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ANALYSIS OF LABOR PRODUCTIVITY IN THE CONTEXT OF TECHNOLOGICAL TRANSFORMATIONS

Purpose. Conceptual explanation of the productivity paradox when using artificial intelligence (AI) technologies, as well as theoretical and empirical justification for the identification of a new macroeconomic phase determined by the introduction of intelligent systems.

Methodology. The study is based on a comprehensive approach that combines secondary data analysis (aggregated statistical series of the US Bureau of Labor Statistics) and methods of theoretical analysis and generalization. For the mathematical and statistical calculation of long-term average annual rates of productivity change (AAPC), the index method and the geometric mean growth rate formula were used. Comparative analysis was used to retrospectively compare macroeconomic cycles and identify deviations from the long-term trend. In addition, the analysis of corporate cases and empirical reports was used to assess the micro-level effects of AI implementation in organizations.

Findings. Eight distinct macroeconomic cycles of productivity change in the United States from 1947 to 2025 are identified. The advent of the "artificial intelligence phase" is justified. It is demonstrated that the gap between anticipated macroeconomic efficiency gains (expressed through the aggregate labor productivity index) and micro-level outcomes (specifically, the localized reduction in operational task execution time, the enhanced quality of generated solutions, and the accelerated skill acquisition by employees) is attributed to organizational and behavioral factors. The key micro-mechanisms of the labor productivity paradox have been identified: task expansion, the blurring of boundaries between work and non-work time, the intensification of multitasking, and the accumulation of "AI debt" by organizations.

Originality. The theoretical explanation of the labor productivity paradox under conditions of systemic artificial intelligence implementation has been further developed. The periodization of US macroeconomic cycles was refined by calculating AAPC indices and identifying emerging stages, specifically the "pandemic and adaptation phase" and the "artificial intelligence phase". A conceptual model of the AI productivity paradox has been proposed to explain the underlying causes of efficiency loss. Furthermore, the understanding of micro-mechanisms governing AI's impact on organizational efficiency has been systematized and deepened, with their specific role in decelerating the growth of aggregate macroeconomic indicators being formalized.

Practical value. A theoretical framework has been established for the development of targeted organizational and managerial measures aimed at overcoming micro-level productivity barriers and ensuring the harmonious integration of innovations into business processes. The study demonstrates the necessity of systemic alignment between the technological potential of artificial intelligence algorithms, organizational support, and the human factor to transform AI-driven benefits into sustainable economic growth.

Keywords: *artificial intelligence, productivity paradox, labor productivity*

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Introduction. The modern global economy is at the crossroads of technological eras, where traditional methods of intensification of production are exhausting their potential and are being replaced by digital solutions based on artificial intelligence. In this context, labor productivity continues to act as a key indicator of economic efficiency and the main driver of long-term growth of social welfare.

However, at the stage of active implementation of the latest intelligent systems, a fundamental scientific and practical contradiction arises. Despite the explosive growth of investments in artificial intelligence and the unprecedented capitalization of technology companies, which reflect the colossal expectations of the market, official indicators of productivity growth in developed economies remain moderate, and in some places – lower than the historical trends of the second half of the 20^{th} century.

So, the scientific community is faced with a problem: why is the undeniable technological potential of artifi-

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cial intelligence algorithms not currently being converted into sustainable macroeconomic growth?

This situation forms the so-called "AI productivity paradox". Its essence is that the expected efficiency gains at the macro and meso levels critically lag behind the striking micro-level effects that have already been empirically confirmed in specific tasks and teams.

At its core, the modern AI paradox is a logical successor to the paradox of the early computerization era, when expectations of "instantaneous" macroeconomic effects clashed with the inertia of institutions and governance systems.

The historical experience of the IT revolution demonstrates the need for a theoretical understanding of such paradoxes. It is necessary to prove that the identified gap is due to a combination of measurement, organizational and behavioral factors, and not to the lack of a real impact of AI on labor productivity.

Literature review. The theoretical understanding of the impact of artificial intelligence on productivity is closely related to the historical context of the information revolution and the phenomenon known as the "Solow paradox". In modern scientific literature, this phenomenon has been developed into the concept of the "modern productivity paradox". A fundamental explanation for this gap between high expectations and macroeconomic statistics was proposed by E. Brynjolfsson, D. Rock and C. Syverson [1]. The authors argue that delays in implementation are the main cause of the paradox, since AI, as a breakthrough (radical) technology, requires significant time and investment in complementary innovations, organizational changes and new skills that form the so-called intangible capital of the enterprise.

At the same time, at the microeconomic level, the impact of generative AI is actively confirmed through the prism of field experiments. For example, S. Noy and V. Zhang [2] empirically proved the effectiveness of large language models in a professional environment: in their study, the use of ChatGPT by specialists led to an unprecedented reduction in task completion time by 40 % and an increase in the quality of the result by 18 %. Additional confirmation of micro-level successes is a large-scale study by E. Brynjolfsson, D. Li and L. Raymond [3], who analyzed the work of more than 5 thousand support agents. Their results show that access to generative AI increases productivity by an average of 14 %, with the greatest gain (up to 34 %) for less experienced workers due to the rapid assimilation of the tacit knowledge of experts.

However, the implementation of intelligent systems directly affects working conditions and the psychological state of employees. Yu. Fukumura, et al. [4] studied the perspectives of employees on the integration of AI into the office space, emphasizing the importance of taking into account the human factor and potential risks to the well-being of personnel. It is this aspect, combined with the need to develop organizational capital, that indicates that the local benefits of AI can easily be offset by the increase in costs of coordination and revision of work processes.

Despite a significant number of thorough works devoted to both the macroeconomic paradox and microeconomic experiments, the mechanics of the transformation of the micro-effects of generative AI (in particular, through the phenomena of task expansion and emotional burnout) into the stagnation of aggregate organizational productivity remains insufficiently disclosed in the literature.

Purpose. The main goal of the study is to comprehensively reveal the essential causes of the productivity paradox in the context of the integration of artificial intelligence, as well as to empirically prove the transition to the latest macroeconomic cycle based on a retrospective analysis of the dynamics of the efficiency of the United States economy.

In accordance with the defined goal, the following main tasks are set in the work:

- to analyze the long-term statistical dynamics of the labor productivity index in the non-agricultural business sector of the United States;
- to identify and quantitatively characterize key macroeconomic eras by calculating the average annual rates of change in productivity, in particular, to statistically substantiate the beginning of the "artificial intelligence phase";
- to investigate the genesis and specifics of the modern AI productivity paradox through comparison with the historical experience of the implementation of information technologies; to systematize organizational, managerial and behavioral micromechanisms that inhibit the macroeconomic effect of innovations;
- to form a conceptual model that explains the gap between nominal (technological), organizational and perceived (subjective) productivity when using intelligent systems.

Methodology. The methodological basis of this study is based on the use of open statistical series of the US Bureau of Labor Statistics, in particular the aggregated labor productivity index in the non-agricultural business sector. The base period for calculating the official index is 2017, the value of which is taken as one hundred percent. The use of the index method of aggregation of macroeconomic data allows us to reliably eliminate inflationary and price distortions, reflecting only the real change in the volume of output per hour worked by all categories of workers.

To calculate the average annual rate of change in labor productivity over certain macroeconomic cycles, the formula for the geometric mean growth rate was used, which in international statistical and financial practice is classified as Average Annual Percent Change

$$AAPC = \left[\left(\frac{V_n}{V_0} \right)^{\frac{1}{n}} - 1 \right] \cdot 100,$$

where V_n is the value of the indicator at the end of the period; V_0 is the value of the indicator at the beginning of the period; n is the number of years in this period.

This mathematical toolkit allows us to correctly take into account the effect of compound interest over multi-year time periods, smoothing out short-term seasonal or conjunctural quarterly fluctuations. The use of the geometric mean, rather than the arithmetic mean, is critically important for objectively comparing the dynamics of economic growth in the long term.

Since the Bureau of Labor Statistics' output is generated quarterly, the variable for the period length in

years required additional normalization. To ensure high accuracy, the total number of years was calculated by counting the total number of quarters between the start and end dates of the period and then dividing this number by four. This approach allowed us to account for fractional parts of years when macroeconomic cycles transition in the middle of a calendar year.

The specified mathematical logic provides absolute methodological compatibility of the author's calculations with retrospective analytical data of US government agencies. This made it possible to verify historical indicators of the industrial and computer eras, as well as independently calculate and isolate the latest coefficients for the pandemic era and the era of artificial intelligence. All indicators of productivity dynamics for the periods after 2019 given in the study were calculated using this methodology based on the latest revisions of macroeconomic data as of the beginning of 2026. This guarantees high representativeness and scientific reliability of the formulated conclusions.

In addition to quantitative macroeconomic analysis, the methods of theoretical generalization, comparative analysis and synthesis were used to study the micro-level mechanisms of the productivity paradox. The information base for this part of the study was the results of field experiments, empirical reports of leading think tanks and corporate surveys of recent years. The formalization of the gap between nominal, organizational and perceived productivity was carried out using the method of conceptual modeling.

Results. The AI productivity paradox is the logical successor to the so-called "Solow paradox" regarding information technology, formulated in 1987: "the computer age can be seen everywhere except in productivity statistics" [5].

The experience of the 1970–1990ss showed that the wave of IT investment did not translate into accelerated growth in total factor productivity for a long time until companies invested in organizational capital [6], retraining employees, and redesigning business processes (Fig. 1). Further research has shown that the impact of digital technologies on productivity has a pronounced lag and strongly depends on the quality of management practices, the structure of labor markets, and the regulatory environment [7].

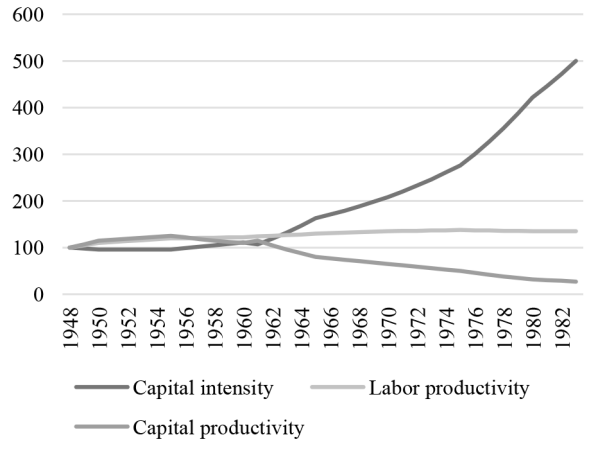

Fig. 1. Chart of US financial sector indices (base period – 1948)

In the case of modern AI, and in particular generative models, the historical experience of the IT revolution turns out to be extremely relevant, as expectations of "instantaneous" macroeconomic effects again clash with the inertia of institutions and management systems. That is why the theoretical understanding of the AI productivity paradox is appropriate as a continuation of the discussion about complementary assets, organizational design and knowledge management, initiated in the economics of information technology.

The study of the dynamics of labor productivity is a fundamental task, since it is this macroeconomic indicator that determines the long-term rates of economic growth, the level of competitiveness of national economies and the living standards of the population. Productivity, as a measure of the efficiency of converting input resources into added value, has historically not developed linearly [8], but is subject to certain patterns that are closely related to changes in technological patterns (Fig. 2).

In the context of global transformations, studying the impact of new technologies, among which artificial intelligence algorithms currently occupy a dominant position, is becoming particularly relevant.

To achieve this goal, a comprehensive analysis of official data from the U.S. Bureau of Labor Statistics was carried out on the dynamics of the labor productivity index in the non-agricultural business sector for the period from the first quarter of 1947 to the fourth quarter of 2025 (Fig. 3).

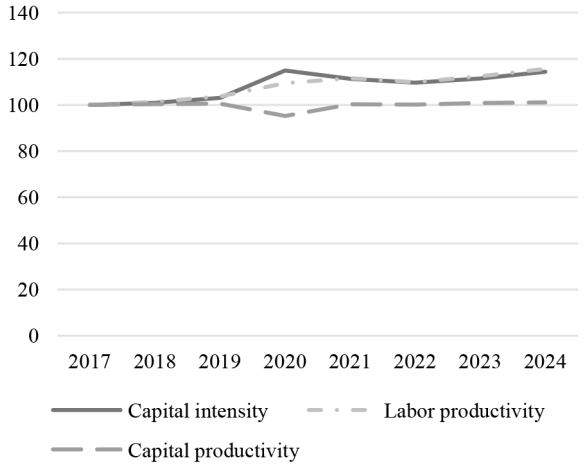

Fig. 2. Chart of US non-farm business sector indices (base period – 2017)

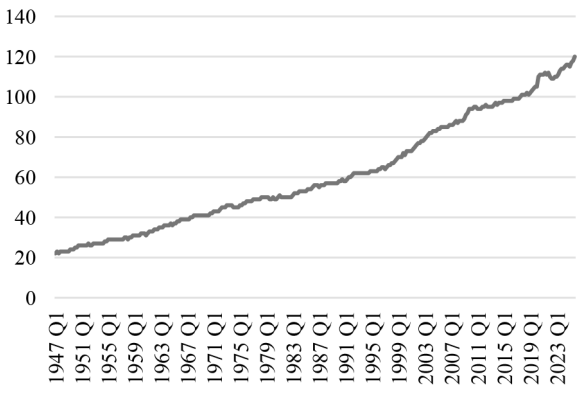

Fig. 3. Graph of the labor productivity index in the US non-agricultural sector (base period – 2017)

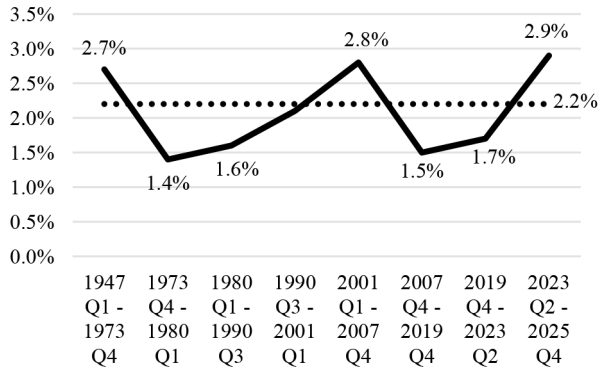

Fig. 4. Graph of average annual change in labor productivity in the US non-farm sector

The long-term average annual rate of change in productivity (Average Annual Percent Change) over this seventy-eight-year period is 2.2 percent. This baseline indicator serves as a kind of axis of symmetry against which the efficiency or stagnation of economic processes can be assessed in the context of individual historical eras (Fig. 4).

An in-depth analysis of deviations from this long-term trend allows us to identify eight distinct macroeconomic cycles, each characterized by a unique configuration of technological, organizational, and socio-economic drivers (Table 1).

The initial phase to be analyzed is the post-war industrial boom, which spans the period from the first quarter of 1947 to the fourth quarter of 1973. This cycle is marked by the highest sustained productivity growth rates in recent history, at 2.7 percent annually.

This unprecedented leap in efficiency was driven by the synergistic effects of the massive scaling of assembly line production [9, 10], the complete electrification of industry [11], the development of interstate transportation infrastructure, and the implementation of Fordist principles in corporate governance [12]. Enterprises of this period reaped the maximum benefits of economies of scale by transforming the scientific discoveries of World War II into commercial technologies for mass consumption.

The end of the post-war cycle was abrupt under the influence of external macroeconomic shocks, which marked the transition to an era of stagflation and energy crises (fourth quarter of 1973 – first quarter of 1980) [13]. The OPEC oil embargo in the fall of 1973 led to a multiple increase in energy prices, which destroyed the energy-intensive business model of previous decades. The growth rate of labor productivity during this period fell dramatically to 1.4 percent. Enterprises were forced

Table 1

Macroeconomic phases of labor productivity in the United States (1947–2025)

Phase name	Time period	Average annual growth (AAPC), %	Key dates and explanations of the period
The post-war industrial boom phase	1947 Q1–1973 Q4	2.7	1947–1973: Mass industrialization, infrastructure development, standardization of production after World War II. The golden age of classical capitalism
The phase of stagflation and energy crises	1973 Q4–1980 Q1	1.4	October 1973: Oil Crisis (OPEC embargo). The sharp rise in energy prices led to a global recession and a decline in production efficiency
Early computerization phase	1980 Q1–1990 Q3	1.6	1980s: The first personal computers appear in the workplace. Basic document workflow is automated, but the technologies are not yet networked
Internet Phase (Dot-com Boom)	1990 Q3–2001 Q1	2.1	1990s: Mass spread of the World Wide Web, introduction of corporate management systems (ERP, CRM), which significantly accelerated data exchange
The Golden Phase of IT Productivity	2001 Q1–2007 Q4	2.8	2000s: The transition to broadband internet, the complete digitalization of databases, the globalization of supply chains. Maximum return on IT investments
Mobile and cloud technology phase	2007 Q4–2019 Q4	1.5	2007 (release of the first iPhone)/2008 (global financial crisis): There were more technologies (smartphones, social networks, clouds), but a "productivity paradox" occurred – real economic growth slowed down due to the exhaustion of the effect of previous innovations
Pandemic and adaptation phase (remote work)	2019 Q4–2023 Q2	1.7	Early 2020: Lockdowns and emergency transition to remote work (Zoom, Teams). November 2022: ChatGPT release. This is a period of society's familiarization with generative AI, testing technologies without large-scale optimization of corporate processes. May 2023: The World Health Organization officially canceled the status of a global emergency due to COVID-19
Artificial Intelligence Phase (Active Implementation)	2023 Q2–2025 Q3	2.9	Mid-2023 – present: Transition from "playing with neural Networks" to systemic business use. Purchase of enterprise licenses (e.g., Copilot), automation of routine, coding, and content generation, which gave a new sharp jump in productivity (above the level of the 2000s)

to redirect capital investments not to expand production or introduce innovations, but to energy-saving measures and survive in conditions of galloping inflation, which significantly slowed down the generation of added value.

The next chronological phase, which lasted from the first quarter of 1980 to the third quarter of 1990, can be characterized as an era of early computerization [14]. Productivity growth recovered somewhat, reaching 1.6 percent, but it remained well below the long-term historical trend.

It was during this period that the first personal computers were introduced into the workplace, basic document management was automated, and the first business software was introduced [15]. However, the macroeconomic impact of these technologies was modest. This phenomenon has gone down in the history of economic thought as the "Solow paradox", named after Nobel laureate Robert Solow.

The main reason for the paradox was the lack of full network interaction: computers worked in isolation, and the organizational structures of enterprises had not yet adapted to digital realities [16]. Overcoming the productivity paradox occurred during the next cycle, known as the Internet and dot-com phase, which lasted from the third quarter of 1990 to the first quarter of 2001 [17]. The average annual growth rate accelerated to 2.1 percent.

This breakthrough was made possible by the massive spread of the global Internet, which dramatically reduced transaction costs for information search and communication. Enterprises began to integrate local computers into corporate networks, implementing complex enterprise resource planning (ERP) and customer relationship management (CRM) systems. Business models were transformed: companies moved from isolated automation of individual tasks to reengineering entire business processes, which ensured a significant increase in output per employee [18].

The culmination of the development of information and communication technologies was the golden phase of IT productivity (the first quarter of 2001 – the fourth quarter of 2007). During this period, the economy achieved a phenomenal growth rate of 2.8 percent, surpassing even the indicators of the post-war boom. The driving force of this process was the full return on investments made in the previous decade [19]. Broadband Internet, globalization of supply chains, transfer of production capacities to countries with lower costs (offshoring) and optimization of logistics allowed transnational corporations to maximize their operational efficiency. Technology became not just an auxiliary tool, but the basis for creating added value.

After the 2008 financial crisis, a long phase of mobile and cloud technologies began (Q4 2007–Q4 2019), which brought new disappointment to the scientific community. Despite the emergence of smartphones, the development of social networks, the spread of mobile Internet and cloud computing, the growth rate of labor productivity fell again to 1.5 percent. Researchers explain this return of the "productivity paradox" by several factors. The emergence of new gadgets and social platforms has had a greater impact on the sphere of consumption and leisure, rather than on the efficiency of production processes. Moreover, mobile devices have created new forms of distraction for workers in the workplace. The digital economy of this period often had the character of a zero-sum game, where companies spent huge resources on digital advertising and the struggle for user attention, without creating fundamentally new material goods or services, which slowed down national productivity growth.

The period from the fourth quarter of 2019 to the second quarter of 2023, which is defined as the pandemic and adaptation phase, requires a separate in-depth analysis. The global lockdown led to an emergency transition of a significant part of the workforce to a remote work format using video conferencing and data sharing platforms. There was a hypothesis that saving time on commuting to the office and accelerated digitalization would lead to a structural leap in productivity. However, empirical calculations refute this thesis: the average annual growth rate during this period was 1.7 percent. Although this figure marginally exceeds the level of the previous decade, it remains below the historical long-term trend. This indicates that remote technologies performed the function of ensuring business continuity, but did not become a catalyst for a new industrial revolution. The management costs of coordinating distributed teams, psychological burnout of personnel and disruption of logistical chains offset the benefits of digitalization of the workplace. In addition, at the end of this period (November 2022), there was a public release of large language models, in particular ChatGPT. However, the first six months after this event were characterized by the stage of familiarizing society with generative artificial intelligence technology, rather than its deep integration into corporate structures.

The latest macroeconomic formation is recorded starting from mid-2023. The period from the second quarter of 2023 to the third quarter of 2025 is reasonably distinguished into a new macroeconomic formation – the Era of Artificial Intelligence. Statistical data confirm a sharp acceleration in productivity growth rates to 2.9 percent annually. Such a jump, which has overtaken the record figures of the golden era of IT in the early 2000s, demonstrates the completion of the initial testing stage and the beginning of the stage of large-scale operationalization of artificial intelligence algorithms in the activities of enterprises.

The theoretical justification for such an impact is based on the concept of general-purpose technologies. Artificial intelligence algorithms, unlike highly specialized software, have a universal application, the ability to continuously improve themselves and the potential for synergistic combination with other innovations. Artificial intelligence transforms not just individual tools, but the very nature of decision-making and information processing within the enterprise [20].

At the microeconomic level, the impact of artificial intelligence algorithms on enterprise productivity is realized through an extensive system of transmission mechanisms. The fundamental change is the transition from the automation of physical or standardized labor to the automation of cognitive activity. Neural network models are able to independently analyze unstructured data sets, identify hidden patterns and generate analytical reports, which frees up enormous amounts of time for highly qualified specialists (analysts, lawyers, financiers). Workers in the intellectual sphere are transformed

from performers of routine operations into operators and verifiers of AI systems, which multiplies the amount of added value generated per working hour.

Generative algorithms are having a revolutionary impact on the creative and creative industries. The processes of developing software code, writing marketing texts, creating industrial design or generating legal contracts are accelerated dozens of times thanks to the use of AI-based corporate assistants. The enterprise gains the ability to generate an infinite number of variations of content or design solutions with marginal costs close to zero. This allows you to radically shorten the development cycle of new products and respond faster to market changes.

Operations management and logistics are undergoing a significant transformation. The introduction of predictive analytics algorithms allows enterprises to move from reactive management models to proactive ones. Artificial intelligence with high accuracy predicts fluctuations in consumer demand, optimizes raw material supply schedules, predicts the probability of production equipment failure and minimizes inventory. Reducing the level of uncertainty in making management decisions directly translates into reducing unproductive costs and increasing asset profitability.

In customer service, natural language processing algorithms are enabling businesses to deliver 24/7, high-quality, deeply personalized interactions with millions of consumers simultaneously. Virtual assistants and intelligent bots are taking on up to ninety percent of initial customer inquiries, providing instant problem resolution without human intervention. This breaks the classic limitation of the service industry, where increasing service quality inevitably required a linear increase in staff.

A critical aspect of implementing artificial intelligence is its impact on the organizational structure and corporate culture of enterprises. The use of AI leads to the flattening of hierarchical structures, as algorithms take over the functions of control and distribution of tasks that were traditionally performed by middle management. Agility (flexibility) of the organization becomes the main criterion for survival, because the pace of updating AI tools requires continuous training and adaptation from employees.

Analyzing the macroeconomic consequences of this phenomenon, one should realize that the current productivity jump to 2.9 percent is only the initial phase of the deployment of a new technological order. Unlike previous information technologies, artificial intelligence algorithms have the ability to exponentially self-learn. With each new iteration of neural networks, the expansion of the context window and the improvement of logical inference, the economic effect of their application will multiply. We are observing the phenomenon of "smart capital", which does not simply replace human labor, but creates fundamentally new forms of organizing economic activity.

However, a number of macroeconomic reviews have noted that despite the explosive growth in AI investment, official productivity growth rates in advanced economies remain modest, and in some cases below historical trends in the second half of the *20th* century. McKinsey and MIT reports estimate that even optimistic scenarios for the spread of generative AI add only fractions of a percentage point to annual productivity growth rates over the next decade, which contrasts sharply with the discourse about the "revolutionary" effect on economic growth. Financial analysts, including the Financial Times and Fortune, have drawn attention to the paradoxical situation where the capitalization of S&P 500 companies largely reflects expectations for AI, while aggregate macro indicators have yet to confirm such a jump in performance.

The explanation for this discrepancy is primarily related to the methodology of measuring productivity, the difficulties of accounting for intangible assets, the effects of redistribution, and the lags between investments in technology and the conversion of these investments into sustainable increases in output per unit of labor or capital. Another important problem is that a significant part of the benefits of AI manifest themselves in the form of improved product quality, personalization, reduced risks, or faster decision-making, which are difficult to convert into traditional indicators such as GDP or productivity per hour worked.

At the micro level, empirical work by NBER, MIT, and corporate case studies demonstrate sustained, often double-digit productivity gains across a range of tasks, from word processing and coding to marketing analysis and customer service. Experiments with generative assistants in support teams show significant reductions in response times, error rates, and performance alignment between less and more experienced workers, demonstrating the potential of AI as a "performance leveling technology".

Separate business surveys indicate that most companies are already recording point benefits in the form of reduced manual routines, faster reporting and analytics, and automation of communications and marketing campaigns.

At the same time, local successes do not always integrate into the aggregate measure of organizational performance, as gains at the level of individual tasks can be offset by the costs of coordination, process revision, staff training, and risk management. Therefore, analyzing the AI productivity paradox requires simultaneously considering micro-level effects, which are often impressive, and macro-level aggregates, which remain inertial (Table 2).

The AI productivity paradox can be conceptualized as a gap between three dimensions: nominal productivity (task completion time), organizational productivity (process or unit-level output), and perceived productivity (subjective perception of one's own effectiveness). Generative models often dramatically increase nominal productivity on narrowly defined tasks, but organizational and psychological mechanisms can neutralize or even reverse this increase at the team or management system level. As a result, workers report "increased workload", a decreased sense of control over their working time, and the phenomenon of "AI burnout", despite formal reductions in time for individual operations [21, 22].

This gap is exacerbated when AI tools are implemented without a deep rethinking of roles, incentive systems, coordination mechanisms, and working time boundaries, reproducing the logic of previous waves of digitalization, but with much more powerful cognitive effects. The AI productivity paradox is therefore not

evidence of the "inefficiency" of the technology itself, but rather indicates the limitations of traditional management paradigms and metrics in the context of the constant availability of intelligent tools.

One of the key micromechanisms of the productivity paradox is the phenomenon of task expansion [23]. That is, the expansion of the scope and complexity of tasks in response to the increase in individual efficiency due to AI. When an assistant based on large language models reduces the time to prepare a report or letter, the manager or organization has a tendency to increase the number of requested options, the level of detail, the frequency of updates, or the number of communication channels.

As a result, savings on a single task are transformed into an increase in the total number of tasks, which restores or even increases the total workload (Table 3).

The expansion of tasks is reinforced by the culture of constant availability and the expectation of "instant" response, which are becoming the norm in an environment where AI tools remove technical barriers to generating texts, presentations, analytical notes. Therefore, classic management approaches to labor rationing and workload planning are inadequate, because they ignore the endogenous reaction of the organization to the emergence of ultra-fast intelligent tools [24].

Another important dimension of the paradox is the phenomenon of blurred boundaries. This is the blurring of the boundaries between work and non-work time due to the constant availability of AI tools on personal devices and in cloud services. Workers are given the opportunity to perform analytical or creative tasks at any time, which on the one hand expands flexibility, but on the other hand stimulates digital hypervigilance and the inability to fully disconnect from work roles. Surveys of large technology companies and consulting firms record that a significant proportion of respondents use generative AI to "catch up" on work in the evenings or on weekends, which increases the risks of emotional burnout [25].

The blurring of boundaries also makes it difficult to measure productivity, as traditional metrics of working hours and workload intensity lose validity in the context of asynchronous hybrid work, where useful output is often created outside of working hours using personal accounts and devices. This leads to a systematic underestimation of "hidden work" and an overestimation of the effectiveness of formal work processes from a management perspective.

Increasing multitasking is another important channel through which AI can simultaneously increase and decrease productivity depending on the horizon of analysis. Automatic prompts, recommendation systems, smart notifications and other "smart" features create the illusion of saving time, but are accompanied by an increase in the number of context switches, which negatively affects the depth of processing of complex tasks. Cognitive psychology studies indicate that each context switch has an invisible cost in the form of loss of concentration, and its accumulation can offset the benefits of speeding up individual operations [26, 27].

In an environment where multiple AI tools are integrated into email, instant messaging, CRM systems, document editors, and task management systems, the employee is constantly balancing between "reaction" and "production" modes [28]. This creates a chronic state of cognitive stress that is subjectively perceived as "constant workload", even though the proportion of time spent creating real added value may not increase or even decrease.

AI burnout is a term used in modern employee surveys to describe a specific type of emotional exhaustion associated with the need to constantly work in a high-tech mode and adapt to new tools. Surveys by Asana, Microsoft Work Trend Index, and research on global

Table 2

Levels of artificial intelligence performance analysis

Level of analysis	Expectations from AI	Observed effects	Key measurement challenges
Macroeconomic (GDP, labor productivity)	Sustainable growth acceleration, a new wave of technological uplift	Moderate or no acceleration, heterogeneity across countries	Accounting for intangible assets, quality improvements, redistribution effects
Mesolevel (industries, clusters)	Formation of "super-productive" sectors and regions	Selective productivity growth in IT, finance, media, but not in all industries	Attribution of benefits between sectors, global value chains
Micro level (firm, team, individual)	Radical reduction of task time, freeing up working time	Significant gains in efficiency in individual tasks, while increasing overload and multitasking	Measuring real usage, quality of results, subjective loads

Table 3

The phenomenon of task expansion in different task categories

Task category	Initial AI effect	Typical task expansion scenario	Potential impact on aggregate productivity
Text analytics, reports	Reducing draft preparation time	Increasing number of versions, customization requirements for different stakeholders	Leveling out time savings, increasing coordination costs
Communications (email, chats)	Automate drafts, reply suggestions	Increasing volume of communications, expectation of quick response, chain of correspondence	Increasing information noise, decision fatigue
Data analytics	Fast generation of queries and visualizations	Continuous improvement of dashboards, special requests from management	Growing fragmentation of attention, instability of analysts' focus

Table 4

Symptoms of AI burnout at the individual and organizational levels

Level	Typical symptoms	Possible impact on performance
Individual	Feeling of constant lag from technology, anxiety about replacement, fatigue from experimenting with new tools	Reduced engagement, avoidance of complex tasks, formal use of AI without real integration
Commanding	Fragmented implementation of tools, lack of uniform standards, conflicts over the "rules of the game" with AI	Coordination costs, duplication of efforts, reduced trust in AI-based results
Organizational	Permanent pilots without scaling, rising license and integration costs, delayed AI policy decisions	The "innovation overload" effect, the gap between AI spending and measurable business results

freelance platforms indicate that a significant proportion of employees feel the pressure to "always be productive" due to AI, which creates anxiety, fear of falling behind, and decreased job satisfaction, even as formal performance indicators increase. Such emotional strain is rarely reflected in traditional KPIs, but directly affects the long-term sustainability of team performance. AI burnout also has an organizational dimension, where managers are forced to support multiple waves of tool implementations in parallel, address data security, ethics, and compliance issues, while remaining accountable for achieving short-term business results (Table 4).

This situation leads to the accumulation of hidden AI debt – a set of unresolved organizational, technological and competency problems that limit the translation of potential benefits into sustainable productivity growth. The concept of AI debt reflects a situation where an organization rapidly accumulates AI tools, integrations and experiments without parallel investment in process standardization, data management and competency development.

Like technical debt in software development, AI debt creates hidden costs that manifest themselves in the form of maintenance complexity, system incompatibility, lack of understanding of model logic, and dependence on individual enthusiasts. In the short term, an organization may demonstrate local productivity gains, but in the medium term, the costs of eliminating AI debt absorb a significant portion of the benefits.

AI debt is directly related to the productivity paradox, as it explains why, even with numerous pilots and local successes, aggregate firm performance indicators remain relatively stable or grow slowly. The lack of a systemic strategy, a single data architecture, transparent AI policies, and management competency development programs turns technological potential into a source of additional complexity, rather than a driver of sustainable efficiency growth.

Summarizing the above, it is advisable to propose a conceptual scheme, centered on three interconnected blocks: the technological potential of AI, organizational and managerial complements, and the human factor. The technological potential includes the capabilities of automation, analytics, and content generation; organizational complements include the structure of processes, data architecture, KPI systems, and policies for using AI; and the human factor includes competencies, motivation, psychological reactions, and ethical attitudes. The productivity paradox occurs when a technological block develops much faster than the other two, creating an asymmetry between potential and realized productivity.

In this scheme, the paradox manifests itself as a gap between the expected productivity curve, which is growing rapidly due to the introduction of AI, the measured productivity curve, which is growing less rapidly, and the perceived productivity curve of employees, which may even temporarily decline due to AI burnout, multitasking, and digital hypervigilance. Aligning these three curves requires targeted management interventions: reviewing success metrics, investing in organizational capital, supporting employee well-being, and developing policies for the conscious and ethical use of AI.

Conclusions. The study proves that the economy has entered a new macroeconomic formation – the "artificial intelligence phase". However, the full macroeconomic return from these technologies is constrained by the current paradox of AI productivity.

The proposed theoretical framework allows us to move on to a more nuanced analysis of specific mechanisms through which technological potential is transformed – or not transformed – into sustainable growth in efficiency at different levels of the economic system. On this basis, in further research, it is advisable to carry out empirical verification of the indicated mechanisms and develop management recommendations for overcoming the productivity paradox when working with AI. It is necessary to implement targeted organizational and management measures. The systemic effect is achieved only if the asymmetry is overcome and the synchronous development of the technological potential of intelligent systems, organizational support (data architecture, processes, updated KPIs) and the human factor (development of new competencies and preservation of psychological resilience) is ensured.

Empirical verification of the proposed mechanisms of the AI productivity paradox can be carried out by synthesizing the results of randomized experiments, field studies and employee surveys that directly measure changes in productivity, task structure and well-being of employees when implementing generative AI. Based on such work, it becomes possible to assess which mechanisms – task expansion, blurring of work-rest boundaries, multitasking, AI burnout or AI debt – have actual support in empirical data, as well as to formulate management recommendations for their mitigation.

The results obtained will have a special practical value for the Ukrainian economy in the context of post-war recovery and European integration. The implementation of the proposed management measures will allow domestic enterprises to avoid the traps of the productivity paradox during digital transformation, which is critically important for increasing global competitiveness.

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Аналіз продуктивності праці в контексті технологічних трансформацій

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Мета. Концептуальне пояснення парадоксу продуктивності праці при використанні технологій штучного інтелекту (ШІ), а також теоретико-емпіричне обгрунтування виокремлення нової макроекономічної фази, детермінованої впровадженням інтелектуальних систем.

Методика. Дослідження ґрунтується на комплексному підході, що поєднує аналіз вторинних даних (агреговані статистичні ряди Бюро статистики праці США) й методи теоретичного аналізу та узагальнення. Для математико-статистичного обчислення довгострокових середньорічних темпів зміни продуктивності (AAPC) застосовано ін-

дексний метод і формулу середньогеометричного темпу зростання. Порівняльний аналіз використано для ретроспективного зіставлення макроекономічних циклів та ідентифікації відхилень від довгострокового тренду. Крім того, залучено аналіз корпоративних кейсів й емпіричних звітів для оцінки мікрорівневих ефектів впровадження ШІ в організаціях.

Результати. Ідентифіковані вісім виразних макроекономічних циклів зміни продуктивності у США з 1947 по 2025 роки. Обґрунтоване настання «фази штучного інтелекту». Доведено, що розрив між очікуваними приростами макроекономічної ефективності (вираженими через агрегований індекс продуктивності праці) й мікрорівневими результатами (зокрема, локальним скороченням часу виконання операційних завдань, підвищенням якості генерованих рішень і прискореним засвоєнням навичок працівниками) зумовлений організаційними й поведінковими чинниками. Виокремлені ключові мікромеханізми парадоксу продуктивності праці: розширення завдань, розмиття меж між робочим і неробочим часом, посилення мультизадачності й накопичення організаціями «ШІ-боргу».

Наукова новизна. Набуло подальшого розвитку теоретичне пояснення парадоксу продуктивності праці в умовах системного впровадження технологій штучного інтелекту. Удосконалена періодизація макроекономічних циклів США шляхом розрахунку індексів AAPC і виокремлення новітніх етапів – «фази пандемії та адаптації» і «фази штучного інтелекту». Запропонована концептуальна модель парадоксу продуктивності ШІ, що пояснює причини втрати ефективності. Систематизоване та поглиблене розуміння мікромеханізмів впливу ШІ на організаційну ефективність, зокрема формалізована їх роль в уповільненні зростання агрегованих макропоказників.

Практична значимість. Сформовано теоретичний каркас для розробки цілеспрямованих організаційно-управлінських заходів, спрямованих на подолання мікрорівневих бар'єрів продуктивності й гармонійну інтеграцію інновацій у бізнес-процеси. Доведена необхідність системного узгодження технологічного потенціалу алгоритмів штучного інтелекту з організаційним забезпеченням і людським фактором для перетворення вигод від ШІ на стале економічне зростання.

Ключові слова: *штучний інтелект, парадокс продуктивності, продуктивність праці*