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Abstract

Artificial intelligence (AI) adoption has become one of the most important economic changes in the United States. The technology is increasingly used in software development, customer service, professional writing, data analytics, health services, logistics, finance, and other knowledge-intensive activities. This paper examines the effect of AI adoption on labour productivity in the United States using a journal-style conceptual and evidence-based approach. The study relies on secondary evidence from the U.S. Census Bureau, U.S. Bureau of Labor Statistics, OECD, IMF, Stanford AI Index, McKinsey Global Institute, NBER, and recent experimental research published from 2020 onward. The paper argues that AI adoption can raise labour productivity by reducing task completion time, improving worker decision-making, automating routine cognitive tasks, supporting software development, and enabling faster knowledge processing. However, the productivity effect is not automatic. It depends on firm-level adoption, worker skills, complementary investment in software and data systems, managerial readiness, task suitability, and the ability of organisations to redesign workflows around AI. Evidence from recent experiments shows strong task-level productivity gains, including faster writing, improved customer support performance, and quicker software development. At the same time, macroeconomic evidence remains cautious because AI diffusion is still uneven across industries and many firms are in early adoption stages. The paper concludes that AI adoption is likely to have a positive effect on labour productivity in the United States, but the magnitude will depend on broad diffusion, responsible governance, reskilling, and effective integration into real production processes.

Keywords: *artificial intelligence, labour productivity, United States, generative AI, digital transformation, economic growth*

1.0 Introduction

Artificial intelligence has moved from a specialist technology into a general business tool used across many parts of the United States economy. Earlier waves of digital transformation were built around computers, enterprise software, internet platforms, cloud computing, and mobile technologies. The current wave is different because AI systems can perform cognitive tasks that were previously associated mainly with human judgement, such as summarising information, writing text, generating computer code, identifying patterns, translating language, producing images, forecasting demand, and supporting decision-making. These capabilities make AI adoption an important issue for labour productivity because labour productivity depends on the amount of output produced per worker or per hour worked.

The United States provides a strong case for studying this topic because it is one of the leading developed economies in AI investment, AI research, and business experimentation. The Stanford AI Index reported that U.S. private AI investment reached $109.1 billion in 2024, far above the amount reported for other major economies, while global business use of AI also expanded rapidly (Maslej et al., 2025). This level of investment suggests that firms expect AI to improve efficiency, reduce costs, increase innovation, and strengthen competitiveness. However, the central economic question is whether this adoption is already improving labour productivity or whether the gains remain concentrated in narrow tasks and selected industries.

Recent evidence points in both directions. On one hand, controlled experiments show large improvements in task-level productivity. Noy and Zhang (2023) found that ChatGPT reduced the average time taken to complete professional writing tasks by 40 percent and improved output quality by 18 percent. Peng et al. (2023) found that software developers using GitHub Copilot completed a programming task 55.8 percent faster than those without the tool. Brynjolfsson, Li, and Raymond (2023) found that generative AI assistance improved productivity in a customer support setting, with particularly strong gains for less experienced workers. These studies suggest that AI can improve labour productivity when it is used for suitable tasks.

On the other hand, the economy-wide effect remains uncertain. The U.S. Census Bureau reported that between December 2025 and May 2026, overall AI use among U.S. businesses hovered between 17 and 20 percent, while expected use in the next six months ranged between 20 and 23 percent (U.S. Census Bureau, 2026). These figures show rapid progress compared with earlier adoption levels, but they also show that many firms still do not use AI in daily production. The U.S. Bureau of Labor Statistics (BLS) also notes that AI is partly captured through software capital used in production, meaning the productivity effect of AI may appear gradually through software investment rather than as a separate immediate category (BLS, 2026a).

The study is therefore timely. Labour productivity matters because it affects wages, profits, competitiveness, inflation pressure, living standards, and long-term economic growth. In 2024, U.S. nonfarm business sector labour productivity increased by 2.3 percent, after rising by 1.6 percent in 2023 and falling by 1.5 percent in 2022 (BLS, 2025). This recent improvement has encouraged debate about whether the United States is entering a new productivity cycle. Yet the productivity pickup cannot be attributed to AI alone. The Federal Reserve Bank of Kansas City observed that the recent U.S. productivity improvement has not been broad-based and that AI adoption is associated with faster productivity growth across industries, but still explains only a limited share of the aggregate shift because AI is still spreading (Glover et al., 2026).

The purpose of this paper is to examine the effect of AI adoption on labour productivity in the United States. The paper focuses on the mechanisms through which AI can raise output per worker, the evidence from recent studies, the barriers that may weaken productivity gains, and the policy measures needed to ensure that AI contributes to inclusive and sustainable productivity growth. The study uses a secondary-data and literature-based approach because AI adoption is still evolving and long time-series data are limited. The main argument is that AI adoption has a positive but uneven effect on labour productivity. The strongest effects are likely to appear where firms combine AI with worker training, digital infrastructure, workflow redesign, data governance, and effective management.

The paper is guided by five research objectives. First, it examines the trend and meaning of AI adoption in the United States. Second, it explains the theoretical relationship between AI adoption and labour productivity. Third, it reviews recent empirical evidence on AI and productivity. Fourth, it discusses the channels through which AI can raise or weaken labour productivity. Fifth, it proposes policy and managerial recommendations for strengthening productivity outcomes from AI adoption.

2.0 Literature Review

AI adoption refers to the use of machine-based systems that can perform tasks normally requiring human intelligence. In business settings, this includes machine learning systems, predictive analytics, natural language processing, computer vision, robotic process automation, recommendation systems, generative AI tools, and decision-support applications. For this paper, AI adoption is treated as the use of AI in the production of goods or services, including the use of AI to support worker tasks, automate routine activities, improve customer interaction, analyse data, and generate new content or code. This definition is consistent with the practical approach used by the U.S. Census Bureau in tracking AI use by businesses (U.S. Census Bureau, 2026).

Labour productivity refers to output per unit of labour input. It is commonly measured as output per worker or output per hour worked. Labour productivity rises when workers produce more value in the same amount of time, when firms use better tools and equipment, when workers have stronger skills, when production processes are better organised, or when technology improves the quality and speed of work. AI adoption can therefore influence labour productivity through several routes: direct automation of tasks, support for human decision-making, better matching of information, improved service quality, faster software development, and lower time spent on routine administrative work.

The relationship between AI and labour productivity can be explained through endogenous growth theory. This theory argues that economic growth is driven by internal factors such as innovation, human capital, knowledge creation, and technological progress. From this perspective, AI can raise productivity by improving the creation, processing, and application of knowledge within firms. AI can also speed up research and development by helping workers search scientific literature, test ideas, generate code, analyse data, and improve product design. In this sense, AI does not only replace labour; it can also expand what labour can achieve.

The task-based theory of technological change also helps explain the effect of AI. Acemoglu (2024) argues that AI affects the economy by changing the cost and productivity of specific tasks. Some tasks may be automated, some may be improved through human-AI collaboration, and some may remain outside the current ability of AI systems. This view is useful because it avoids the simple assumption that AI will raise all productivity immediately. Instead, the productivity effect depends on which tasks are exposed to AI, whether AI can perform those tasks reliably, and whether firms can redeploy workers into higher-value activities.

The idea of AI as a general-purpose technology is also important. General-purpose technologies are technologies with broad use across sectors, continuous improvement over time, and strong effects on complementary innovation. The OECD describes AI as a technology with potential to influence productivity, distribution, and growth because of its ability to support autonomy, prediction, and problem-solving across industries (Filippucci et al., 2024). However, history shows that general-purpose technologies often take time to appear in productivity statistics. Computers, electricity, and the internet required complementary investment in skills, organisation, and business processes before broad productivity gains appeared. AI may follow the same pattern.

Empirical studies provide growing evidence that AI can raise productivity at the worker and task levels. Noy and Zhang (2023) found that generative AI improved both speed and quality in professional writing tasks. Their findings matter because writing and communication tasks are common across professional services, administration, education, marketing, legal work, consulting, and management. Peng et al. (2023) found that GitHub Copilot improved software developer productivity in an experimental programming task. This is important because software has become a core input in many industries, and faster software development can support productivity beyond the technology sector.

Brynjolfsson et al. (2023) found that generative AI improved productivity in customer support work and that gains were especially strong for less experienced and lower-skilled workers. This suggests that AI may reduce knowledge gaps by helping newer workers apply best practices more quickly. Such evidence is important for the United States because services account for a large share of employment, and many service tasks depend on communication, information retrieval, and problem-solving. If AI helps workers resolve customer problems faster and with better quality, it can raise output per hour and improve service performance.

At the same time, AI effects are uneven. Dell'Acqua et al. (2023) introduced the idea of a jagged technological frontier after studying consultants using AI on knowledge-intensive tasks. They found that AI improved performance for some tasks but could reduce performance when used for tasks outside the system's strengths. This finding is important because it shows that AI adoption is not a simple input-output relationship. Productivity gains require workers to understand when AI is helpful, when it is risky, and when human judgement should dominate. Firms that adopt AI without clear task design and quality control may experience errors, rework, and weak productivity results.

Macroeconomic estimates are also mixed. McKinsey Global Institute (2023) estimated that generative AI could increase labour productivity growth by 0.1 to 0.6 percentage points annually through 2040, depending on adoption speed and how worker time is redeployed. The IMF argues that around 60 percent of jobs in advanced economies are exposed to AI, but exposure does not necessarily mean replacement because many exposed jobs may benefit from AI complementarity (Cazzaniga et al., 2024). The OECD also notes that AI has productivity potential, but the size and distribution of its effects remain uncertain because adoption, skills, data quality, and market conditions differ across firms and sectors (Filippucci et al., 2024).

The U.S. evidence shows fast but incomplete diffusion. Census data show that larger firms and knowledge-intensive sectors are more likely to use AI than smaller firms and less digital sectors (U.S. Census Bureau, 2026). This suggests that AI productivity gains may first appear in large enterprises, software-intensive firms, professional services, finance, information industries, and firms with strong data infrastructure. Small firms may face greater barriers because they often lack technical staff, clean data systems, cybersecurity capacity, and funds for complementary investment. As a result, AI may initially widen productivity gaps across firms unless diffusion support and training are strengthened.

2.1 Conceptual Framework

The conceptual framework below summarises the expected relationship between AI adoption and labour productivity. AI adoption is treated as the independent variable, labour productivity as the dependent variable, and complementary factors as conditions that strengthen or weaken the relationship.

Table 1: AI adoption and Labour Productivity

Variable	Indicators	Expected Link to Labour Productivity
AI adoption	Use of AI tools, generative AI, predictive analytics, machine learning, AI-assisted software, automation systems	Expected to increase productivity by reducing task time, improving decision-making, and supporting innovation.
Labour productivity	Output per worker, output per hour worked, value added per employee, task completion speed	Improves when workers produce more output or higher-quality output within the same working time.
Worker skills	Digital skills, AI literacy, education, training, occupational experience	Strengthens the productivity effect because workers must know how to use AI effectively and safely.
Firm readiness	Data quality, software investment, workflow redesign, management support, cybersecurity	Determines whether AI remains a pilot tool or becomes part of real production.
Governance and risk control	Privacy protection, bias control, human review, quality assurance, responsible AI rules	Prevents errors, rework, reputational damage, and harmful automation choices.

3.0 Methodology

This paper uses a qualitative and evidence-based research design supported by secondary data. The design is suitable because the economic effect of AI adoption is still emerging and because broad long-term panel data on firm-level AI use remain limited. Rather than estimating a new econometric model, the paper synthesises recent evidence from official statistics, international organisations, and academic experiments to explain how AI adoption affects labour productivity in the United States. This approach is appropriate for a journal-style review paper because it identifies the main mechanisms, evidence, gaps, and policy implications of a rapidly changing technology.

The study relies mainly on sources published from 2020 onward. Official statistical evidence was obtained from the U.S. Census Bureau and the U.S. Bureau of Labor Statistics. International evidence was drawn from the OECD and IMF because these institutions provide cross-country analysis on AI, labour markets, productivity, and digital transformation. Academic evidence was drawn from recent experimental and working-paper studies on generative AI, software development, customer support, and professional services. The Stanford AI Index and McKinsey Global Institute were also used because they provide widely cited data and estimates on AI investment, adoption, and potential economic value.

The dependent variable in the study is labour productivity. Labour productivity is understood as output per worker or output per hour worked. The independent variable is AI adoption, measured conceptually through the use of AI tools in business operations and work processes. The study also considers mediating and moderating factors such as software investment, human capital, firm size, data infrastructure, management quality, industry structure, and governance. These factors are included because AI adoption alone does not guarantee productivity gains. Firms must combine AI with complementary changes in skills, processes, and organisational design.

The analysis is organised around four questions. First, what is the current level of AI adoption in the United States? Second, what evidence exists that AI improves worker or firm productivity? Third, why might AI productivity gains be uneven across firms and sectors? Fourth, what policy and managerial actions can improve the productivity returns from AI adoption? The paper answers these questions through content analysis of recent literature and comparison of evidence across official data, international reports, and experimental studies.

The main limitation of the methodology is that AI adoption is still too recent for its full economy-wide effect to be measured with certainty. Some productivity gains may not yet appear in national statistics because many firms are still experimenting with AI, while others may use AI in informal ways that are difficult to capture. There is also a difference between task-level productivity gains and aggregate productivity growth. A worker may complete a task faster with AI, but this does not automatically raise national labour productivity unless firms redeploy saved time into more valuable output, reduce waste, improve quality, or expand production. This limitation is addressed by interpreting the evidence cautiously and separating micro-level findings from macroeconomic claims.

4.0 Results and Discussion

The evidence suggests that AI adoption has a positive effect on labour productivity in the United States, but the effect is uneven and still developing. At the firm level, AI can increase productivity by enabling employees to complete certain tasks faster, produce higher-quality outputs, reduce search costs, improve customer service, and automate routine decisions. At the economy level, the effect depends on the speed of diffusion, the share of tasks affected, complementary capital investment, and whether firms redesign work processes to capture the time saved by AI.

The first major finding is that AI adoption in the United States is expanding but remains incomplete. Census Bureau data for December 2025 to May 2026 show that overall business AI use hovered between 17 and 20 percent, while 20 to 23 percent of businesses expected to use AI in the next six months (U.S. Census Bureau, 2026). Adoption is higher among larger firms; for example, firms with at least 250 employees reported higher use than smaller firms. This pattern matters because large firms are more likely to have the data infrastructure, budgets, and managerial capacity required to integrate AI into production. Smaller firms may use off-the-shelf tools but struggle to redesign workflows or measure productivity gains.

The second finding is that AI strongly improves productivity in suitable tasks. In professional writing, Noy and Zhang (2023) showed that generative AI reduced task completion time and improved output quality. In software development, Peng et al. (2023) showed that developers using an AI pair programmer completed a coding task much faster. In customer support, Brynjolfsson et al. (2023) found that AI assistance improved productivity and helped less experienced workers learn from best practices. These findings support the argument that AI adoption can raise labour productivity when tasks involve language processing, coding, documentation, information retrieval, or standardised problem-solving.

The third finding is that AI productivity gains depend on task fit. AI performs better in tasks where the problem is clearly defined, relevant information can be provided, and output can be reviewed by a knowledgeable worker. AI is weaker where tasks require deep contextual judgement, original accountability, sensitive human interaction, or decisions with high legal and ethical risk. Dell'Acqua et al. (2023) showed that AI can improve performance for tasks within its capability frontier but may harm performance outside that frontier. This means firms must avoid blind adoption. They should map tasks carefully, identify where AI adds value, and maintain human review where errors are costly.

The fourth finding is that the macroeconomic effect is likely to be slower than the task-level effect. A task experiment can show an immediate productivity gain, but national labour productivity improves only when millions of workers and firms use AI in production and convert time savings into additional output or better-quality services. The BLS reported that U.S. nonfarm business productivity increased by 2.3 percent in 2024, but this increase cannot be automatically credited to AI because productivity also reflects output growth, hours worked, business cycle effects, capital deepening, labour reallocation, and post-pandemic changes (BLS, 2025). The Kansas City Fed similarly noted that the recent U.S. productivity pickup is not yet broad-based and that AI adoption explains only a limited part of aggregate productivity shifts because diffusion is still underway (Glover et al., 2026).

The fifth finding is that AI adoption can improve labour productivity through automation of routine cognitive work. Many workers spend significant time drafting documents, summarising meetings, preparing reports, responding to emails, entering data, searching for information, and creating basic analytical outputs. AI tools can reduce the time spent on these tasks. When the saved time is redirected toward higher-value work such as client service, analysis, innovation, and decision-making, labour productivity improves. However, if saved time is absorbed by extra checking, correction of AI errors, unnecessary content production, or low-value activities, the productivity effect becomes weaker.

The sixth finding is that AI can improve productivity by supporting worker learning and reducing skill gaps. The evidence from customer support work is especially important because it suggests that AI can help less experienced workers perform closer to the level of more experienced workers (Brynjolfsson et al., 2023). This is economically important for the United States because productivity growth is not only about top-performing firms and elite workers. Broad-based productivity improvement requires ordinary workers and small firms to use better tools. AI can act as a form of embedded training by giving workers examples, suggestions, scripts, explanations, and feedback at the point of work.

The seventh finding is that AI can support innovation. AI can help researchers, engineers, marketers, product designers, and software teams generate ideas, test alternatives, analyse information, and shorten development cycles. The OECD argues that AI may act as a general-purpose technology with the potential to revive productivity growth, although the effect remains uncertain and depends on diffusion and governance (Filippucci et al., 2024). In the United States, where research and development and software-intensive services are major parts of the economy, AI can improve labour productivity not only by cutting costs but also by enabling workers to create new products, new services, and new business models.

The eighth finding is that complementary investment is essential. AI systems do not operate effectively in isolation. Firms need software infrastructure, cloud services, clean data, cybersecurity, training, new performance measures, and quality-control systems. The BLS notes that AI is captured in part through software capital used in production, which means that AI-related productivity improvements are likely linked to broader software investment (BLS, 2026a). Firms that treat AI merely as a chatbot subscription may experience small gains. Firms that redesign workflows, integrate AI with databases, train employees, and build governance systems are more likely to experience measurable productivity improvement.

The ninth finding is that AI may widen productivity gaps across firms and workers. Large firms, highly educated workers, software-intensive sectors, and data-rich organisations may benefit first. Small firms, low-wage workers, and firms with poor digital systems may lag behind. IMF analysis shows that about 60 percent of jobs in advanced economies are exposed to AI, but exposure can mean either substitution or complementarity depending on the nature of the job and the policy environment (Cazzaniga et al., 2024). If AI mainly benefits already productive firms and highly skilled workers, it may increase inequality even while raising average productivity. This makes training and diffusion policies important.

The tenth finding is that AI adoption can reduce productivity if it is poorly managed. Workers may over-rely on AI outputs, produce inaccurate work, or use AI for tasks where it is unsuitable. Managers may overestimate AI's capabilities and cut human expertise too quickly. Firms may also face risks related to privacy, bias, intellectual property, cybersecurity, and accountability. These risks can create rework, legal costs, customer distrust, and operational failures. Therefore, responsible AI governance is not separate from productivity. It is part of productivity because reliable systems reduce waste, errors, and risk.

Overall, the evidence supports a moderate positive relationship between AI adoption and labour productivity in the United States. The relationship is strongest at the task and firm levels, where AI tools are applied to clearly defined activities. The relationship is weaker and harder to measure at the macroeconomic level because AI diffusion is still incomplete and because national productivity statistics reflect many forces beyond AI. The best interpretation is that AI adoption is a productivity-enabling technology rather than an automatic productivity guarantee. Its economic value depends on how well firms, workers, and policymakers convert technical capability into useful production.

4.1 Analytical Model

A simple way of expressing the relationship is presented below:

$$\mathbf{LP = f(AI, HC, ICT, K, M, G)}$$

Where LP represents labour productivity, AI represents artificial intelligence adoption, HC represents human capital, ICT represents digital infrastructure, K represents capital investment, M represents management quality, and G represents governance. The model implies that AI adoption improves labour productivity most strongly when it is combined with skilled workers, digital infrastructure, investment, effective management, and responsible governance.

5.0 Conclusion and Recommendations

This paper examined the effect of AI adoption on labour productivity in the United States. The review shows that AI adoption has strong potential to improve productivity, especially in tasks involving writing, coding, customer support, data analysis, documentation, and information processing. Recent experimental evidence shows meaningful productivity gains at the task level, while official data show that business AI adoption in the United States is growing but remains uneven. Therefore, the effect of AI on labour productivity should be understood as positive but conditional. AI raises productivity when it is integrated into real work processes, supported by worker skills, and governed effectively.

The paper also shows that the macroeconomic effect of AI is still uncertain. U.S. labour productivity improved in recent years, but available evidence does not prove that AI is the main cause of this improvement. AI adoption is still spreading across firms, and many businesses remain at the experimentation stage. The strongest productivity gains are currently visible in specific tasks and sectors rather than across the whole economy. This pattern is normal for major technologies because broad productivity gains often require time, investment, training, and organisational change.

The first recommendation is that firms should adopt AI through workflow redesign rather than simple tool acquisition. Buying AI software is not enough. Firms should identify repetitive, information-heavy, and time-consuming tasks where AI can support workers. They should then redesign work processes to ensure that saved time is used for higher-value activities. Without workflow redesign, AI may create convenience but not measurable productivity improvement.

The second recommendation is investment in worker training and AI literacy. Workers need to know how to prompt AI tools, verify outputs, protect confidential information, recognise bias, and decide when human judgement is required. AI training should not be limited to technology workers. It should include managers, administrative staff, analysts, customer service teams, teachers, health workers, financial workers, and other professionals whose tasks involve information processing.

The third recommendation is support for small and medium-sized enterprises. Larger firms are more likely to benefit from AI because they have stronger data systems and technical capacity. Policymakers should support AI diffusion among smaller firms through training programmes, digital advisory services, cloud adoption support, cybersecurity guidance, and access to affordable AI tools. This would help prevent AI from widening productivity gaps between large and small firms.

The fourth recommendation is stronger measurement of AI adoption and productivity outcomes. Official data agencies should continue improving surveys on AI use, software investment, task automation, and worker outcomes. Better measurement will help researchers distinguish between AI hype and actual productivity gains. It will also help policymakers identify which sectors need support and which forms of adoption produce measurable gains.

The fifth recommendation is responsible AI governance. Firms should create clear rules on privacy, data security, human review, transparency, accountability, and quality control. Responsible AI should not be viewed only as an ethical issue. It is also an economic issue because poor governance can lead to errors, rework, legal exposure, and customer mistrust. Good governance helps firms capture productivity gains safely.

In conclusion, AI adoption is likely to become an important driver of labour productivity in the United States, but it will not transform productivity automatically. The country's advantage in AI investment and innovation gives it a strong starting position. However, the productivity effect will depend on whether firms can move from experimentation to effective implementation. AI will deliver its strongest economic benefits where it complements workers, improves skills, strengthens decision-making, and supports innovation rather than merely replacing human effort without improving output quality.

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