THE ARTIFICIAL INTELLIGENCE (AI) AGENDA: EVALUATING THE IMPACTS ASSOCIATED WITH THE ADOPTION OF AI ON LABOUR, PRODUCTIVITY AND ECONOMIC GROWTH IN OECD COUNTRIES

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ABSTRACT

The Artificial Intelligence (AI) Agenda: Evaluating the impacts associated with the adoption of AI on labour, productivity and economic growth in OECD countries

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This research aims to evaluate the effects of artificial intelligence (AI) adoption on labour, productivity, and economic growth in Organization for Economic Co-operation and Development (OECD) countries. Data were extracted from the OECD database, focusing on countries actively employing AI from 1995 to 2017. The fixed effects model was utilized to test the hypotheses, and the Hausman test confirmed the appropriateness of this method. The results indicate that AI adoption's impact on labour and productivity is statistically insignificant. In contrast, the correlation between AI adoption and economic growth appears to be negative and statistically significant. These findings suggest that while AI holds potential for improving economic indicators, its full benefits may not be immediately apparent. However, these results can inform stakeholders on how to harness AI's potential to drive economic growth, enhance productivity, and manage labour market transitions smoothly, ensuring that the benefits of AI are broadly shared across society.

Keywords

Artificial Intelligence, labour, productivity, economic growth, fixed effects model, pooled OLS model, random effects model

JEL Classification: C01, C02, C05, O03,

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List of Acronyms

AI	Artificial Intelligence
AIOI	Artificial Intelligence Occupational Impact
ASEAN	Association of Southeast Asian Nations
CHISQ	Chi Square
EFF	Electronic Frontier Foundation
FEM	Fixed Effects Model

GPS	Global Positioning System
GPT	Generative Pre-trained Transformer
GDP	Gross Domestic Product
NLP	Natural Language Processing
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
O*NET	Occupational Information Network
R&D	Research and Development
REM	Random Effects Model

1. Introduction

The astounding rate at which AI has progressed over the past few decades is undeniable and since the term was coined by Professor John McCarthy et al in 1956[2], it has become buzz worthy, with much discussion around its transformative impact on labour, productivity and economic growth. However, before determining this transformative impact, one must gain an understanding of exactly what AI is, why it is important and how it supports day-to-day life activities and economic variables. AI refers to a machine's ability to perform cognitive tasks that are typically associated with human intelligence[3]. Cognitive tasks that include perception, reasoning, interaction with environments, learning, problem-solving and even the manifestation of creativity. It is a highly complex technology that encompasses machine learning and deep learning which involves the development of algorithms designed to mimic the decision-making mechanisms of the human brain. These algorithms are capable of 'learning' from existing data, thereby improving their ability to classify or predict with greater accuracy as time progresses. Perhaps the most recent and talked about game-changer has been in natural language processing (NLP) where generative AI[4] has the ability to learn and synthesize human language and other data forms such as images, videos and software codes[5]. Digital assistants, GPS systems, autonomous vehicles, and generative AI tools like OpenAI's ChatGPT are just a few examples of AI technologies that are commonly highlighted in news reports and seamlessly integrated into our daily lives. AI is a major source of innovation that contributes to firms' level of productivity, marketing strategies, customer reach and acquisition, thereby leading to improved customer service, heightened work precision, efficiency and customer satisfaction. Despite it being a major source of innovation humans have always been uneasy about human-machines and robotics given the increasing likelihood of job replacement in the workplace, resulting in a decline labour demand and wages. Alternatively, the obvious benefits of AI on economic activities cannot be ignored. The study conducted by Julius Tan Gonzales (2023)[6] found a significant and positive correlation between the influence of AI patenting on overall long-term economic expansion. Moreover, his research revealed that the effect of AI becomes more pronounced in the later timeframe, attributed to the escalating quantity and calibre of AI innovations produced over time. These conflicting observations provoke much debate and research

[2] Artificial intelligence was first proposed as a discipline in 1956 by Professor John McCarthy, Alan Turing, Marvin Minsky, Nathaniel Rochester and Claude E. Shannon at a summer workshop held at Dartmouth (CHM 2001).
[3] (McKinsey & Company 2023)
[4] Generative AI, involves computational methods with the ability to produce what appears to be original and meaningful content, such as text, images, or audio, derived from training data (Feuerriegel, et al. 2024).
[5] (IBM 2023)
[6] The aim of this study is to investigate the correlation between the extent of AI innovation and sustained economic advancement, utilizing a panel dataset encompassing multiple countries from 1970 to 2019.

surrounding the true magnitude of the AI agenda[7]. This study extends this research direction by delving into the extent of AI's influence on labour, productivity, and economic advancement, with a special focus on 38 countries (chosen based on the availability of AI patent-related data) from the Organization for Economic Co-operation and Development (OECD)[8]. These countries were chosen in particular due to their adoption of the OECD AI Principles[9], which indicates their trust, acceptance and willingness to use AI across industries and sectors.

1.1 Significance of Study

This study has three objectives. First, it seeks to explore the influence of the AI agenda on labour. In essence, it endeavours to determine whether AI functions more as a substitute or a supplement to labour. Secondly, the study aims to investigate the impact of the AI agenda on productivity. Put differently, the analysis explores the degree to which AI is reshaping productivity through streamlining processes, optimizing operations, and fostering innovation. Finally, the study examines the extent to which the AI agenda influences economic growth. That is, the extent to which AI has the capacity to contribute to economic growth by boosting productivity, fostering innovation, creating new jobs and industries, and enhancing human capital. The study makes use of a panel dataset of OECD countries from 1990 to 2020.

1.2 AI Agenda in the Workplace

When AI and labour are mentioned in the same sentence there are two sides of the coin that cannot be ignored. On one side, can AI replace labour? On the other, does AI complement labour? Advances in AI technology have had a transformative effect on the workplace through automation and other technologies. However, while these advances bring unprecedented opportunities for innovation, efficiency and growth, its impact on the labour market is a topic that is met with unease, highlighting widespread apprehension. Particularly as it relates to AI-powered robotics and job displacement as a result of automation. Automation that allows for highly repetitive, routine tasks to be performed more efficiently and with more precision

[7] The term "AI Agenda" generally refers to strategic plans and priorities regarding the development, implementation, regulation, and impact of artificial intelligence (AI). For example, the Olympic AI Agenda (IOC 2024) is a the third in a trilogy of strategy documents launched under the leadership of IOC President Thomas Bach, and presents the envisioned impact that artificial intelligence (AI) can deliver for sport.

[8] Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United (OECD 2022) .

[9] In 2019, the OECD established the AI Principles, which outline a framework comprising ten principles. These principles are categorized into five values-based principles and five recommendations to governments. They serve as guidelines for OECD Members and adhering non-Members to advocate and incorporate responsible management of reliable AI into their policies (OECD 2023).

than with humans. This is the case especially in industries such as manufacturing, retail and customer service where sophisticated AI systems can increasingly replace human workers in tasks ranging from data entry to assembly line operations. For instance, in manufacturing facilities, robots utilizing AI algorithms can efficiently perform tasks such as assembly, welding, and quality control with high accuracy and speed. In warehouses, autonomous vehicles and robotic arms can streamline logistics and inventory management. The framework created by Acemoglu and Restrepo (2019) observes that robotics and the present state of AI are perpetuating the trend seen in previous automation technologies: employing machines and computers to replace human labour across an expanding spectrum of tasks and industrial operations. This underscores the fact that while advancements enhance productivity and cut costs for businesses, they also bring into question the future of human workers in these sectors and the probability of being substituted by AI. Figure 1 below shows that the proliferation of AI has dramatically increased over the past decade, which is expected to have a significant impact on the economies of many countries.

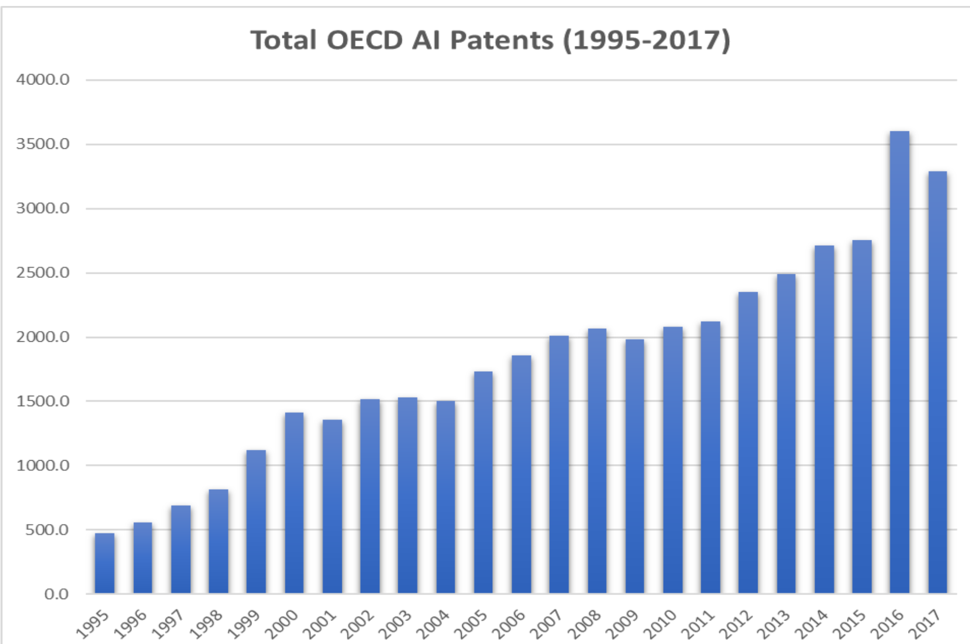

Figure 1: Total OECD AI Patents Granted per Year (1995 to 2017) - Source: Organization for Economic Co-operation and Development (OECD 2024)

Despite the potential for job displacement, the adoption of AI in the workplace does present opportunities for reskilling/upskilling the workforce. As certain monotonous tasks become automated, there is a growing demand for workers with skills in data analysis, programming, cybersecurity, and AI development. This scenario encourages companies to invest in training programs that equip their employees with the necessary skills to work effectively alongside AI systems. For example, according to Mohammed Yousef Shaheen (2021), healthcare systems globally are encountering significant challenges, including limited access to on-demand healthcare services, high costs, a shortage of healthcare professionals, and aging populations. However, he suggests that technology-based systems such as AI-powered diagnostic tools can be used by healthcare professionals to enhance patient care, emphasizing the need for continuous learning and adaptation in the face of AI-driven changes. Rather than replacing humans, AI can complement and enhance human capabilities, by serving as tools to assist workers in making better decisions, improving efficiency, and delivering higher-quality services.

Exploring the multifaceted effects of AI on labour, by examining both challenges and opportunities, it is difficult to ignore the polarizing effect it presents to the labour market. While AI presents opportunities for skilled workers, there are concerns about widening inequality and job polarization. Workers with high levels of education and specialized skills may benefit from the AI-driven economy, while low-skilled workers face the risk of job losses or underemployment. Moreover, the adoption of AI technologies may exacerbate income inequality if the benefits primarily accrue to shareholders and executives.

1.3 AI Agenda and Productivity

Labour productivity is a fundamental driver of economic growth, business success and individual prosperity. By improving efficiency, reducing costs, fostering innovation, and enhancing competitiveness, higher labour productivity contributes to a more vibrant and resilient economy. Businesses, policymakers, and workers alike benefit from efforts to increase productivity through investments in technology, skills development, and process improvements. As a result of such investments in technology, AI has become a revolutionary force that is reshaping productivity through streamlining processes, optimizing operations, and fostering innovation (Davenport, Holweg and Jeavons 2023). AI has the ability to process vast amounts of data, learn from patterns, automate tasks, and has the potential to significantly enhance productivity across various sectors of the economy. That being said, there is an ongoing debate about the present and future positive impacts of the deployment of AI on productivity and the possible disruption it can cause across sectors and industries worldwide. For example, by automating repetitive and routine tasks with AI, employees are now able to concentrate on more complex responsibilities that demand creativity, critical analysis, and emotional insight. By augmenting human capabilities, AI has the ability to empower employees to perform their jobs more effectively, which can facilitate the efficient allocation of limited resources, thereby enhancing productivity (Nurlia , Rosadi and Daud 2023). While AI offers numerous benefits for productivity enhancement, there are a myriad of challenges and considerations that should be addressed or at least mentioned here. These include concerns about data privacy and security, potential biases in AI algorithms, and the need for upskilling and reskilling the workforce to adapt to AI-driven changes. From the costs and resource allocation required to the time constraints, potential resistance from employees, and mismatched skill sets, addressing these drawbacks requires careful planning, communication, and investment in learning and development initiatives (Nurlia , Rosadi and Daud 2023). Furthermore, the deployment of AI brings up ethical issues, such as the need to maintain transparency, ensure accountability, and promote fairness in AI-powered decision-making processes (OECD 2024). While the fast-paced transformation of the AI landscape does hold immense promise for driving productivity gains, it also presents significant challenges and risks that can negatively impact productivity.

1.4 AI Agenda and Economic Growth (Long-Run Economic Growth)

Artificial Intelligence (AI) has emerged as a game-changing technology with the potential to reshape economies globally. By leveraging this technology, AI has the capacity to contribute to economic growth by boosting productivity, fostering innovation, creating new jobs and industries, and enhancing human capital. As previously mentioned, AI has the potential to significantly enhance productivity across various industries by automating tasks, streamlining processes, and optimizing resource allocation. By enabling businesses to accomplish more with fewer resources, AI can drive overall economic output and contribute to sustained productivity growth. A study conducted by Wang, Sarker, Alam, & Sumon (2021) highlights AI as a distinctive factor of production. The models developed by these researchers suggest that AI capital reduces capital costs, raises wages, and enhances productivity. As a result, the study concludes that AI has the potential to foster economic growth. AI facilitates innovation by providing new tools and capabilities for problem-solving, data analysis, and decision-making. As AI technologies continue to evolve and mature, they are expected to drive breakthroughs in areas such as healthcare, manufacturing, finance, and transportation, leading to the development of new products, services, and industries. As a result, advanced economies with access to growing digital technology and other types of innovation, have been found to benefit from the influence of AI on economic growth. Gonzales (2023) explores the effects of AI innovation on economic growth, aiming to uncover the connection between AI innovation levels and long-term economic expansion. Utilizing a panel dataset spanning countries from 1970 to 2019, the study reveals a notable positive correlation between AI patenting and average long-term economic growth. Moreover, it underscores that the influence of AI becomes more pronounced in later years, attributable to the growing quantity and quality of AI innovations over time. While AI has the potential to automate certain tasks and jobs, it also creates opportunities for new types of employment and skill development. As AI technology becomes more widespread, there will be an increasing demand for workers with skills in AI development, data analysis, machine learning, and related fields. Moreover, AI can augment human capabilities and enable workers to focus on higher-value tasks that require creativity, critical thinking, and emotional intelligence. Manyika and Bughin (2018) reinforce these perspectives in their McKinsey Global Institute publication titled "The promise and challenge of the age of artificial intelligence." Overall, AI has the potential to be a transformative force in driving long-term economic growth by enhancing productivity, fostering innovation, creating new opportunities for employment and skill development, and reshaping industries and markets. However, realizing this potential requires careful planning, investment in research and development, and proactive policies to address the opportunities and challenges associated with AI adoption.

1.5 AI Agenda and the OECD

As AI technologies continue to advance at an unprecedented pace, international organizations like the Organization for Economic Co-operation and Development (OECD) play a crucial role in understanding, regulating, and harnessing the potential of AI for the benefit of all. The OECD helps member countries harness the economic benefits of AI by promoting policies that encourage investment in AI research and development, foster entrepreneurship, and facilitate technology adoption. The organization also supports innovation-driven growth by promoting policies that facilitate collaboration between governments, businesses, and research institutions, encourage knowledge-sharing, and protect intellectual property rights. It is crucial to guarantee that AI technologies are implemented to advance social inclusion, equity, and human rights, tackling challenges such as the digital divide, algorithmic bias, and privacy protection. Moreover, ethical and legal considerations regarding privacy, security, accountability, and transparency must not be overlooked. In this regard, the OECD formulates guidelines, standards, and principles to tackle these concerns, fostering responsible AI development and deployment while upholding individual rights and freedoms. AI governance and regulation are complex issues that require international cooperation and coordination. As such, a dialogue and cooperation must be facilitated among member countries to develop common frameworks, standards, and best practices for AI governance, ensuring that AI technologies are used in ways that are ethical, safe, and beneficial for society. As a leading international organization, the OECD plays a critical role in shaping the future of AI by promoting policies that maximize its benefits while mitigating its risks. The OECD helps navigate the opportunities and challenges presented by AI in the digital era and this comprehensive approach is the reason why this particular group of countries was selected as the primary focus of this study.

While existing studies examine the effects of artificial intelligence on labour, productivity, and economic growth, there is a lack of recent empirical research specifically focusing on these economic variables within the OECD region. This research specifically focuses on the OECD countries, which are at the forefront of AI adoption. This regional focus allows for a detailed analysis of how advanced economies integrate AI and the specific challenges and opportunities they face. Additionally, the study adopts a multi-dimensional approach by evaluating the impacts of AI on labour markets, productivity levels, and overall economic growth simultaneously. This holistic perspective provides a more integrated understanding of AI's transformative potential compared to studies that may only focus on one aspect. By highlighting these contributions, the study aims to provide significant and original insights into the AI agenda, particularly within the context of OECD countries, thereby filling existing gaps within the literature.

The remainder of this paper is organized as follows: The next section provides an overview of the theoretical and empirical literature investigating the relationship between AI, labour, productivity, and economic growth. Section three outlines the study's methodology. Section four presents the summary statistics, data analysis, and results. Section five discusses the findings, and finally, section six concludes with remarks and recommendations.

2. Literature Review

The literature review examines both the theoretical frameworks related to technology and innovation, as well as empirical studies focused on the influence of AI on labour, productivity, and economic growth. These variables have been the focal point of numerous theoretical debates and discussions. The first is the Solow Growth Model, developed by Nobel Prize-winning economist Robert Solow (1956), which primarily focuses on understanding long-term economic growth by analysing the contributions of capital accumulation, labour force growth, and technological progress. The Solow model emphasizes the role of capital accumulation in economic growth and assumes that investment contributes to an increase in the capital stock, which, in turn, boosts output and positively impacts long-term economic growth. The Solow Growth Model also recognizes the importance of technological progress. It assumes that technological advancements occur exogenously (i.e., independently of other factors) and are a key driver of productivity growth. Research indicates that countries actively investing in research and development (R&D) and adopting new technologies experience sustained economic growth. The research conducted by Bart Verspagen (2001) offers insights from evolutionary economic theory[10] regarding the contemporary growth disparities within the OECD region. This evolutionary viewpoint on economic growth highlights the importance of ground-breaking innovations in fostering economic progress. Conversely, the Endogenous Growth Theory proposed by Romer (1990), significantly advances economists' comprehension of internal technological change. Romer's growth model, known as the Romer model, suggests that technological progress arises from the creation of new products, which is fuelled by research and development (R&D) efforts conducted by entrepreneurs motivated by profit. The model attempts to explain what determines technological progress, unlike the Solow model which only accepts that technological progress determines long-run growth in output per worker.

2.1 AI and Labour

Recent, rapid advancements in AI have spurred conversations and debates about whether AI acts as a substitute or complement to human labour and the consequential policy implications. Felten, Raj, and Seamans (2019) explore the correlation between AI and labour dynamics through the development of a new metric termed the Artificial Intelligence Occupational Impact (AIOI). By employing this metric, they analyse the links between AI and wages, employment, and labour market polarization. Utilizing this metric,

[10] Evolutionary economics offers insights into phenomena such as technological change, industrial dynamics, institutional evolution, and economic development. It provides a framework for understanding how economies evolve over time, emphasizing technological innovation as a key driver of economic progress (Hodgson 2019).

they presented findings indicating that AI and human labour often complement each other, with a more favourable effect of AI observed on high-income occupations compared to low- and middle-income ones. It is therefore plausible that advancements in AI could result in a more substantial increase in employment and wages for high-income occupations compared to low- and middle-income ones, potentially raising concerns regarding income inequality. The AIOI is constructed using data from two independent databases. The Electronic Frontier Foundation (EFF) AI Progress Measurement dataset and the Occupational Information Network (O*NET) database, developed by the United States Department of Labour. Data from the nine EFF databases is utilized to gauge technological advancement between 2010 and 2015, alongside the 52 distinct abilities outlined by O*NET to characterize workplace activities across various occupations within its database.

Felten, Raj, and Seamans (2019) concluded that AI and human labour often complement each other, with a more favourable impact on high-income jobs compared to low- and middle-income ones. Building on their research, Moilanen (2020) explores the extent of AI's impact on labour in the finance industry to better understand perceptions of AI's role in shaping future employment. This modern approach acknowledges individual perceptions of AI's impact and provides valuable insights for developing guidelines and policies to promote efficient labour markets that benefit all stakeholders. Moilanen conducted a survey on LinkedIn for quantitative analysis, posing several research questions: Do perceptions vary based on individuals' knowledge of the finance industry and its developments? What are the advantages and disadvantages of implementing AI technology versus relying mainly on human labour in the finance industry? Are there differing perceptions of AI's impact on employment across various departments, such as banking and accounting, within the finance industry? Finally, how does the extent of AI implementation influence perceptions of employment levels in the financial labour market? The analysis revealed that individuals well-versed in the finance industry were more likely to perceive a significant impact of AI on labour market levels. It also suggested that people recognize the benefits of AI in finance processes but do not necessarily see these benefits as directly affecting the labour market. Additionally, perceptions of AI's impact on employment varied by department, and there was a weak correlation between the perceived increase in AI implementation and changes in employment levels.

2.2 AI and Polarization Effect

As much as AI has been seen as being a complement to human labour (Felten, Raj and Seamans 2019) it also has the potential to exacerbate labour market polarization as it can lead to greater disparities between high-income and low-income occupations, leaving fewer opportunities for middle-income occupations.

This trend is mainly due to the fact that AI depends on the involvement and collaboration of highly skilled professionals, which greatly increases the demand for skilled labour (Loong, et al. 2021). Meanwhile, middle-skilled labour, often involved in routine tasks, is gradually being replaced by intelligent machines—hence the phrase "machines instead of labour." Consequently, the demand for middle-skilled workers is decreasing. In contrast, low-skilled labour often involves service-oriented tasks that require communication and situational awareness, which machines cannot replicate. Morikawa (2017) explores the AI trend and its impact on high-skilled versus low-skilled labour by analysing how various personal characteristics—such as age, education, and occupation—influence perceptions of AI and robotics on employment prospects. The study hypothesizes that highly skilled individuals generally view AI and robotics positively, while lower-skilled workers do not. The analysis was based on a survey titled "Survey of Life and Consumption Under the Changing Economic Structure and Policies," which sampled 10,000 individuals, stratified by gender, age, and region. The results suggest a strong link between advanced education, especially postgraduate studies in natural sciences, and positive views on AI technologies. However, an interesting finding is that both broadly applicable skills from higher education and job-specific skills from vocational training or occupational licenses contribute to perceptions of job security. Workers in human-intensive services like childcare, healthcare, and education recognize the value of human contact and thus perceive a lower risk of being replaced by AI.

2.3 AI and Productivity

Progress in AI technology raises hopes that would translate into higher productivity and economic growth due to improved efficiency, reduction of costs and continued investment in innovation. Advancements in AI technology foster optimism that they will result in increased productivity and economic expansion, driven by enhanced efficiency, cost reduction, and sustained investment in innovation. Damioli, Roy, and Vertesy (2021) presented recent research results demonstrating a favourable relationship between the rise in AI patent applications and the labour productivity of companies. This study encompassed a sample of 5257 companies globally (manufacturing and services), each of which had filed at least one patent related to AI between 2000 and 2016. While controlling for firms' patenting activities in fields unrelated to AI, the findings uncover a positive and significant impact of AI patent applications on labour productivity. Their results also suggest that the implementation, onboarding and adaptability of AI-based applications within an organization, is a rather important determinant of its impact observed to date.

While the macroeconomic impact of AI on productivity has been extensively studied, its effects at the firm level remain underexplored. However, Grahof and Kopa addressed this gap by conducting a study on a unique sample of German firms that filed a single patent between 2013 and 2019. They formulated the following three research hypotheses based on the assumptions that AI knowledge has a positive influence on labour productivity at the firm level, frontier firms[11] are better able to adopt AI and as a result benefit more from the technology compared to laggard firms[12] and lastly, that laggard firms, in particular, benefit from the available knowledge spill overs within clusters, aligning with the adverse selection effect highlighted by Shaver and Flyer (2000). To test their hypotheses, the authors compiled a unique unbalanced panel dataset. This dataset combines patent information from the PATSTAT database with firm-specific characteristics and productivity data from the comprehensive ORBIS firm database. Their fixed effects panel regression analysis showed a significant direct positive impact of AI on firms' labour productivity. Additionally, their empirical findings suggest that AI knowledge has an insignificant effect on firms, regardless of whether they are at the forefront or trailing in their industry. Finally, they found that AI significantly and positively influences the labour productivity of firms located within clusters.

2.4 AI and Economic Growth

AI innovation has transformed the types of inputs used in production, shifting from traditional resources to more technologically-based ones. Therefore, it is crucial to understand how this shift affects economic variables such as economic growth. The study conducted by Gonzales (2023), aims to measure the effect of AI on long-term economic growth. To assess this impact on the economy, the study utilizes a panel dataset of countries from 1970 to 2019 and uses the number of AI patents as a proxy for AI. By employing fixed effects and generalized method of moments (GMM) estimation, Gonzales discovered a positive and significant relationship between AI and economic growth. Furthermore, he found that this relationship was more robust in advanced economies, especially in the later years of the dataset.

[11] Frontier firms are defined as the most productive companies within each two-digit industry across 23 countries, frontier firms are generally larger, more profitable, younger, and exhibit a higher propensity for patenting and multinational operations compared to their counterparts (Andrewsi, Criscuolo and Gali 2015).

[12] laggard firm is a company that adopts new technologies or practices later or improves more slowly than others in its industry. This term often refers to businesses that are slow to embrace innovation, causing them to lag behind their competitors. Regarding productivity, laggard firms usually fall within the bottom 40% of the productivity spectrum but have substantial growth potential if they can overcome obstacles related to technology and knowledge dissemination (Berlingierii, et al. 2020).

Furthermore, the contributions of Dampitakse, Kusuma, et al (2021) indicates that the adoption of AI has a positive correlation with economic growth, financial development and financial performance in the Association of Southeast Asian Nations (ASEAN). The study utilized data from the World Bank database, focusing on ASEAN countries from 2001 to 2017 and made use of the random effects model to test the hypotheses after its appropriateness was confirmed with the Hausman test. Additionally, Dampitakse, Kusuma, et al, also suggests that the positive correlation found between the adoption of AI and economic growth, financial development, and financial performance in the ASEAN countries, indicates that countries with strong economic growth, sound financial stability and good financial health are better able to facilitate the implementation of AI. These findings offer guidance for policymakers to focus on economic and financial conditions that can enhance AI adoption within organizations and across various industries and regions.

As highlighted by numerous studies, the integration of AI technologies can drive productivity, innovation, and efficiency across various sectors, thereby contributing to overall economic expansion. For instance, research by Wang, Sarker, Alam, & Sumon (2021) demonstrates how AI-enabling businesses and advancements can lead to substantial gains in economic productivity and growth, reshaping industries and creating new opportunities for development. This can be particularly beneficial for countries striving to achieve economic growth, as AI can help overcome existing barriers and accelerate progress in both emerging and established economies (Gonzales 2023). Xu (2022) conducted a study focused on leveraging AI to facilitate high-quality economic growth for a country. The author begins by examining the four economic effects of AI: the penetration effect[13], boundary extension effect[14], knowledge creation effect[15], and self-deepening effect[16], analyzing how AI integrates into and impacts the economy and society. Then, the impact of AI on economic growth is examined through the lenses of labor, capital, and productivity channels. The author concluded that AI impacts economic growth by influencing labor employment and income, promoting economic growth through capital accumulation and structural enhancement, and boosting economic growth by advancing cutting-edge technology and improving technical efficiency.

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[13] Penetration effect refers to the potential of innovative technology to integrate and penetrate all sectors of economic society and all links of production and life and to change the economic operation mode0 (Xu 2022).
[14] Boundary extension refers to the potential of expanding the boundaries of social work tasks and improving the work tasks through some innovative technologies and economic and social integration (Xu 2022).
[15] Knowledge creation refers to the continuous combination, transfer, and conversion of different kinds of knowledge (Xu 2022).
[16] The self-deepening effect manifests in two main aspects. First, machine learning and deep learning have enabled breakthroughs in computer technologies, enhancing AI's capabilities and expanding its range of tasks, such as those performed by intelligent machines, algorithms, and software. Second, self-learning improves the efficiency of work tasks through intelligent automation (Xu 2022).

3. Methodology

This section outlines the research design and analytical approach employed to evaluate the impact of AI adoption on labor, productivity, and economic growth in OECD countries. To achieve this, we utilize pooled OLS, fixed effects and random effects models to address the hypotheses and examine the data extracted from the OECD database covering the period from 1990 to 2020. The Hausman test is employed to confirm the most suitable model for the regression analysis. This section also details the data sources, variable definitions, and the statistical techniques applied to ensure the robustness and validity of our findings.

3.1 Description of Research Design and Methods

This section aims to review the previously outlined research questions using a quantitative methodological approach. Employing quantitative methods enables a statistical understanding of the relationship between the independent and dependent variables (Firestone 1987). Consequently, the study employs econometric analysis as its chosen method. A panel dataset was constructed to evaluate the impact of AI on labour, productivity, and economic growth. This approach offers significant advantages by capturing both time-series dynamics and cross-sectional variations across different units of economic activity in econometrics (Mohamed, Liu and Nie 2022).

3.2 Population, Sample and Data Collection Procedures

The primary challenge in conducting the econometric analysis for this study is data availability. Therefore, the sample was selected based on the availability of data for the study variables. The panel dataset, spanning from 1990 to 2020, comprises secondary data sourced from the OECD database[17], focusing on a sample of 38 countries[18] actively utilizing AI. The variables of interest include Average Annual Wages, AI Patents, AI Grants, Capital Productivity Rate, Employment Rate, GDP Per Capita, and real GDP.

The data collection process involved:

[17] OECD iLibrary (OECD 2024)

[18] Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States (OECD 2022).

1. Identifying and obtaining relevant data from reliable sources.
2. Cleaning and pre-processing the data to handle missing values and outliers.
3. Structuring the data into panel format suitable for econometric analysis.

3.3 Data Analysis Technique

The econometric analysis was conducted using statistical software, R. The primary model used is a panel data regression model, specifically Pooled OLS, Fixed Effects, and Random Effects. Using panel data regression methods in this study offers several advantages. By combining cross-sectional and time series data, this approach provides richer variability and more efficient statistical estimates. It effectively controls for unobserved heterogeneity through fixed or random effects models, enhancing the reliability of the results. Additionally, panel data facilitates the detection of dynamic changes and causal relationships, reduces multicollinearity, and allows for modelling complex behaviours and interactions (Mohamed, Liu and Nie 2022). These benefits make panel data regression a robust choice for analysing the impact of AI on labour, productivity, and economic growth.

The general form of the Panel Data Regression Model is:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \epsilon_{it} \quad (1)$$

Where:

- Y_{it} is the dependent variable for entity i at time t.
- X_{it} represents the independent variable(s) for entity i at time t.
- α is the intercept term.
- β denotes the coefficient(s) of the independent variable(s).
- μ_i captures the unobserved individual-specific effect, which is constant over time but varies across entities.
- ϵ_{it} is the error term, varying across both entities and time.

3.3.1The Basic Models of Panel Analysis:

Pooled Ordinary Least Squares (OLS) Model: In this study, the Pooled Ordinary Least Squares (OLS) model is employed to analyse the relationship between the independent and dependent variables across multiple entities and time periods. This approach assumes that there are no unique attributes of individuals within the dataset that could influence the dependent variable and that these attributes do not change over time. By pooling the data, the model provides a straightforward estimation technique, which can be useful for preliminary analysis. However, it is important to note that pooled OLS does not account for individual-specific or time-specific effects and may not adequately control for unobserved heterogeneity, potentially leading to biased estimates if such heterogeneity is present. Despite this limitation, pooled OLS serves as a valuable baseline model for understanding the general trends and relationships within the dataset before more complex models, such as fixed effects or random effects, are applied.

The general form of a Pooled Ordinary Least Squares (OLS) model is expressed as follows:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \epsilon_{it} \qquad (2)$$

Where:

- Y_{it} is the dependent variable for entity i at time t.
- X_{it} represents the independent variable(s) for entity i at time t.
- α is the common intercept term.
- β denotes the coefficient(s) of the independent variable(s).
- ϵ_{it} is the error term for entity i at time t.

Fixed Effects (within-group) Model (FEM): The Fixed Effects (within-group) model allows for individual-specific intercepts, thereby controlling for time-invariant characteristics unique to each entity that may influence the dependent variable. By focusing on within-group variation, this approach effectively eliminates the bias from omitted variables that are constant over time within each entity. This method involves transforming the data by subtracting the entity-specific mean, thereby isolating the impact of the independent variables on the dependent variable. The fixed effects (within-group) model is particularly advantageous in ensuring that the estimates are not biased by individual-specific effects, providing more reliable and accurate results for the study’s objectives.

The general form of a Fixed Effects (within-group) model involves transforming the data to focus on within-group variations by subtracting the entity-specific means. Here is the formulation:

$$Y_{it} - \bar{Y}_i = \beta(X_{it} - \bar{X}_i) + (\epsilon_{it} - \bar{\epsilon}_i) \quad (3)$$

Where:

- Y_{it} is the dependent variable for entity i at time t.
- X_{it} represents the independent variable(s) for entity i at time t.
- α_i is the entity specific intercept, capturing the effect of unobserved individual characteristics that are constant over time.
- β denotes the coefficient(s) of the independent variable(s).
- ϵ_{it} is the error term for entity i at time t.
- $\bar{Y}_i$ is the mean of the dependent variable for entity i over time.
- $\bar{X}_i$ is the mean of the independent variable(s) for entity i over time.
- $\bar{\epsilon}_i$ is the mean of the error term for entity i over time.

Random Effect Model (REM): The Random Effects model is employed to explore the relationship between the independent and dependent variables, taking into consideration both cross-sectional and longitudinal variations. This model assumes that individual-specific effects are random and independent of the independent variables. By incorporating these effects into the error term, the Random Effects Model yields efficient estimates that capture the variability within and between entities over time. It provides a robust method to examine how the independent variables affect the dependent variable across various entities and time periods.

The general form of a Random Effects model is:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \epsilon_{it} \quad (4)$$

Where:

- Y_{it} is the dependent variable for entity i at time t.
- X_{it} represents the independent variable(s) for entity i at time t.
- α is the common intercept term.
- β denotes the coefficient(s) of the independent variable(s).
- μ_i is the individual-specific effect, assumed to be uncorrelated with X_{it}.
- ϵ_{it} is the error term for entity i at time t.

3.3.2 Model Comparison and Selection Tests

Two methods are used to select the appropriate model for panel regression: The Restricted F Test and the Hausman test. The Restricted F Test is applied to choose between the pooled OLS and the fixed effects model by determining if the fixed effects model, which accounts for individual-specific variations, provides a significantly better fit than the pooled OLS model, which assumes homogeneity across entities. The Hausman test is used to decide between the fixed effects model and the random effects model by evaluating whether the individual-specific effects are correlated with the independent variables (Mohamed, Liu and Nie 2022). The test statistic compares the difference between the coefficient estimates from the fixed effects and random effects models. If the null hypothesis is rejected, the fixed effects model is preferred, as it accounts for the correlation between individual-specific effects and the independent variables, ensuring more reliable and unbiased estimates (Mohamed, Liu and Nie 2022). Below outlines the hypotheses for each model selection test:

1. Restricted F Test: This test compares the Pooled OLS and Fixed Effects models to determine if the fixed effects model provides a significantly better fit.

    - Null Hypothesis (H_0): All entity-specific intercepts are equal (no fixed effects).
    - Alternative Hypothesis (H_a): At least one entity-specific intercept is different.
    - The test statistic compares the residual sum of squares (RSS) of the two models. A significant F-statistic indicates that the fixed effects model is preferred.

2. Hausman Test: This test helps choose between the fixed effects and random Effects models by evaluating if the random effects are uncorrelated with the regressors.
    - Null Hypothesis (H_0): Random effects model is appropriate (no correlation).
    - Alternative Hypothesis (H_a): Fixed effects model is appropriate (correlation exists).
    - The test statistic compares the coefficient vectors from both models. A significant result favours the fixed effects model.

3.3.3 Regression Models

In this study, three models are used for panel data analysis: pooled OLS model, the fixed effects model, and the random effects model. The appropriate model is then determined. The general formula of the model follows the equations below:

Equation One: Labour

$$\text{EmployRate}_{it} = \beta_0 + \beta_1\text{AI\_Pat\_Log}_{1,it} + \beta_2\text{AI\_Grants\_Log}_{2,it} + \beta_3\text{AvgWages}_{3,it} + \beta_4\text{GDPpc}_{4,it} + \beta_5\text{CapProd}_{5,it} + \epsilon_{it} \quad (5)$$

where:

- $\beta_0\ \beta_1\beta_2\beta_3\beta_4\beta_5$ represents the parameters of the model.
- EmployRate represents the number of employed persons as a percentage of the working age population.
- AI_Pat_Log represents the natural logarithm of patents by technologies related to artificial intelligence.
- AI_Grants_Log represents the natural logarithm of grants by technologies related to artificial intelligence.
- AvgWages represents average annual wages per employee in full-time equivalent unit in the total economy.
- GDPpc represents gross domestic product per capita (per person) annual growth rate.
- CapProd represents capital productivity growth rate over 1 year.
- ϵ represents the random variable or error term.

Equation Two: Productivity

$$\text{GDPpc}_{it} = \beta_0 + \beta_1\text{AI\_Pat\_Log}_{1,it} + \beta_2\text{AI\_Grants\_Log}_{2,it} + \beta_3\text{EmployRate}_{3,it} + \beta_4\text{CapProd}_{4,it} + \beta_5\text{GDPpc\_Lag1}_{5,it} + \epsilon_{it} \quad (6)$$

where:

- $\beta_0\ \beta_1\beta_2\beta_3\beta_4\beta_5$ represents the parameters of the model.
- GDPpc represents gross domestic product per capita (per person) annual growth rate.

- AI_Pat_Log represents the natural logarithm of patents by technologies related to artificial intelligence.
- AI_Grants_Log represents the natural logarithm of grants by technologies related to artificial intelligence.
- EmployRate represents the number of employed persons as a percentage of the working age population.
- CapProd represents capital productivity growth rate over 1 year.
- GDPpc_Lag1 represents gross domestic product per capita (per person) annual growth rate lagged by one year.
- ϵ represents the random variable or error term.

Equation Three: Economic Growth

$$\mathrm{GDP}_{it} = \beta_0 + \beta_1 \mathrm{AI\_Pat\_Log}_{1,it} + \beta_2 \mathrm{AI\_Grants\_Log}_{2,it} + \beta_3 \mathrm{GDP\_Lag1}_{3,it} + \beta_4 \mathrm{CapProd}_{4,it} + \epsilon_{it} \quad (7)$$

where:

- $\beta_0\ \beta_1\beta_2\beta_3\beta_4$ represents the parameters of the model.
- GDP represents gross domestic product annual growth rate.
- AI_Pat_Log represents the natural logarithm of patents by technologies related to artificial intelligence.
- AI_Grants_Log represents the natural logarithm of grants by technologies related to artificial intelligence.
- GDP_Lag1 represents gross domestic product per capita (per person) annual growth rate lagged by one year.
- CapProd represents capital productivity growth rate over 1 year.
- ϵ represents the random variable or error term.

Table 1 below presents the variables along with their corresponding interpretations.

Table 1: Description of the study variables

Variables	Interpretation of Variables
AI_Pat_Log	The natural logarithm of patents by technologies related to artificial intelligence.
AI_Grants_Log	The natural logarithm of grants by technologies related to artificial intelligence.
AvgWages	Average annual wages per employee in full-time equivalent unit in the total economy (constant prices)
CapProd	Capital productivity growth rate over 1 year
EmployRate	Employment growth rate over 1 year
GDP	Gross domestic product annual growth rate
GDP_Lag1	Gross domestic product annual growth rate from the previous year
GDPpc	Gross domestic product per capita (per person) annual growth rate
GDPpc_Lag1	Gross domestic product per capita (per person) annual growth rate from the previous year

Data source: Data for each of the variables was obtained from the OECD dataset (OECD 2024).

3.3.4 Hypothesis Testing

- **Hypothesis 1: AI and Employment Levels**
  - H1: The adoption of AI technologies in OECD countries has a statistically significant impact on employment levels.

Rationale: AI automation replaces routine tasks but also creates new opportunities in AI development and maintenance.

- **Hypothesis 2: AI and Labour Productivity**
  - H2: The integration of AI technologies in business processes significantly enhances labour productivity in OECD countries.

Rationale: AI improves efficiency, reduces errors, and accelerates decision-making, leading to higher productivity levels.

- **Hypothesis 3: AI and Economic Growth**
  - H3: Countries within the OECD that invest heavily in AI research, development, and implementation experience higher rates of economic growth compared to those with lower levels of AI investment.

Rationale: AI drives innovation, creates new markets, and enhances the efficiency of existing industries, contributing to overall economic growth.

Significance Testing: For each model, the statistical significance of the coefficients is tested to determine the impact of AI on the dependent variables. This involves calculating t-statistics and p-values for the coefficients.

Goodness of Fit: R-squared and Adjusted R-squared values are calculated to assess how well the models explain the variability in the dependent variable.

Robustness Checks: Additional tests, such as heteroskedasticity and serial correlation tests, are conducted to validate the assumptions of the models.

Significance Level: The significance level was set at alpha level 0.05 for all tests.

3.3.5 Software and Tools

Statistical software R is used to perform the regression analyses, hypothesis testing, and diagnostic checks. This tool facilitates efficient computation and provides comprehensive outputs for interpreting the results.

3.3.6 Ethical Considerations

Ethical considerations were integral to this research. All data used was publicly available and did not involve confidential or sensitive information and therefore did not require permission be obtained from the data providers. The analysis was conducted in a manner that adhered to ethical standards, ensuring the integrity and accuracy of the findings.

4. Data Analysis and Results

It is reasonable to assume that emerging innovative technologies such as AI, can ignite economic activity, enhance productivity and efficiency, and generate a higher demand for new skills and professions, thereby necessitating an increase in workforce upskilling. These assumptions are well-supported by both historical context and economic theories. For example, within the historical context, during the Industrial Revolution, the introduction of steam engines and mechanized manufacturing processes revolutionized production and created new industries and job opportunities (Mohajan 2019). In more recent decades, the advent of computers and the internet during the information age transformed nearly every sector of the economy, leading to the emergence of new professions in IT, software development, and digital communication (Irmgard 2016). In economic theory, Joseph Schumpeter's idea of "creative destruction" suggests that innovation results in the collapse of outdated industries and the rise of new ones, thereby fuelling economic growth (Aghion and Howitt 1990). This concept is crucial for understanding the dynamic nature of capitalist economies and the role of technological advancements in fostering long-term economic development. Additionally, Theodore Schultz's Human Capital Theory emphasizes the importance of investing in human capabilities to enhance economic growth and productivity (Breton 2014). By prioritizing education, health, and continuous learning, societies can cultivate a more skilled and adaptable workforce, resulting in sustained economic benefits and improved living standards. This theory highlights human capital as a fundamental driver of economic development and prosperity. Based on these assumptions, this paper aims to explore these discussions within the context of OECD countries using the outlined methodology.

In Section 4.1, the descriptive statistics for each of the variables used are presented. Section 4.2 offers a correlation matrix displaying the relationships between AI adoption, labour market indicators, productivity metrics, and economic growth, accompanied by an interpretation and discussion of significant positive and negative correlations. Finally, Section 4.3 provides the estimation and interpretation of the regression analysis results.

4.1 Descriptive Statistics

Table 2 below provides a summary of the descriptive statistics for the variables used in the model, leading to the following conclusions:

- The natural logarithm of AI-related grants served as a proxy for AI adoption. Within the sample period, the average logged value of AI-related grants is 1.31, with a range from -0.84 to 4.00 and a standard deviation of 0.89 percent.
- Similarly, the natural logarithm of AI-related patents was used as a proxy for AI adoption. The average logged value of AI-related patents during the sample period is 1.51, ranging from -0.84 to 4.23, with a standard deviation of 0.89 percent.
- The mean average annual wage is USD $53,172.43, with values ranging from USD $25,828.31.00 to USD $78,703.39 and a standard deviation of USD $11,352.13.
- The capital productivity growth rate has a mean value of -1.43 percent, ranging from -11.97 to 3.82 percent, with a standard deviation of 2.06 percent.
- The average annual employment growth rate is 1.07 percent, fluctuating between -6.67 percent and 6.40 percent, with a standard deviation of 1.58 percent.
- The mean real GDP growth for the 38 OECD countries in the sample is 2.11 percent, ranging from -10.15 to 11.47 percent, with a standard deviation of 2.21 percent.
- The average value of real GDP growth lagged by one year for the 38 OECD countries in the sample is 2.0 percent, with a range from -11.1 to 11.47 percent and a standard deviation of 2.47 percent.
- The average GDP per capita growth rate is 1.41 percent, ranging from -10.01 to 10.68 percent, with a standard deviation of 2.12 percent.
- The average GDP per capita growth rate lagged by one year is 1.36 percent, ranging from -11.64 to 10.68 percent, with a standard deviation of 2.37 percent.
- Additionally, the statistics in Table 2 indicate that all variables are significant at the five percent level, based on the probability value of the Jarque-Bera test.
- Regarding the skewness of the variables, the number of AI grants (log), AI patents (log) and average annual wages exhibited positive skewness, whereas the capital productivity rate, employment rate, real GDP, real GDP (T-1), GDP per capita and GDP per capita (T-1), demonstrated negative skewness. Negative skewness indicates that the data distribution has a longer left tail, meaning that there are more low-value outliers. Most data values are clustered on the higher end, with the mean typically being less than the median.
- Lastly, with the exception of average annual wages, the kurtosis values for all the variables are greater than three, indicating the presence and extremity of outliers.

Table 2: Descriptive Statistics of Variables[19]

	AI_GRANTS_LOG	AI_PAT_LOG	AVGWAGES	CAPPROD	EMPLOYRATE	GDP	GDP_LAG1	GDPPC	GDPPC_LAG1
Mean	1.31	1.51	53172.43	-1.43	1.07	2.11	2.07	1.41	1.36
Median	1.20	1.48	52533.93	-1.11	1.16	2.23	2.26	1.55	1.60
Maximum	4.00	4.23	78703.39	3.82	6.40	11.47	11.47	10.68	10.68
Minimum	-0.84	-0.84	25828.31	-11.97	-6.67	-10.15	-11.17	-10.01	-11.64
Std. Dev.	0.89	0.89	11352.13	2.06	1.58	2.21	2.47	2.12	2.37
Skewness	0.38	0.26	0.13	-0.86	-0.86	-0.61	-1.03	-0.65	-1.10
Kurtosis	3.08	3.06	2.27	5.20	6.24	7.10	8.01	7.00	8.18
Jarque-Bera	14.04	6.87	14.74	190.08	326.51	445.10	713.28	430.41	770.52
Probability	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	764.22	883.23	31052700.00	-836.56	629.78	1210.21	1210.21	822.71	793.68
Sum Sq. Dev	462	463.72	7.51 E+10	2463.59	1451.61	3550.31	3550.31	2629.03	3281.93
Observations	584	584	584	584	584	584	584	584	584

Source: Prepared by author based on R output.

4.2 Correlation Analysis

Table 3 below presents a correlation matrix illustrating the relationships between pairs of variables, allowing for a better understanding of the strength and direction of their linear associations. The following conclusions can be drawn:

AI Adoption (AI Grants):

- Strong positive correlation between AI patents and AI grants (0.951): This suggests that as the number of AI-related grants increases, the number of AI-related patents also tends to increase, and vice versa. AI grants and patents may be closely linked in practice since receiving AI-related grants could provide the financial resources necessary to conduct research, which could lead to the development of new AI patents.

[19] AI_Grants_Log, AI_Pat_Log, AvgWages, CapProd, EmployRate, GDP, GDP_Lag1, GDPpc, GDPpc_Lag1.

- Weak positive correlation between AI grants and average annual wages (0.11): A correlation of 0.11 suggests that, while there is a slight tendency for average yearly wages to increase as AI grants increase, the relationship is weak. Changes in AI grants don't strongly predict changes in wages. The weak correlation implies that there are likely many other factors influencing average yearly wages beyond the level of AI grants. AI grants may have some minor effect, but other variables (e.g., overall economic conditions, industry-specific trends, labour market dynamics) probably have a much stronger impact.

- Weak positive correlation between AI grants and capital productivity rate (0.163): The correlation of 0.163 indicates that as AI grants increase, capital productivity tends to increase slightly. However, the relationship is not strong, meaning the increase in AI grants only has a small impact on capital productivity. This suggests that regions or sectors with more AI-related patents tend to also achieve slightly higher capital productivity rates (Damioli, Roy and Vertesy 2021). Companies investing in AI technologies often incorporate other advanced technologies and innovations that boost capital productivity by streamlining processes, cutting costs, and enhancing overall efficiency. Moreover, AI innovations can lead to workforce upskilling, further bolstering capital productivity rates. While the correlation is weak, it suggests a modest association between AI patent activity and improved capital productivity rates.

- Weak negative correlation between AI grants and annual employment growth rate (-0.065): This correlation hints at a slight pattern for regions or sectors with higher rates of AI adoption to experience slightly lower annual employment growth rates (Mohamed and Abdi 2024). Several factors could contribute to this correlation. Firstly, automation may reduce the demand for certain jobs, slowing overall employment growth in affected sectors. Secondly, industries investing heavily in AI may focus on hiring skilled workers with AI expertise, limiting opportunities for less-skilled workers and negatively impacting overall employment growth. Thirdly, AI advancements can shift industry composition, with high-tech sectors growing while traditional sectors see slower employment growth. Additionally, economic shifts toward more capital-intensive industries can affect employment growth rates. Lastly, the adoption of AI technologies may cause temporary labour market disruptions as companies adjust to new technologies, potentially slowing employment growth. Although the correlation is weak, these factors collectively indicate a slight pattern where regions or sectors with higher AI patent activity tend to experience slower rates of annual employment growth.

- Weak negative correlation between AI grants and real GDP (-0.016): Indicates a minor pattern where regions or sectors with more AI-related patents tend to have slightly lower real GDP growth. Some potential reasons for this correlation include the disruption period that occurs in existing industries and economic structures when AI technologies are initially introduced and adopted, leading to short-term decreases in GDP growth as businesses adapt to new processes and technologies. Additionally, while AI can enhance productivity, it can also result in job losses in certain sectors, with the resulting unemployment or underemployment reducing consumer spending and negatively impacting GDP growth (Gordon 2018). Implementing AI technologies often involves significant costs for training, infrastructure, and integration, which can outweigh the immediate productivity gains, leading to slower GDP growth in the short term. Furthermore, the benefits of AI adoption on GDP might take time to materialize and be reflected in economic data. During this transition period, the correlation between AI patents and real GDP growth might appear weak or negative. Although the correlation is weak, these factors collectively suggest that higher AI patent activity might coincide with modest short-term challenges to real GDP growth. However, it's important to note that correlations do not imply causation, and various other economic and social factors also influence GDP trends alongside AI adoption.

- Weak negative correlation between AI patents and GDP per capita lagged by one year (-0.018): This correlation is so close to zero that it suggests almost no relationship between the amount of AI grants and real GDP from the previous year. This means changes in AI grants are not meaningfully related to the GDP of the prior year and therefore might not have an immediate or direct effect on GDP.

- No correlation between AI grants and GDP per capita (0.001): A correlation of 0.001 between AI grants and real GDP per capita indicates virtually no linear relationship between these two variables. Suggesting that changes in AI grants are almost entirely unrelated to changes in real GDP per capita. In other words, variations in AI grant amounts do not appear to correspond with changes in GDP per capita in any meaningful way.

- No correlation between AI grants and GDP per capita lagged one year (-0.003): A correlation of -0.003 indicates virtually no linear relationship between these two variables, and the very small negative value suggests an almost negligible inverse association. The fact that this correlation is near zero, even with a one-year lag, suggests that the effects of AI grants might not manifest in GDP per capita after a one-year period. It's possible that the benefits of AI-related investments, such as increased productivity or innovation, take longer than a year to affect the broader economy, or that their impact on GDP per capita is not easily captured through a linear relationship.

AI Adoption (AI Patents):

- Weak positive correlation between AI patents and average annual wages (0.183): This implies that there is a slight tendency for average annual wages to increase as the number of AI patents rises. However, this relationship is weak, meaning that while there is some association, it is not strong or consistent across all cases. AI patents could reflect innovation and technological advancement within industries that are adopting AI. Companies or sectors producing more AI patents may see increased productivity or demand for skilled labour, which could lead to a modest rise in wages. However, since the correlation is weak, this effect may not be substantial across the board.

- Moderate positive correlation between AI patents and capital productivity (0.216): suggests that as the number of AI patents increases, capital productivity also tends to rise, albeit not strongly. This indicates a relationship where advancements in AI technology may enhance how effectively capital (e.g., machinery, equipment) is used in production processes (Damioli, Roy and Vertesy 2021).

- Weak negative correlation between AI patents and annual employment growth rate (-0.022): The correlation coefficient suggests that there is almost no linear relationship between the number of AI patents and the employment growth rate. In other words, changes in the number of AI patents do not significantly predict changes in employment levels, whether positively or negatively. If firms are still in the early stages of implementing AI technologies, the potential negative impact on employment may not yet be fully realized or may not have been captured in employment statistics.

- Moderate negative correlation between AI patents and real GDP (-0.453): The negative correlation suggests that as the number of AI patents increases, GDP tends to decrease, or vice versa. This could imply that regions or sectors with a higher concentration of AI patents are experiencing lower levels of economic output as measured by GDP. The introduction of AI technologies could be leading to a decline in traditional industries that contribute significantly to GDP. As businesses innovate and adopt AI, they might be optimizing processes or automating jobs, which could result in reduced output from conventional sectors (Gordon 2018). The correlation may reflect lagged effects where the positive impacts of AI patents on GDP are not yet fully realized. It's possible that while AI patents are increasing, the economic benefits of those innovations have yet to translate into GDP growth, leading to the observed negative relationship.

- Weak negative correlation between AI patents and real GDP lagged by one year (-0.022): The correlation is very close to zero, suggesting that there is almost no linear relationship between AI patents and GDP from the previous year. This implies that fluctuations in AI patents do not significantly correlate with changes in lagged GDP, indicating that they may operate independently.

- Weak negative correlation between AI patents and real GDP per capita (-0.031): This suggests that, while there is a relationship between these two variables, it is very small and negative. This means that, as the number of AI patents increases, real GDP per capita slightly tends to decrease, though the effect is so weak it might not be meaningful.

- Weak negative correlation between AI patents and real GDP per capita lagged by one year (-0.008): The weak negative correlation between AI patents and real GDP per capita lagged by one year (-0.008) suggests that even when a time delay is considered, the relationship between AI patent activity and economic growth (as measured by GDP per capita) remains very weak and slightly negative. In this case, the correlation is even closer to zero than the previous one (-0.031), meaning there is almost no meaningful relationship.

Table 3: Matrix of correlation between study variables

	AI_GRANTS_LOG	AI_PAT_LOG	AVGWAGES	CAPPROD	EMPLOYRATE	GDP	GDP_LAG1	GDPPC	GDPPC_LAG1
AI_GRANTS_LOG	1.000								
AI_PAT_LOG	0.951	1							
AVGWAGES	0.110	0.183	1						
CAPPROD	0.163	0.216	0.053	1					
EMPLOYRATE	-0.065	-0.022	0.093	0.376	1				
GDP	-0.016	-0.453	-0.095	0.616	0.66	1			
GDP_LAG1	-0.018	-0.022	-0.065	-0.046	0.496	0.373	1		
GDPPC	0.001	-0.031	-0.161	0.666	0.961	0.961	0.311	1	
GDPPCLAG1	-0.003	-0.008	-0.121	-0.012	0.33	0.33	0.968	0.334	1

Source: Prepared by author based on R output.

4.3 Results of the Pooled OLS Model

The results of the pooled OLS model estimation are presented in Table 4, specifically in columns 1 (EmployRate), 4 (GDPpc), and 7 (GDP). The corresponding interpretations are provided below:

Dependent Variable: Employment Rate (Labour)

The analysis of the impact of AI-related patents and grants on labour reveals a statistically significant positive relationship at the 0.05 level, and a statistically significant negative relationship at the 0.01 level, respectively. Specifically, a one-unit increase in AI_Pat_Log is associated with a 1.0439 unit rise in EmployRate, while a one-unit increase in AI_Grants_Log corresponds to a 1.1146 unit decrease in EmployRate. Regarding the relationship between average annual wages and labour, the pooled OLS model found a statistically significant positive association, where a one-unit increase in AvgWages results in a 0.000024 unit increase in EmployRate. Similarly, GDP per capita showed a statistically significant positive effect, with a one-unit rise in GDPpc leading to a 0.5179 unit increase in EmployRate. Additionally, capital productivity exhibited a negative but statistically significant relationship with labour, where a one-unit increase in CapProd resulted in a 0.0942 unit decrease in EmployRate. The overall regression model was statistically significant ($F = 75.60$, $p < 0.01$), explaining 39.50 percent of the variation in EmployRate.

Dependent Variable: GDP Per Capita (Productivity)

The analysis of the impact of AI-related patents on productivity shows a negative but statistically significant relationship. Specifically, a one-unit increase in AI_Pat_Log leads to a 1.9704 unit decline in GDP per capita (GDPpc). Conversely, the impact of AI-related grants on productivity reveals a positive and statistically significant relationship, where a one-unit increase in AI_Grants_Log results in a 1.6786 unit increase in GDPpc. Additionally, capital productivity is positively and significantly associated with GDP per capita, with a one-unit increase in CapProd resulting in a 0.6596 unit rise in GDPpc. Similarly, GDP per capita lagged by one year has a positive and statistically significant effect on productivity, as a one-unit increase in GDPpc_Lag1 leads to a 1.02133 unit rise in GDPpc. Lastly, the relationship between labour and productivity is also positive and statistically significant, as a one-unit increase in EmployRate increases GDPpc by 0.3462 units. The overall regression model is statistically significant ($F = 239.44$, $p < 0.01$), explaining 67.29 percent of the variation in GDPpc.

Dependent Variable: Real GDP (Economic Growth)

The analysis of the relationship between AI-related patents and economic growth reveals a negative and statistically significant correlation, with a one-unit increase in AI_Pat_Log leading to a 1.9136 unit decrease in GDP. In contrast, AI-related grants show a positive and statistically significant impact on economic growth, where a one-unit increase in AI_Grants_Log results in a 1.4984 unit rise in GDP. Furthermore, capital productivity also has a positive and significant effect on economic growth, with a one-unit increase in CapProd leading to a 0.7577 unit rise in GDP. Lastly, the one-year lagged GDP value demonstrates a positive and significant relationship, where a one-unit increase in GDP_Lag1 leads to a 0.3522 unit rise in GDP. The overall regression model is statistically significant ($F = 218.81$, p-value < 0.01), accounting for 60.02 percent of the variation in GDP.

4.4 Results of the Fixed Effects Model (FEM)

The corresponding results of the Fixed Effects Model (FEM) estimation are presented in Table 4, specifically in columns 2 (EmployRate), 5 (GDPpc), and 8 (GDP). The corresponding interpretations are provided below:

Dependent Variable: Employment Rate (Labour)

The analysis of the impact of AI-related patents on labour reveals a positive and statistically significant effect, with a one-unit increase in AI_Pat_Log leading to a 0.7022 unit rise in EmployRate. Conversely, AI-related grants show a negative but insignificant relationship with labour, as a one-unit increase in AI_Grants_Log results in a 0.4190 unit decline in EmployRate. The correlation between average annual wages and labour is positive and statistically significant, with a one-unit increase in AvgWages contributing to a 0.000042 unit rise in EmployRate. Similarly, productivity demonstrates a positive and statistically significant relationship with labour, where a one-unit increase in GDPpc leads to a 0.5934 unit increase in

EmployRate. However, capital productivity has a negative and statistically significant impact, indicating that a one-unit increase in CapProd causes a 0.1653-unit decline in EmployRate. The overall model is statistically significant (F = 93.05, p-value < 0.01), accounting for 45.51 percent of the variability in EmployRate.

Dependent Variable: GDP Per Capita (Productivity)

In analysing the impact of AI on productivity, we find that AI-related patents have a negative but statistically significant effect. Specifically, a one-unit increase in AI_Pat_Log decreases GDPpc by 1.2859 units. On the other hand, AI-related grants show a positive but insignificant association with productivity. The model also highlights a positive and statistically significant relationship between labour and productivity, where a one-unit increase in EmployRate leads to a 0.4080 unit increase in GDPpc. Similarly, capital productivity growth is positively and significantly correlated with GDP per capita, with a one-unit increase in CapProd resulting in a 0.7009 unit increase in GDPpc. Additionally, the growth rate of GDP per capita lagged by one year shows a positive and statistically significant effect, where a one-unit increase in GDPpc_Lag1 boosts the next period's GDP per capita by 0.1146 units. Overall, the model is statistically significant (F = 362.35, p-value < 0.01) and accounts for 76.34 percent of the variation in GDPpc based on the independent variables.

Dependent Variable: Real GDP (Economic Growth)

In analysing the impact of AI-related patents on economic growth, there is a negative and statistically significant relationship. Specifically, a one-unit increase in AI_Pat_Log leads to a 1.3021 unit decrease in GDP. Conversely, the impact of AI-related grants on economic growth shows a positive but statistically insignificant association. Additionally, capital productivity shows a positive and statistically significant influence on GDP growth, where a one-unit increase in CapProd leads to a 0.8247 unit rise in GDP. The effect of lagged GDP from the previous year is also positive and statistically significant, with a one-unit increase in GDP_Lag1 leading to a 0.2300 unit increase in the following year's GDP. Overall, the model is statistically significant (F = 318.95, p-value < 0.01) and explains 69.45 percent of the variability in GDP based on the independent variables.

4.5 Results of the Random Effects Model (REM)

The results of the random effects model (REM) estimation are presented in Table 4, specifically in columns 3 (EmployRate), 6 (GDPpc), and 9 (GDP). The corresponding interpretations are provided below:

Dependent Variable: Employment Rate (Labour)

In analysing the effect of AI-related patents on labour, the REM shows a positive and statistically significant relationship, with a one-unit increase in AI_Pat_Log resulting in a 0.8268 unit rise in EmployRate. Conversely, the impact of AI-related grants on labour is negative and statistically significant, where a one-unit increase in AI_Grants_Log leads to a 0.6820 unit decrease in EmployRate. The correlation between average annual wages and labour is positive and statistically significant, with a one-unit increase in AvgWages resulting in a 0.000037 unit rise in EmployRate. Similarly, the relationship between productivity and labour is positive and statistically significant, as a one-unit increase in GDPpc leads to a 0.5710 unit increase in EmployRate. However, capital productivity has a negative but statistically significant effect on labour, with a one-unit increase in CapProd causing a 0.1434-unit decline in EmployRate. The overall model is statistically significant (Chisq. = 459.30, p-value < 0.01), explaining 44.39 percent of the variability in EmployRate through the independent variables.

Dependent Variable: GDP Per Capita (Productivity)

In analysing the impact of AI on productivity, the findings reveal that AI-related patents have a negative and statistically significant effect. Specifically, a one-unit increase in AI_Pat_Log results in a 1.9704 unit decrease in GDPpc. Conversely, AI-related grants show a positive and statistically significant relationship, where a one-unit increase in AI_Grants_Log leads to a 1.6785 unit rise in GDPpc. Similarly, capital productivity growth positively and significantly affects GDP per capita, with a one-unit increase in CapProd contributing to a 0.6596 unit increase in GDPpc. The lagged growth rate of GDP per capita also exhibits a positive and statistically significant relationship, where a one-unit increase in GDPpc_Lag1 results in a 0.1946 unit rise in GDPpc. Lastly, labor shows a positive and statistically significant effect on productivity, as a one-unit increase in EmployRate increases GDPpc by 0.3462 units. Overall, the model is statistically significant (Chisq = 1197.2, p-value < 0.01), explaining 67.29 percent of the variation in GDPpc through the independent variables.

Dependent Variable: Real GDP (Economic Growth)

In analysing the impact of AI adoption on economic growth, there is a statistically significant negative relationship. Specifically, a one-unit increase in AI_Pat_Log is associated with a 1.9136 unit decrease in GDP. In contrast, AI-related grants have a positive and statistically significant effect, with a one-unit increase in AI_Grants_Log resulting in a 1.4984 unit increase in GDP. Additionally, capital productivity shows a positive and statistically significant influence, with a one-unit increase in CapProd contributing to a 0.7577 unit increase in GDP. Finally, GDP growth from the previous year positively affects the next year's growth, where a one-unit increase in GDP_Lag1 leads to a 0.3522 unit increase in GDP. Overall, the model is statistically significant (Chisq = 875.24, p-value < 0.01), explaining 60.02 percent of the variation in GDP through the independent variables.

Table 4: Model Estimation by Pooled OLS, Fixed Effects, and Random Effects

	Dependent Variables								
	EmployRate	EmployRate	EmployRate	GDPpc	GDPpc	GDPpc	GDP	GDP	GDP
Explanatory Variable	Pooled OLS	Fixed Effects (FEM)	Random Effects (REM)	Pooled OLS	Fixed Effects (FEM)	Random Effects (REM)	Pooled OLS	Fixed Effects (FEM)	Random Effects (REM)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI_Grants_Log	-1.1146*** (0.19844)	-0.41898 (0.25682)	-0.68620** (0.22869)	1.678549*** (0.185195)	0.147317 (0.235755)	0.147317 (0.235755)	1.498407*** (0.214091)	0.018273 (0.267950)	-1.302107*** (0.203343)
AI_Pat_Log	1.0494*** (0.20497)	0.70223*** (0.20868)	0.82678*** (0.20081)	-1.970368*** (0.185641)	-1.285889*** (0.178578)	-1.285889*** (0.178578)	-1.913585*** (0.215373)	-1.302107*** (0.203343)	-1.302107*** (0.203343)
AvgWages	0.000024*** (0.0000)	0.000042** (0.000014)	0.000037*** (0.000009)						
CapProd	-0.094231* (0.0037)	-0.1653*** (0.038476)	-0.14343*** (0.037353)	0.659596*** (0.027900)	0.700932*** (0.024753)	0.700932*** (0.024753)	0.757663*** (0.029448)	0.824682*** (0.024676)	0.824682*** (0.024676)
EmployRate				0.346234*** (0.038215)	0.408048*** (0.036871)	0.408048*** (0.036871)			
GDP									
GDP_Lag1							0.352176*** (0.023316)	0.230007*** (0.020555)	0.230007*** (0.020555)
GDPpc	0.51786*** (0.05074)	0.59341*** (0.036891)	0.57103*** (0.035870)						
GDPpc_Lag1				0.194584*** (0.023561)	0.114636*** (0.020612)	0.114636*** (0.020612)			
R-Squared	0.39499	0.45514	0.44387	0.67289	0.76389	0.76389	0.6002	0.69458	0.69458
Adjusted R-Squared	0.38977	0.42872	0.43907	0.67008	0.7525	0.7525	0.59746	0.68042	0.68042
F-Statistic	75.602	93.05	459.30	239.439	362.345	362.35	218.81	318.85	318.95
Prob (F-Statistic)	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
***p<.01, **p<.05, *p<.1									

Note: Standard errors in parentheses.

4.6 Model Justification Results

Pooled OLS Model Vs. Fixed Effects (The Restricted F Test)

Table 5 below presents the results of the restricted F test. The calculated F-statistic values are 11.31, 15.93, and 17.70, all of which exceed the critical value of 1.42 at the 5 percent significance level. Furthermore, the p-values are all less than 0.01, indicating strong evidence against the null hypothesis.

Table 5: The Restricted F Test - Partial F Test Results

Statistic	Value (Labour)	Value (Productivity)	Value (Economic Growth)
F-Statistic	11.31	15.93	17.70
Critical Value (5%)	1.42	1.42	1.42
p-value	< 0.01	<0.01	<0.01

Since the F-statistic values are greater than the critical values and the p-values are less than 0.01, we reject the null hypothesis. This indicates that the fixed effects model is preferred over the pooled OLS model, as the individual-specific effects are significant. Consequently, we will use the fixed effects model in the discussion section.

Fixed Effects Vs. Random Effect (Hausman test)

Table 6 below displays the results of the Hausman test. The Hausman statistics are 8.40, 30.10, and 55.36, with degrees of freedom of 5 for labour and productivity, and 4 for economic growth, respectively. The associated p-values are less than 0.01, for each of the models, indicating strong evidence against the null hypothesis. Therefore, we can reject the null hypothesis in favour of the alternative hypothesis. This suggests that the random effects are correlated with the regressors, making the fixed effects model more appropriate than the random effects model for our panel data analysis.

Table 6: Hausman Test Results

Statistic	Value (Labour)	Value (Productivity)	Value (Economic Growth)
Chisq.	8.40	30.10	55.36
Degrees of Freedom	5	5	4
p-value	<0.01	< 0.01	<0.01

Based on the Hausman test results, we conclude that the fixed effects models should be used instead of the random effects models due to the significant correlation between random effects and regressors observed in our dataset.

4.7 Diagnostic Test Results

Heteroskedasticity (Breusch-Pagan Test)

Table 7 below displays the results of the Breusch-Pagan test, with test statistics of 307, 235.71, and 310.89, and corresponding degrees of freedom of 27 for labour and productivity, and 26 for economic growth, respectively. The associated p-values are less than 0.01, which is less than the conventional significance level of 0.05. This indicates strong evidence against the null hypothesis of homoskedasticity. Therefore, we can reject the null hypothesis and conclude that there is significant heteroskedasticity present in our regression models.

Table 7: Breusch-Pagan Test Results

Statistic	Value (Labour)	Value (Productivity)	Value (Economic Growth)
Breusch-Pagan Test Statistic	307	235.71	310.89
Degrees of Freedom	27	27	26
p-value	< 0.01	<0.01	<0.01

Based on the results of the Breusch-Pagan test, we find evidence of heteroskedasticity in our models. To address this issue, we may consider using robust standard errors or applying a transformation to the dependent variable to stabilize the variance of the error terms.

Serial Correlation (Breusch-Godfrey/ Wooldridge Test)

Table 8 below presents the results of the Breusch-Godfrey/Wooldridge test, where the test statistics are 73.91, 198.65 and 197.47 with corresponding degrees of freedom of 11 for each respectively. The associated p-values are less than 0.01, which is less than the conventional significance level of 0.05. This indicates strong evidence against the null hypothesis of no serial correlation. Therefore, we can reject the null hypothesis and conclude that there is significant serial correlation present in the residuals of our regression model.

Table 8: Serial Correlation (Breusch-Godfrey/ Wooldridge Test) Results

Statistic	Value (Labour)	Value (Productivity)	Value (Economic Growth)
Breusch-Godfrey/ Wooldridge Test	73.91	198.65	197.47
Degrees of Freedom	11	11	11
p-value	< 0.01	<0.01	<0.01

Based on the results of the Breusch-Godfrey/ Wooldridge test, we find evidence of serial correlation in our model. To address this issue, we may consider using robust standard errors that account for serial correlation or applying a different model specification.

5. Discussion

This study sought to assess the impact of AI adoption on labour, productivity, and economic growth within OECD countries. Despite the considerable hype surrounding AI technology adoption, its actual impact appears to be modest. Based on the results from the fixed effects model, our study identifies a negative and statistically insignificant relationship between AI adoption (AI grants) and labour. Comparisons with existing literature reveal possible reasons for this outcome. For instance, the study conducted by Mohamed and Abdi (2024), highlights significant displacement effects attributed to AI adoption, particularly in routine and repetitive tasks. The authors discuss the nuanced impact of AI adoption on labour markets, emphasizing the dual effects of displacement and potential reinstatement. They note that while the introduction of AI technologies often leads to the displacement of workers, especially in roles involving routine and repetitive tasks, there is also potential for job creation in areas requiring human-AI collaboration and advanced technical skills. This dynamic can result in a complex labour market response where initial job losses are counterbalanced by new opportunities, contributing to a statistically insignificant overall effect of AI adoption on labour. Moreover, the negative and statistically insignificant relationship observed in our study may reflect the initial stages of AI integration into the workforce, where the full benefits and new employment opportunities have yet to materialize. Mohamed and Abdi's insights suggest that over time, as AI technologies become more entrenched and the workforce adapts, the positive effects on labour might become more pronounced and statistically significant.

The fixed effects model also revealed a positive and statistically significant relationship between AI adoption (AI patents) and labour. This effect differs to that AI grants and can be explained when we consider that AI grants reflect early-stage research, while AI patents indicate market-ready innovation. AI grants typically fund exploratory or early-stage research and development. At this stage, the technologies being developed may still be far from market application and unlikely to immediately affect labour markets. Researchers may be experimenting with new ideas that are not yet influencing real-world employment, hence the weak and negative impact on labour. AI patents, on the other hand, often represent innovations that are closer to commercialization or implementation. Once a technology is patented, it is more likely to be deployed in real-world applications, creating demand for new roles and skills, and thereby having a positive impact on labour.

When exploring the impact of AI adoption on productivity, the fixed effects model reveals a positive but statistically insignificant association between AI grants and productivity. This reflects the early-stage nature of AI research, where potential gains are far off, and the immediate effects are neither large nor consistent enough to influence labour productivity in the short term. The positive direction could be an indication of optimism about future benefits, but the insignificant impact underscores the uncertain nature of early AI research. On the other hand our analysis also shows a negative and statistically significant relationship between AI adoption (AI patents) and productivity. This relationship found in the fixed effects model could be related to the disruptive nature of AI technologies and the dynamics of adoption. The theoretical implications of this result are noteworthy. AI technologies, such as machine learning and automation, are widely believed to hold significant promise for enhancing efficiency and increasing output per worker. These technologies can streamline operations, reduce error rates, and enable more sophisticated decision-making processes, thereby boosting overall productivity. However, the practical realization of these theoretical benefits faces several challenges. One major challenge is the implementation of AI technologies across different industries. The integration of AI systems requires substantial investment in infrastructure, training, and change management. Nurlia, Rosadi, and Daud (2023) noted this challenge in their research, emphasizing the necessity for significant investments in infrastructure, training, and change management. Their study underscores the importance of a proactive approach, not only in integrating AI technologies but also in preparing the workforce and adapting organizational frameworks. Organizations face considerable costs and efforts in purchasing and installing new technologies. Beyond the initial investment, there is a need to adapt existing processes and train the workforce to effectively utilize these advanced tools. This transition phase can be time-consuming and expensive, potentially offsetting the immediate productivity gains that AI adoption might promise. Therefore, while AI technologies theoretically offer significant productivity enhancements through efficiency improvements and advanced decision-making capabilities, the practical challenges of implementation and adaptation can dilute these benefits in the short term. The negative and statistically significant relationship we observed may reflect these transitional challenges, indicating that the full productivity benefits of AI have yet to be realized. This highlights the need for tailored policy interventions and skill development initiatives to support the effective integration of AI technologies and maximize their potential productivity gains.

Similar to the connection between AI adoption(AI grants) and productivity, our fixed effects model uncovers a positive but statistically insignificant relationship between AI grants and economic growth. AI grants typically fund early-stage research and development, which is often focused on innovation and experimentation. At this stage, AI projects are far from being fully realized or applied in the market, meaning they have yet to generate tangible contributions to economic growth. Nelson (1959) explains how basic research, such as that funded by grants, often takes time to impact the economy. The long and uncertain path from research to commercialization and economic application means that the immediate effects on growth are often insignificant, despite the potential for future breakthroughs. Therefore, technologies funded by these grants are still in the research or prototype phase, which delays their influence on productivity, employment, or business expansion—factors that directly drive economic growth.

Lastly, our findings also reveal a negative statistically significant association between AI adoption (AI patents) and economic growth. This unexpected result warrants a deeper investigation into the broader economic factors influencing growth dynamics in OECD countries. Again, one possible explanation for this outcome is the disruptive nature of AI technologies. The integration of AI can lead to significant shifts in labour markets, where automation and AI-driven processes displace traditional jobs faster than new ones can be created. This displacement can result in short-term economic disruptions, including increased unemployment and underemployment, which can negatively impact overall economic growth. This disruptive impact was the main focus of the paper written by Mohamed and Abdi (2024), who highlight how the displacement effect of AI can lead to economic instability and reduced growth in the short term. Additionally, the adoption of AI technologies often requires substantial upfront investments in infrastructure, research and development, and workforce training. These costs can strain public and private resources, potentially diverting funds from other critical areas that drive economic growth. For example, significant investments in AI may reduce the capital available for investments in other productive sectors or public services, thus dampening immediate economic growth prospects. The result also prompts consideration of the fact that the rapid pace of AI innovation might outstrip the ability of institutions to adapt, creating uncertainty and potentially hindering economic growth.

Our findings contribute significantly to the theoretical understanding of the impact of AI adoption on labour, productivity, and economic growth within OECD countries. Findings that provide nuanced insights into the complexities of integrating AI technologies into established economic systems. The promising yet statistically non-significant correlation between AI adoption and labour, productivity and economic growth indicates that while AI shows promise in improving productivity, its full benefits may not be immediately apparent. This aligns with existing theories that emphasize the lag between technological innovation and its widespread adoption and effective implementation. Our findings underscore the importance of considering the transitional phase where initial productivity gains may be offset by the costs and challenges associated with AI integration.

The observed relationship between AI adoption and improvements in labour and productivity, although not statistically significant, suggests that AI has potential benefits that may not be immediately observable. This finding is consistent with theories[20] that highlight the delay between technological innovation and its

[20] (Mohamed and Abdi 2024)

broad adoption and effective use. Our results highlight the need to account for the transitional period where initial productivity gains might be tempered by the costs and challenges of integrating AI.

The negative statistically significant relationship between AI adoption and economic growth challenges the often-optimistic theoretical perspectives that predict immediate economic benefits from AI. This finding supports the view that AI-induced labour market disruptions, as highlighted by Mohamed and Abdi (2024), can lead to short-term economic instability. It contributes to the theoretical framework that acknowledges the dual effects of AI as both a driver of innovation and as a source of disruption.

6. Concluding Remarks and Recommendations

The results of this study enhance the theoretical understanding of AI's effects by highlighting the significance of accounting for transitional dynamics and the influence of policy measures. The findings suggest that the integration of AI into existing economic systems is a much more complex and multifaceted process that requires substantial investment, regulatory adaptation, and workforce training. These elements are critical when realizing the potential benefits of AI while mitigating its disruptive effects.

To ensure a smooth, disruption-free onboarding of AI activity in the economic system, will require substantial investment in workforce training and development programs. By equipping workers with the necessary skills to adapt to AI-driven changes, policymakers can help mitigate the negative effects of job displacement and enhance the overall productivity of the workforce. Also, critical will be investment in infrastructure, particularly in digital and technological capabilities. This includes upgrading existing systems and ensuring that organizations have the resources needed to integrate AI seamlessly. Lastly, establishing mechanisms for continuous monitoring and evaluation of AI adoption is important. By tracking the impact of AI on labour markets, productivity, and economic growth, policymakers and stakeholders can make informed decisions and adjust strategies as needed to maximize benefits and minimize disruptions.

In conclusion, while AI adoption presents significant opportunities for enhancing labour markets, productivity and economic growth, it also poses challenges that require careful monitoring and management. By implementing strategic policy interventions, investing in workforce development, and supporting infrastructure and R&D, OECD countries can harness the potential of AI while addressing its disruptive effects. This balanced approach is essential for fostering sustainable economic growth and ensuring that the benefits of AI are widely shared. (Nurlia , Rosadi and Daud 2023)

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