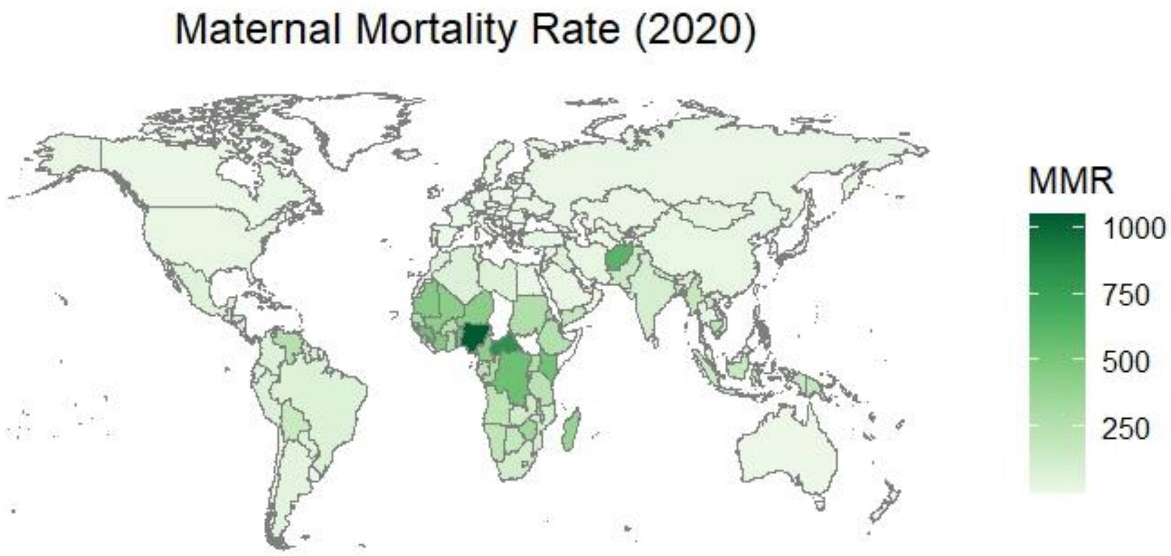

Figure 3: distribution of maternal mortality rates across countries

Figure 4 maps the distribution of robotic flows (upper map) and stocks (lower map) worldwide. Countries with no data are absent from the maps. In 2020, the global flow was characterized by significant progress, as countries progressively integrated AI into many areas, including healthcare, manufacturing, banking, and education. There was significant variations in AI adoption and utilization between countries and regions, driven by factors including technological infrastructure, investment, and digital preparedness. Many countries in East Asia, North America and Europe show high AI flow in 2020. Countries that recorded the highest AI inflow were predominantly high-income countries, with advanced digital infrastructures and significant investments in AI research and development (R&D). East Asia countries recorded AI flow of over 150,000. Many of these countries experienced significant AI inflow in healthcare sectors to improve diagnosis accuracy, personalize treatment plans, and streamline clinical workflows (Topol, 2019).

Figure 4: Maps of industrial and services robot flows and stocks

However, low-income countries, particularly in sub-Saharan Africa and South Asia experienced relatively low AI flow in 2020, mainly due to weak technological infrastructure, inadequate digital literacy, and lack of investments in AI R&D and skilled AI professionals. While some countries like South Africa and Kenya have started to adopt AI in various sectors like agriculture and healthcare, the overall AI flow in Africa remain low (Manyika et al., 2020).

Consequently, countries with the highest AI stocks were generally high-income countries in North and Central America, Europe and East Asia. These countries are characterized by high investment in AI, with strong digital infrastructure, and significant AI research and development. AI stocks in these countries are predominantly concentrated in healthcare, autonomous vehicles, defense, and finance (Zhang and Lu, 2021).

3.2 ***Difference-in-Difference estimations***

In 2000, Breazeal (2000) developed Kismet, the first robot capable of simulating human emotions. Two years later, in 2002, the release of the first Roomba, a consumer-grade autonomous robotic vacuum cleaner, showcased how robots could be integrated into everyday life for practical use. These advancements highlight the rapid progress in robotics at the turn of the millennium, making 2000 a pivotal year for AI and robotic developments. The year 2000 is therefore chosen as the post-treatment cut-off for assessing the impact of AI robots on maternal mortality due to rapid advancements in AI and robotics starting in that period.

The difference-in-difference (DiD) results in Table 4 and Figure 5, indicate varying impacts of AI depending on the level of development. The treated group in the developing countries included in the study has on average 92.04 (113.82) higher maternal mortality rate than the control group for robots stock (flow), however, there are fewer maternal deaths per 100,000 live births post-year 2000 relative to pre. In developed countries, the treated groups and post year show lower maternal mortality rates.

Table 4: The effects of AI on maternal mortality using difference in difference estimator

	(1)	(4)	(2)	(5)	(3)	(6)
	AI stock	AI Flow	AI stock	AI flow	AI stock	AI flow
VARIABLES	all countries		Developed		Developing	
treat	74.250***	86.238***	-12.265***	-13.138***	92.041***	113.826***
	(8.118)	(8.847)	(0.912)	(0.984)	(11.324)	(12.442)
post	-21.349**	-40.848***	-9.603***	-15.222***	-28.146**	-60.420***
	(9.712)	(7.709)	(0.974)	(0.771)	(14.174)	(11.386)
treat_post	-88.133***	-68.541***	4.8217***	11.002***	-109.832***	-77.365***
	(10.488)	(8.686)	(1.115)	(0.949)	(15.049)	(12.478)
Constant	203.884***	195.064***	26.433***	26.899***	268.800***	251.737***
	(6.762)	(7.242)	(0.684)	(0.7190)	(9.7455)	(10.556)
Observations	4,956	4,956	1,260	1,260	3,696	3,696
R-squared	0.140	0.141	0.338	0.326	0.175	0.176
Number of cid	177	177	45	45	132	132
ll	-30011	-30009	-4147	-4158	-22845	-22841
F	259.7	260.7	206.3	195.5	251.0	254.1

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The interactions between the treatment and post-treatment period (treat_post), which captures the actual impact is significant and negative in all the countries and the developing country sample (-88.133 and -68.541 for all countries and -109.83 and -77.37 for developing countries respectively for AI stocks and flows). This indicates that as AI technologies are increasingly integrated into healthcare systems, their positive impact becomes more pronounced in developing countries, resulting in significant decreases in maternal mortality rates over time. This is consistent with Wilson and Daugherty (2018), who emphasize the transformative potential and cumulative benefits of AI to improve healthcare access and outcomes in developing regions.

In developed countries where maternal mortality rates are already low, the adoption of AI has a positive but less pronounced effect.

These results suggest that increasing adoption of AI is, and will increasingly be beneficial for developing countries characterized by very high maternal mortality rates where current levels of AI adoption are low. This is consistent with prior research on AI's positive long-term effects in healthcare (Hamet & Tremblay, 2017(Obermeyer et al., 2019)).

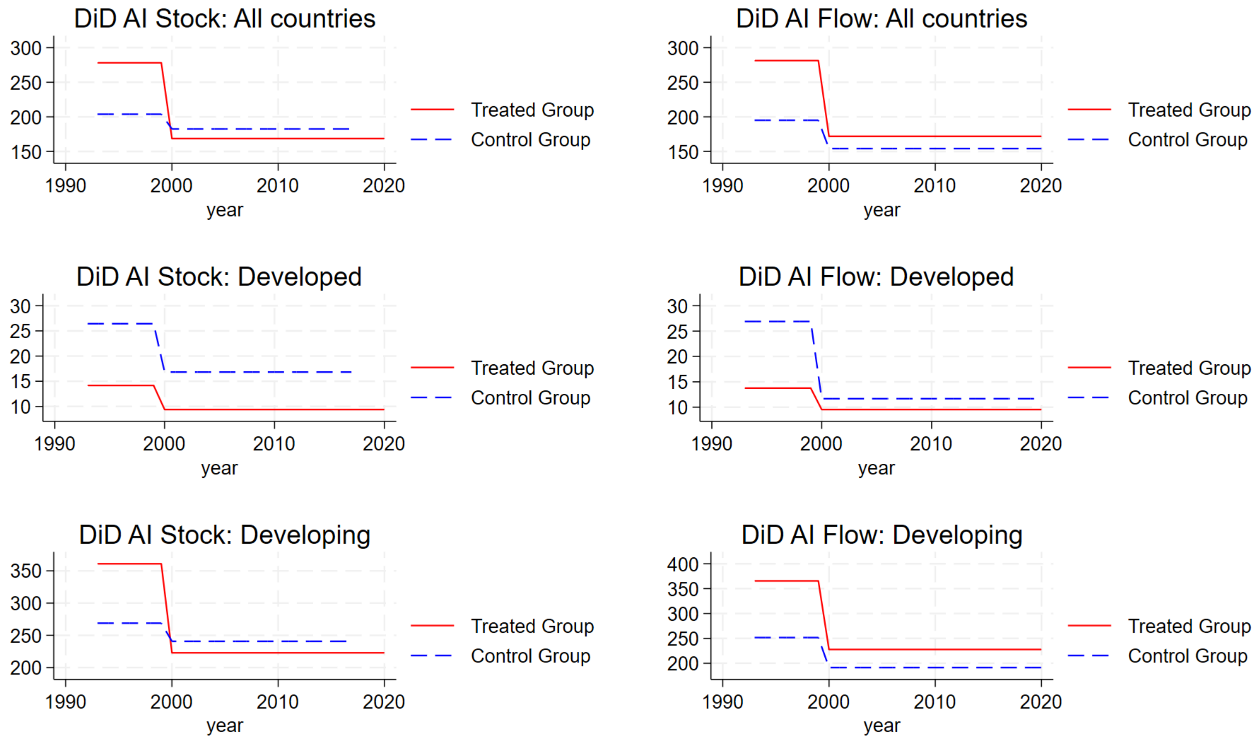

Figure 5: Comparison of treated versus control groups in developed and developing countries

3.3 Panel ARDL modelling

Table 5a and 5b presents the results for the panel ARDL model assessing the impact of artificial intelligence (AI) in robotics flow (aiapflow) on maternal mortality (mmr) across all, developed, and developing countries. The analysis distinguishes between short-run (SR), long-run (LR), and adjustment (ADJ) effects. For the Adjustment Coefficients (ADJ term) in Table 5a, for developing countries, the adjustment term is significant at 5% and negative (-0.2717), indicating that deviations from the long-run equilibrium in maternal mortality are corrected by 27% in each period. In developed countries, the ADJ term is also significant and negative at both level or log (-0.1336 or -0.0701), suggesting a 13.36% or 07.01% correction towards equilibrium per period. For all countries, the coefficient is positive (0.0488) but not statistically significant, implying weak or no adjustment in global trends. This suggests that in developing countries, there is a slightly faster adjustment towards equilibrium after a shock in maternal mortality rates compared to developed countries. *Figure 6a,* showing the cumulative sum (CUSUM), reveals that all the variables fall within the 95% confidence band. This indicates that the model parameters remain stable over time, allowing us to conclude that the models are reliable. This is further supported by the diagnostic tests results in Table 5b which shows that the estimated models can be relayed upon. For instance, the Durbin-Watson (DW) results suggest little to no autocorrelation in the majority of the models since most values are close to 2 (e.g., 2.288, 2.102, 2.218). The Breusch-Godfrey (BG) Chi2 and p-values indicate no significant serial correlation in any of the models. The White's test indicates no significant heteroskedasticity, implying that the error variance is consistent. The Pesaran, Shin, and Smith (PSS F-statistics) and p-values confirm the presence of cointegration in most models, implying a stable long-term relationship between AI in robotics and maternal mortality across the different countries.

For the long-run (LR) effects of AI Robotics Flow, in all countries, the coefficient on AI Robotics Flow is significant and negative, indicating that an increase in AI robotics flow is associated with a reduction in maternal mortality in the long-run. In developing countries, the coefficient is larger and more significant, suggesting a stronger long-term reduction in maternal mortality from AI robotics flows in developing countries. However, in developed countries, the coefficient is positive but insignificant, implying no strong long-run effect of AI robotics flow on maternal mortality. The negative long-run coefficients in developing countries suggest that AI technologies, particularly in industrial and service robotics, can reduce maternal mortality over time. This is consistent with theories on technological diffusion improving healthcare efficiency and access, especially in labor-intensive sectors (e.g., obstetric care). AI-driven automation can enhance service delivery, reduce human error, and enable better monitoring in healthcare settings. In developing countries, the stronger negative long-run effect of AI robotics flow might reflect a "technological catch-up" process. The results suggest that developing economies stand to benefit significantly from adopting frontier technologies that are already widespread in developed countries as AI-driven innovations can improve healthcare systems and infrastructure, reduce barriers to medical access, and support maternal health programs (Ramakrishnan et al. 2021; Khan et al., 2022; Panda and Sharma, 2024).

The positive short-run effects in both global and developing contexts imply potential transitional disruptions. This is because according to Panayides et al. (2020) integrating AI systems can initially strain existing healthcare structures due to costs, technical challenges, or workforce displacement before long-term benefits are realized. The absence of a significant long-run impact in developed countries may indicate that AI technologies have reached a saturation point where additional investments in AI do not yield substantial improvements in maternal health. Developed countries likely already possess advanced healthcare systems, where the marginal effect of new technology on health outcomes, such as maternal mortality, diminishes.

The relationship between AI and health outcomes, such as maternal mortality, aligns with several economic and public health theories. For instance, the innovation and public health theory, as discussed by Bloom and Canning (2000), argues that technological advancements can enhance public health by improving efficiency and accessibility. Similarly, Rogers et al. (2014) diffusion of innovations theory explains the differences in impact between developing and developed countries, suggesting that the stage of technological adoption and its contextual application influence its effectiveness.

Table 5a: Panel ARDL modelling results for the impact of AI in industrial and services robotics flow on maternal mortality

	(1)	(2)	(3)	(4)	(5)	(6)
	all countries		Developing countries		Developed countries	
Variables	level	log	level	log	level	log
ADJ						
L.mmr	0.0268	0.0488	0.0347**	-0.2717**	-0.1336***	-0.0701**
	(0.0164)	(0.0328)	(0.0126)	(0.1263)	(0.0220)	(0.0272)
LR						
L.aiapflow	-0.0289**	-0.7092***	-0.0386***	-0.1462***	0.0013*	0.0504
	(0.0125)	(0.2103)	(0.0107)	(0.0157)	(0.0007)	(0.4227)
SR						
L2D.lmmr				0.3980	-0.0885	0.2909
				(0.2505)	(0.1483)	(0.2866)
L3D.lmmr				0.9369***		0.1254
				(0.2968)		(0.2455)
D.aiapflow	0.0008***	0.0346*	0.0021***	-0.0129	0.0001	-0.0051
	(0.0002)	(0.0182)	(0.0006)	(0.0154)	(0.0001)	(0.0267)
LD.aiapflow			-0.0015**	0.0114	-0.0003**	-0.0319
			(0.0006)	(0.0167)	(0.0001)	(0.0239)
L2D.aiapflow					-0.0001	
					(0.0001)	
L3D.aiapflow					-0.0001	
					(0.0001)	
Constant	-5.0879***	-0.4874*	-9.4008***	1.5030*	0.2323	0.1009
	(1.3263)	(0.2608)	(1.6618)	(0.7164)	(0.3554)	(0.2782)
Observations	27	27	26	24	24	24
R-squared	0.4531	0.1396	0.7290	0.6101	0.8885	0.6457

Note: *, **, *** denotes the level of significance at 10%, 5%, or 1%, respectively. Standard errors in parentheses. LR represents the long-run results; SR represents the short-run results; ADJ represent the adjustment term. The dependent variable is maternal mortality ratio (per 100,000 live births) (mmr). **Source**: Author's computations.

Table 5b: Diagnostic statistics test results for (AI) in robotics flow and maternal mortality model

	All countries		developing		Developed	
	non-logged	logged	non-logged	logged	non-logged	logged
Durbin-Watson (DW)	2.288	2.102	2.032	2.218	1.448	1.782
BG Chi2	0.943	1.952	0.022	2.154	1.362	0.653
BG P>Chi2	0.331	0.162	0.882	0.142	0.243	0.419
White Chi2	19.15	22.84	14.52	24.00	9.99	5.97
White P>Chi2	0.512	0.297	0.803	0.404	0.351	0.310
PSS F	9.943***	1.947***	19.222***	6.486***	25.023***	5.876***
PSS p-val I(0)	0.004	0.431	0.000	0.030	0.000	0.042
PSS p-val I(1)	0.008	0.555	0.000	0.057	0.000	0.076

Note: *, **, *** denotes the level of significance at 10%, 5%, or 1%, respectively. **Source**: Authors' computations

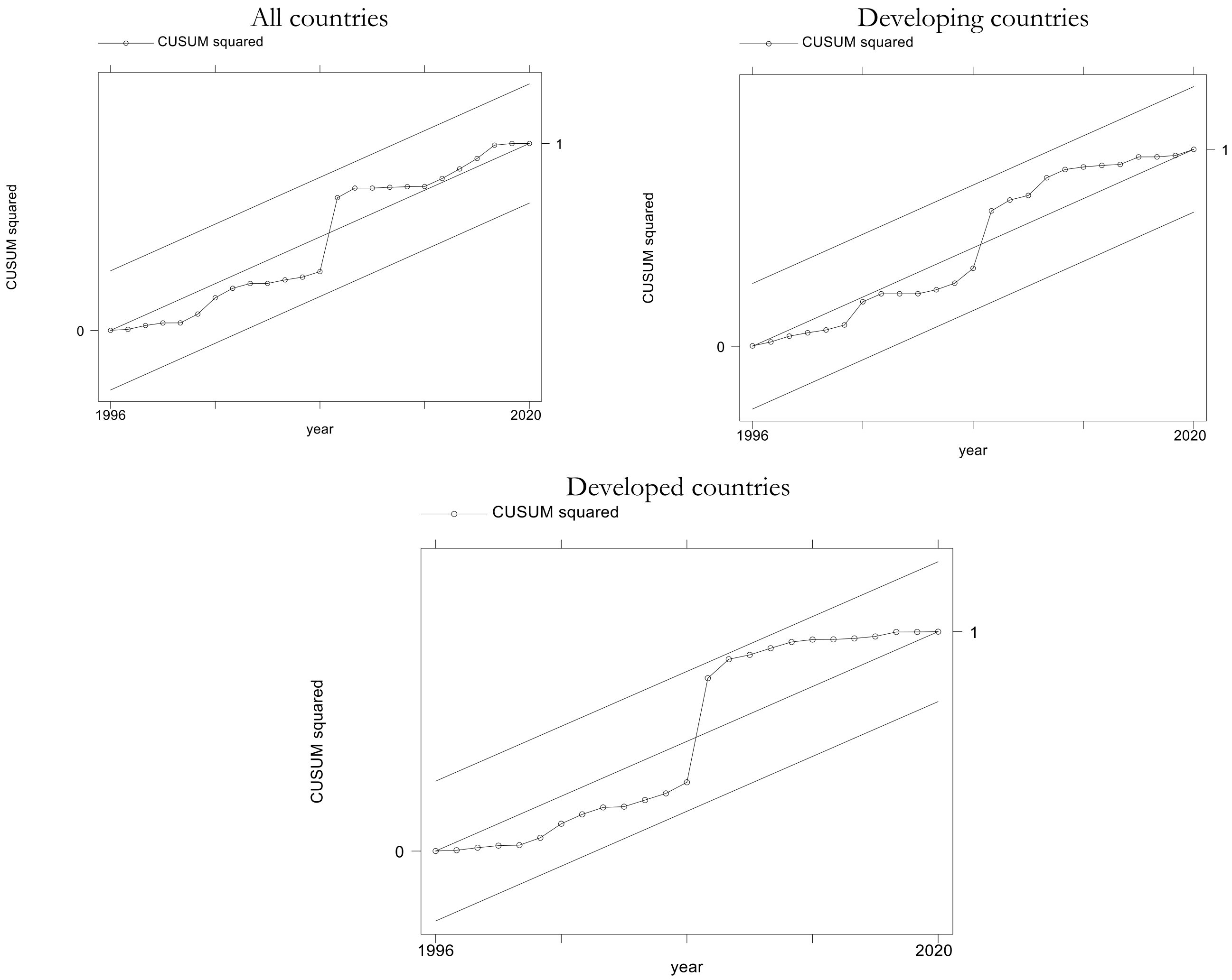

***Figure 6a**: CUSUM graphs for AI Robotic flows*

Panel ARDL modelling results and discussion for the impact of artificial intelligence (AI) in robotics stock on maternal mortality

Table 6a and 6b presents panel ARDL (Auto-Regressive Distributed Lag) modeling results on the impact of artificial intelligence (AI) in robotics stock (aiapstock) on maternal mortality across global, developed, and developing countries. From Table 6a, the adjustment coefficients for maternal mortality are positive in all groupings and significant at various levels, indicating a degree of inertia in maternal mortality rates. This implies that after any deviation from the long-run equilibrium due to changes in AI robotics stock, the rate of adjustment back towards equilibrium is noticeable and faster especially in all countries and developing countries. *Figure 6b,* which displays the cumulative sum (CUSUM), shows that not all variables remain within the 95% confidence band, as some portions fall outside of it for both all countries and developed countries. Despite this, the model parameters can still be relied upon, allowing us to conclude that the models are fit for interpretation. This is also supported by the diagnostic tests results in Table 6b which demonstrate that the models are generally well-specified, with minor issues of heteroscedasticity in some cases. For example, the Durbin-Watson and Breusch-Godfrey tests suggest that there is no major issue of autocorrelation in the residuals of most models. This is important because the presence of autocorrelation could bias the model's standard errors and lead to misleading inference. The White test indicates heteroscedasticity in some models, particularly in the logged models for all countries and developed countries. While the significant PSS F-statistics across all models indicate that there is a long-run relationship between the maternal mortality ratio (mmr) and AI (robotics stock) variables. This means that the variables move together over time, and deviations from the long-term equilibrium are corrected in the future. The long-run relationship between maternal mortality and AI is robust, and the results support the hypothesis of cointegration, meaning AI advancements are likely to have long-term implications for maternal mortality across different country groups.

Focusing on our variable of interest, at global level, in the long-run, AI robotics stock has a statistically significant negative impact on maternal mortality in all countries. This implies that as AI technologies in industry and services expand, maternal mortality decreases globally. Specifically, a 1-unit increase in aiapstock reduces the maternal mortality ratio (mmr) by 0.0042 units (level) or 0.8390% (log). The short-run impact also shows a significant and positive effect on reducing maternal mortality, particularly in the log model (0.1158), highlighting the immediate benefits of AI adoption. AI-enhanced medical technologies and automation can improve healthcare delivery, especially in obstetric care, leading to better maternal health outcomes. Technologies such as AI-driven diagnostic tools or automated surgical robots may lower mortality by addressing complications more effectively.

For the developing Countries (see Columns 3 and 4), in the long-run, the results are mixed. In the level model, there is a significant negative long-run impact of AI robotics stock on maternal mortality (0.0108), but the log model shows no significance. This suggests that the level of AI stock influences maternal mortality in developing countries, though the impact may not be logarithmic. In the short run, AI robotics stock shows significant negative impacts (both at first and second lags), suggesting that the adoption of AI technologies has immediate and persistent effects in reducing maternal mortality in developing countries. The impact of AI on healthcare may be more noticeable in developing countries due to the large gaps in healthcare access and quality. Introducing AI technologies can bridge these gaps by providing advanced diagnostic tools, telemedicine, and efficient healthcare services, leading to reduced mortality rates. However, the lower log results indicate that AI penetration might not be widespread enough to create logarithmic scale effects. The results can be interpreted within the framework of the Grossman (2017) health production function, which views health outcomes as a function of various inputs, including technology. AI robotics, as a technological input, enhances healthcare production, by reducing maternal mortality. This aligns with the findings of Alami et al. (2020), Nti et al. (2023), Shrivastava et al. (2023), and Zuhair et al. (2024), which highlight the positive effects of AI in healthcare on reducing mortality rates in developing regions.

For the Developed Countries (see Columns 5 and 6), in the long-run, there is no significant long-run relationship in the level model, but the log model shows large variability (insignificant). This could indicate that AI robotics stock does not influence maternal mortality significantly in developed countries in the long term, likely due to already high standards of healthcare. While in the short-run, some lagged terms for AI robotics stock show significant negative coefficients (LD.aiapstock, L2D.aiapstock, L3D.aiapstock), implying that AI technologies have more short-term effects in developed countries. This might be due to the integration of cutting-edge AI technologies that enhance short-term medical interventions. The intuition behind these results is that developed countries may already have robust healthcare systems, so AI's long-run effect on maternal mortality may be minimal. However, in the short run, new AI technologies could still enhance operational efficiency, resource allocation, or emergency response in maternal healthcare. The differing impacts of AI between developed and developing countries align with economic convergence theory, which suggests that less developed nations can experience more pronounced benefits from adopting advanced technologies (Mouteyica and Ngepah, 2023a, 2023b). Developing countries, with lower baseline healthcare standards, may gain significantly more from AI integration compared to developed countries.

Table 6a: Panel ARDL modelling results for the impact of artificial intelligent (AI) in industrial and services robotics stock on maternal mortality

	(1)	(2)	(3)	(4)	(5)	(6)
	all countries		Developing		Developed	
Variables	level	log	level	log	level	log
ADJ						
L.mmr	0.0387**	0.1381***	0.0337**	-0.1395	-0.0508**	0.0383
	(0.0159)	(0.0390)	(0.0121)	(0.1753)	(0.0227)	(0.0404)
LR						
L.aiapstock	-0.0042***	-0.8390***	-0.0108*	-0.1093	0.0028	-4.8868
	(0.0011)	(0.0718)	(0.0056)	(0.0956)	(0.0017)	(3.7848)
SR						
LD.lmmr				0.0146	-0.6682***	-0.4546*
				(0.2707)	(0.1298)	(0.2301)
L2D.lmmr				0.3786	-0.3283**	0.1430
				(0.2555)	(0.1122)	(0.2320)
L3D.lmmr				0.7905**		0.3188
				(0.3016)		(0.2096)
D.aiapstock	0.0002***	0.1158***	0.0018***	-0.0081	0.0000	-0.1528
	(0.0000)	(0.0296)	(0.0006)	(0.0721)	(0.0001)	(0.2058)
LD.aiapstock			-0.0023***	-0.1331*	-0.0003***	-0.5995**
			(0.0008)	(0.0735)	(0.0001)	(0.2433)
L2D.aiapstock					-0.0002**	
					(0.0001)	
L3D.aiapstock					-0.0002**	
					(0.0001)	
Constant	-6.7561***	-1.6960***	-9.2775***	0.7979	-3.3681***	-1.9870**
	(1.4141)	(0.4350)	(1.6000)	(1.0579)	(0.7907)	(0.6855)
Observations	27	27	26	24	24	24
R-squared	0.5465	0.3959	0.7522	0.6218	0.9507	0.7686

Note: *, **, *** denotes the level of significance at 10%, 5%, or 1%, respectively. Standard errors in parentheses. LR represents the long-run results; SR represents the short-run results; ADJ represent the adjustment term. The dependent variable is maternal mortality ratio (per 100,000 live births) (mmr). **Source**: Author's computations.

Table 6b: Diagnostic statistics test results for (AI) in robotics stock and maternal mortality model

	All countries		developing		Developed	
	non-logged	logged	non-logged	logged	non-logged	logged
DW	2.070	2.082	2.058	2.324	1.933	2.080
BG Chi2	0.189	0.919	0.043	3.091	0.031	0.616
BG P>Chi2	0.663	0.338	0.836	0.079	0.860	0.432
White Chi2	9.37*	18.89***	9.35	24.00	24.00	24.00
White P>Chi2	0.095	0.002	0.808	0.404	0.404	0.404
PSS F	14.463***	7.863**	9.102**	7.037**	64.961***	16.453***

PSS p-val I(0)	0.000	0.012	0.007	0.023	0.000	0.001
PSS p-val I(1)	0.001	0.023	0.014	0.044	0.000	0.001

Note: *, **, *** denotes the level of significance at 10%, 5%, or 1%, respectively. **Source**: Author's computations.

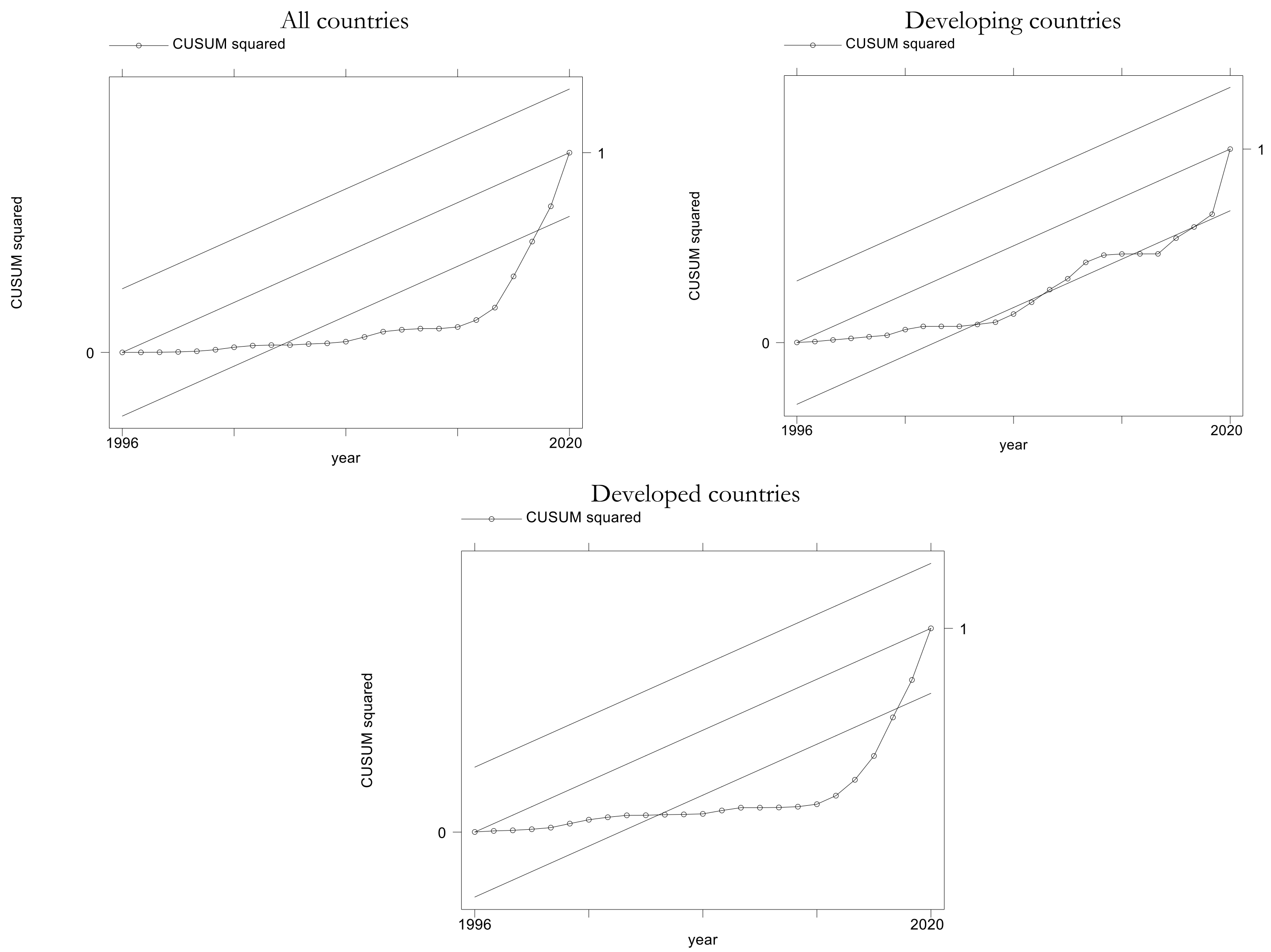

Figure 6b: CUSUM graphs for AI Robotic stock

Fixed effect regression results and discussion for the impact of artificial intelligence (AI) on maternal mortality

For all countries (Columns 1 & 2) in Table 7, AI stock coefficient (-0.00003) is statistically significant at the 5% level, suggesting that an increase in AI stock is associated with a marginal decrease in maternal mortality rates. The negative relationship indicates that higher AI stock, which represents the accumulation of industrial and service robotics, contributes to improving maternal health outcomes by reducing maternal mortality. The coefficient (-0.00013) of AI flow is also significant at the 5% level, showing that the flow of AI (i.e., the yearly introduction of new AI technologies) has a stronger negative effect on maternal mortality than AI stock. This implies that ongoing advancements in AI technology and their applications, particularly in healthcare services, might be more impactful in reducing maternal deaths. This finding aligns with the studies of Davies (2019), Chattu (2021), Kaur et al. (2021), Morley et al. (2024), Silcox et al. (2024), Olorunsogo et al. (2024), and others.

For developing countries (Columns 3 & 4), the coefficient (-0.00005) of AI stock is significant at the 10% level. This reinforces the idea that in developing countries, increased AI stock helps reduce maternal mortality, though the effect is slightly larger than in the overall sample. The use of AI in maternal health services (such as robotic-assisted procedures and diagnostics) could help overcome gaps in healthcare infrastructure. The coefficient (-0.000152) of AI flow is also significant at the 10% level, showing a stronger reduction in maternal mortality in developing countries compared to developed ones. New AI innovations seem to be more effective at addressing healthcare deficiencies, possibly through cost-effective diagnostic tools and telemedicine solutions. The significant negative coefficients for AI stock and AI flow in developing countries suggest that AI technologies can fill critical gaps in healthcare systems where maternal mortality is high. AI applications, such as automated diagnostics, telemedicine, and AI-based training for healthcare workers, provide efficient and scalable solutions in regions where access to skilled medical personnel is limited. Studies by Wahl et al. (2018) emphasize that AI has the potential to revolutionize healthcare in developing regions by providing affordable access to high-quality care through AI-driven diagnostics and predictive analytics. These findings align with the theory of technological leapfrogging, which posits that developing nations can benefit more from newer technologies than developed countries with already advanced infrastructures (Steinmueller, 2001).

For developed countries (Columns 5 & 6), the coefficient (0.000023) for AI stock is positive but not significant, implying no clear relationship between AI stock and maternal mortality in developed countries. This might suggest that AI stock, while beneficial in other sectors, has a limited incremental effect on maternal health in countries with already advanced healthcare systems. While the coefficient (0.000049) for AI flow is positive but also not significant, indicating that the introduction of new AI technologies might not have a discernible impact on reducing maternal mortality in developed countries, possibly because these countries already have well-established maternal healthcare infrastructure and access to skilled medical staff. In these nations, where healthcare systems are already robust, the integration of AI technologies is more likely to enhance efficiency rather than directly reduce mortality. This supports the theory of diminishing returns to technology adoption—once a certain level of technological saturation is reached, further advancements yield less substantial improvements (Rosenberg, 1976).

Table 7: Fixed effect regression results (forecast)

	(1)	(2)	(3)	(4)	(5)	(6)
	All countries		Developing		Developed	
Variables	AI stock	AI flow	AI stock	AI flow	AI stock	AI flow
AI stock	-0.00003**		-0.00005*		0.000023	
	(0.00001)		(0.00002)		(0.000017)	
AI flow		-0.00013**		-0.000152*		0.000049
		(0.00006)		(0.000088)		(0.000096)
ha_ind	-5.48207***	-5.52103***	-5.478213***	-5.567772***	-4.370444***	-4.189829***
	(0.92313)	(0.91457)	(2.10145)	(2.098164)	(0.843351)	(0.841969)
oca_bsw	-2.66166***	-2.65660***	-2.78832***	-2.790786***	0.457653	0.406633
	(0.10833)	(0.10832)	(0.15677)	(0.156862)	(0.352817)	(0.351136)
cm_ind	-1.64990	-1.65288	-0.93356	-1.034104	-4.724388*	-4.706678*
	(2.22262)	(2.22021)	(3.98890)	(3.989495)	(2.541885)	(2.546307)
Cons.	287.33172***	286.66343***	314.65147***	314.73471***	-35.271658	-30.051272
	(10.52861)	(10.52733)	(14.80255)	(14.81535)	(35.458956)	(35.279466)
Obs.	709	709	233	233	476	476
R-sq.	0.52	0.52	0.64	0.64	0.078	0.08
Num. of cid	62	62	28	28	34	34

Log Lik	-2346	-2345	-842.5	-842.7	-1404	-1405

Note: *, **, *** denotes the level of significance at 10%, 5%, or 1%, respectively. **Source**: Author's computations.

Oxford Economics (2019) has highlighted the remarkable three-fold increase in the number of robots in use worldwide, at 2.25 million in 2018. The same report projects that by 2030, the global stock of robots will reach 20 million. This will translate into about 19% growth rate. We use this growth rate to expand the yearly flows and stocks of industrial and service robots to 2035. It is noteworthy that this applied growth rate is conservative as World Robotics (2023) reports that the worldwide sales of professional service robots grew by 48% in 2022.

Actual data spanning 1993 and 2020 is used to estimate panel fixed effects models of the effects of industrial and service robots (AI stock and AI flow) on maternal mortality ratios (MMR) across various country groupings—global, developing, and developed countries. The graphs in Figure 7 are based on fixed-effects (FE) regression models that control for health access, obstetric care, and comorbidities, while the AI indicators (stock and flow) serve as key independent variables. The forecast holds all other control variables at their 2018-2020 mean values, leaving only AI indicators to vary. The forecasts are fairly accurate as the 95% confidence intervals (shaded grey area) around the forecast indicate a reasonably narrow range, especially in developed countries.

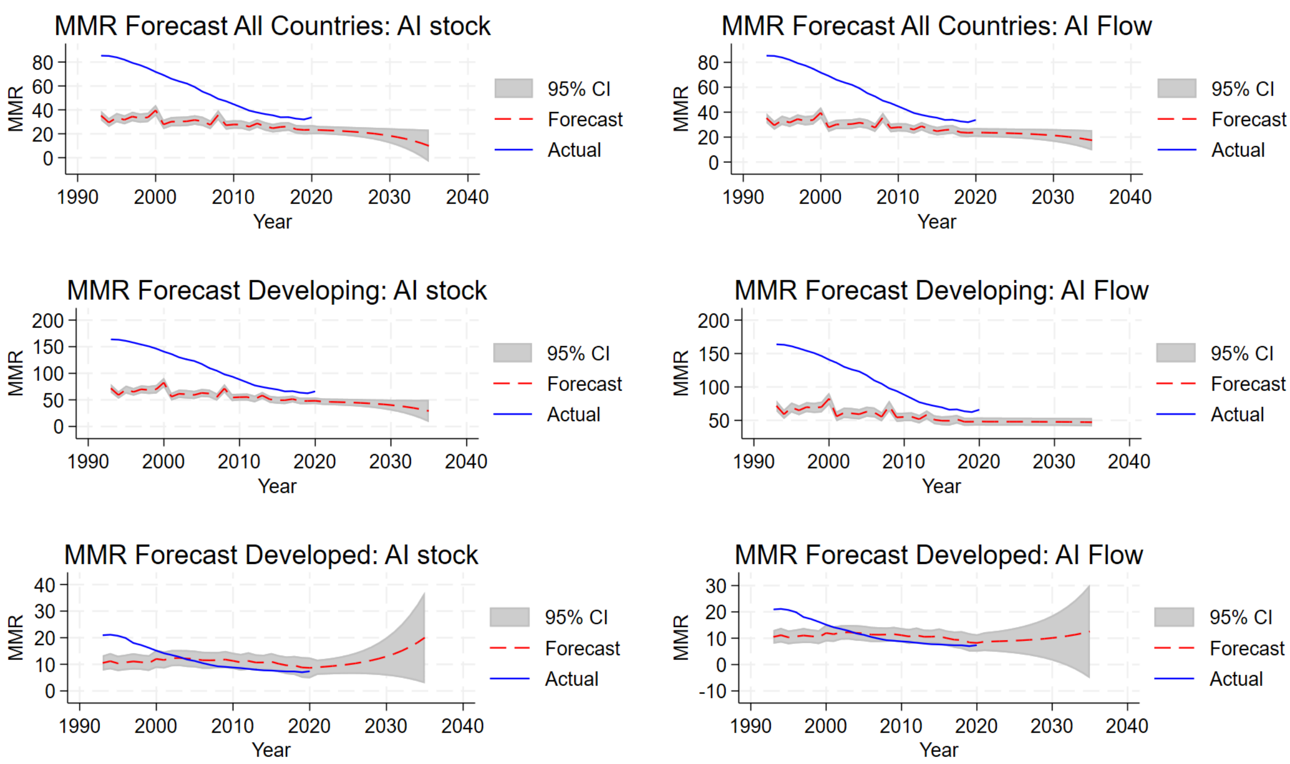

Figure 7: forecast graphs of the impact of AI robotics on maternal mortality

Robotics flow forecast a slightly stronger impact on maternal mortality than the stock. Globally**,** The maternal mortality rate (MMR) shows a clear declining trend in both AI stock and AI flow forecasts. Actual values (blue line) remain relatively stable from 1990 to 2020, but the forecast (red line) shows a marked decline in MMR from 2020 onwards. By 2035, MMR values drop to below 20 per 100,000 live births. In developing countries, the MMR shows a steeper initial decline. For both AI stock and

AI flow, the forecast suggests a continuous reduction, reaching levels below 50 MMR by 2030. The declining trajectory is slightly more pronounced in the AI flow model compared to the AI stock model. Given that developed countries already have a low MMR (below 20 per 100,000), the forecast shows only a modest further reduction. The AI stock model shows almost no further decline from 2020 to 2035, while the AI flow model shows a slight reduction, though MMR remains below 10 in developed countries.

4. Conclusion

The conclusion of this research study highlights the transformative potential of artificial intelligence (AI) in reducing maternal mortality, particularly in the context of Sustainable Development Goal 3.1. The study utilizes a range of econometric techniques, including Difference-in-Differences (DiD), Dynamic Panel ARDL, and fixed effects regression, to assess the effects of AI on maternal health outcomes across 70 countries, divided into developed and developing regions.

The findings demonstrate that AI, particularly in the form of industrial and service robotics, has significant potential to reduce maternal mortality globally, with a more pronounced impact in developing countries. The study shows that countries with higher AI adoption, particularly in healthcare, exhibit lower maternal mortality rates. This effect is more substantial in developing nations, where healthcare infrastructure is often weaker and maternal mortality rates are higher. The research underscores the importance of integrating AI technologies to bridge healthcare gaps and improve access to maternal health services.

In developed countries, while the overall maternal mortality rates are already low, the adoption of AI technologies continues to have a positive, though less pronounced, impact. The study attributes this to the already advanced healthcare systems in these countries, where the marginal benefits of AI are limited compared to developing regions.

Key Policy Recommendations

Governments in developing countries should prioritize investments in AI technologies, specifically in maternal healthcare, to address high maternal mortality rates. This includes promoting the use of AI-powered diagnostics, telemedicine, and AI-assisted healthcare worker training to improve healthcare outcomes in resource-constrained settings.

To maximize the benefits of AI, countries should invest in the necessary digital infrastructure, including robust internet connectivity, digital literacy programs, and AI research and development. This is crucial for enabling the effective integration of AI in healthcare systems, especially in developing nations.

Policymakers in developing countries should leverage AI technologies to leapfrog traditional barriers in healthcare, allowing for faster adoption of advanced diagnostic and treatment tools. This can help address critical gaps in healthcare access and quality, particularly in rural and underserved areas.

Governments and international organizations must ensure that AI technologies do not exacerbate existing inequalities in healthcare. Policies should be designed to make AI tools affordable and accessible to all populations, particularly those in low-income and rural areas.

Caveats and Areas for Further Research:

The study relies on AI robotics flow and stock data, which may not fully capture all dimensions of AI's impact on healthcare. Further research should explore additional AI applications, such as machine learning models and AI-driven healthcare interventions. While AI demonstrates strong potential in reducing maternal mortality, its success depends on local healthcare contexts.

Future research should investigate how factors such as healthcare worker skills, cultural practices, and regulatory environments influence the effectiveness of AI in different regions. AI adoption in healthcare, particularly in developing countries, may face challenges such as costs, lack of technical expertise, and resistance from healthcare workers. Further research is needed to identify strategies for overcoming these barriers and ensuring the smooth integration of AI technologies in healthcare systems. The study highlights the short-term and long-term benefits of AI, but more longitudinal studies are needed to understand the sustained impact of AI on maternal mortality and other health outcomes over extended periods.

Overall, the integration of AI in healthcare presents a promising avenue for reducing maternal mortality and improving health outcomes globally, particularly in developing countries. However, careful attention must be paid to infrastructure, equitable access, and long-term sustainability to fully realize the benefits of AI in maternal healthcare.

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Appendix: AI robots usage country list by levels of development

Developing	Developed
Argentina	Australia
Brazil	Austria
Chile	Belarus
China	Belgium
Colombia	Bosnia and Herzegovin
Costa Rica	Bulgaria
Denmark	Canada
Egypt	Czechia
India	Estonia
Indonesia	Finland
Iran (Islamic Republi	France
Kuwait	Germany
Malaysia	Greece
Mexico	Hungary
Morocco	Iceland
Oman	Ireland
Pakistan	Israel
Peru	Italy
Philippines	Japan
Puerto Rico	Latvia
Qatar	Lithuania
Saudi Arabia	Malta
Sierra Leone	Netherlands (Kingdom
Singapore	New Zealand
South Africa	Norway
Thailand	Poland
Tunisia	Portugal
TÃ¼rkiye	Republic of Korea
United Arab Emirates	Republic of Moldova
Uzbekistan	Romania
Venezuela (Bolivarian	Russian Federation
Viet Nam	Serbia
	Slovakia
	Spain
	Sweden
	Switzerland
	Ukraine
	United Kingdom of Gre
	United States of Amer