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Artificial Intelligence Adoption, Digital Infrastructure, and Business Productivity: A Cross-Country Empirical Analysis Using Secondary Data

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ABSTRACT

Artificial intelligence (AI) has emerged as a transformative technology reshaping business operations and economic productivity across industries and countries. As organizations increasingly integrate AI-driven systems into operational processes, understanding the relationship between AI adoption and productivity outcomes has become a critical research concern. This study employs a cross-country quantitative secondary data analysis using harmonized datasets from the OECD Artificial Intelligence Policy Observatory, the Stanford Artificial Intelligence Index, the World Bank World Development Indicators, and the McKinsey Global AI Survey. The sample includes five economies representing varying levels of digital development. Descriptive statistics, correlation analysis, and multivariate regression modeling are applied to examine relationships among AI adoption, digital infrastructure, and business productivity. Findings reveal a positive and statistically significant effect of AI adoption on productivity, with digital infrastructure strengthening this relationship. Industries characterized by higher data intensity demonstrate greater AI adoption rates. The findings contribute a structured cross-country empirical framework linking artificial intelligence adoption, digital infrastructure, and productivity performance across developed and emerging economies. The results emphasize the importance of technological readiness, innovation ecosystems, and data-driven capabilities in supporting productivity growth within digitally transforming economies. The findings provide insights for policymakers, leaders, and digital transformation strategists seeking to strengthen economic competitiveness.

Keywords: Artificial Intelligence Adoption, Digital Infrastructure, Business Productivity, Technological Readiness, Cross-Country Analysis, Digital Economy
JEL Classifications: O33; D24; L86; M15

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies has significantly transformed contemporary economic systems and business operations. Recent developments in machine learning, big data analytics, and automation have enabled organizations to enhance operational efficiency, improve decision-making processes, and generate productivity gains across multiple sectors. AI is increasingly recognized as a general-purpose technology with broad economic implications, capable of reshaping production processes, labor dynamics, and value creation mechanisms within modern economies (Acemoglu and Restrepo, 2020; Brynjolfsson et al., 2021; OECD, 2023). As firms adopt data-driven technologies, artificial intelligence plays a central role in enabling more efficient resource allocation and strategic decision-making, thereby contributing to improved organizational and economic performance.

In recent years, the adoption of artificial intelligence has expanded rapidly across industries such as finance, manufacturing, healthcare, and retail. Organizations increasingly deploy AI systems for applications including predictive analytics, process automation, customer behavior analysis, and operational optimization. Empirical evidence suggests that firms adopting AI technologies are able to enhance productivity by reducing operational inefficiencies and improving decision accuracy (Brynjolfsson et al., 2021; Autor et al., 2022; McKinsey Global Institute, 2023). Furthermore, advances in cloud computing, data infrastructure, and computational capabilities have accelerated the diffusion of AI technologies, making them more accessible across both developed and emerging economies (OECD, 2023; Stanford Institute for Human Centered Artificial Intelligence, 2024; World Economic Forum, 2023).

Despite the growing importance of artificial intelligence, substantial variation exists in adoption levels across countries and industries. Developed economies such as the United States, the United Kingdom, and China demonstrate higher levels of AI adoption due to stronger research and development investments, advanced digital infrastructure, and well-established innovation ecosystems. In contrast, emerging economies are still in earlier stages of AI integration but are rapidly expanding their digital capabilities through investments in infrastructure and technological development (OECD, 2023; World Bank, 2024; UNCTAD, 2023). These disparities highlight the importance of examining cross-country differences in AI adoption and understanding how technological readiness influences productivity outcomes.

Recent global developments further emphasize the strategic importance of artificial intelligence in driving economic performance. Following the COVID-19 pandemic, organizations accelerated digital transformation initiatives and increased investments in automation technologies to improve resilience and efficiency (McKinsey Global Institute, 2023). AI has become a critical component of business strategy, supporting applications such as supply chain optimization, financial risk management, and customer analytics. These developments underscore the growing role of AI in shaping productivity and competitiveness within the global digital economy (McKinsey Global Institute, 2023; World Economic Forum, 2023).

Although existing research has extensively examined the relationship between digital technologies and productivity, much of the literature remains concentrated at the firm or industry level. Relatively fewer studies provide a comprehensive macro-level analysis of artificial intelligence adoption and its relationship with business productivity across multiple countries. In particular, there is limited research that integrates multiple international datasets to examine cross-country variations in AI adoption, digital infrastructure, and productivity performance within a unified analytical framework. This gap limits the understanding of how artificial intelligence contributes to economic outcomes at a broader systemic level.

Furthermore, prior studies often treat technological adoption as a homogeneous process, without sufficiently accounting for the role of enabling factors such as digital infrastructure and industry characteristics. Recent research suggests that the productivity effects of AI are contingent upon complementary assets, including data availability, technological infrastructure, and organizational capabilities (Autor et al., 2022; Klinger et al., 2023; OECD, 2023). However, empirical studies that examine these interactions across countries remain limited. This highlights the need for research that not only analyzes AI adoption but also considers the structural conditions under which its productivity benefits are realized.

Addressing these gaps, this study investigates the empirical relationship between artificial intelligence (AI) adoption and business productivity across selected developed and emerging economies. Specifically, the study examines the effect of AI adoption (independent variable) on business productivity measured by GDP per worker (dependent variable), while also evaluating the role of digital infrastructure as an enabling factor and industry data intensity as a contextual variable influencing AI adoption patterns.

Using cross-country secondary datasets from the OECD Artificial Intelligence Policy Observatory, the Stanford AI Index, the World Bank World Development Indicators, and the McKinsey & Company, the study applies descriptive, correlation, and regression analyses to assess how variations in technological adoption and digital readiness influence productivity outcomes.

The study aims to (1) Compare levels of AI adoption across selected countries, (2) Determine the statistical relationship between AI adoption and business productivity, and (3) Assess how digital infrastructure and industry data intensity shape AI adoption and its productivity effects. By explicitly linking variables, analytical methods, and empirical outcomes, the study provides a structured macro-level framework for understanding how artificial intelligence contributes to productivity performance across diverse economic contexts.

Accordingly, this study investigates the relationship between artificial intelligence adoption, digital infrastructure, and business productivity across selected developed and emerging economies using a comparative cross-country secondary data analytical approach. Specifically, the study examines how technological readiness, digital infrastructure capacity, and industry data intensity shape patterns of artificial intelligence adoption and productivity performance across diverse economic contexts.

The study specifically seeks to answer the following research questions:

1. What differences in artificial intelligence adoption exist across the selected developed and emerging economies?
2. Is there a significant relationship between artificial intelligence adoption and business productivity across countries?
3. To what extent does digital infrastructure influence artificial intelligence adoption and productivity performance?

4. Do industries characterized by higher levels of data intensity demonstrate greater levels of artificial intelligence adoption?
5. How do technological readiness and digital infrastructure conditions shape productivity outcomes within AI-driven business environments?

2. LITERATURE REVIEW

The growing integration of artificial intelligence (AI) into business operations has generated significant academic and policy interest in its implications for productivity and economic performance. As a general-purpose technology, AI has the capacity to transform production systems, improve decision-making processes, and enhance organizational efficiency across industries (Agrawal et al., 2019; Cockburn et al., 2019). AI-driven systems enable firms to automate routine tasks, analyze large-scale datasets, and optimize operational processes, thereby contributing to improved productivity outcomes.

At the macroeconomic level, technological innovation has long been recognized as a key driver of productivity growth. However, recent studies emphasize that the productivity effects of AI are not automatic but depend on complementary factors such as digital infrastructure, data availability, and institutional readiness (Tambe et al., 2019; Goldfarb and Tucker, 2019). This suggests that the benefits of AI adoption are contingent upon broader technological and economic conditions.

2.1. Theoretical Foundation

The present study is anchored on complementary theoretical perspectives explaining technological adoption, digital capability, and productivity performance within digitally transforming economies. Specifically, the study draws from Diffusion of Innovation Theory, the Technology–Organization–Environment (TOE) framework, the Resource-Based View (RBV), and Dynamic Capabilities Theory to explain how artificial intelligence adoption and digital infrastructure influence productivity outcomes across national business environments.

Diffusion of Innovation Theory explains how technological innovations spread across organizations and societies over time (Rogers, 2003). Recent studies further suggest that the diffusion of artificial intelligence technologies is influenced by digital readiness, institutional support, and technological capability across countries (Klinger et al., 2023). In the context of the present study, variations in AI adoption may therefore reflect differences in innovation diffusion capacity and technological preparedness across economic environments.

The Technology–Organization–Environment (TOE) framework emphasizes that technological adoption is shaped by technological infrastructure, organizational readiness, and external environmental conditions (Tornatzky and Fleischer, 1990). Contemporary research similarly highlights that digital infrastructure and technological ecosystems significantly influence the implementation and scalability of artificial intelligence technologies within organizations and national economies (Tambe et al., 2019). This perspective supports the study's argument that digital infrastructure functions as an enabling condition for AI adoption and productivity performance.

The Resource-Based View (RBV) proposes that technological resources and organizational capabilities may serve as strategic assets that strengthen competitiveness and performance (Barney, 1991). Recent artificial intelligence research further indicates that firms possessing advanced digital capabilities and data-driven resources are better positioned to generate productivity gains and operational advantages through AI adoption (Brynjolfsson et al., 2021). In this study, AI systems and digital infrastructure are viewed as strategic technological resources contributing to productivity improvement.

Dynamic Capabilities Theory highlights the ability of organizations to integrate, adapt, and reconfigure technological resources in rapidly changing business environments (Teece et al., 1997). More recent studies also emphasize that economies and organizations capable of adapting to digital transformation are more likely to sustain innovation and productivity growth in AI-driven environments (World Economic Forum, 2023). This perspective is particularly relevant in explaining how countries leverage artificial intelligence and digital infrastructure to enhance productivity and competitiveness.

Taken together, these theoretical perspectives provide an integrated analytical foundation explaining how artificial intelligence adoption, supported by digital infrastructure and data-driven capabilities, contributes to productivity performance across diverse economic contexts.

2.2. Artificial Intelligence Adoption and Business Productivity

Artificial intelligence adoption refers to the extent to which firms integrate AI technologies into operational and strategic processes. Empirical evidence indicates that AI adoption enhances business productivity by improving efficiency, reducing costs, and enabling more accurate decision-making (Brynjolfsson et al., 2021). AI technologies facilitate automation, predictive analytics, and process optimization, allowing organizations to increase output while minimizing resource utilization.

Recent research highlights that firms implementing AI technologies experience measurable productivity gains, particularly when supported by complementary organizational capabilities and digital systems (Cockburn et al., 2019; Tambe et al., 2019). At the national level, countries with higher AI adoption rates tend to demonstrate stronger productivity performance due to widespread digital integration across industries.

2.3. Digital Infrastructure and Artificial Intelligence Adoption

Digital infrastructure plays a critical role in enabling the adoption and effective deployment of artificial intelligence technologies. It includes broadband connectivity, cloud computing systems, data storage capacity, and digital platforms that support large-scale data processing (Goldfarb and Tucker, 2019). Strong digital infrastructure provides the technological foundation required for AI implementation and scalability.

Empirical studies indicate that countries with advanced digital infrastructure exhibit higher levels of AI adoption due to improved access to computational resources and data ecosystems (Tambe et al., 2019). Conversely, countries with limited infrastructure face constraints in adopting AI technologies due to inadequate connectivity and technological limitations.

At the cross-country level, differences in digital infrastructure contribute significantly to variations in AI adoption patterns, particularly between developed and emerging economies.

2.4. Industry Data Intensity and Artificial Intelligence Adoption

Industry characteristics, particularly data intensity, play a significant role in shaping the adoption of artificial intelligence technologies. Data intensity refers to the extent to which industries generate, process, and rely on large volumes of digital data. Data-intensive industries such as technology and financial services are more likely to adopt AI due to their reliance on advanced analytics and large datasets (Varian, 2019).

Research shows that industries with higher data intensity are better positioned to implement AI technologies for predictive analytics, automation, and decision support systems (Brynjolfsson and McElheran, 2016). In contrast, industries with lower data intensity, such as healthcare and education, often face constraints related to data availability, regulatory requirements, and lower levels of digital integration.

The effectiveness of AI systems depends heavily on data availability and quality, making data intensity a critical determinant of AI adoption across industries.

2.5. Synthesis and Research Gap

Although existing studies provide important insights into the relationship between artificial intelligence and productivity, most prior research focuses on firm-level or industry-specific analyses. There remains limited empirical research that integrates AI adoption, digital infrastructure, and industry characteristics within a macro-level cross-country framework.

Furthermore, previous studies often examine these variables independently, without capturing their combined effects on productivity outcomes. This limits the understanding of how technological adoption interacts with structural and institutional factors across different national contexts.

Collectively, the reviewed literature suggests that artificial intelligence adoption, digital infrastructure, and industry data intensity operate as interconnected dimensions shaping productivity outcomes within digitally transforming economies. While prior studies have examined these variables independently, fewer studies have analyzed their combined structural relationships within a unified cross-country analytical framework. This highlights the importance of examining how technological readiness, infrastructure capacity, and data-driven industry environments jointly influence productivity performance across diverse national contexts.

By addressing these gaps, the present study develops a unified empirical framework that examines how artificial intelligence adoption, supported by digital infrastructure and industry data intensity, influences business productivity across selected developed and emerging economies.

2.6. Hypotheses

Based on the reviewed literature on artificial intelligence adoption, digital infrastructure, and productivity performance, the present study examines the following hypotheses:

- H_1: Higher levels of artificial intelligence adoption are associated with higher levels of business productivity across the selected countries.
- H_2: Countries with stronger digital infrastructure demonstrate higher levels of artificial intelligence adoption among businesses.
- H_3: Industries with greater data intensity demonstrate higher levels of artificial intelligence adoption compared to industries with lower data intensity.

3. METHODOLOGY

3.1. Research Design

This study employed a quantitative secondary data analysis research design to examine the relationship between artificial intelligence (AI) adoption and business productivity across selected developed and emerging economies. Secondary data analysis involves the systematic use of existing datasets and institutional statistics to generate new empirical insights without collecting primary data (Heaton, 2008; Johnston, 2017).

This research design is widely used in economic and technological studies because it enables researchers to integrate multiple large-scale datasets produced by credible international organizations. The use of secondary datasets allows for the analysis of macro-level technological trends and cross-country comparisons of innovation adoption and productivity performance.

By synthesizing datasets related to AI adoption, digital infrastructure development, and economic productivity, the study provides a comparative analysis of technological adoption patterns across countries with different levels of economic development and digital readiness.

This study adopts a cross-sectional analytical approach using the most recent available data from 2018 to 2025. Panel data techniques were not applied due to differences in reporting periods and data availability across sources. Instead, harmonized country-level indicators were used to ensure consistency and comparability across datasets.

3.2. Data Sources and Measurement

The datasets utilized in this study were obtained from internationally recognized institutional sources providing comparable indicators related to artificial intelligence adoption, digital infrastructure, and economic productivity across countries.

Artificial intelligence adoption was measured as the percentage of firms reporting AI utilization in at least one business function based on the McKinsey & Company (2024). Digital infrastructure was measured using indicators related to internet penetration, cloud computing readiness, and digital connectivity obtained from the OECD AI Policy Observatory (2023). Business productivity was measured using GDP per worker (constant 2015 USD) sourced from the World Bank World Development Indicators (2024). In addition, AI investment was measured using total national investment in artificial intelligence technologies (USD billions) derived from the Stanford AI Index Report (Maslej et al., 2024).

3.3. Sample and Analytical Scope

The study focuses on selected economies representing varying levels of technological development, digital infrastructure, economic structure, and artificial intelligence readiness. The countries included in the analysis are the United States, United Kingdom, China, India, and the Philippines.

The selection of these countries was based on purposive comparative analytical criteria rather than statistical representativeness alone. Specifically, the study aimed to capture variation across advanced and emerging economies with differing levels of AI adoption, digital infrastructure maturity, technological investment, and economic development. The United States and the United Kingdom represent advanced economies characterized by highly developed digital ecosystems, strong innovation capacity, and widespread AI integration across industries. China represents a major emerging technological power with rapid AI expansion, large-scale digital transformation initiatives, and substantial national AI investment. India and the Philippines were included to represent developing economies undergoing accelerating digitalization and technological adoption within emerging market contexts.

Rather than attempting broad global generalization, the study adopts a comparative macro-level analytical approach intended to examine how differing technological conditions and digital readiness environments relate to variations in artificial intelligence adoption and productivity outcomes across contrasting economic contexts. The selected countries therefore provide analytically meaningful variation appropriate for exploratory cross-country comparative analysis using harmonized international secondary datasets.

Consistent with comparative secondary data methodologies, the study prioritizes cross-contextual analytical diversity and data comparability over large-sample statistical generalization. Similar cross-country studies using purposive national selection frameworks have been employed in recent educational and technological comparative research utilizing international datasets.

Nevertheless, the study acknowledges that the limited number of countries constrains broader global generalizability. Future research may expand the analytical scope by incorporating larger cross-national datasets, additional regional contexts, and longitudinal panel analyses to further examine global patterns of AI adoption and productivity performance.

3.4. Variables and Measurement

The dependent variable, business productivity, refers to the efficiency with which economic output is generated relative to labor input within national business environments. Consistent with cross-country productivity research, business productivity is measured using GDP per worker (constant 2015 USD) obtained from the World Bank World Development Indicators. GDP per worker is widely used in macroeconomic and comparative productivity studies because it captures aggregate labor efficiency, technological utilization, and output performance across national economies (Syverson, 2011). Although measured at the macro level, GDP per worker reflects the broader productivity conditions under which firms operate, including technological capability, operational efficiency, and innovation-driven economic performance. In the context of the present study, the indicator provides a standardized and internationally comparable proxy for examining how artificial intelligence adoption and digital infrastructure relate to productivity outcomes across different economic environments.

3.5. Data Harmonization and Comparability

Given that the study integrates multiple international datasets, a structured data harmonization process was implemented to ensure consistency and comparability across variables and countries.

First, all variables were aligned to a common reference period (2018-2025) by selecting the most recent and overlapping observations available across datasets. This approach minimizes temporal inconsistencies and ensures comparability in cross-country analysis.

Second, variables measured in different units were standardized. Specifically, productivity indicators were expressed in constant USD, AI adoption was measured as percentage values, and investment indicators were expressed in monetary terms (USD billions). Standardization is essential in cross-country empirical research to ensure meaningful comparison of variables measured using different scales (DeStefano et al., 2020).

Data from multiple sources were integrated using a country-level matching approach, where each variable corresponds to the same country and reference period. Indicators from the OECD AI Policy Observatory, World Bank, Stanford AI Index, and McKinsey & Company were systematically aligned to ensure consistency in cross-country comparisons.

Third, only indicators with consistent definitions across international datasets were selected. This ensures that observed differences across countries reflect actual variations rather than measurement inconsistencies.

Finally, missing or incomplete observations were addressed by selecting overlapping reporting periods and excluding non-comparable data points. This approach enhances the reliability and internal consistency of the integrated dataset.

Overall, this harmonization process ensures that the dataset used in the study maintains validity, comparability, and methodological rigor in cross-country empirical analysis.

3.6. Analytical Techniques

The empirical analysis proceeds in three stages, following established approaches in quantitative economic and technological research.

First, descriptive statistics are used to summarize patterns of artificial intelligence adoption, digital infrastructure development, and business productivity across countries and industries. This stage provides an overview of the distribution, central tendencies, and variation of key variables within the dataset.

Second, correlation analysis is employed to examine the strength and direction of relationships among AI adoption, digital infrastructure, and business productivity. Pearson correlation coefficients are computed to identify linear associations between variables and to provide preliminary evidence of potential relationships prior to regression estimation.

Third, multiple regression analysis is conducted using the ordinary least squares (OLS) estimation method to evaluate the effect of AI adoption and digital infrastructure on business productivity. OLS regression is widely used in cross-country empirical studies to estimate relationships between technological innovation and economic performance (Wooldridge, 2015).

The baseline regression model is specified as:

$$Productivity_i = \beta_0 + \beta_1\ AI\ Adoption_i + \beta_2 Digital\ Infrastructure_i + \varepsilon_i$$

where:

- $Productivity_i$ represents business productivity measured as GDP per worker
- $AI\ Adoption_i$ represents the level of artificial intelligence adoption
- $Digital\ Infrastructure_i$ represents technological readiness
- ε_i is the stochastic error term

The model estimates whether higher levels of AI adoption and digital infrastructure are associated with statistically significant improvements in productivity outcomes across countries.

To ensure robustness, standard diagnostic considerations for OLS estimation—including linearity, independence, and homoscedasticity—are assumed in the analysis. Statistical significance is evaluated at conventional levels ($P < 0.05$).

Together, these analytical techniques provide a structured and rigorous framework for examining the relationship between artificial intelligence adoption and business productivity in a cross-country context.

The operational definitions and measurement indicators used in the analysis are summarized in Table 1.

4. RESULTS

4.1. Cross-Country Comparison of Key Variables

To address the study's objective of examining differences across countries, a structured comparison of AI adoption, digital infrastructure, and business productivity was conducted.

Among the selected countries, the United States and the United Kingdom demonstrate the highest levels of AI adoption and digital infrastructure, reflecting their advanced technological ecosystems and strong innovation capacity. China shows high levels of AI investment and rapid adoption growth, supported by large-scale government initiatives and expanding digital infrastructure.

In contrast, India and the Philippines exhibit relatively lower levels of AI adoption, which can be attributed to developing digital infrastructure and varying levels of technological readiness. However, both countries demonstrate emerging growth in digital transformation and increasing adoption of artificial intelligence technologies across industries.

These cross-country differences indicate that economic development level and digital infrastructure capacity are key determinants of AI adoption and productivity performance, reinforcing the study's analytical framework.

Overall, the comparison highlights the importance of technological readiness, infrastructure development, and investment capacity in shaping the adoption of artificial intelligence and its contribution to business productivity across countries.

This section presents the empirical findings of the study based on the analysis of international datasets related to artificial intelligence adoption, digital infrastructure development, and business productivity. The results describe patterns of AI adoption across industries and countries and examine how these patterns relate to productivity performance.

Table 2 presents the correlation matrix among the key variables defined in Table 1, ensuring consistency between variable operationalization and empirical analysis.

The correlation analysis reveals positive relationships among artificial intelligence adoption, digital infrastructure, and business productivity. Countries demonstrating higher levels of AI adoption tend to exhibit stronger productivity outcomes. Similarly, digital infrastructure shows a strong positive association with both AI adoption and productivity performance. These findings suggest that technological readiness plays an important role in facilitating the diffusion of artificial intelligence technologies across business environments. The results provide preliminary empirical support for Hypotheses 1 and 2, indicating that both AI adoption and digital infrastructure are closely related to productivity performance across countries.

Table 3 reports regression results examining the effects of the independent and explanatory variables on the dependent variable as defined in Table 1.

Table 1: Operational definition and measurement of variables

Variable	Role	Definition	Measurement	Source
AI adoption	Independent variable	The extent to which firms integrate AI technologies into business operations	% firms using AI	McKinsey
Business productivity	Dependent variable	Efficiency of production and output generated by firms	GDP per worker	World Bank
Digital infrastructure	Explanatory variable	Technological readiness supporting digital innovation	Internet %, etc.	OECD
AI investment	Control variable	Financial resources allocated to AI development and innovation	USD billions	Stanford
Industry data intensity	Contextual variable	The extent to which industries generate, process, and utilize large volumes of digital data for operational and analytical purposes	Sector classification	McKinsey

Source: Adapted from OECD (2023); McKinsey Global Institute (2023); Stanford AI Index (Maslej et al., 2024); World Bank (2024)

Table 2: Correlation matrix of key variables

Variable	AI adoption	Digital infrastructure	Business productivity
AI adoption	1.00	0.64**	0.58**
Digital infrastructure	0.64**	1.00	0.61**
Business productivity	0.58**	0.61**	1.00

Source: Author's calculations using OECD, World Bank, and AI Index datasets

Table 3: Regression analysis predicting business productivity

Variables	Model 1	Model 2	Model 3
AI adoption	0.41*	0.36*	0.31*
Digital infrastructure	—	0.37*	0.29*
AI adoption×Digital infrastructure	—	—	0.24*
Constant	1.72	1.65	1.58
R^2	0.34	0.49	0.57
Adjusted R^2	0.29	0.43	0.50
ΔR^2	—	0.15	0.08
F-value	11.70*	14.83*	16.42*

Standardized beta coefficients are reported. Model 3 includes the interaction effect between AI adoption and digital infrastructure. $P<0.05$

Table 3 presents the hierarchical regression analysis predicting business productivity across the selected countries. Model 1 shows that artificial intelligence adoption has a positive and statistically significant relationship with productivity performance. In Model 2, the inclusion of digital infrastructure increases the explanatory power of the model, indicating that technological readiness contributes to productivity outcomes beyond AI adoption alone. Model 3 further demonstrates a significant interaction effect between AI adoption and digital infrastructure, suggesting that the productivity benefits of artificial intelligence become stronger in countries with more advanced digital ecosystems. Overall, the results support Hypotheses 1 and 2, highlighting the importance of both AI adoption and digital infrastructure in shaping productivity performance across economies.

Table 4 shows the relationship between industry data intensity and artificial intelligence adoption. Industries with high data intensity, such as technology and financial services, demonstrate the highest AI adoption rate at approximately 63%, reflecting their reliance on large-scale data processing and predictive analytics. Industries with moderate data intensity, including automotive and retail sectors, exhibit moderate adoption levels at around 47%, where legacy systems and operational structures may slow full AI integration. In contrast, industries with lower data intensity, such as healthcare and education, report lower adoption rates at approximately 32%, partly due to regulatory constraints and limited digital data availability. Overall, these results support Hypothesis 3, indicating that industries with higher data intensity demonstrate greater adoption of artificial intelligence technologies.

Table 4: Data intensity and AI adoption by industry

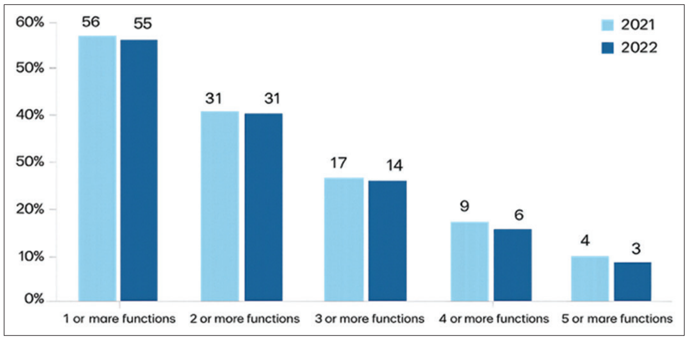
Industry category	Average AI adoption (%)
High data intensity (Technology, Finance)	63%
Moderate data intensity (Automotive, Retail)	47%
Low data intensity (Healthcare, Education)	32%

Source: McKinsey & Company

Figure 1 presents organizational adoption of artificial intelligence across multiple business functions based on recent global survey data. The findings indicate that a majority of organizations reported implementing AI technologies in at least one business function in both 2021 and 2022. However, adoption rates decline as the number of integrated business functions increases, suggesting that many organizations continue to implement AI selectively rather than fully integrating it across operational systems. The results indicate that while artificial intelligence adoption has expanded significantly within business environments, comprehensive enterprise-wide integration remains comparatively limited. These patterns highlight the continuing transition from experimental AI implementation toward broader organizational deployment across industries.

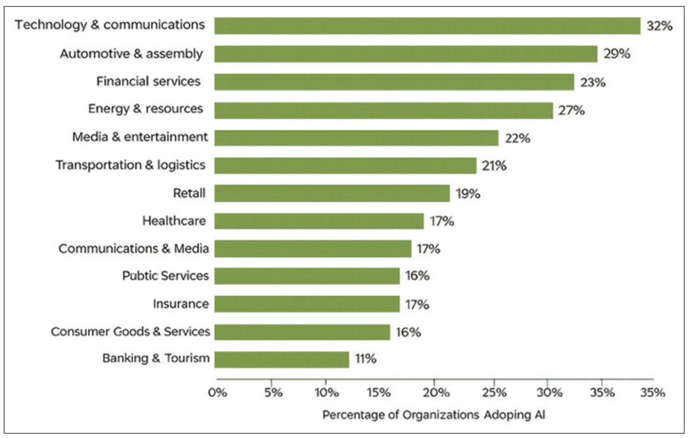
Figure 2 illustrates variations in artificial intelligence adoption across major industry sectors. Technology-related and financial service industries demonstrate relatively higher levels of AI adoption compared with several traditional sectors. These industries benefit from stronger digital infrastructure, higher levels of data availability, and greater reliance on data-driven operational systems, which facilitate the implementation of artificial intelligence technologies. Other sectors, including automotive, transportation, retail, and energy industries, show moderate levels of adoption as organizations increasingly integrate AI into operational planning, automation, and predictive analytics. In contrast, sectors characterized by lower digital integration and more complex regulatory environments demonstrate comparatively lower levels of AI adoption. Overall, the figure supports Hypothesis 3, suggesting that industries with greater data intensity are generally more likely to adopt artificial intelligence technologies.

Figure 1: Global adoption of artificial intelligence in businesses (2021-2023)



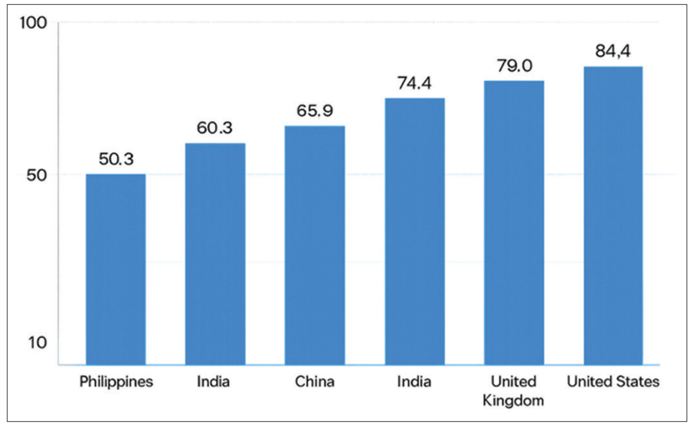
Source: McKinsey and Company, The State of AI in 2023: Generative AI's Breakout Year (2023)

Figure 2: Artificial intelligence adoption by industry sector



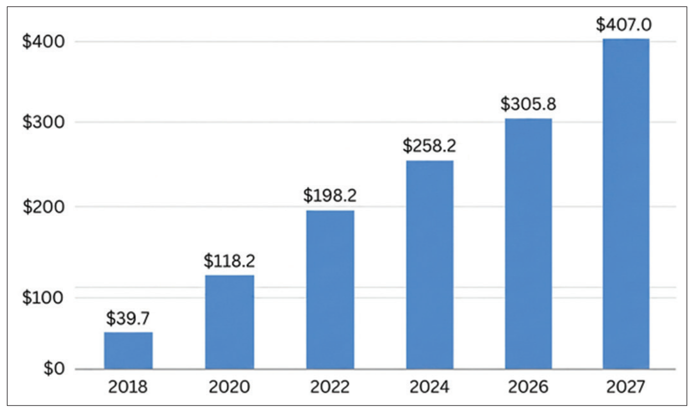
Source: McKinsey Global Institute (2017).

Figure 3: AI readiness among selected countries (2023)



Source: Oxford Insights. (2023). Government AI Readiness Index 2023

Figure 4: Global investment and market growth in artificial intelligence technologies (2018-2027)



Source: Adapted from Stanford AI Index Report (2024), PwC Global Artificial Intelligence Study (2022), and industry market forecasts

Figure 3 compares artificial intelligence readiness across the selected countries. The United States and the United Kingdom demonstrate the highest AI readiness levels, reflecting strong digital infrastructure and advanced innovation ecosystems. China also shows high readiness supported by significant investment and rapid technological development. In contrast, India and the Philippines exhibit lower readiness levels but demonstrate increasing progress in digital infrastructure and AI adoption. These cross-country differences support Hypothesis 2, indicating that stronger digital infrastructure is associated with higher levels of AI adoption.

Figure 4 illustrates the continuing expansion of global investment in artificial intelligence technologies from 2018 to projected estimates for 2027. The findings indicate a substantial increase in financial resources allocated to AI research, development, and implementation across industries and national economies. Investment growth accelerated considerably after 2020 as organizations intensified digital transformation initiatives and expanded the use of automation, machine learning, and advanced analytics systems. The projected rise in investment through 2027 further reflects the growing strategic and economic importance of artificial intelligence within the global digital economy. Increasing investment levels also support the expansion of digital infrastructure, innovation ecosystems, and AI-driven business applications that facilitate broader technological adoption across industries.

5. DISCUSSION

The findings of this study provide empirical evidence supporting the relationship between artificial intelligence (AI) adoption and business productivity across national economies. The results indicate that countries demonstrating higher levels of AI adoption tend to exhibit stronger productivity performance. This pattern supports the argument that advanced digital technologies enable organizations to improve operational efficiency, automate routine processes, and enhance data-driven decision-making capabilities. Previous research has similarly emphasized the transformative potential of artificial intelligence and digital technologies in improving productivity and organizational performance (Brynjolfsson and McAfee, 2014; Davenport and Ronanki, 2018). These findings are directly consistent with the regression results, which demonstrate statistically significant positive effects of AI adoption and digital infrastructure on productivity outcomes (OECD, 2023; World Economic Forum, 2023).

The correlation and regression results further demonstrate that digital infrastructure plays a crucial role in facilitating the adoption of artificial intelligence technologies. Countries with stronger technological ecosystems—including advanced internet connectivity, data infrastructure, and digital innovation systems—are more likely to implement AI technologies within business environments. This finding aligns with technological innovation theory and endogenous growth perspectives, which emphasize that technological capabilities and knowledge infrastructure are critical drivers of productivity and economic development (Romer, 1990; Acemoglu and Restrepo, 2020). In this context, digital infrastructure functions as an enabling environment that allows firms to adopt and deploy AI-based systems effectively.

The analysis also highlights important industry-level differences in artificial intelligence adoption. Sectors characterized by high levels of data intensity—such as technology and financial services—demonstrate substantially higher AI adoption rates compared with industries that generate or utilize smaller volumes of digital data. These findings are consistent with prior research suggesting that industries relying heavily on data analytics and digital technologies are more likely to integrate artificial intelligence into operational processes (Brynjolfsson et al., 2017). Data-rich environments provide the informational resources necessary for training machine learning models and implementing predictive analytics systems, thereby facilitating the practical application of artificial intelligence in business operations.

From a broader economic perspective, the results suggest that artificial intelligence adoption represents an important component of ongoing digital transformation within the global economy. As organizations increasingly integrate AI-driven technologies into operational processes, productivity improvements may arise through enhanced automation, improved forecasting capabilities, and more efficient resource allocation. These outcomes reinforce the view that technological innovation and digital transformation play a central role in shaping long-term economic performance (Acemoglu and Restrepo, 2020; Brynjolfsson et al., 2021).

Unlike many previous studies that focus primarily on firm-level applications of artificial intelligence, the present research provides a macro-level cross-country perspective on the relationship between AI adoption and productivity performance. By integrating datasets from multiple international institutions, the study contributes to the growing literature examining how technological adoption patterns influence economic outcomes across different national contexts.

Overall, the findings suggest that artificial intelligence adoption, supported by strong digital infrastructure and data-intensive industries, represents a significant driver of productivity improvements in the modern digital economy. These insights highlight the importance of technological readiness, innovation ecosystems, and digital capabilities in enabling countries and organizations to fully realize the productivity benefits associated with artificial intelligence technologies.

The findings are generally consistent with prior research emphasizing the productivity-enhancing role of artificial intelligence and digital technologies within modern economies (Brynjolfsson et al., 2021; OECD, 2023). The results further indicate that digital infrastructure and technological readiness function as important enabling conditions supporting the productivity effects of AI adoption. Unlike many previous studies focused primarily on firm-level contexts, the present study contributes a broader macro-level comparative perspective by integrating multiple international datasets within a unified analytical framework. Overall, the findings suggest that productivity gains associated with AI adoption depend not only on technological implementation itself but also on supportive digital and infrastructural conditions across economies.

5.1. Limitations of the Study

Several limitations should be acknowledged in interpreting the findings of the study. First, the analysis was limited to a relatively small cross-country sample consisting of selected developed and emerging economies, which may constrain broader generalizability. Second, the study relied on harmonized secondary datasets obtained from multiple international institutions with varying reporting structures, definitions, and reference periods, limiting the application of longitudinal and panel-data analytical techniques. Third, the study employed descriptive, correlational, and regression-based analyses without advanced robustness testing, mediation modeling, or structural equation approaches commonly applied in larger-scale datasets. In addition, diagnostic and regression assumption testing were limited by the structure and scope of the available international datasets. Finally, the macro-level analytical design does not directly capture firm-level organizational practices or micro-level productivity mechanisms associated with artificial intelligence implementation. Future research may address these limitations by utilizing larger international samples, longitudinal datasets, firm-level analyses, and more advanced multivariate analytical frameworks.

6. CONCLUSION AND RECOMMENDATIONS

This study examined the relationship between artificial intelligence (AI) adoption and business productivity using a cross-country secondary data analysis of international datasets. By integrating data from the OECD Artificial Intelligence Policy Observatory, the Stanford AI Index, the World Bank World Development Indicators, and the McKinsey & Company, the study provides empirical insight into global patterns of AI adoption and productivity performance across developed and emerging economies. The findings indicate a positive and statistically significant relationship between artificial intelligence adoption and business productivity. Countries with higher levels of AI adoption tend to demonstrate stronger productivity outcomes, suggesting that the integration of intelligent technologies enhances operational efficiency and data-driven decision-making within business environments. The results also highlight the importance of digital infrastructure in facilitating artificial intelligence adoption, as economies with stronger technological ecosystems exhibit higher levels of AI implementation. Industry-level analysis further shows that sectors characterized by higher data intensity demonstrate greater levels of artificial intelligence adoption. Overall, the findings support technological innovation and endogenous growth perspectives, emphasizing the role of advanced digital technologies in improving productivity and economic development. By providing a macro-level cross-country analysis linking AI adoption patterns with productivity indicators, this study contributes to a broader understanding of how artificial intelligence influences economic performance in the global digital economy. The findings are consistent with the proposed hypotheses and confirm the critical role of AI adoption and digital infrastructure in driving productivity across countries.

The findings of the study provide several implications for policymakers, business organizations, and future research. Governments should prioritize investments in digital infrastructure, technological education, and innovation ecosystems that support the development and diffusion of artificial intelligence technologies. Expanding high-speed internet connectivity, cloud computing capability, and national data infrastructure may strengthen the technological environment necessary for effective AI implementation across industries and economies.

Business organizations should strategically integrate artificial intelligence technologies into operational and decision-making processes to enhance productivity and competitiveness. Firms may leverage AI-driven systems to improve automation, forecasting, operational efficiency, and data analytics capabilities, particularly within industries characterized by high levels of data intensity and digital integration.

For emerging economies, strengthening digital infrastructure and technological capability remains essential for facilitating broader AI adoption and long-term productivity growth. Investments in digital skills development, research capacity, and technology education may improve workforce readiness and support AI-driven economic transformation.

Future studies may extend the present research by examining firm-level productivity outcomes associated with artificial intelligence adoption using larger international samples and micro-level datasets. Longitudinal and panel-data approaches may further provide deeper insights into how technological readiness, policy frameworks, and digital investment influence productivity performance across industries and countries over time.

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