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THE INFLUENCE OF ARTIFICIAL INTELLIGENCE ON ECONOMIC INEQUALITY IN THE CONTEXT OF INTERNATIONAL TRADE: EVIDENCE FROM THE MIDDLE EAST

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Abstract

This study aimed to investigate the impact of artificial intelligence (AI) on a sample of three countries in the Middle East during the period from 2010 to 2023. Using panel data and multiple log-linear and linear regression models and the fixed effects model, this study reported the following findings: (1) AI investments had a positive and significant impact on international trade. (2) AI investments had a positive impact on income distribution through international trade channels. (3) AI investments created structural shifts in production and employment by driving the momentum of production and, hence, employment, from the agriculture and industry sectors to the services and high-tech services sectors. (4) AI investments had a negative impact on the employment share in the agriculture and industry sectors but a positive impact on the services sector. Accordingly, this study offers important recommendations for policymakers and

researchers. The limitations of this study call for future research to investigate the influence of adoption of AI on structural shifts in the subsectors of all sectors. Furthermore, current global data on AI and AI-related variables are limited to a few variables and years; therefore, global research is needed to establish accurate and comprehensive AI databases.
Keywords: International Trade; Middle East; Employment and Structural Shifts; Artificial Intelligence and Income Inequality; Log-Linear Regression and Fixed Effects

INTRODUCTION

Artificial intelligence (AI) is a key player in reshaping current and foreseeable future economies and is considered the latest wave in the long process of automation (Gordon, 2016). The intensity of AI capabilities in the global economy surpasses that of human capabilities in several economic subsectors and activities, such as object categorization, data analytics, natural language processing, recommendations, intelligent data retrieval, complex predictions, and forecasting. While some consider AI a continuation of the long process of automation (Gordon, 2016), others argue that AI is not only a continuation of the long process of automation but also the culmination of technological progress reshaping a new course of history that would be described as a new and “final invention” (Barrat, 2013).

However, several studies showed different results for the impact of AI on economic inequality. While some researchers argue that AI has a positive influence on the total factor productivity and national incomes (McKinsey Global Institute, 2021), others (Russell & Norvig, 2009) argue that AI has both fascinated and frightened humanity.

AI may impact socio-economic welfare of nations through its various economic channels and aspects, such as economic development (Tang et al., 2024); economic growth (Philippe et al., 2017) and (Solos & Leonard, 2022); income inequality and unemployment (Korinek and Stiglitz, 2019) and (Cornelli et al., 2023); labor market (Maria et al., 2025), (Caragnano, 2024), (Zhou et al, 2025), and (Salari et al, 2025); output and inflation (Aldasoro et al., 2024); international trade (Meltzer, 2023) and (Ozturk, 2024); investment (Faheemu Ullah, 2024) and (Onyenahazi and Antwi, 2024); human capital (Pradeep and Karunakaran, 2024); capital (Drydakis, 2024); and budgeting and government decision-making (Valle-Cruz et al., 2022).

The impact of AI on income inequality is one of the most debated topics in economics. Adoption of AI in the overall economy may have different implications.

This study aimed to investigate the impact of AI on economic inequality. Specifically, this study attempted to identify and assess the impact of AI on income inequality and employment after controlling for the effect of international trade in a sample of three countries in the Middle

East: Jordan, Saudi Arabia, and Turkey. To the best of our knowledge, these countries have not been studied previously.

The remainder of this paper is organized as follows. Section II presents the performance of global and sample countries with respect to AI capacity. Section III states the theoretical framework and presents a literature review. Section IV discusses the methodology and empirical model. Section V presents data, empirical findings, and discussion. Section VI concludes the paper and provides recommendations.

PERFORMANCE OF GLOBAL AND SAMPLE COUNTRIES WITH RESPECT TO AI CAPACITY

The Global AI Index (GAII) ranks countries based on their AI capacity[1]. The ranks range from 1 (top) to 83 (bottom), and the number of countries included in the GAII is 83. Table 1 shows the top ten countries based on AI capacity, with the United States and China leading the world as of September 2024. It should be noted that the GAII covers 83 countries.

Table 1: Global AI Index – Top 10 countries in AI Capacity (as of September 2024)

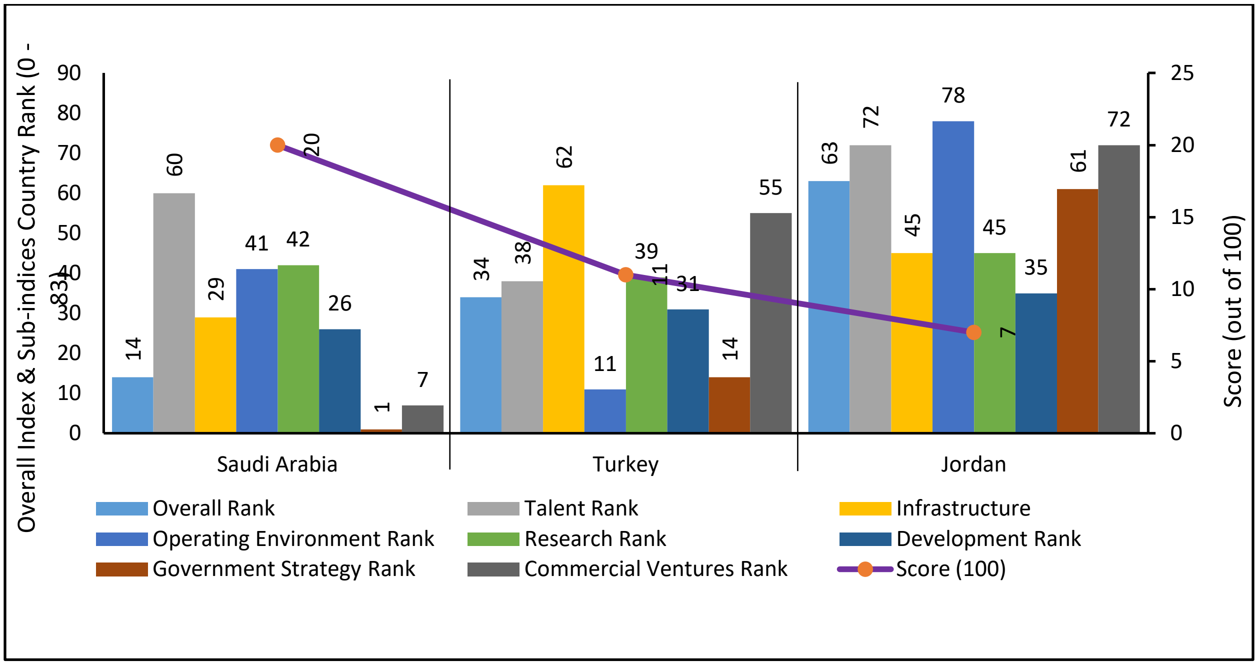
Country	**Overall Rank**	**Talent**	**Infrastructure**	**Operating Environment**	**Research**	**Development**	**Government Strategy**	**Commercial Ventures**
USA	1	1	1	2	1	1	2	1
China	2	9	2	21	2	2	5	2
Singapore	3	6	3	48	3	5	10	4
UK	4	4	17	4	4	16	7	5
France	5	10	14	19	6	4	9	8
S. Korea	6	13	6	35	13	3	4	12
Germany	7	3	13	8	8	11	8	9
Canada	8	8	18	16	9	10	3	6
India	9	2	68	3	14	13	11	13
Japan	10	23	5	53	20	14	12	14

Source: Global AI Index (September 2024), Tortoise Media: https://www.tortoisemedia.com, Date Retrieved: 20/04/2025.

[1] GAII is constructed and published by Tortoise Media (https://www.tortoisemedia.com). GAII is a measure for AI capacity constructed based on 122 sub-indicators, covering 83 countries. The GAII methodology report can be obtained from Tortoise Media website.

Regarding the sample countries in this study, that is, Jordan, Saudi Arabia, and Turkey, their ranks in the GAII are 63, 14, and 34, respectively, as shown in Figure 1. The overall score is out of 100 (the top or best performance with respect to AI capacity), and the minimum score indicates weak performance with respect to AI capacity. Saudi Arabia is taking the lead worldwide with a score of 100 out of 100 in the sub-index "government strategy," boosted mainly by government spending on AI strategy with respect to AI capacity, whereas Jordan and Turkey scored very low in the sub-index "government spending score," with scores of zero and 5.1 out of 100, respectively.

Figure 1: Global AI Capacity Index for Jordan, Saudi Arabia, and Turkey (as of September 2024)



Source: Global AI Index (September 2024), Tortoise Media: https://www.tortoisemedia.com, Date Retrieved: 20/04/2025

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Various mechanisms and possibilities exist for the effects of AI on the global economy. One possibility is that adoption of AI may lead to business growth, higher efficiency, better quality, and cost-effectiveness in various sectors and subsectors of the economy (Sadat, 2023), but this is beyond the scope of this study.

The second possibility, which is debatable in the economic literature, is that adoption of AI may replace human labor with machines and high-tech machines, leading to higher unemployment in the economy. This means that AI may have a negative impact on the aggregate employment level (Cornelli et al., 2023), which is called technological unemployment

(Korinek and Stiglitz, 2017). Considering the effect of AI on employment in China, Shen and Zhang (2024) stated that the introduction and installation of AI technologies, as represented by industrial robots in Chinese enterprises, has increased the number of jobs.

The third possibility for the economic impact of AI is its effect on income inequality. The effect of AI on income inequality depends mainly on whether the adopted AI tools and technologies are skill-substituting or skill-complementary and on the nature of production activities in the economic sectors. In the 20th century, the rapid increase in the supply of skilled workers was accompanied by skill-complementary (rather than skill-substituting) technologies (Acemoglu, 2022) because skilled workers can apply AI tools, such as program developers, computer programmers, data scientists, and many other professionals. In other words, the demand for skilled labor increases as technology advances and adoption of AI tools increases, leading to increase in wages and/or wage premiums for skilled workers. However, if the adopted AI tools and technologies are skill-substituting, then the demand for skilled workers decreases and wages and/or wage premiums fall, such as ChatGPT, which has easily replaced human translators. Furthermore, increase in adoption of AI promotes economic structural shifts in low-productivity service firms and traditional manufacturing firms, as well as what is today called high-tech service firms (such as AI firms), thus benefiting the high-tech services sector, owners of such firms, and workers in the services sector. Nevertheless, income in other sectors may be negatively affected (as the relative demand for labor services may decrease) or at least unaffected (Mishra et al., 2020a). Therefore, this study empirically examined the effects of these structural shifts on employment and the effects of AI on the agricultural, industrial, and services sectors.

The economic literature is rich in theoretical and empirical research on the impact of international trade on economic growth, income, employment, and income inequality (F. Al Akayleh, 2014), which is beyond the scope of this study. However, we regarded the effect of international trade as the control variable when investigating the impact of AI on income inequality and employment.

RESEARCH QUESTIONS AND HYPOTHESES

Research hypotheses should be clearly identified to build a sound research methodology. To achieve the previously stated study objectives, this study attempted to answer the following research questions:

1. Do AI investments affect international trade?
2. Do adoption and implementation of AI tools and investments affect income inequality?
3. What is the effect of AI investments on the aggregate employment level?

4. Do AI investments create economic structural shifts that, in turn, affect the sectoral employment share?

The methodological answers to the aforementioned research questions depend on testing the following research hypotheses:

1) H_{01}: AI investments do not affect international trade.
   H_{11}: AI investments affect international trade.
2) H_{02}: Adoption and implementation of AI tools and investments do not affect income inequality.
   H_{12}: Adoption and implementation of AI tools and investments affect income inequality.
3) H_{03}: AI investments do not affect the aggregate employment level.
   H_{13}: AI investments have a direct and significant effect on the aggregate employment level.
4) H_{04}: AI investments do not create economic structural shifts that affect the sectoral employment share.
   H_{14}: AI investments create economic structural shifts that affect the sectoral employment share.

RESEARCH METHODOLOGY

Model Specification

This study used econometric models to test the research hypotheses and used the following specifications:

First: International trade (TO):

$$TO_{i,t} = \beta_1 GDP_{i,t-1} + \beta_2 \left(\frac{AI_{INV}}{POP}\right)_{i,t} + \beta_3 D_{1i} + \beta_4 D_{2i} + \beta_5 D_{3i} + e_{i,t} \ldots\ldots (1)$$

Here, $TO_{i,t}$ is the Trade Openness Index measured as the total exports plus the total imports divided by the gross domestic product (GDP) for country i in time t, all in nominal terms. We employed a simple and more informative trade openness index as a proxy for international trade because it is based on real data on the main components of international trade, which are total exports ($X_{i,t}$) and total imports ($M_{i,t}$), adjusted for the size of economies measured by GDP, that is, ($TO_{i,t} = \frac{(X_{i,t}+M_{i,t})}{GDP_{i,t}}$).

$GDP_{i,t-1}$ is the GDP for country i in time $t-1$, all in nominal terms. We took the lagged values of GDP (i.e., GDP_{t-1} rather than GDP_t) to avoid an endogeneity problem that may exist because the GDP variable was a component of the dependent variable ($\text{where,} TO_{i,t} = \frac{(X_{i,t}+M_{i,t})}{GDP_{i,t}}$), where GDP was entered into regression equation (1) as a control variable, not as an explanatory variable.

$\left(\frac{AI_{INV}}{POP}\right)_{i,t}$ denotes AI investments in country i in year t divided by the population size of country i in year t (AI investments per capita) and is used as a proxy for adoption of AI tools. β_1, β_2, β_3, β_4, and β_5 are parameters or variable coefficients, and e is the error (stochastic) term.

As we used panel data (time-series and cross-sectional data), dummy variables were entered into regression equation (1) to adjust for the fixed effect (FE) reflecting country-specific characteristics[2], specified as follows.

D_{1i}, D_{2i}, and D_{3i} are dummy variables for the countries included in the analysis.

D_{1i} is a dummy variable that takes a value of 1 if the country is Jordan and zero otherwise.

D_{2i} is a dummy variable that takes a value of 1 if the country is Saudi Arabia and zero otherwise.

D_{3i} is a dummy variable that takes a value of 1 if the country is Turkey and zero otherwise.

The robustness of the regression results of equation (1) was tested based on the t-value of the regression. If the impact of AI investments on international trade was statistically significant, then the international trade openness representative (i.e., $TO_{i,t}$) was employed as a control variable to examine the effect of AI investments on income inequality, employment, and structural shifts according to the following specifications:

Second: Income inequality ($lnGini$):

$$lnGini_{i,t} = \psi_1 GDP_{i,t} + \psi_2 TO_{i,t} + \psi_3 \left(\frac{AI_{INV}}{POP}\right)_{i,t} + \psi_4 D_{1i} + \psi_5 D_{2i} + \psi_6 D_{3i} + \varepsilon_{i,t} \ldots\ldots\ldots\ldots(2)$$

Here, $lnGini_{i,t}$ denotes the natural logarithm of the Gini coefficient for country i in time t, ψ_1, ψ_2, ψ_3, ψ_4, ψ_5, and ψ_6 are regression parameters, and ε is the error (stochastic) term. The remaining symbols are as explained above in regression equation (1).

Third: Share of the aggregate employment level to population (AEP):

$$AEP_{i,t} = \gamma_1 GDP_{i,t} + \gamma_2 TO_{i,t} + \gamma_3 \left(\frac{AI_{INV}}{POP}\right)_{i,t} + \gamma_4 D_{1i} + \gamma_5 D_{2i} + \gamma_6 D_{3i} + \omega_{i,t} \ldots\ldots\ldots\ldots\ldots(3)$$

Here, $AEP_{i,t}$ denotes share of the aggregate employment to population for country i in time t, γ_1, γ_2, γ_3, γ_4, γ_5, and γ_6 are regression parameters, and ω is the error (disturbance) term. The remaining symbols are as explained above in regression equation (1).

Fourth: Employment share of the agriculture sector in aggregate employment (ESA):

$$ESA_{i,t} = \theta_1 GDP_{i,t} + \theta_2 TO_{i,t} + \theta_3 \left(\frac{AI_{INV}}{POP}\right)_{i,t} + \theta_4 D_{1i} + \theta_5 D_{2i} + \theta_6 D_{3i} + \delta_{i,t} \ldots\ldots\ldots(4)$$

[2] See Section V for more details about the rationale for selecting the sample countries, which are Jordan, Saudi Arabia, and Turkey.

Here, $ESA_{i,t}$ denotes the employment share in the agricultural sector in aggregate employment for country i in time t, θ_1, $\theta_2, \theta_3, \theta_4, \theta_5$, and θ_6 are regression parameters, and δ is the error (disturbance) term.

Fifth: Employment share of the industry sector in aggregate employment (ESI):

$ESI_{i,t} = \lambda_1 GDP_{i,t} + \lambda_2 TO_{i,t} + \lambda_3 \left(\frac{AI_{INV}}{POP}\right)_{i,t} + \lambda_4 D_{1i} + \lambda D_{2i} + \lambda_6 D_{3i} + \eta_{i,t}$…………(5)

Here, $ESA_{i,t}$ denotes the employment share of the industry sector in aggregate employment for country i in time t, λ_1, $\lambda_2, \lambda_3, \lambda_4, \lambda_5$, and λ_6 are regression parameters, and η is the error (disturbance) term.

Sixth: Employment share of the services sector in aggregate employment (ESS):

$ESS_{i,t} = \mu_1 GDP_{i,t} + \mu_2 TO_{i,t} + \mu_3 \left(\frac{AI_{INV}}{POP}\right)_{i,t} + \mu_4 D_{1i} + \mu_5 D_{2i} + \mu_6 D_{3i} + \varphi_{i,t}$……………(6)

Here, $ESS_{i,t}$ denotes employment share of the services sector in aggregate employment for country i in time t, μ_1, $\mu_2, \mu_3, \mu_4, \mu_5$, and μ_6 are regression parameters, and φ is the error (disturbance) term.

THE DATA

The econometric specifications identified in the previous section require accurate, reliable, and diverse data. This study was conducted in three countries: Jordan, Saudi Arabia, and Turkey. These three countries were selected for several reasons. First, they are the most economically and geopolitically stable countries in the Middle East. Second, they represent a random sample of countries in the Middle East, including oil- and non-oil-producing economies, a country in G20-Group 1 (Saudi Arabia), a country in G20-Group 2 (Turkey), and a small, open economy (Jordan). Despite the rationale behind this selection, more comprehensive studies should include a wider range of regional and/or global regions.

We obtained data for nominal gross domestic product (GDP), exports (X), and imports (M) from the United Nations Conference on Trade and Development (UNCTAD) – Statistics Center. We used GDP as the control variable in the regression models and computed a proxy for international trade performance, that is, the trade openness index. We obtained data for AI investments from the OECD.AI (2025) and population sizes from the World Bank Group – World Bank Databases. Moreover, we collected data for the Gini coefficient from the UNU-WIDER, World Income Inequality Database (WIID), Version 28 November 2023. We obtained data for the share of aggregate employment to population and data for the employment share in the agriculture, industry, and services sectors from the International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT.

This study covered the period from 2010 to 2023 for the three selected countries. Table 2 summarizes the descriptive statistics of the collected dataset. The rationale behind the selections of particular data time series (2010 – 2023) is that data on AI investments for the sample countries are available only from the year 2010 to the year 2023.

Table 2: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Observations
$GDP_{i,t}$	562,761.3	389,891.6	27,134.0	1,118,253.0	42
$GDP_{i,t-1}$	535,767.8	372,583.6	24,537.0	1,108,572	42
$lnGini_{i,t}$	3.70	0.08	3.54	3.80	42
$AEP_{i,t}$	44.00	9.16	31.00	63.93	42
$ESA_{i,t}$	9.23	7.78	2.70	24.20	42
$ESI_{i,t}$	23.39	3.39	16.30	27.90	42
$ESS_{i,t}$	67.38	10.48	49.38	80.82	42
D1	0.33	0.48	0.00	1.00	42
D2	0.33	0.48	0.00	1.00	42
D3	0.33	0.48	0.00	1.00	42
AI_INV_POP	3.0657	7.0858	0.0045	28.2563	42
$TO_{i,t}$	0.7499	0.2090	0.4669	1.1870	42

Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT; author's calculations. For a few missing data, the averages for the previous and next 3 years were taken as proxies to the missing data, and by examining the results, this mechanism did not cause any significant changes in the results.

EMPIRICAL FINDINGS AND DISCUSSION

Six regression models were used to analyze the six dependent variables. The dependent variables were international trade (TO), income inequality (Gini coefficient), aggregate employment share (AES), employment share of the agriculture sector (ESA), employment share of the industry sector (ESI), and employment share of the services sector (ESS).

Using the fixed effects regression models (FEM) and the control variables specified in the previous section, we reached the following results.

International trade

Table 3 summarizes the FEM regression results that show how international trade (TO) varies in response to changes in AI investments.

Table 3: Regression results – the impact of AI investments on international trade

Dependent Variable: International Trade ($TO_{i,t}$)						
Independent Variables	Variable Type	Coefficient	t-value	p-value	Adjusted-R^2	Significance F
AI investments	Explanatory	0.005	1.80	0.05	0.95	0.00
GDP_{t-1}	Control	-4.01	-2.20	0.03		
D_1 (FE)	Dummy (Jordan)	0.99	30.59	0.00		
D_2 (FE)	Dummy (Saudi Arabia)	0.97	7.04	0.00		
D_3 (FE)	Dummy (Turkey)	0.89	5.81	0.00		

Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; author's calculations.

For multiple regression models, as in our study, the adjusted-R^2 was considered to test the whole mode. The adjusted-R^2, as shown in Table 3, is statistically significant, which indicates that our regression model in equation (1) represents goodness of fit, where 95 percent of the variation in the international trade variable ($TO_{i,t}$) is attributed to the list of independent variables entered in equation (1).

The analysis target variable was the effect of AI investments on international trade. The coefficient of AI investments per capita was 0.005 and was statistically significant at the 90 percent confidence level. This finding indicates that a 1-monetary-unit increase in AI investments results in 0.005 monetary units in international trade, and vice versa. It is worth mentioning that trade openness was increasing even before growth in AI adoption. These results showed that AI investments have facilitated and paved the way for faster international trade.

The regression control variable was the initial (lagged) value of gross domestic product (GDP_{t-1}), and its coefficient was -4.01 and was statistically significant at the 95 percent confidence level. This result is consistent with the econometric theory regarding the lagged or initial values of the components of the dependent variable (Keele and Kelly, 2005). Fixed effects (FE) variable coefficients, that is, the coefficients of D_1, D_2, and D_3, were all statistically significant at the 99 percent confidence level and their value was relatively high. This finding supports use of the fixed effects model (FEM) in our regression equation (1).

Income inequality

Table 4 summarizes the regression results for the impact of AI investments on income inequality, for which the Gini coefficient was employed as a proxy. The Gini coefficient was constructed with a value between zero and 1.00, where a Gini coefficient of 0.00 indicated perfect equality and a Gini coefficient of 1.00 indicated maximal inequality. That is, the higher the Gini coefficient, the higher (lower) the level of income inequality (income equality), and vice versa.

Table 4: Regression results – the impact of AI investments on income inequality

Dependent Variable: income inequality – lnGini coefficient ($lnGini_{i,t}$)						
Independent Variables	Variable Type	Coefficient	t-value	p-value	Adjusted-R^2	Significance F
AI investments	Explanatory	-0.001	-1.02	0.30	0.97	0.00
International Trade	Explanatory	0.14	2.34	0.02		
GDP_t	Control	0.00	3.6	0.00		
D_1 (FE)	Dummy (Jordan)	3.55	58.58	0.00		
D_2 (FE)	Dummy (Saudi Arabia)	3.31	40.28	0.00		
D_3 (FE)	Dummy (Turkey)	3.47	42.68	0.00		

Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; author's calculations.

The coefficient of AI investments per capita was -0.001 but was statistically insignificant, meaning that as AI investments per capita increased, income inequality (InGini coefficient) decreased, and vice versa. In other words, AI investments per capita seem to have a positive impact on income redistribution in the sample countries, but with a statistically insignificant level where the t-value of AI investments per capita is in the acceptance region of the null hypothesis. This indicates that we accept the null hypothesis "H_{02}: Adoption and implementation of AI tools and investments do not affect income inequality" and reject the alternative hypothesis "H_{12}: Adoption and implementation of AI tools and investments do affect income inequality."

The regression control variable in equation (2) is the nominal gross domestic product (GDP_t). Table 4 shows that the GDP_t coefficient has a very low positive value (0.0000003) but is statistically significant at the 0.99 confidence level, consistent with the theoretical statement that GDP has a positive effect on income equality because the spillovers and positive externalities of

GDP growth should positively affect the income of all factors of production if they pay the value of their marginal productivity in the absence of corruption, nepotism, and favoritism.

Similar to the findings for the dummy variables in equation (1), all the coefficients of the dummy variables in equation (2) have relatively high values and are statistically significant at the 99 percent confidence level, which again supports the use of the FEM.

Aggregate Employment

The representative for aggregate employment is the share of aggregate employment to population ($\mathrm{AEP}_{\mathrm{i,t}}$). Table 5 presents the regression results for equation (3). The regression model of equation (3) represents goodness of fit, and the regression results show that 97% of the variation in the dependent variable ($\mathrm{AEP}_{\mathrm{i,t}}$) is attributed to the variation in the variables of the model specified in equation (3) and Table 5.

Table 5: Regression results – the impact of AI investments per capita on aggregate employment

Dependent Variable: Share of aggregate employment to population $(AEP_{i,t})$						
Independent Variables	Variable Type	Coefficient	t-value	p-value	Adjusted-R^2	Significance F
AI investments	Explanatory	0.02	0.43	0.67	0.97	0.00
International Trade	Explanatory	0.90	0.38	0.71		
GDP_t	Control	1.60	5.27	0.00		
D_1 (FE)	Dummy (Jordan)	30.97	12.94	0.00		
D_2 (FE)	Dummy (Saudi Arabia)	40.54	12.48	0.00		
D_3 (FE)	Dummy (Turkey)	31.38	9.76	0.00		

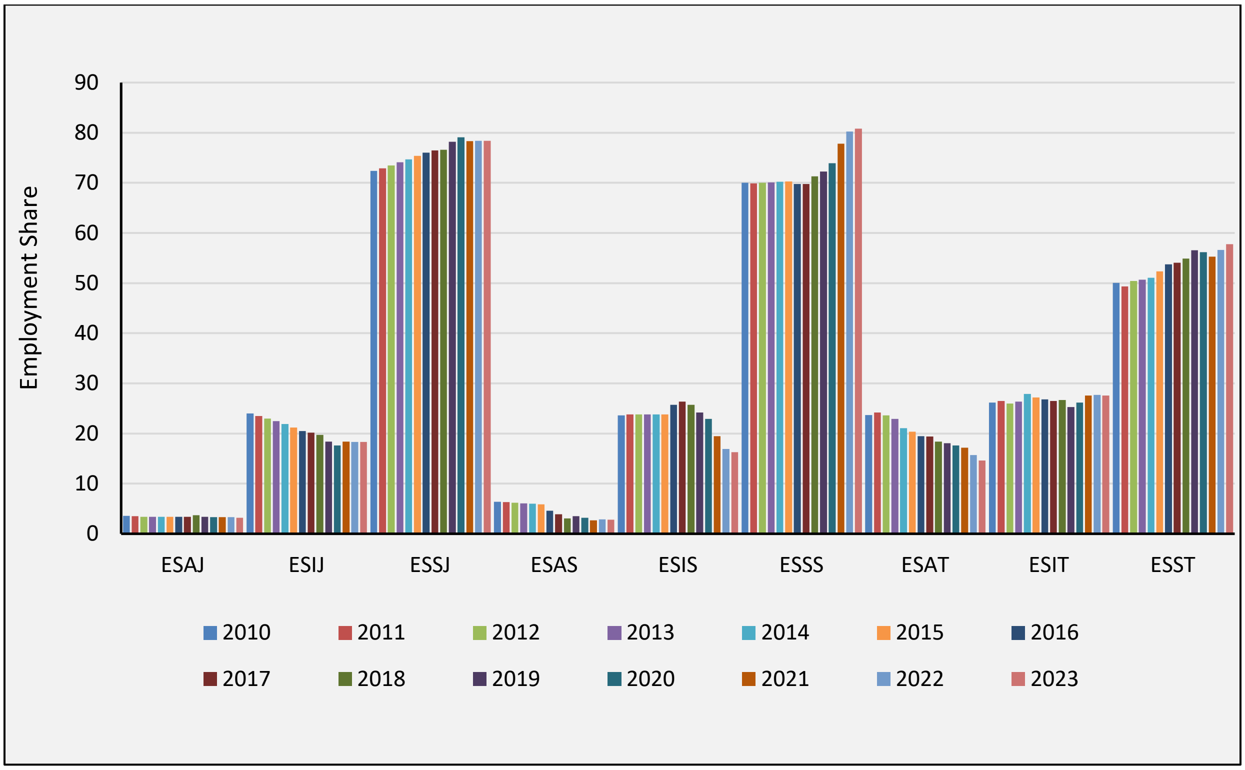
Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT; author's calculations.

AI investments per capita have a statistically insignificant positive effect on the aggregate employment share. Although insignificant, this positive effect on aggregate (total) employment may be due to the strong and positive effect of AI investments on employment in the services sector because it has the largest employment share (67.4% on average) compared to the industrial and agricultural sectors in the sample countries (and may be worldwide). However, the insignificance coefficient of AI investments in Table 5 may be due to the accuracy of data or shortness in time-series data.

Employment share of the agriculture sector in aggregate employment

The employment share of the agricultural sector in aggregate employment (hereafter referred to as the employment share of agriculture) is the total number of employed persons in the agricultural sector (formal and informal) divided by the total employment in the country. Figure 2 illustrates the levels and trends of the sectoral employment share for the sample countries during the period 2010-2023.

Figure 2: Employment share by sector (% of total employment)



Source: ILO Modelled Estimates (ILOEST) database, ILOSTAT , Date Retreived: 14/04/2025

The employment share of agriculture in Jordan (ESAJ) is very low, and it continuously decreased from 3.6 percent in 2010 to 3.2 percent in 2023 (a drop of -11% between 2010 and 2023). This is very similar to the case of Saudi Arabian economy, but with a larger fall than that of Jordan, where the employment share of agriculture in Saudi Arabia (ESAS) declined from a high of 6.4 percent in 2010 to a low of 2.8 percent in 2023 (a drop of -56% between 2010 and 2023). In Turkey, ESAT also experienced a continuous decline, but the ESAT level was relatively high and declined from 23.7 percent in 2010 to 14.6 percent in 2023 (a drop of -38% between 2010 and 2023).

The regression results for the effect of AI investments on the employment share of agriculture are outlined in Table 6. The value of the adjusted-R^2 is 0.96 and is statistically significant at 99 percent, which indicates that the regression specification model for the effect of AI investments on the employment share of agriculture represents goodness of fit of the model. In other words, 96% of the variation in the employment share of agriculture is attributed to the set of independent variables listed in Table 6 and equation (4).

Table 6: Regression results – the impact of AI investments per capita on employment share of agriculture (ESA)

Dependent Variable: Employment share of agriculture in aggregate employment $(ESA_{i,t})$

Independent Variables	Variable Type	Coefficient	t-value	p-value	Adjusted-R^2	Significance F
AI investments	Explanatory	-0.20	-4.90	0.00	0.96	0.00
International Trade	Explanatory	0.73	0.36	0.28		
GDP_t	Control	-0.000001	-0.38	0.71		
D_1 (FE)	Dummy (Jordan)	2.94	1.45	0.15		
D_2 (FE)	Dummy (Saudi Arabia)	5.23	1.90	0.06		
D_3 (FE)	Dummy (Turkey)	21.30	7.82	0.00		

Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT; author's calculations.

An important but not surprising result is the effect of AI adoption on the employment share of agriculture. The coefficient of "AI investments" is -0.20 and is statistically significant at the 99 percent confidence level. This finding suggests that AI investments have a negative and robust impact on the employment share of agriculture, indicating that a 100 percent increase in AI investments results in a 2 percent decrease in the employment share of agriculture. The effect of AI adoption, as presented by AI investments, on structural shifts is evident in this study. As AI adoption intensified with increasing AI investments, the employment share of agriculture decreased, and vice versa. This is due to the shift in demand for skilled labor from the traditional sectors to the high-tech services sectors, resulting in decreased employment in the traditional sectors, such as agriculture.

The effect of international trade on the employment share of agriculture for the sample countries is positive but weak, where the international trade coefficient is 0.73 and is statistically insignificant at the 95 percent level. The use of the FEM is valid and important because the value of the three dummy variables is high and statistically significant.

Employment share of the industry sector in aggregate employment

The employment share of the industry sector in aggregate employment (hereafter referred to as the employment share of industry) is the total number of employed persons in the industrial sector (formal and informal) divided by the total employment in the country.

Figure 2 shows that the employment share of industry in the three sample countries is greater than that of agriculture but smaller than that of the services sector. The employment share of industry in Jordan (ESIJ) decreased throughout the study period from 24 percent in 2010 to 18.3 percent in 2023 (a drop of -24% between 2010 and 2023). The employment share of industry in Saudi Arabia (ESIS) does not show a systematic trend, but it has been fluctuating over time. Generally, it showed a downward trend, decreasing from 23.6 percent in 2010 to 16.3 percent in 2023 (i.e., a drop of -30% between 2010 and 2023). The trend of the employment share of industry in Turkey (ESIT) is relatively stable, but the level of share is much greater in Turkey than in Jordan and Saudi Arabia, where ESIT fluctuated between 25.4% and 27.9%.

Table 7: Regression results – the impact of AI investments per capita on employment share of industry (ESI)

Dependent Variable: Employment share of industry in aggregate employment $(ESI_{i,t})$						
Independent Variables	Variable Type	Coefficient	t-value	p-value	Adjusted-R^2	Significance F
AI investments	Explanatory	-0.01	-0.23	0.82	0.97	0.00
International Trade	Explanatory	6.78	2.68	0.01		
GDP_t	Control	-0.000008	-2.63	0.01		
D_1 (FE)	Dummy (Jordan)	14.24	5.58	0.00		
D_2 (FE)	Dummy (Saudi Arabia)	24.92	7.19	0.00		
D_3 (FE)	Dummy (Turkey)	30.18	8.80	0.00		

Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT; author's calculations.

The effect of AI investments on the employment share of industry $(\mathrm{ESI}_{i,t})$ is summarized in Table 7. The value of the determination coefficient, adjusted-R^2, is 0.97 and is statistically significant at the 0.01 significance level, indicating that the model specification in equation (5) and Table 7 represents goodness of fit and that 97 percent of the variation in the employment share of industry is attributed to the dependent variables specified in the estimated regression model.

Similar to the employment share of agriculture, the employment share of industry was subject to structural shifts in production and, hence, the demand for employment due to adoption of AI tools presented by AI investments. The coefficient of "AI investments" was -0.01, indicating that a 100 percent increase in AI investments leads to a structural shift in production from the traditional sectors to the high-tech services sectors and consequently a decrease in the employment share of industry by 1 percent. However, the regression results were not statistically significant. Nevertheless, by rerunning the regression for time-series data only for each country independently for the same study period, we found that the coefficient of "AI investments" had negative signs and was statistically significant for both Jordan and Saudi Arabia, indicating that AI investments in Jordan and Saudi Arabia created significant structural shifts in production and employment from the traditional sectors (i.e., agriculture and industry) to the services and high-tech services sectors at the expense of agricultural and industrial production and employment (Table 8). This is not the same for Turkey because when we reran regression for time series data using the same study period (2010-2023) for Turkey only, we found that the coefficient of "AI investments" in relation to employment in the industry sector was positive but statistically insignificant (Table 8). This means that AI investments did not create significant structural shifts in the Turkish economy. Since AI investments per capita in Turkey are at least three times greater than those in Jordan and Saudi Arabia, the total effect of AI investments on the employment share of industry is driven by Turkey's AI investments per capita, thus making the coefficient of "AI investments per capita" insignificant.

Table 8: Time series regression analysis results for the sample countries independently of each other.

		Jordan		
Independent Variables	Coefficient	t-value	p-value	Adjusted-R^2
Intercept	23.64	22.34	0.00	0.99
AI investments	-0.48	-4.66	0.00	
GDP_t	-0.0002	-8.97	0.00	
TO_t	4.25	-7.27	0.00	
		Saudi Arabia		
Independent Variables	Coefficient	t-value	p-value	Adjusted-R^2
Intercept	34.95	13.97	0.00	0.92
AI investments	-0.96	-7.14	0.34	
GDP_t	-3E-06	-0.99	0.00	
TO_t	-11.58	-4.57	0.00	

Table 8…

Turkey				
Independent Variables	Coefficient	t-value	p-value	Adjusted-R^2
Intercept	25.21	7.14	0	0.33
AI investments	0.04	1.1	0.3	
GDP_t	0.000002	0.92	0.38	
TO_t	-0.97	-0.26	0.8	

United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT; author's calculations.

Employment share of the services sector in aggregate employment

The employment share of the services sector in aggregate employment (ESS) (hereafter referred to as the employment share of services) is the total number of employed persons in the services sector (formal and informal) divided by the total employment in the country.

In contrast to the employment shares of agriculture (ESAJ) and industry (ESIJ) in Jordan, both of which showed a downward trend throughout the study period, the employment share of services in Jordan (ESSJ) showed an increasing trend during the same period because of structural shifts that were partly due to AI adoption (Figure 2). The employment share of services in Jordan (where the period average was 76.0%) was greater than that in Saudi Arabia (73.0%) and Turkey (54.0%). The employment share of services in Saudi Arabia and Turkey increased almost by the same percentage (15.4% for each) between 2010 and 2023.

Table 9 shows the estimated impact of AI investments per capita on the employment share of services. The regression equation (6) and the overall regression model showed that 97 percent of the variation in the employment share of services is explained by the list of independent variables shown in Table 9, where the determination coefficient (adjusted-R^2) is 0.97 and the overall regression model represents goodness of fit.

Table 9: Regression results: the impact of AI investments per capita on employment share of services (ESS)

Dependent Variable: Employment share of services sector in aggregate employment $(ESS_{i,t})$						
Independent Variables	Variable Type	Coefficient	t-value	p-value	Adjusted-R^2	Significance F
AI investments	Explanatory	0.21	3.35	0.00	0.97	0.00
International Trade	Explanatory	-7.63	-2.43	0.02		
GDP_t	Control	0.00001	2.34	0.02		
D_1 (FE)	Dummy (Jordan)	82.91	26.25	0.00		

Table 9…

D_2 (FE)	Dummy (Saudi Arabia)	70.02	16.34	0.00
D_3 (FE)	Dummy (Turkey)	48.69	11.48	0.00

Source: United Nations Conference on Trade and Development (UNCTAD) – Statistics Center; OECD.AI (2025); World Bank Group – World Bank Databases; UNU-WIDER, World Income Inequality Database (WIID). Version 28 November 2023; International Labor Organization (ILO) - Modelled Estimates (ILOEST) database, ILOSTAT; author's calculations.

The findings summarized in Table 9 are interesting and consistent with the theoretical statements and our previous findings on the employment share of agriculture and industry. The findings of the regression analysis of the employment share of agriculture and industry showed that AI investments per capita had a negative effect on both the employment shares of agriculture and industry, indicating structural shifts in production and employment from the traditional sectors (i.e., agriculture and industry) to the services and high-tech services sectors. This argument is supported by our finding as shown in Table 9, where the coefficient of "AI investments per capita" is 0.21 and is statistically significant at the 1 percent significance level. This indicates that AI adoption created structural shifts in production from the industrial and agricultural sectors to the services and high-tech services sectors, leading to increase in the employment share of services at the expense of the employment share of agriculture and industry. This finding indicates that a 100 percent increase in AI investments led to a 21 percent increase in the employment share of services.

International trade, as presented by the trade openness index (TO), negatively affected the employment share of services. This may also be attributed to the structural shifts in production caused by "AI investments." The control variable (GDP_t) had positive and statistically significant values. The test for using Fixed Effects' dummy variables (D_1, D_2, and D_3) is now complete for the whole models used in this study, where the coefficients of the dummy variables had relatively high values at the 0.99 confidence level.

CONCLUDING REMARKS AND RECOMMENDATIONS

The adoption of AI tools is increasing rapidly worldwide. There is a huge debate on the pros and cons of adopting AI tools in all aspects of life. This study examined the influence of AI on income inequality, employment, and international trade in a sample of three countries in the Middle East: Jordan, Saudi Arabia, and Turkey. Most of the effects of AI investments were explored directly, but a few were explored indirectly through other channels, specifically, the effect of AI investments on income inequality, which was depicted indirectly through the international trade channel. The study findings indicated that AI investments had a positive influence on international trade and income distribution (negative impact on Gini coefficient values). AI investments did not have a direct significant positive impact on income inequality, but an indirect impact through international trade channels. Furthermore, AI investments created structural shifts in production and, hence, employment, which resulted in higher demand for jobs in the services and high-tech services sectors (leading to higher incomes of the production factors of this sector) at the expense of employment in the traditional agricultural and industrial sectors (which may lower the incomes of production factors in the agriculture and industry sectors).

To address these effects, policymakers should develop and implement prudential policies and regulations that allow for the adoption of AI tools in all economic sectors to avoid negative externalities arising from the structural shifts caused by adoption of AI tools. To address the negative impact of structural shifts on affected workers, effective and efficient taxation can be imposed on the segments that AI favors to compensate those who might be negatively affected by replacing human labor with machines.

The limitations of this study call for future research to investigate the influence of adoption of AI on structural shifts in the subsectors of all sectors. Furthermore, except for investments, current global data on AI and AI-related variables are limited to a few years; therefore, global research is needed to establish accurate and comprehensive AI databases.

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Data Availability

The data that support the findings of this research are available from the corresponding author, F. Al Akayleh, upon reasonable request.

Declarations of Interests

This is to confirm that there are no relevant financial or non-financial competing interests to report.

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