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Estimating the True Impact of Artificial Intelligence on Labor Productivity in a Global Context

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Abstract

With the impressive growth AI and ICT have seen in the latest years, our study aims to measure the impact this development has on labor productivity, a key component of economic prosperity. We study 185 countries for the period 2005-2022, using panel data regression models to examine varying levels of economic development determining the impact of AI, ICT, and other socioeconomic and cultural factors. We find that AI and ICT positively contribute to productivity, and that higher-income countries better utilize these technologies for productivity boosts. Inequalities in the power or economic structure of a country hinders its ability to efficiently benefit from AI and ICT advancements while damaging labor productivity overall. Individualistic societies with great levels of education get the most out of the technological advancements and have overall higher productivity levels. Overall, we find that a 1% increase in AI patents translates to a 0.0678% increase in GDP per worker.

Keywords: Artificial Intelligence, Labor Productivity, Information and Communication Technologies, Economic Growth, Technological Revolution

Introduction

Within the last few decades Information and Communication Technologies' (ICT) development has been consistent and promising, especially through the rapid development of Artificial Intelligence (AI) in the most recent years: the marketplace for AI is expected to grow at a CAGR of 28.46% from 2024 to 2030, reaching $826.70 billion.

In the United States alone this market has a value of $50.16 billion out of the $184.00 billion globally. With this in mind it is fundamental to analyze not only ICT and AI's impact on global labor productivity but also for different types of countries by their development levels.

We also focus on a global perspective, trying to fill the research gaps created by studies only focusing on specific companies or scenarios, or limiting to a small number of developed countries in their studies.

Our studies addresses the following research questions:

1. How effective is AI's adoption in countries with different development levels and how does this development affect its effectiveness in boosting labor productivity levels?
2. What is the individual impact of the ICT proxies such as R&D expenditure or internet penetration on productivity and how do they help AI's adoption at being a more effective productivity booster?
3. How do our socioeconomic control variables (Education, Inequality) influence productivity and its increase with AI's adoption?
4. What is the impact of Hofstede's cultural dimensions in the relation between AI adoption and productivity increase?

In summary, the main objectives of this research are the following:

- To examine and quantify the impact of ICT and AI's adoption of labor productivity, while also accounting for different macroeconomic contexts.
- Providing evidence-based valuable information for business owners and policymakers to better use AI and ICT for economic prosperity through increased labor productivity.
- Examining the role of socioeconomic and cultural variables in the relationship between the technological variables and labor productivity to better understand how policymakers can improve their specific economic context.

By answering all these questions and research gaps our study aims to provide valuable information for both future studies and policymakers that want to estimate the impact of these variables and labor productivity growth, as well as for engaging in appropriate measures that can help a country's economy grow through the increase of labor productivity, benefitting from our approach to multiple levels of development for the countries analyzed.

Literature Review

We review the existing literature supporting ICT and AI's impact on labor productivity, as well as the relationship between productivity and our other control variables and the differentiated impact that these have based on a country's development level.

ICT's Impact on Productivity

A study by Czernich et al (2011), on broadband infrastructure and its impact on economic growth found that a 10 percentage increase in broadband penetration raised GDP growth by 0.9-1.5 percent. Likewise, another research made by Koutrompis (2009), focusing on the broadband impact on the economic growth from a simultaneous approach found a positive link between broadband infrastructure and economic growth, especially when this infrastructure is already developed in the targeted country. Another study made by Wamboye et al (2016), focusing on low-income countries from sub-Saharan Africa found that doubling the proliferation rate of fixed telephones increased productivity by 0.12-0.15 percent, while doubling the one for mobile telephones increased productivity by 0.05 percent.

Artificial Intelligence's Impact on Productivity

PwC's study (2018), found AI's influence on economic growth with the global GDP being influenced by 14% ($15.7 trillion), with China and North America having the greatest impact (GDP increase of 26.1% and 14.5% respectively).

Another research by Damioli et al (2022), found that AI adoption increased labor productivity especially in high-tech sectors with larger and more advanced companies benefitting more from AI.

Bonsay et al (2021), explored AI's influence on the productivity of four Asian countries (China, India, Japan, and Singapore) and concluded that the example of Japan of proper AI utilization and trade liberalizations can produce economic growth, increasing foreign investments, technology transfers and expanding the labor markets. Keeping up with the Asian continent, Yang et al (2022), also analyzed AI technology's impact on Taiwan's electronic industry, acknowledging potential job creation but also potential destruction of employment.

Wamba et al (2020), discovered AI's performance improvement through process optimization, automatization, information and human interaction; the study emphasizes proper integration and process reconfiguration are critical to achieve the full potential of AI. On the experimental side, the results that Noy et al (2023), achieved pointed to a productivity increase with a decrease in productivity inequality between workers, but acknowledged the limited real-life application to the job market of the skills tested in the study.

Differential Impacts Across Countries with Different Levels of Development

ICT's impact on economic growth is not uniform across all economic contexts, as Bonsay's study (2021) points out, country-specific characteristics exists that have to be taken into account that affect both ICT's and AI's impact on labor productivity and economic growth. Typically developed countries with considerable amount of existing infrastructure benefit more from these technologies.

The Influence of Socioeconomic and Cultural Factors

The influence of a country's cultural factors on economic growth and productivity are studied by Gorodnichenko & Roland (2017), and Paquin et al (2007), the former concluded that individualism is a cultural characteristic that is linked to a higher innovation and economic growth, while the latter noted that national cultural factors are crucial in understanding productivity and its influencing factors.

On the socioeconomic side, Espoir & Ngepah (2021), explored income inequality's relationship with the total factor productivity (TFP) across different South African districts (South Africa is a country with great levels of income inequality), finding a negative impact of inequality on productivity, suggesting more equal economies in terms of income could potentially present higher levels of economic growth.

Research Gaps and Contributions

As noted before, many research gaps exist deriving from a closed perspective focusing only on specific economic context and individual firms, not the whole global economic context. This study examines 185 countries for the period 2005-2022 (more recent data than most scientific papers on the subject) while also analyzing different clusters of countries by income level, offering a more global and complete perspective that other studies fail to present.

Data and Methodology

Data sources and Sample Description

We analyze 185 countries for the period 2005-2022, using for our database sources with an adequate degree of reputability and authority, for example:

We use ILO Modelled Estimates and Projections (ILOEST) for our variable proxy for labor productivity (GDP per Worker).

Our ICT database is extracted from the World Data Bank, together with the socioeconomic factor variables (Gini income inequality and the Education index).

The data regarding AI patents at a worldwide level comes from the World Intellectual Property Organization (WIPO), with data as recent as 2023.

Hofstede’s cultural variables are collected by The Culture Factor Group.

We account for different categories of countries by income levels, categorization established by the World Data Bank, consisting in low-income, lower-middle-income, higher-middle-income, and high-income countries.

Variables

Dependent Variables

Labor Productivity: GDP per Worker (GDPPW) as the total GDP per of a country divided by the number of its workers expressed in constant 2015 US$.

Independent Variables

AI: Artificial Intelligence Patents (AIPATENTS) as the total number of patents in AI screened using more general ICO classes expressed in absolute numbers.

ICT:

- Internet Penetration Rates (Internet) as individuals who have used the internet from any location in the last 3 months expressed as a percentage of population
- Mobile Cellular Subscriptions (Mobile) as subscriptions to a public mobile telephone service providing access to the Public Switched Telephone Network expressed as the average number of cellular subscriptions per 100 people.
- Secure Internet Servers (Servers) as the number of distinct and publicly trusted TLS/SSL certificates found in the Netcraft Secure Server Study expressed as the average number of secure internet servers per 1 million people.
- Fixed Telephone Subscriptions (Tel) as the sum of the active fixed telephone services and derivates expressed as the average number of fixed telephone subscriptions per 100 people.
- Research and Development Expenditures (RDE) as the gross domestic expenditures in R&D including capital and current expenditures expressed as a percentage of GDP.
- Researchers in Research and Development (ResRD) as the number of researchers engaged in Research and Development expressed as an average number of researchers in R&D per 1 million people.

Control Variables

Socioeconomic indicators:

- Gini Income Inequality Index (GINI) as the extent to which the individual income among individuals of the same economy differ from a perfectly equal distribution using the Lorenz curve and ranging from 0 to 100 points (perfect equality being represented by 0).

- Education Index (EI), being a component of the Human Capital Index (HCI) and ranging from 0 to 1 (with maximum potential reached at 1).

Hofstede's six cultural dimensions:

- Individualism (IDV).
- Power Distance (PD).
- Masculinity vs Femininity (MAS).
- Uncertainty Avoidance (UAI).
- Long Term Orientation (LTO).
- Indulgence (IND).

Methodology

Our econometric function is the following:

$$\ln(GDPPW)_{it} = \beta_0 + \beta_1 \ln(AIPATENTS)_{it} + \beta_2 ICT_{it} + \beta_3 SOCIO_{it} + \beta_4 CULTURE_i + \alpha_i + \varepsilon_{it}$$

We use panel data regression approach for our model, with the following description:

I. Ln(GDPPW) as the natural logarithm of GDP per worker for the country i in the year.

II. Ln(AIPATENTS) as the natural logarithm of AI patents for the country i in the year t.

III. ICT as the vector of Internet, Mobile, Servers, Tel, RDE, and ResRD for the country i in the year t.

IV. SOCIO as the vector of Gini Income Inequality Index (GINI) and Education Index (EI) for the country i in the year t.

V. CULTURE as the vector of Individualism (IDV), Power Distance (PD), Masculinity vs Femininity (MAS), Uncertainty Avoidance (UAI), Long Term Orientation (LTO), and Indulgence (IND) for the country i in the year t.

VI. α_i as the country-specific fixed effects.

VII. ε_{it} as the error term

Utilizing the Pooled Ordinary Least Squares (OLS), Fixed Effects (FEM), and Random Effects (REM) Models and determining the most appropriate one through the Breusch-Pagan Lagrange Multiplier (LM, choosing between pooled OLS and REM) and the Hausman (choosing between FEM and REM) tests helps us achieve more realistic and polished results for determining the real impact of Artificial Intelligence on Labor Productivity.

Results and Discussions

Descriptive Statistics

The following table will present the summary statistics of our proxy variables:

Variable	Obs	Mean	Std. Dev.	Min	Max
GDPPW	3239	28850.2	36497.48	618.82	256671.1
AIPATENTS	2556	564.0301	2975.01	0	37715
Internet	2871	40.5547	30.7116	0	100
Mobile	3063	91.5302	46.2248	0	420.8531
Servers	1993	4233.835	17594.28	0	277330.6
Tel	3033	16.9424	16.4912	0	69.3247
Gini	1235	36.6090	7.9260	23.2	64.8
RDE	1512	1.0030	1.0087	0.0104	5.56
ResRD	1190	2204.334	2089.835	5.9388	8713.594
EI	1760	0.6401	0.1775	0.18	0.943
PD	2142	66.6975	20.5309	11	100
IDV	2142	38.2353	20.8483	6	91
MAS	2142	46.7563	17.6410	5	100
UAI	2142	66.7647	21.4647	8	100
LTO	1890	41.7905	22.3477	4	100
IND	1728	46.1563	22.5465	4	100

The high standard deviation compared to the mean indicates strong variations between countries of different economic backgrounds.

Regression Results

Pooled OLS Model

The following table describes our regression results using the pooled OLS Model:

LogGDPPW	**Pooled OLS technique for panel data, multiple regressions**						
	(1’)	(2’)	(3’)	(4’)	(5’)	(6’)	(7’)
LogAIPATENTS	0.0681***						
Internet		0.0173***					
Mobile			-0.0009				
Tel				0.0120***			
LogServers					0.0464***		
LogRDE						0.3146***	
LogResRD							0.4596***
Gini	-0.0140***	-0.0036	-0.0054	-0.0019	-0.0049	0.0003	0.0106***
PD	-0.0150***	-0.0119***	-0.0142***	-0.0129***	-0.0134***	-0.0120***	-0.0101***
IDV	0.0043***	0.0081***	0.0081***	0.0067***	0.0081***	0.0043***	0.0049***
MAS	0.0029***	0.0045***	0.0048***	0.0042***	0.0049***	0.0031***	0.0032***
UAI	0.0066***	0.0041***	0.0044***	0.0012	0.0050***	0.0051***	0.0044***
LTO	0.0040***	0.0030***	0.0053***	0.0036***	0.0045***	0.0034***	0.0032***
IND	0.0147***	0.0113***	0.0147***	0.0122***	0.0138***	0.0141	0.0163***
EI	2.9866***	1.7596***	4.2023***	3.6501***	3.4764***	2.8782***	0.8201**
Constant term	7.5208***	7.1181***	6.3499***	6.6533***	6.5472***	7.3818***	5.0001***
R^2	0.8014	0.8392	0.8063	0.8211	0.8106	0.8103	0.8117
Adj R^2	0.7978	0.8368	0.8034	0.8184	0.8078	0.8070	0.8079
Obs	508	609	611	611	610	522	465

Key Takeaways

1. With a statistically significant and positive correlation, AIPATENTS presents a coefficient of 0.0681, meaning, a 1% increase in this variable will cause a 0.0678% increase in the dependent variable GDPPW. This aligns well with Damioli's findings in 2021 about AI's impact on labor productivity.

2. The variable Internet also presents a statistically significant and positive coefficient, indicating that internet penetration contributes to labor productivity growth, as well as with fixed telephones (Tel) and secure internet servers (Servers); each percentage growth in these variables results in a GDPPW percentage growth of 0.0172%, 0.0119%, 0.0462% respectively.

3. Research and Development Expenditures (together with researchers in the field) have the greatest impact on GDPPW, with a coefficient of 0.3146, meaning a 1% increase in the variables RDE and ResRD result in 0.3136% and 0.4584% increases in GDPPW.

4. Regarding the socioeconomic variables, the Gini variable presents a negative, although not statistically significant, coefficient in most cases, aligning with the findings of Espoir & Ngepah on African countries. The education index has a much more significant and positive correlation with GDPPW emphasizing the true importance of human capital on productivity.

5. Analyzing the cultural variables, we confirm Gorodnichenko & Roland's hypothesis about individualism as a characteristic that promotes productivity growth in economies with individualistic societies. Also, variables that generally promote GDPPW growth are also masculinity vs femininity, uncertainty avoidance, long-term orientation, and indulgence; while power distance has a negative impact on productivity (the more a society feels like they live in an unequal society, the less productive it is, even more so than with the Gini index).

Fixed and Random Effects Models

LogGDPPW	Fixed effects modelling versus random effects modelling, multiple regressions													
	(1'')		(2'')		(3'')		(4'')		(5'')		(6'')		(7'')	
	FEM	REM	**FEM**	REM	**FEM**	REM	**FEM**	REM	**FEM**	REM	FEM	**REM**	FEM	**REM**
LogAIPATENTS	0.0148 **	0.0159 ***												
Internet			0.0035 ***	0.0033 ***										
Mobile					0.0016 ***	0.0016 ***								
Tel							-0.0027 ***	-0.0018 ***						
LogServers									0.0204 ***	0.0187 ***				
LogRDE											0.0005	0.0076		
LogResRD													0.0946 ***	0.1086 ***
Gini	-0.0136 ***	-0.0137 ***	-0.0050 ***	-0.0057 ***	-0.0083 ***	-0.0087 ***	-0.0112 ***	-0.0112 ***	-0.0067 ***	-0.0074 ***	-0.0130 ***	-0.0128 ***	-0.0125 ***	-0.0123 ***
PD	omitted	-0.0169 ***	omitted	-0.0163 ***	omitted	-0.0156 ***	omitted	-0.0165 ***	omitted	-0.0171 ***	omitted	-0.0162 ***	omitted	-0.0155 ***
IDV	omitted	0.0124 ***	omitted	0.0183 ***	omitted	0.0169 ***	omitted	0.0168 ***	omitted	0.0190 ***	omitted	0.0110 ***	omitted	0.0107 ***
MAS	omitted	0.0037	omitted	0.0052 *	omitted	0.0058 *	omitted	0.0059 *	omitted	0.0052 *	omitted	0.0029	omitted	0.0033
UAI	omitted	0.0061 **	omitted	0.0090 ***	omitted	0.0079 ***	omitted	0.0088 ***	omitted	0.0096 ***	omitted	0.0062 **	omitted	0.0071 **
LTO	omitted	0.0041	omitted	0.0035	omitted	0.0024	omitted	0.0031	omitted	0.0041	omitted	0.0072 **	omitted	0.0047
IND	omitted	0.0118 ***	omitted	0.0089 ***	omitted	0.0095 ***	omitted	0.0101 ***	omitted	0.0091 ***	omitted	0.0164 ***	omitted	0.0142 ***
EI	1.9428 ***	1.9744 ***	1.1764 ***	1.4122 ***	2.1117 ***	2.2447 ***	2.0339 ***	2.2886 ***	1.0267 ***	1.2998 ***	2.0699 ***	2.1213 ***	1.5658 ***	1.5739 ***
Constant term	9.3388 ***	8.3251 ***	9.2847 ***	7.8207 ***	8.7058 ***	7.4296 ***	9.1298 ***	7.6355 ***	9.5548 ***	7.9969 ***	9.2009 ***	7.9316 ***	8.9761 ***	7.6516 ***
within R^2	0.3983	0.3983	0.5067	0.5054	0.4338	0.4336	0.4053	0.4030	0.5088	0.5068	0.3277	0.3273	0.4246	0.4241
between R^2	0.5658	0.7899	0.7348	0.7773	0.6596	0.7917	0.6240	0.7837	0.6929	0.7581	0.5197	0.8114	0.6097	0.7879
overall R^2	0.5135	0.7799	0.6493	0.7832	0.5400	0.7811	0.4825	0.7752	0.5824	0.7671	0.4168	0.7654	0.4862	0.7571
Obs	508	508	609	609	611	611	611	611	610	610	522	522	465	465
Panel diagnosis tests	Hausman test probability: 0.0300		Hausman test probability: 0.0000		Hausman test probability: 0.0000		Hausman test probability: 0.0000		Hausman test probability: 0.0000		Hausman test probability (general): 0.0517		Hausman test probability (general): 0.1061	
	Breusch-Pagan LM test p: 0.0000		Breusch-Pagan LM test p: 0.0000		Breusch-Pagan LM test p: 0.0000		Breusch-Pagan LM test p: 0.0000		Breusch-Pagan LM test p: 0.0000		Breusch-Pagan LM test p: 0.0000		Breusch-Pagan LM test p: 0.0000	

Fixed Effects is the preferred model for most variables over Random Effects, aside from Research and Development Expenditures and researchers in the field, underlining the importance of both country-specific factors and overall trends when assessing the impact of these variables on GDPPW. This hypothesis is confirmed by the Hausman test ($p < 0.05$ confirms Fixed Effects' superiority).

Between Random Effects and pooled OLS, Breusch-Pagan LM test strongly indicates Random Effects' superiority (with p values of 0), suggesting the presence of significant individual or time effects in the database, making the pooled OLS method inappropriate.
Our main findings include:

1. AIPATENTS still presented a significant but smaller coefficient than in pooled OLS, pointing that although there are specific factors that influence GDPPW, AI still has a positive impact on labor productivity.
2. ICT variables conserved their positive and even more significant coefficients when accounting for country-specific factors.
3. Gini income inequality variable reinforced its negative impact this time with significant coefficients for all of the variables. Education Index also remained positive and statistically significant.

Discussions

Our study's findings reinforce our thesis that Artificial Intelligence may contribute positively to labor productivity, although not homogeneously across all country income groups, those of higher levels of income utilizing AI more effectively to achieve productivity boosts, this phenomenon occurs for a number of reasons:

- High-income countries may be able to better and more effectively utilize AI and ICT technologies for labor productivity growth, countries presenting better institutions, wider markets, an already productive and competitive economy, critical mass of digital infrastructure existing (as noted by Koutroumpis in 2009), etc.
- As noted by Damioli in 2021, high-income countries usually present a different sectorial composition, with a smaller part of the economy representing the primary and secondary sector, which can benefit less from AI and ICT technologies than the tertiary sector.

The Gini Income Inequality Index presents a negative relationship with labor productivity, suggesting more egalitarian societies can better take advantage of AI and ICT developments, this also holds true for power distribution, as societies with a low Power Distance value are linked to higher productivity levels. Individualism also presents an influence on labor productivity, but unlike Power Distance, its influence is a positive one, this is because, as specified by Gorodnichenko and Roland in 2017, individualism and creativity in a society enhance innovation and productivity growth.

Robustness Checks

To verify the robustness of our findings and main hypothesis, we have to run some robustness checks:

- Regional subsampling: analyzing different subsamples of countries based on their income category by the World Data Bank (from low to high income countries), we still find a positive and statistically significant AI influence on productivity across all income groups, although with notable differences between them as hypothesized by Bonsai in 2021.

Limitations

We must acknowledge some of the limitations of our study that may influence the generalizability of our results, as such:

1. Data: there is not a great amount of data for some of the variables and countries and it's more difficult to find the most recent one up until 2023.
2. AI and Productivity proxies: another difficult task is the one of defining and finding the proxy variables for AI and Productivity, especially for AI adoption; in this study we decided to use GDP per worker for Productivity and AI patents for its adoption.
3. Long-term effects: AI is a quite new technology that is still in development and its implementation is in the earliest of stages, therefore it may still be early to fully capture its effects on labor productivity, especially in the long term as there may be many benefits that we probably cannot calculate yet.

These limitations can be seen as future research directions and corrections instead of weaknesses.

Conclusions

1. AI and ICT development contributes to productivity growth, as seen in our general and subsample results across different regression models.
2. Not all income groups are affected the same, with higher-income countries better at implementing AI technologies and using them for productivity boosts.
3. Income and power inequalities hinder productivity and AI's ability to produce economic benefits.
4. Education is an AI and ICT enhancer that promotes productivity growth and improves technology's ability to boost productivity.
5. Individualistic societies are more productive and are better at utilizing AI and ICT for economic benefits.

Authorities should use this information for the benefit of their economy to promote real economic growth by productivity increases, by investing in AI and ICT infrastructure, developing Human Capital, fixing economical and institutional inequalities, promoting innovation, and adapting the policies to their own economic reality.

Some of the future direction our studies may go to are the following:

- Analyzing different sectors, as not all of them are affected the same, with the primary sector for example being the less affected one.
- With more recent data in hand, analyzing the long-term effects of AI and ICT, something which it's not possible to this date (AI is very new and still in the early stages of development).
- Using many and more representative proxies for Productivity and AI could provide a better picture of how labor productivity is affected by AI and ICT technologies.

Contributions of the Study

- Theoretically, the study extends the knowledge on AI and ICT's impact on worker productivity across different macroeconomic contexts, analyzing 185 different countries for the period 2005-2022 and filling an existing research gap caused by a microeconomic focus of the previous studies in the literature.

- Contextually, the research also takes into consideration different socioeconomic contexts by analyzing subsamples of countries of different economic development and also accounting for the influence of socioeconomic and cultural factors, with the Gini and Education Index for the socioeconomic factors, and Hofstede's six cultural dimensions for the cultural factors. This allows us to provide a more holistic understanding of the relationship between technology adoption and labor productivity.

In conclusion, though AI is a very new and still developing technology, its effects have already been noted on productivity, it is only a matter of time until we have newer and more reliable data that will help us understand the real impact that these technologies have on labor productivity and economic prosperity.

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References

Bonsay, J. O., Cruz, A. P., Firozi, H. C., & Camaro, P. J. C. (2021). Artificial intelligence and labor productivity paradox: The economic impact of AI in China, India, Japan, and Singapore. Journal of Economics, Finance and Accounting Studies, 3(2), 120–139. https://doi.org/10.32996/jefas.2021.3.2.13

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. The Economic Journal, 121(552), 505-532. https://doi.org/10.1111/j.1468-0297.2011.02420.x

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. Eurasian Business Review, 11, 1–25. https://doi.org/10.1007/s40821-020-00172-8

Espoir, D. K., & Ngepah, N. (2021). The effects of inequality on total factor productivity across districts in South Africa: A spatial econometric analysis. GeoJournal, 86, 2607–2638. https://doi.org/10.1007/s10708-020-10215-2

Gorodnichenko, Y., & Roland, G. (2017). Culture, institutions, and the wealth of nations. The Review of Economics and Statistics, 99(3), 402–416. https://doi.org/10.1162/REST_a_00599

Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. Telecommunications Policy, 33(9), 471-485. https://doi.org/10.1016/j.telpol.2009.07.004

Paquin, A. R., Roch, S. G., & Sanchez-Ku, M. L. (2007). An investigation of cross-cultural differences on the impact of productivity interventions: The example of ProMES. The Journal of Applied Behavioral Science, 43(4), 427–448. https://doi.org/10.1177/0021886307307346

PwC. (2018). The macroeconomic impact of artificial intelligence. https://www.pwc.co.uk/economic-services/assets/macroeconomic-impact-of-ai-technical-report-feb-18.pdf

Noy, S. & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6598), 187–192. https://doi.org/10.1126/science.adh2586

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wamboye, E., Adekola, A., & Sergi, B. (2016). ICTs and labour productivity growth in sub-Saharan Africa. International Labour Review, 155(2), 231-252. https://doi.org/10.1111/j.1564-913X.2014.00021.x

Yang, C.-H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. Research Policy, 51(6), 104536. https://doi.org/10.1016/j.respol.2022.104536