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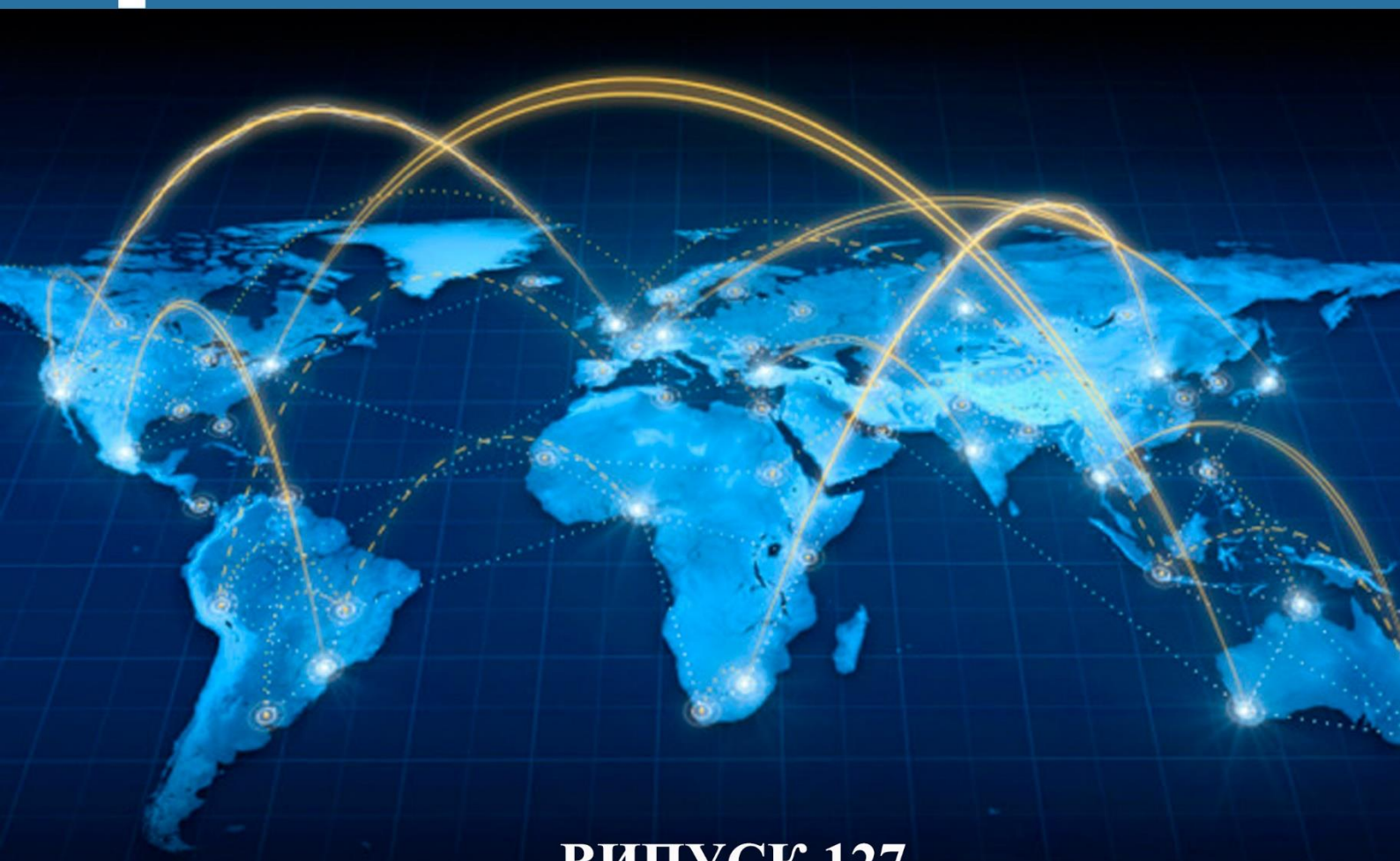

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ARTIFICIAL INTELLIGENCE AS A CATALYST FOR ECONOMIC GROWTH IN THE MODERN WORLD

This article examines the role of artificial intelligence (AI) as a transformative force in the global economy during the critical scaling phase of 2025-2026. Drawing on recent empirical research, macroeconomic modelling, and industry data, the paper analyses how AI is reshaping productivity, accelerating innovation, and fundamentally altering labour markets worldwide. The study explores the emergence of agentic AI systems, the growing movement toward sovereign AI infrastructure, and the widening skills gap that threatens to undermine AI's economic promise. It also examines the systemic risks associated with unprecedented capital investments in artificial intelligence infrastructure and the urgent need to establish effective governance mechanisms. The study's findings indicate that, while artificial intelligence has significant potential as a driver of economic recovery, realizing this potential depends on coordinated efforts by business, government, and educational institutions.

Keywords: *information retrieval; artificial intelligence; economic growth; productivity; labour market transformation; agentic AI; sovereign AI; skills gap; AI governance.*

У цій статті досліджується роль штучного інтелекту (ШІ) як трансформаційної сили у світовій економіці на критичному етапі масштабування 2025-2026 років. Спираючись на новітні емпіричні дослідження, макроекономічне моделювання та галузеві дані, стаття аналізує, як ШІ змінює продуктивність, прискорює інновації та докорінно трансформує ринки праці у всьому світі. Дослідження розглядає появу агентного ШІ, зростаючий рух до суверенної ШІ-інфраструктури та поглиблення розриву в навичках. Також розглядаються системні ризики, пов'язані з безпрецедентними капітальними інвестиціями в інфраструктуру штучного інтелекту, та нагальна потреба у створенні ефективних механізмів управління.

Ключові слова: *штучний інтелект; економічне зростання; продуктивність; трансформація ринку праці; агентний ШІ; суверенний ШІ; дефіцит навичок; управління ШІ.*

Introduction. Around 2024, changes took place in the global economy, and by early 2026, they could no longer be ignored. Artificial intelligence, once a niche topic for computer scientists and a handful of forward-thinking executives, found itself at the very center of macroeconomic discussions. Central bank governors mention it in their policy speeches. Finance ministers factor it into their budget forecasts. And the world's largest corporations are investing hundreds of billions of dollars in infrastructure designed to support it. The question is no longer whether AI will matter for economic growth. The question is how much, how quickly, and who will benefit from it.

The timing of this transition is significant. After years of pilot experiments and proof-of-concept demonstrations, AI is entering what technology historians would recognise as a scaling phase. A major 2024 OECD paper classified AI as a potential new General-purpose technology – a category that encompasses innovations such as electricity and the Internet – has the potential to revitalize sluggish productivity growth across many sectors, while acknowledging that its development is concentrated in the hands of a small number of large technology companies and taking into account the uncertainty surrounding its long-term impact [3, p. 4]. Eloundou et al. (2024), in a landmark study published in Science, provided the granular empirical justification of these claims through the classification of specific jobs in the U.S. labor market that can be partially or fully automated using large language models; it was found that approximately 80% of workers

are employed in sectors where at least 10% of their tasks are affected by artificial intelligence, and approximately 19% of workers hold positions where at least half of their tasks may be subject to change [6, p. 2].

Even the most ardent sceptic in this field has acknowledged that something significant is happening. Daron Acemoglu, winner of the 2024 Nobel Prize in Economics, used a model based on Hulten's theorem to estimate that AI could boost total factor productivity by 0.53-0.66% over a decade – a modest figure by Silicon Valley's optimistic standards, but significant by the standards of an economist who has spent decades studying the uneven impacts of technological change [1, p. 15]. Charles Jones of Stanford, approaching the issue from a different angle in the journal American Economic Review: Insights, outlined the economic challenges even more sharply by modeling the contradiction between AI's extraordinary growth potential and its existential risks, and concluded that standard economic models are unable to strike a balance between these two aspects [5, p. 576].

This article examines the mechanisms through which artificial intelligence will influence economic growth in 2025-2026 and beyond. It analyzes issues related to productivity and operational efficiency, the acceleration of the innovation process, the transformation of labor markets, as well as the systemic risks associated with such rapid technological adoption.

The most direct path from AI to economic growth runs through productivity. When workers accomplish more in less time, or when firms produce the same output with fewer resources, the economy expands. This logic is as old as economics itself; what is new is that there is growing evidence that generative AI is actually delivering on this promise in terms of task performance, and in ways that differ significantly from previous waves of automation.

The gold-standard empirical study in this space is Brynjolfsson, Li, and Raymond, published in the Quarterly Journal of Economics in 2025. The authors tracked 5,172 customer support agents as their employer rolled out a generative AI conversational assistant. Agents with access to the tool resolved 15% more customer issues per hour on average, with the largest gains accruing to less experienced and lower-skilled workers, who improved both the speed and quality of their output, while the most experienced and highest-skilled workers saw small gains in speed and small declines in quality [2, p. 889]. What makes this study particularly valuable is its scale, its real-world workplace setting, and the length of observation. The researchers also found evidence that AI assistance facilitated genuine worker learning and improved English fluency among international agents, suggesting that the tool functions not merely as a crutch but as a training accelerator [2, p. 920].

Translating these micro-level gains into macro-level GDP impact is where the disagreement begins. Acemoglu (2025) argues that the aggregate effect depends on two things: the share of economic activity actually exposed to AI, and the average cost savings from adoption. Using Eloundou et al.'s (2024) task exposure estimates alongside cost-feasibility data from Svanberg et al., he arrives at a cumulative TFP gain of less than 0.66% over a decade [1, p. 18]. He further notes that early evidence comes disproportionately from "easy-to-learn" tasks with straightforward success metrics, and that future applications targeting harder, more context-dependent problems may yield smaller productivity improvements per task [1, p. 25]. The OECD takes a somewhat more expansive view, noting that AI's unique capacity for autonomy and self-improvement could generate productivity effects that compound over time in ways that static task-based models may underestimate [3, p. 8].

Siddik et al. (2024) provide an important sectoral lens on this debate. Examining AI's role in sustainable tourism across the top ten global tourist destinations from 2010 to 2022, they combine artificial neural network analysis with traditional econometric models to show that AI adoption is a critical driver of tourism efficiency, significantly enhancing both productivity and sustainability outcomes [4, p. 1]. Given that tourism accounts for roughly 10% of global GDP, these findings suggest that AI-driven productivity effects are already measurable in specific sectors, even if the aggregate macroeconomic picture remains incomplete.

A significant development in 2025-2026 is the rapid maturation of agentic AI - systems capable of setting goals, making decisions, and executing multi-step tasks with minimal human oversight. Gartner projects that by the end of 2026, 40% of enterprise applications will embed task-specific AI agents. If earlier generations of AI helped individual workers do their jobs faster, agentic AI promises to reorganise entire workflows. A supply chain that currently requires a dozen handoffs between procurement, logistics, and finance could be compressed into a coordinated sequence managed by interacting agents. Whether these gains materialise at scale remains an open question. McKinsey's 2025 research found that only 39% of companies report real bottom-line impact from AI investments, and a mere 6% capture significant enterprise value. The gap between pilot success and operational reality is one of the defining challenges of this period.

Beyond incremental productivity gains, AI is changing the speed at which new ideas reach the economy. In scientific research, AI models are generating hypotheses, predicting molecular structures, and accelerating drug discovery timelines. Google DeepMind's protein structure prediction work earned the 2024 Nobel Prize in Chemistry. Google's AI co-scientist, released in early 2025, was explicitly designed to help researchers generate novel hypotheses and accelerate biomedical discovery. These developments are not marginal improvements to existing processes; they represent a qualitative shift in how knowledge is produced. The OECD notes that AI's capacity for self-improvement could accelerate innovation itself, potentially reviving the sluggish productivity growth that has characterised advanced economies for two decades [3, p. 6].

Jones (2024) frames this innovation potential within a broader growth-theoretic framework. In his analysis for the American Economic Review: Insights, he models a scenario in which AI delivers extraordinary economic benefits – raising growth to 10% per year – but simultaneously carries a one-time risk of catastrophic failure. The surprising result is that under standard economic preferences with log utility, agents would be willing to accept alarmingly high levels of existential risk to secure such growth [5, p. 578]. This finding matters not because the scenario is likely, but because it reveals how deeply AI has disrupted conventional assumptions about the relationship between technological progress and human welfare. The implication is that governance frameworks must evolve as fast as the technology itself.

Lewandowski (2024) demonstrates that AI's innovation effects extend well beyond commercial R&D into the social sphere. Through a systematic literature review based on a five-component model of the social innovation process, the study shows that AI contributes to each stage – from identifying challenges and enabling participation to generating creative solutions and empowering communities [7, p. 128]. This finding is economically significant because social innovation drives improvements in public services, healthcare delivery, and education systems that are not fully captured by conventional GDP measures but nonetheless contribute to long-run economic wellbeing.

A parallel development with far-reaching consequences is the rise of Sovereign AI - the drive by national governments to build and control their own AI infrastructure rather than depend on US-based hyperscalers. France announced 109 billion euros in AI infrastructure investments in early 2025. South Korea committed to deploying over 260,000 GPUs across sovereign cloud facilities. The EU's AI Factories initiative is expanding a network of supercomputing resources accessible to startups and universities across Europe. The economic model emerging from these efforts is a layered strategy: countries leverage global frontier models where possible but develop or fine-tune domain-specific models where sovereignty and security needs are highest. The success of these strategies will depend on sequencing – establishing governance and demand before scaling infrastructure.

No discussion of AI and economic growth can avoid the question of jobs. Eloundou et al. (2024) established the empirical baseline: approximately 80% of the US workforce belongs to occupations with at least some task exposure to large language models, with around 19% of workers in occupations where half or more of tasks could be affected [6, p. 3]. The World Economic Forum's Future of Jobs Report 2025, drawing on data from over 1,000 companies across

55 economies, translates this exposure into projected displacement and creation: 170 million new roles created and 92 million displaced by 2030, yielding a net gain of 78 million positions. But aggregate numbers can be deeply misleading. The displaced roles – clerical workers, administrative assistants, data entry operators – are concentrated in lower-income brackets. The created roles – AI engineers, data scientists, cybersecurity specialists – require advanced training.

The empirical evidence on who benefits from AI at work carries a hopeful nuance. Brynjolfsson, Li, and Raymond (2025) found that the largest productivity gains accrued to less experienced and lower-skilled workers, who improved both speed and quality, while top performers saw modest gains in speed alongside small quality declines [2, p. 905]. The researchers also found evidence that AI assistance facilitated genuine learning effects that persisted beyond tool use and improved English fluency among international agents [2, p. 925]. If that pattern holds as AI tools proliferate, the technology could act as an equaliser within occupations, helping entry-level workers close the gap with veterans.

But the same dynamic creates a paradox at the occupational level. If AI makes certain tasks dramatically cheaper to perform, firms may eventually automate those tasks entirely rather than keeping human workers in the loop. Acemoglu (2025) warns that even when AI improves the productivity of low-skill workers in certain tasks without creating new tasks for them, this may increase rather than reduce inequality, because the gains flow disproportionately to capital owners while the labour share of national income declines [1, p. 35]. The OECD's analysis adds that knowledge-intensive, high-productivity activities seem much more affected by AI than manual work, which means an eventual fall in employment shares of these sectors could drag on aggregate productivity growth – a new form of what economists call Baumol's disease [3, p. 12].

Entry-level job postings have fallen 29% worldwide since January 2024 – a trend that appears at least partly structural. Youth unemployment reached 10.8% in the United States in mid-2025, more than double the overall rate. The skills gap has become the single most frequently cited barrier to business transformation, with 63% of employers identifying it as their top constraint. The response from governments and corporations has been growing but uneven. Corporate reskilling commitments are expanding, yet the pace of institutional adaptation still lags the pace of technological change by a margin that shows no sign of closing.

The scale of capital flowing into AI infrastructure in 2025-2026 is historically unusual. Amazon, Alphabet, Meta, and Microsoft alone spent nearly $300 billion on capital expenditures in 2025, with the collective AI-related capex of the hyperscalers estimated at 1.3% of US GDP in 2025, projected to reach 1.6% in 2026. The hyperscalers are trapped in a prisoner's dilemma: if any one holds back from the AI arms race, it risks being overtaken. This dynamic more or less guarantees collective overinvestment.

The critical question is whether this spending will generate commensurate returns. Enterprise AI currently generates approximately $100 billion in actual revenue against roughly $400 billion in infrastructure spending. Acemoglu's framework offers a structural explanation for this disconnect: even when AI's microeconomic effects are real and measurable, the macroeconomic consequences may remain modest for years because many future applications will target "hard-to-learn" tasks with context-dependent factors that limit cost savings [1, p. 30]. A February 2026 NBER study found that 90% of firms reported no immediate impact of AI on workplace productivity, even as executives continued to project significant future gains – a pattern reminiscent of Robert Solow's famous observation that computers were everywhere except in the productivity statistics.

There are reasons for cautious optimism. Unlike the dot-com era, much of the current build-out is funded by free cash flow rather than speculative debt. The five major hyperscalers, excluding Oracle, can fund their forecast capex entirely from cash from operations. Analysts have noted that today's AI sector differs structurally from dot-com-era technology: profitable operations, robust cash generation, and measurable revenue growth underpin the sector's strength, even if valuations are elevated.

The governance challenge extends well beyond financial risk. The OECD warns that AI-driven threats to market competition may weigh on its potential benefits: the high fixed costs and returns to scale related to data and computing power may lead to excessive concentration of AI development, while AI-powered pricing algorithms have already shown a tendency to charge supra-competitive prices [3, p. 14]. Jones (2024) drives this point further by showing that standard cost-benefit analysis breaks down when applied to technologies carrying tail risks of catastrophic harm, and that society may systematically underinvest in governance relative to the stakes involved [5, p. 585]. The EU AI Act, which reached full enforcement provisions in 2025, represents the world's first comprehensive risk-based regulatory framework. Beyond Europe, governance efforts remain fragmented. Lewandowski (2024) emphasises that governance is not merely a compliance matter but a precondition for AI to generate genuine social innovation rather than reproduce existing inequalities at scale [7, p. 136].

Conclusion. Artificial intelligence in 2026 occupies an unusual position in economic history. It is simultaneously one of the most promising drivers of productivity growth in decades and one of the largest concentrations of capital risk in modern financial markets. The empirical evidence confirms that AI delivers real productivity gains at the task level, particularly for less experienced workers [2]. The macroeconomic evidence, while still incomplete, suggests that those gains will compound as adoption deepens and capabilities evolve from assistive tools to autonomous agents.

But the path from technological potential to broad-based economic prosperity is not automatic. It requires governance frameworks that keep pace with deployment timelines [3, 5]. It requires honest accounting of the gap between infrastructure spending and revenue generation. It requires reskilling programmes that anticipate rather than react to displacement. And it requires the kind of institutional adaptability that, historically, societies have found difficult to sustain over the long periods that general-purpose technologies take to mature.

The economists disagree on the magnitude. Acemoglu sees a modest, steady contribution of 0.53-0.66% in TFP over a decade [1]. Brynjolfsson and his co-authors have established that the technology's benefits at the micro level flow disproportionately to workers who need them most [2]. Siddik et al. have shown that AI is already a measurable catalyst for economic cycles in specific sectors [4]. Jones has revealed the deep tension between AI's growth promise and its catastrophic risk potential [5]. Eloundou et al. have mapped the task-level exposure that underpins all these estimates [6]. And Lewandowski has demonstrated that AI's innovation effects extend into the social sphere in ways that conventional growth accounting may miss [7]. What all these scholars share is the recognition that AI is not a passing trend, and that the decisions made in the next few years - by firms, governments, and educational institutions - will shape the distribution of its benefits for a generation. The research agenda is rich. The stakes, for once, match the hype.

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BALANCING AI MODEL PERFORMANCE WITH ROBUST DATA ENCRYPTION

This article examines the critical challenge of maintaining high performance in artificial intelligence models while integrating robust data encryption mechanisms. It analyzes the fundamental trade-offs between computational overhead introduced by encryption and the accuracy, latency, and throughput requirements of modern AI systems, and explores emerging techniques such as homomorphic encryption, federated learning, and secure multi-party computation.

Keywords: *artificial intelligence, data encryption, homomorphic encryption, federated learning, model performance, privacy-preserving machine learning, secure computation, neural networks.*

У статті досліджується критична проблема забезпечення високої продуктивності моделей штучного інтелекту при одночасній інтеграції надійних механізмів шифрування даних. Аналізуються фундаментальні компроміси між обчислювальними витратами, що виникають внаслідок шифрування, та вимогами до точності, затримки і пропускної здатності сучасних систем ШІ, а також розглядаються перспективні технології, такі як гомоморфне шифрування, федеративне навчання та безпечні багатосторонні обчислення.

Ключові слова: *штучний інтелект, шифрування даних, гомоморфне шифрування, федеративне навчання, продуктивність моделей, машинне навчання зі збереженням конфіденційності, безпечні обчислення, нейронні мережі.*

The rapid advancement of artificial intelligence across pivotal domains is presently positioning data security as the paramount concern in technological discourse. "The growing reliance on AI systems that process sensitive personal and corporate data has intensified the need for robust encryption frameworks" [3, p. 12].

Nonetheless, implementing encryption throughout AI workflows incurs considerable computational overhead. Processing secured datasets may trail their unprotected equivalents by a significant margin in speed, and certain protective mechanisms intrinsically alter the procedures by which data is managed. This piece endeavors to offer an in-depth examination of viable approaches that harmonize robust data security with efficient AI operation – as well as the real-world obstacles impeding the practical realization of confidential AI systems.

Fundamentals of AI and Encryption Integration. It runs on math-heavy processes that need raw data to learn patterns. "Modern AI systems, particularly deep neural networks, require direct arithmetic access to training data, which fundamentally conflicts with the goal of keeping that data encrypted" [6, p. 142].

1. Homomorphic Encryption (HE). Encryption usually means you must unlock data before working with it. Yet homomorphic encryption changes that idea completely. Instead of unlocking, math happens right inside the locked package. "Homomorphic encryption enables computations on ciphertexts, generating an encrypted result that, when decrypted, matches the result of