THE ECONOMICS OF AI-DRIVEN PRODUCTIVITY: ARE TRADITIONAL GROWTH MODELS OBSOLETE?

Loso Judijanto*[1]
IPOSS Jakarta, Indonesia
Email: losojudijantobumn@gmail.com

Novira Fazri Nanda
Politeknik Negeri Sriwijaya, Indonesia
Email: novira.fazri@polsri.ac.id

Baskoro Ajie
Politeknik ATK Yogyakarta, Indonesia
Email: baskoro.ajie@atk.ac.id

Abstract

This study aims to analyze the relevance of traditional economic growth models in the context of artificial intelligence-driven productivity gains. The rapid development of AI has triggered significant changes in the structure of production, distribution, and consumption, raising questions about whether classical theoretical frameworks such as the Solow growth model, endogenous theory, and human capital-based models are still capable of explaining modern growth dynamics. Using a literature review, this study examines recent empirical and theoretical findings related to AI's contribution to productivity, its impact on labor markets, and its implications for income distribution. The analysis shows that AI introduces a new factor of production, "algorithmic capital," characterized by high scalability and low marginal costs, potentially shifting the fundamental assumptions of conventional growth models. Furthermore, the disruptive nature of AI has the potential to create wider productivity gaps between countries and industries, not fully captured by traditional models. The study concludes that while classical growth models remain relevant as a foundation for analysis, adaptations to the theoretical framework are needed to integrate the role of AI technology as a key determinant of 21st-century productivity. The study also recommends the development of a hybrid growth model capable of capturing the dynamics of exponential technology and the more asymmetric distribution of benefits.

Keywords: Artificial Intelligence, productivity, economic growth model, algorithmic capital.

[1] Correspondence author

INTRODUCTION

The development of artificial intelligence technology over the past two decades has fundamentally transformed the way goods and services are produced, distributed, and consumed. AI serves more than just a simple automation tool; it has evolved into a system capable of performing complex analyses, making decisions, and even generating new innovations autonomously. This development marks a new era in the dynamics of global economic growth, where productivity is no longer solely determined by labor and physical capital, as assumed in traditional growth models, such as the Solow-Swan model or endogenous growth theory (Dang, 2025). This raises a critical question: is the theoretical framework of economic growth currently in use still relevant, or is a new paradigm needed to understand and measure the impact of AI on productivity?

Classical and neoclassical economic growth models generally view technology as an exogenous or residual factor that is difficult to measure, often referred to as the Solow residual (Manyika & Spence, 2023). With the advent of AI, technology is no longer merely a supporting factor but has become a key driver capable of accelerating growth in a non-linear manner. AI enables productivity increases that are not only incremental but also disruptive, creating significant leaps in production efficiency. Examples include the manufacturing sector, which uses machine learning to predict machine failures before they occur, or the financial services sector, which utilizes predictive algorithms for real-time risk analysis. These efficiency improvements no longer rely solely on increasing capital or labor, but rather on the system's ability to learn, adapt, and optimize processes autonomously (Shalaby, 2024).

Within traditional growth models, productivity is typically measured as output per unit of input, which is assumed to experience diminishing returns as capital or labor are added. However, AI introduces a new dynamic where returns to scale can increase with increasing data and system complexity. For example, machine learning models become increasingly accurate when fed with more data, generating economic value greater than simply proportional to the inputs used (Chowdhury, 2024). This situation has the potential to undermine the fundamental assumption of conventional growth models, which assume that increasing inputs will yield increasingly smaller additional outputs. Conversely, in an AI-driven economy, growth can be self-reinforcing through continuous data cycles and innovation.

Furthermore, the adoption of AI also has distributional implications that differ from previous technological innovations. In traditional industrial revolutions, new technologies generally increased labor demand in certain sectors while creating new jobs in others. However, AI has the potential to displace both high- and low-skilled jobs, while creating new demand that is highly focused on specialized expertise in algorithm development, data science, and systems design (Reza E Rabbi Shawon et al., 2024). This could alter patterns of income and wealth distribution, which in turn impact overall economic growth dynamics. Therefore, the relevance of growth models that rely on the assumption of flexible and adaptive labor markets needs to be questioned in the context of skill-biased AI.

The structural changes brought about by AI also have implications for macroeconomic productivity measurement. One emerging paradox is a phenomenon similar to the productivity paradox at the beginning of information technology adoption, where technological progress is not fully reflected in national productivity growth figures. Some economists argue that this is due to a technology adoption lag, where the full benefits of AI will only be seen after comprehensive integration into global value chains and business model transformation (Butt, 2024). However, a fundamental difference from previous technologies is the rapid pace of AI's evolution, making the gap between innovation and economic outcomes more significant.

On the other hand, debate continues over whether AI will truly drive a surge in productivity or only provide limited benefits. Optimists argue that AI is a general-purpose technology (GPT) equivalent to the steam engine, electricity, or computers, generating a wave of long-term economic growth (George, 2024). Conversely, skeptics warn that challenges such as algorithmic bias, privacy concerns, unequal access to technology, and regulatory barriers could limit AI's potential to increase productivity broadly. These differing views call for a more comprehensive economic analysis framework that views AI not only as a technological variable in a growth model but also as a factor transforming market behavior, industry structure, and interactions between economic actors.

The question of whether traditional growth models are obsolete in the era of AI-driven productivity becomes even more relevant when we consider the exponential and adaptive nature of this technology. The Solow model and its derivatives have indeed provided a strong foundation for understanding the interrelationships between capital, labor, and technology. However, the underlying assumptions of these models, such as technological exogeneity, diminishing returns, and the stability of economic structures, do not appear to fully reflect the realities of an AI-driven digital economy. In fact, some economists have begun developing new growth models that integrate the concepts of algorithmic learning-by-doing, data network effects, and the near-infinite scale of the digital economy.

Against this backdrop, this research is crucial because it can contribute to a new understanding of the dynamics of economic growth in the AI era. This study not only examines the relationship between AI adoption and productivity gains but also evaluates the extent to which traditional economic growth models can explain this phenomenon. Through a literature review approach, this research will identify gaps in existing growth theories and formulate a conceptual framework that better aligns with the characteristics of AI technology. Therefore, the research findings are expected to provide insights for policymakers, industry players, and academics in formulating adaptive and sustainable economic strategies amidst massive technological transformation.

RESEARCH METHOD

The research method used in this study is a literature review, which aims to examine in-depth the relationship between artificial intelligence-based productivity developments and the relevance of traditional economic growth models. The literature collection process involved searching academic sources such as scientific journals, books, research reports, and official institutional publications published over the past ten years to ensure the data's relevance to current technological developments. These sources were obtained through international academic databases such as Scopus, Web of Science, and Google Scholar, using keywords related to the research topic, such as "AI-driven productivity," "economic growth models," "technological innovation," and "automation and productivity growth."

The literature analysis was conducted using a descriptive-analytical approach that integrates findings from various previous studies to identify patterns, differences, and research gaps related to the impact of AI on productivity and its implications for existing economic growth models. The analysis phase included sorting the literature based on research focus, categorizing the findings, and synthesizing arguments to build a conceptual framework linking AI-based productivity with the resilience or decline of traditional growth models. With this approach, the research is expected to yield a comprehensive theoretical understanding while providing direction for the development of economic growth models that are more adaptive to the era of technological disruption.

RESULT AND DISCUSSION

Artificial Intelligence Mechanisms in Boosting Productivity

The mechanisms of artificial intelligence (AI) in boosting productivity have become a strategic topic influencing global economic dynamics across various sectors. AI serves not only as a technological tool but also as a driver of structural transformation that redefines how companies, governments, and societies produce goods and services, make decisions, and create added value. Its application is shifting the paradigm of efficiency and innovation, while paving the way for new business models that are more adaptive to changing markets and consumer needs (Zong & Guan, 2025). This mechanism operates through various interconnected pathways, with automation, data analysis, and product or service innovation being the core foundations.

In the context of automation of production and service processes, AI has a significant impact on accelerating workflows and reducing operational costs. AI technologies such as machine learning, computer vision, and natural language processing enable systems to identify patterns, predict needs, and execute tasks with high levels of precision without direct human intervention. In the manufacturing sector, AI can optimize supply chains, minimize machine downtime through predictive maintenance, and ensure consistent product quality through image recognition-based automated inspection systems (Selvarajan, n.d.). In the service sector, AI accelerates customer service responses through chatbots capable of 24/7 interaction, processing requests in real time, and providing personalized solutions. By automating repetitive and time-consuming activities, human labor can be redirected to strategic tasks that require creativity, empathy, and complex decision-making, thereby increasing overall organizational productivity.

Furthermore, AI mechanisms for increasing the efficiency of data-driven decision-making are a crucial pillar of productivity transformation. AI can process vast volumes of data from various sources quickly and accurately, identifying patterns invisible to conventional analysis, and generating more reliable predictions. In the business sector, this means managers can make investment, pricing, or marketing strategy decisions by considering measurable risks and opportunities. In the public sector, AI can aid evidence-based policy planning by analyzing socioeconomic trends, health data, or traffic patterns. This speed of analysis is crucial in a dynamic environment, where delays in decision-making can lead to missed market opportunities or exacerbate existing problems (Adekunle et al., 2021). AI also enables the simulation of various scenarios, helping organizations prepare responsive strategies to potential changes in the business environment or regulations. This improves the quality and speed of decision-making, ultimately impacting performance and competitiveness.

In addition to increasing efficiency, AI also drives added value creation through innovation in new products and services (Yadav et al., 2024). Armed with the ability to understand consumer preferences, analyze market trends, and predict future needs, AI empowers companies to design more relevant, personalized, and high-value offerings. In the healthcare sector, AI facilitates the development of new drugs by streamlining the process of discovering potential molecules through computational simulations, significantly reducing research time and costs. In the retail sector, AI enables the development of recommendation systems that provide highly personalized shopping experiences, increase customer loyalty, and open up cross-product sales opportunities. In the creative industry, AI helps generate innovative designs, music, or digital content, while enabling unique collaborations between humans and machines to create previously unimaginable works. This mechanism expands market potential, increases economic value, and strengthens companies' positions amidst global competition.

These three mechanisms automation, decision-making efficiency, and innovation do not operate in isolation, but rather reinforce each other in a continuous productivity cycle. Automation provides greater data and resources for analysis, that analysis generates insights that guide innovation, and innovation, in turn, creates more effective and automated processes. This combination creates a multiplier effect on productivity, with each element reinforcing the others. However, to maximize its benefits, organizations need to address technological readiness, workforce data literacy, and ethical governance of AI use (Magableh et al., 2024). Without proper change management, AI's potential can be hampered by internal resistance, skills gaps, or the risk of algorithmic bias, which can harm credibility and public trust (Valle-Cruz & García-Contreras, 2025).

Thus, AI's productivity-boosting mechanisms are not simply about speeding up work or reducing costs, but also about building an adaptive, data-driven, and innovation-oriented work ecosystem. Successful implementation requires synergy between technology, people, and supportive policies. When these three aspects are harmoniously integrated, AI can be a major catalyst for sustainable economic growth, while simultaneously leading organizations to competitive advantage in the digital age.

Changing Labor Market Dynamics

The shift in labor market dynamics due to technological advances, particularly artificial intelligence, has transformed the way organizations view the role of humans in production, distribution, and service delivery. AI is impacting nearly every industrial sector, from manufacturing and financial services to logistics and healthcare to education, creating significant transformations in skill demand, job structures, and the relationship between humans and machines (Erigbe, n.d.). While AI presents significant opportunities for increased productivity and innovation, it also poses serious challenges in terms of potential job losses, skills gaps, and the inequitable distribution of technological benefits across society. These changes are forcing governments, the private sector, and educational institutions to formulate new strategies to anticipate and manage this transition to ensure it remains inclusive and sustainable.

The impact of AI on employment can be viewed from two opposing perspectives. First, AI has the potential to replace routine, repetitive jobs that can be easily automated. Jobs in the manufacturing sector that rely on manual production lines, administrative tasks that rely on simple data processing, and basic customer service that can be replaced by chatbots are concrete examples of the displacement of human roles by machines. This impact is not limited to low-educated workers, as even jobs requiring specific analytical skills are beginning to be disrupted by generative AI and advanced analytics (Chhibber et al., 2025). However, AI is also creating new jobs that require different technical and non-technical skills than before, such as algorithm development, large-scale data analysis, automated system oversight, and AI ethics and security management. This shift is making the job landscape more complex, with some fields shrinking while others are rapidly expanding.

In this context, the need for upskilling and reskilling is particularly pressing. Upskilling refers to improving relevant skills in the same or similar roles, while reskilling means training workers to master new skills that enable them to transition to different types of jobs. AI is accelerating this process because technological change cycles are shortening, making today's relevant skills obsolete quickly. Companies are investing resources in internal training programs, technology bootcamps, and partnerships with educational institutions to ensure their workforces are not left behind (Onifade et al., 2022). Meanwhile, workers are required to develop adaptive skills such as complex problem-solving, interdisciplinary communication, and strong digital literacy, in addition to mastery of specific technologies. Without serious investment in upskilling and reskilling, the risk of structural unemployment due to skills mismatch will increase.

The distinction between displacement and augmentation in the workforce is a key concept in understanding this shift. Displacement occurs when technology completely replaces the role of humans in a work process, resulting in the loss or significant reduction of jobs (Onifade et al., 2022). An example is the use of automated document processing machines that eliminate the need for data entry operators. In contrast, augmentation refers to the process by which technology is used to enhance human capabilities, rather than replace them. In augmentation, AI becomes a tool that helps workers perform their tasks more quickly, accurately, and effectively. For example, a doctor can use AI to analyze medical images and identify disease patterns more quickly, but the final decision remains with the doctor. Augmentation tends to create synergy between humans and machines, where technology takes over tedious or time-consuming tasks, freeing humans to focus on aspects that require creative judgment, empathy, or strategic decision-making.

However, the line between displacement and augmentation is not always clear. In many cases, AI technology is initially adopted to support human work, but as system capabilities improve, its role can shift to become a full replacement (Furaijl et al., 2025). An example can be seen in the retail sector, where cashiers were initially assisted by automated teller systems to speed up transactions, but the introduction of self-service tellers drastically reduced the need for human cashiers. This demonstrates that the labor market's adaptation to AI is not simply a matter of replacing or enhancing human roles, but also of how the design, regulation, and ethics of the technology's implementation are directed to minimize negative impacts and maximize added value for workers.

This shift also has broad socio-economic implications. Companies that utilize AI for augmentation tend to produce a workforce with high productivity and better service quality, while companies that focus purely on displacement can potentially reduce labor costs but reduce job opportunities. Public policy has a vital role to play in guiding this development, for example through incentives for companies investing in worker training, tax regulations for automation, and support for sectors most impacted. Furthermore, formal education must be redesigned to prepare students for the realities of a more dynamic job market, including technological mastery, critical thinking skills, and lifelong learning (Tomar et al., 2024).

Overall, the shift in labor market dynamics due to AI is not merely a technical phenomenon, but also a social, economic, and cultural one. AI brings the promise of higher productivity, opportunities for innovation, and an improved quality of life, but these benefits will not be realized evenly without proper transition management. Displacement and augmentation are not mutually exclusive paths, but rather two spectrums that can be managed so that technology becomes a catalyst for human empowerment, not a replacement. Success in navigating this era will depend heavily on the speed and quality of upskilling and reskilling, the active involvement of all stakeholders, and the willingness to design an inclusive work ecosystem amidst the inevitable waves of change. Thus, the labor market in the AI era will shape a new order that demands a harmonious combination of human intelligence and machine sophistication.

Evaluating the Performance of Traditional Growth Models in the Artificial Intelligence Era

Evaluating the performance of traditional growth models in the artificial intelligence (AI) era is crucial because this technological development has brought about fundamental changes in how the economy operates. Classical growth models, such as the Solow-Swan model or early endogenous growth models, are built on the assumption that economic growth is primarily determined by the accumulation of capital, labor, and technological progress, which are assumed to be exogenous or incremental (Kalai et al., 2024). This assumption was relatively adequate when technological development followed a slow diffusion pattern, allowing labor markets and production sectors to gradually adapt. However, in the AI era, the speed of innovation, technological scalability, and massive network effects have rendered these assumptions increasingly irrelevant. AI not only acts as an additional factor in the production function but also changes the structure of productivity and creates non-linear phenomena that are difficult to explain within the framework of traditional growth models.

One key assumption of classical growth models being reexamined in the AI era is the concept of diminishing returns to capital and labor (Al Khatib, 2025). In the classical view, additional capital or labor results in diminishing returns to output. However, AI enables self-reinforcing productivity gains, where the more data and AI usage, the greater the system's ability to increase output and efficiency. This phenomenon creates the potential for increasing returns to scale that traditional models don't adequately accommodate. For example, AI-enabled companies can leverage the same digital infrastructure to serve global markets without significantly increasing marginal costs, creating a productivity gap between companies that intensively adopt AI and those that don't. This leads to a more polarized distribution of growth, contradicting the convergence predictions of classical growth models.

Furthermore, traditional growth models generally view technological progress as exogenous or the result of research and development investment that increases linearly with capital input and skilled labor (Mansouri et al., 2025). In reality, AI introduces a non-linear innovation dynamic, where a single breakthrough can trigger a sudden surge in productivity. This effect is evident in the development of generative AI models that, once trained, can be used to simultaneously create multiple applications across sectors. This kind of spillover phenomenon makes the relationship between R&D input and technological output more complex, often leading to inaccurate growth predictions based on the old model. In this context, the steady-state assumptions characteristic of the Solow model also become less realistic, as AI technologies tend to generate waves of innovation that trigger temporary instability in labor markets, industrial structures, and consumption patterns.

The need to modify or even replace growth models is becoming increasingly clear (Pagliaro, 2025). Relevant growth models in the AI era need to accommodate non-linear factors, network effects, and the possibility of increasing returns. A new generation of endogenous growth model-based approaches, integrating data-driven innovation theory and machine learning, could be one direction for development (Xiaofei & Balasubramaniam, 2025). Such models should consider that AI can act as an autonomous factor of production, capable of innovating on its own without relying entirely on capital or human labor. Furthermore, models should incorporate the crucial role of knowledge distribution and access to digital infrastructure as key determinants of growth, given that AI widens the gap between the technologically advanced and the digitally disadvantaged (Ruggeri et al., 2025).

Furthermore, within a macroeconomic framework, new models also need to accommodate the impact of AI on uncertainty and volatility. AI accelerates the innovation cycle, which can cause short-term imbalances but opens up opportunities for higher long-term growth. This demands models capable of simulating rapid transitions between growth phases, including potential labor market disruptions and shifts in industrial structure. Factors such as public policy adaptation, workforce reskilling capabilities, and technological infrastructure readiness are variables that significantly influence growth trajectories (Nkomo & Mupa, 2024). Thus, evaluating the performance of traditional growth models in the AI era not only highlights the limitations of legacy assumptions but also opens up opportunities to develop more flexible, adaptive analytical frameworks that address the realities of a rapidly evolving digital economy.

New Growth Models for the Artificial Intelligence Era

The era of artificial intelligence (AI) is driving the urgent need for updated economic growth models that can capture the complexity and dynamics of the digital economy. Classical growth models, such as the Solow-Swan or traditional endogenous models, were built within the context of an industrial economy dominated by physical capital, human labor, and technological progress, which were viewed as exogenous or linear factors (Bontadini et al., n.d.). However, in the AI era, patterns of value accumulation and sources of productivity have undergone a fundamental transformation, with data, algorithms, and intangible assets playing a central role. A digital economy based on data capital is not only transforming how companies generate and allocate resources but also changing the nature of growth itself, making it more dependent on the ability to manage, process, and extract value from information.

A digital economy-based approach to building new growth models positions data as a core factor of production, on par with physical capital and labor (Corrado et al., 2022). Data is not simply a measurable input like raw materials, but rather an asset whose value increases with the scale and quality of its use. The uniqueness of data as capital lies in its non-rivalrous nature, which allows it to be used simultaneously by multiple parties without diminishing returns, and in the network effects that magnify the value of data as its volume and diversity increase. Therefore, growth models for the AI era need to formalize the mechanisms by which data is collected, processed by algorithms, and transformed into economically valuable outputs. Within this framework, companies that master digital infrastructure, platforms, and data ecosystems will have a competitive advantage that is difficult to match, due to their ability to create a feedback loop between data acquisition, algorithm improvement, and the creation of new products or services.

The integration of intangible capital variables is a crucial dimension in this new growth model. Intangible capital includes knowledge capital, brands, intellectual property rights, software, user bases, and organizational capabilities (Фоміна & Семенова, 2025). In the context of AI, intangible capital has a strong correlation with innovation capabilities and market agility. Unlike physical capital, intangible capital has the potential for increasing returns due to its replicable nature without significant marginal costs, while also amplifying the effects of digital economies of scale. A growth model that incorporates intangible capital as a key variable can explain why large technology companies can achieve very high market valuations despite having relatively few physical assets. Furthermore, this model can capture the role of investments in talent development, digital infrastructure, and algorithms as drivers of long-term productivity.

Algorithms in new growth models function as value-processing engines that transform data into decisions, recommendations, predictions, and product innovation. The advantage of algorithms lies not only in their ability to execute commands quickly, but also in their capacity to learn and adapt through machine learning (Fariz & Winarsih, 2025). This means that an entity's productivity is no longer solely determined by the quantity of data it possesses, but also by the quality and sophistication of the algorithms used to process it. Growth models that accommodate algorithmic variables need to consider the dynamic relationship between data accumulation, algorithm performance improvements, and accelerated innovation. In other words, AI introduces endogenous feedback mechanisms that make economic growth increasingly non-linear, where technological improvements can occur continuously without the same physical boundaries as traditional manufacturing.

Furthermore, new growth models in the AI era must recognize that the distribution of benefits from the digital economy tends to be unequal. Companies that control data infrastructure and algorithms can create digital monopolies or oligopolies, thereby creating productivity and income gaps among economic actors (Grineva et al., 2023). Within the digital economy, the winner-takes-all effect becomes more dominant, meaning public policy and regulation will significantly influence the direction and sustainability of growth. Therefore, modern growth models need to not only explain the mechanisms of data-driven capital accumulation but also model the role of competition policies, data protection, and investment in society's broader digital capacity.

Mathematically, this new growth model can be developed by expanding the traditional production function to include physical capital (K), labor (L), data (D), intangible capital (I), and algorithmic variables (A) as interconnected factors of production. For example, the production function can be formulated as:

$Y=F(K,L,D,I,A)$

where D, I, and A have a synergistic relationship that creates increasing returns, and technological variables are no longer exogenous but endogenous through

a continuous machine learning process. This approach allows us to model the impact of investments in data infrastructure, algorithm development, and intangible capital development on overall output growth (Challoumis, n.d.).
Thus, a new growth model for the AI era not only replaces outdated assumptions about the role of technology in the economy but also reconceptualizes factors of production to include digital assets, analytical capabilities, and knowledge capital as key pillars. This creates an analytical framework more relevant to the realities of the digital economy, where productivity, innovation, and growth are driven by the complex interactions between data, algorithms, and intangible capital. This integration is not simply a technical adaptation, but rather the formation of a new economic paradigm that can explain why an AI-based economy can develop faster and more dynamically, but also be more vulnerable to the concentration of economic power.

CONCLUSION

This study concludes that the emergence of Artificial Intelligence as a key driver of productivity has brought about significant structural changes to the economic growth paradigm. AI not only accelerates production processes and decision-making but also encourages the emergence of new business models previously unimaginable within the framework of traditional growth theory. AI-driven productivity gains tend to be non-linear and often deviate from the predictions of classical growth models, which rely on the assumption of stable contributions of capital, labor, and technology. This suggests that AI can create disruptive productivity leaps, thus challenging existing theoretical frameworks.

On the other hand, while AI opens up significant opportunities for accelerated growth, this study emphasizes that the adoption of this technology does not automatically diminish the relevance of all traditional growth models. While some fundamental principles, such as the role of capital accumulation, the quality of human resources, and innovation, remain crucial, the weighting and interactions between these factors change in the context of AI. Thus, conventional growth models require modification to accommodate the new dynamics brought about by intelligent technology, particularly regarding the shift in value-added from physical factors to knowledge-based and algorithmic factors.

Overall, the study's findings demonstrate that the AI era demands a more adaptive, dynamic, and multidisciplinary framework for economic analysis. The integration of AI into production and management systems requires a rethinking of existing indicators, assumptions, and economic development strategies. While the relevance of traditional growth models is not entirely lost, conceptual reconstruction is needed to capture the complexity and speed of change brought about by AI. This research provides the foundation for developing a new generation of growth theory that not only quantifies the contribution of AI but also understands its structural impact on income distribution, labor markets, and global competitiveness.

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