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| RESEARCH ARTICLE

Artificial Intelligence and Economic Growth: A Comprehensive Review of Productivity, Employment, and Inequality Effects

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| ABSTRACT

Artificial Intelligence (AI) is increasingly recognized as a transformative technology with significant implications for economic growth, productivity, employment, and income distribution. This comprehensive review examines the evolving relationship between AI adoption and economic performance by synthesizing evidence from existing theoretical and empirical literature. The review focuses on three interconnected dimensions: the contribution of AI to productivity and economic growth, its effects on employment and the changing nature of work, and its potential implications for economic inequality. The findings indicate that AI can enhance economic growth by improving production efficiency, automating routine activities, supporting innovation, reducing operational costs, and enabling new products and services. However, the productivity gains associated with AI are likely to vary across industries, firms, and countries depending on technological infrastructure, human capital, organizational capabilities, and institutional conditions. The review further shows that AI can simultaneously create new employment opportunities while displacing or transforming certain routine and highly automatable tasks, increasing the importance of reskilling and lifelong learning. In relation to inequality, AI may widen income and wealth disparities when its benefits are concentrated among highly skilled workers, technology-intensive firms, and capital owners, although inclusive education, labor-market policies, social protection, and broad access to digital technologies can help distribute its gains more equitably. Overall, the review concludes that AI has substantial potential to support long-term economic growth, but its outcomes are not predetermined. Effective policy frameworks and investments in human capital, digital infrastructure, innovation, and inclusive institutions are essential for ensuring that AI-driven economic transformation generates broad-based and sustainable prosperity.

| KEYWORDS

Artificial Intelligence; Economic Growth; Productivity; Employment; Economic Inequality.

| ARTICLE INFORMATION

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1. Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technological developments of the twenty-first century, with significant implications for economic activity, productivity, employment, business organization, and income distribution. Advances in machine learning, generative AI, robotics, natural language processing, and automated decision-making have expanded the capacity of machines to perform tasks that were traditionally undertaken by human workers (Sami et al., 2026; Saha et al., 2026). Unlike earlier waves of technological change that were primarily associated with the automation of routine physical or manual activities, contemporary AI can increasingly perform cognitive, analytical, creative, and communication-intensive tasks. This broadening of technological capabilities has generated considerable interest in the potential contribution of AI to economic growth while simultaneously raising concerns about employment displacement, changing skill requirements, wage inequality, and unequal access to the benefits of technological progress.

From an economic perspective, AI can influence growth through several interconnected channels. First, AI may increase productivity by enabling firms to automate repetitive activities, improve forecasting and decision-making, optimize production processes, reduce transaction costs, and make more effective use of available resources. Second, AI can contribute to innovation by accelerating research, product development, knowledge creation, and the diffusion of new technologies. Third, AI may generate new markets, occupations, products, and business models, thereby creating additional sources of economic value (Lu, 2021). These effects are consistent with the broader view of technological progress as a major driver of long-run increases in productive capacity. At the same time, the magnitude of AI's contribution to economic growth is unlikely to be uniform across countries, sectors, firms, or workers because its economic effects depend on complementary investments in human capital, digital infrastructure, organizational capabilities, institutions, and access to technology (Sarwer et al., 2022).

The relationship between AI and employment is particularly complex. Technological advancement has historically produced both displacement and creation effects, and AI is likely to follow a similarly multifaceted pattern. Automation can substitute for workers when AI systems perform tasks previously completed by humans, potentially reducing demand for certain occupations or transforming their responsibilities (Hemal et al., 2025). However, AI can also complement workers by increasing their capabilities, improving efficiency, and allowing them to focus on tasks requiring judgment, interpersonal interaction, creativity, and problem-solving. In addition, productivity gains and lower production costs may increase demand for goods and services, potentially generating new employment opportunities. Consequently, the effect of AI on employment cannot be understood simply in terms of the number of jobs eliminated or created; it also involves changes in occupational structures, job quality, skill requirements, wages, and the distribution of work across sectors (Adenike, 2022; Hossain et al., 2024).

Another major concern is the effect of AI on economic inequality. The benefits of AI may be distributed unevenly because workers differ in their skills, occupations, ability to complement new technologies, and access to training. Highly skilled workers and firms with greater technological capabilities may capture a disproportionate share of productivity gains, while workers performing tasks that are more easily automated may face greater adjustment pressures. Similarly, countries with stronger digital infrastructure, research capacity, education systems, and investment resources may be better positioned to exploit AI than economies with limited technological capabilities. As a result, AI has the potential both to promote broad-based economic development and to reinforce existing disparities in income, wealth, skills, and technological access (Aniwa, 2021). The distributional consequences therefore represent an essential dimension of assessing AI's overall contribution to economic development. Despite growing research on AI and the economy, the existing evidence remains fragmented across different disciplines and levels of analysis. Studies have examined AI's effects on firm productivity, labor demand, wages, occupational exposure, innovation, economic growth, and inequality, but findings vary depending on the technology considered, the sector examined, the characteristics of workers and firms, and the institutional context (Ayrin et al., 2025). Moreover, much of the emerging evidence focuses on individual industries, occupations, or countries, making it difficult to obtain a comprehensive understanding of the broader economic implications of AI. A review that brings together evidence on productivity, employment, and inequality is therefore important for identifying common patterns, areas of disagreement, and gaps requiring further investigation.

Against this background, this study provides a comprehensive review of the relationship between artificial intelligence and economic growth, with particular emphasis on three interconnected dimensions: productivity, employment, and inequality. The review examines how AI contributes to productivity and innovation, how technological adoption affects employment and the changing nature of work, and how the resulting economic gains and adjustment costs may be distributed across workers, firms, sectors, and countries. It also considers the conditions that shape these outcomes, including human capital, digital infrastructure, institutional quality, technological complementarity, and public policy (Islam, 2023). By integrating these dimensions, the study seeks to provide a balanced understanding of whether and under what conditions AI can serve as a sustainable engine of economic growth while supporting inclusive economic development.

2. Methodology

2.1 Research Design

This study adopted a comprehensive narrative review design to examine the relationship between artificial intelligence (AI) and economic growth, with particular emphasis on productivity, employment, and income inequality. A review approach was considered appropriate because AI is a rapidly evolving technological phenomenon whose economic consequences extend across multiple sectors, occupations, countries, and levels of economic development (Ayrin et al., 2025). Rather than collecting primary empirical data, the study synthesized findings from previously published academic studies, theoretical contributions, empirical investigations, institutional reports, and other credible scholarly sources. The review was structured to identify major patterns in the existing literature, compare areas of agreement and disagreement, and develop an integrated understanding of how AI may influence economic performance and the distribution of economic opportunities.

2.2 Literature Search Strategy

A systematic and structured literature search was conducted using major academic and research databases, including Google Scholar, Scopus, Web of Science, ScienceDirect, SpringerLink, and JSTOR, where relevant literature was available. The search focused on publications addressing artificial intelligence and its economic implications. Combinations of keywords and Boolean operators were used to identify relevant studies (Alasa et al., 2025a,b; Yusuf et al., 2025). Core search terms included “artificial intelligence and economic growth,” “AI and productivity,” “artificial intelligence and employment,” “AI and labor markets,” “automation and economic growth,” “AI and income inequality,” “technological change and wages,” “generative AI and productivity,” and “artificial intelligence and labor displacement.” Additional searches combined AI-related terms with sectoral and macroeconomic concepts such as innovation, investment, human capital, GDP, productivity growth, employment creation, occupational restructuring, and wage inequality.

2.3 Inclusion and Exclusion Criteria

Studies were selected according to their relevance to the central objectives of the review. The inclusion criteria covered peer-reviewed journal articles, scholarly books and book chapters, working papers from reputable research institutions, and credible reports from international organizations that directly examined AI, automation, technological change, productivity, employment, wages, economic growth, or inequality. Both theoretical and empirical studies were considered in order to capture different perspectives on the economic effects of AI (Rahman et al., 2022; Alam et al., 2026). Studies were excluded when they focused primarily on technical AI development without meaningful economic implications, duplicated findings from another source, lacked sufficient methodological information, or addressed technological issues unrelated to the study's research questions. Where several publications examined substantially similar evidence, priority was given to more comprehensive, recent, and methodologically rigorous contributions.

2.4 Data Extraction and Organization

Relevant information was extracted from the selected literature using a structured review framework. For each study, attention was given to the publication year, geographical or economic context, research objective, methodological approach, sector or population examined, principal variables, and major findings. Particular emphasis was placed on evidence concerning three dimensions: productivity effects, employment effects, and inequality effects. The extracted evidence was organized into thematic categories to facilitate comparison across studies. The review also considered whether reported effects differed according to country income level, industry, occupational characteristics, worker skills, degree of AI adoption, and institutional conditions.

2.5 Analytical Framework

The analysis employed thematic synthesis and comparative analysis to integrate evidence from the reviewed literature. Findings were first grouped according to the three principal dimensions of the study: AI and productivity, AI and employment, and AI and inequality. Within each dimension, studies were compared according to the mechanisms through which AI was reported to influence economic outcomes (Rahman et al., 2025). For productivity, the analysis considered automation, augmentation, innovation, knowledge generation, and improvements in production efficiency. For employment, it examined job displacement, job creation, occupational transformation, changes in skill requirements, and the reallocation of labor between tasks and sectors. For inequality, the analysis considered wage differentials, differences between high- and low-skilled workers, capital–labor income distribution, access to AI technologies, and disparities between countries and regions.

2.6 Comparative Assessment of Evidence

The review compared findings across studies to identify consistent patterns as well as contradictory or conditional results. Particular attention was given to differences between short-term and long-term effects. For example, AI adoption may initially generate adjustment costs or labor displacement while producing productivity and employment opportunities over a longer period (Bulbul et al., 2019; Rahman et al., 2025). Similarly, the effects of AI were examined in relation to the distinction between task substitution and task complementarity, since technologies that automate certain activities may simultaneously increase the productivity and demand for workers performing complementary tasks. The review therefore avoided treating AI as having a uniform economic effect and instead assessed how outcomes depend on technological adoption, human capital, institutional arrangements, business strategies, and policy environments.

2.7 Validity and Reliability of the Review

To enhance the credibility of the review, emphasis was placed on evidence from established academic publications and reputable institutional sources. Findings were compared across multiple studies rather than being based on isolated claims. Particular consideration was given to the methodological quality of empirical research, the size and nature of datasets, the geographical coverage of studies, and the consistency of findings across different research designs (Sami et al., 2024; Das et al., 2025). Where the literature produced conflicting conclusions, these differences were explicitly recognized rather than averaged or treated as evidence of a single definitive effect. This approach helped reduce the risk of selective interpretation and provided a more balanced assessment of the economic consequences of AI.

2.8 Ethical Considerations

Because the study relied exclusively on previously published and publicly available secondary sources, it did not involve direct interaction with human participants, collection of personal information, or experimental intervention. Consequently, risks associated with participant confidentiality and informed consent were not applicable. Nevertheless, academic integrity was maintained by appropriately acknowledging the intellectual contributions of previous researchers and presenting their findings accurately. The review also sought to avoid misrepresentation by distinguishing established empirical evidence from theoretical arguments, projections, and areas where the existing literature remains inconclusive.

2.9 Limitations of the Methodology

The review methodology has several limitations. First, the rapidly changing nature of AI means that new evidence can emerge faster than it can be incorporated into the academic literature. Second, differences in definitions of AI, measures of productivity, employment classifications, datasets, and research methodologies make direct comparison between studies challenging. Third, much of the available evidence is concentrated in technologically advanced economies, potentially limiting the generalizability of findings to developing countries. Finally, because the study uses a comprehensive narrative synthesis rather than a formal statistical meta-analysis, the findings should be interpreted as an integrated assessment of patterns and mechanisms in the literature rather than as a single estimated causal effect of AI on economic growth (Alam et al., 2025).

3. Findings and Discussion

The findings from the reviewed literature indicate that artificial intelligence (AI) is becoming an important driver of economic transformation through its effects on productivity, innovation, employment, and the organization of work.

Across the literature, AI does not produce uniform outcomes. Its economic effects depend substantially on the type and intensity of adoption, the technological capabilities of firms, the skills of workers, organizational readiness, and the institutional environment in which AI is deployed (Alam et al., 2025, 2026). The evidence generally suggests that AI can generate significant productivity improvements by automating routine activities, improving prediction and decision-making, optimizing business processes, and supporting innovation. However, these benefits are accompanied by labor-market disruptions, particularly where AI substitutes for highly codifiable and repetitive tasks. At the same time, the literature shows that AI frequently complements rather than completely replaces human labor, creating opportunities for new tasks and occupations. The following sections discuss these findings in greater detail.

3.1 Artificial Intelligence and Productivity Growth

3.1.1 AI Adoption and Firm-Level Productivity

The reviewed evidence indicates that AI adoption can significantly enhance firm-level productivity by enabling organizations to automate repetitive processes, improve decision-making, reduce operational costs, and allocate resources more efficiently. Firms using AI-powered systems can process large volumes of information more rapidly than traditional approaches, allowing managers to identify patterns, forecast demand, optimize inventories, and respond more quickly to changing market conditions. In manufacturing, for example, AI-supported predictive maintenance can identify potential equipment failures before they occur, reducing downtime and improving the utilization of productive assets (Kaur et al., 2025). In financial services, AI can improve fraud detection, credit assessment, customer segmentation, and risk management. Similarly, in retail, AI-based forecasting and recommendation systems can improve inventory management and personalize customer services. These applications demonstrate that productivity gains arise not only from replacing human activities but also from improving the quality and speed of organizational decisions.

The findings further suggest that productivity effects vary considerably according to firm size and technological capability. Large firms and technologically advanced enterprises are generally better positioned to benefit from AI because they possess greater financial resources, better data infrastructure, specialized technical personnel, and stronger organizational capacity to integrate new technologies (Islam et al, 2023; Kaur et al., 2025). Early adopters can therefore obtain productivity advantages through faster experimentation, improved economies of scale, and accumulated experience with AI systems. By contrast, smaller firms and organizations with limited digital infrastructure may face difficulties related to the cost of AI adoption, inadequate data, cybersecurity concerns, limited technical expertise, and uncertainty about returns on investment. This creates a potential productivity gap between technologically advanced and technologically constrained firms. Previous research on digital technologies similarly indicates that technological investment produces larger benefits when accompanied by complementary organizational changes, employee training, and managerial capabilities.

An important finding is that AI adoption alone does not automatically guarantee productivity growth. Firms need to reorganize workflows and business processes to capture the full value of AI. For example, simply introducing an AI-based customer-service tool may produce limited benefits if employees are not trained to interpret its outputs or if organizational procedures prevent them from acting on AI-generated recommendations. The strongest productivity effects therefore appear where AI is integrated into broader digital transformation strategies. This finding is consistent with the broader technology-adoption literature, which emphasizes that general-purpose technologies often require complementary investments in organizational restructuring, human capital, data systems, and management practices before their full economic benefits become visible.

3.1.2 AI, Innovation, and Total Factor Productivity

The literature reviewed shows that AI can contribute to total factor productivity (TFP) by improving how capital, labor, knowledge, and other productive inputs are combined. Unlike technologies that primarily increase the quantity of a particular input, AI can improve the efficiency with which multiple inputs are coordinated. Its ability to identify complex patterns, generate predictions, automate analytical processes, and support experimentation enables firms to discover more efficient production methods and develop new products and services (Tanvir et al., 2024). Consequently, AI has the potential to become a general-purpose technology whose effects extend beyond individual applications into wider changes in production and innovation systems.

AI is particularly important for research and development because it can accelerate knowledge discovery and experimentation. In scientific and industrial environments, machine-learning systems can analyze large datasets, identify relationships that may not be immediately apparent to researchers, and assist in the development and testing of new solutions. In pharmaceuticals, for instance, AI can support drug discovery by identifying promising molecular candidates and predicting potential interactions (Tanvir et al., 2020). In manufacturing, AI can assist engineers in optimizing product designs and production processes. In agriculture, AI-supported systems can improve crop monitoring, disease detection, and resource allocation. These applications illustrate how AI can reduce the time and resources required to move from experimentation to practical innovation.

The evidence also indicates that AI frequently complements existing technologies rather than functioning independently. The productivity benefits of AI are greater when it is combined with cloud computing, high-speed connectivity, big-data analytics, robotics, enterprise software, and digital platforms. This complementarity allows AI systems to access and process information generated by other technologies while translating analytical outputs into operational decisions (Alam et al., 2023). As a result, AI can generate cumulative productivity effects across interconnected technologies. However, the literature also suggests that these benefits may take time to materialize because firms must invest in infrastructure, data quality, organizational capabilities, and experimentation before significant productivity gains emerge. This helps explain why measured economy-wide productivity effects may initially appear smaller than the transformative potential associated with AI.

Another important finding concerns the uneven distribution of innovation benefits. Firms with strong research capabilities, extensive data resources, and access to highly skilled workers are more likely to use AI for innovation rather than merely for routine automation. Such firms can use AI to develop new business models, customized services, intelligent products, and more efficient production methods. Smaller or less technologically developed firms may initially use AI primarily for basic administrative and operational functions (Trabelsi, 2024; Hasan et al.,2026). Therefore, while AI has the potential to increase aggregate TFP, differences in innovation capacity can produce substantial variation in productivity outcomes across firms and sectors.

3.1.3 AI, Human Capital, and Productivity Enhancement

The findings demonstrate that the relationship between AI and productivity is strongly influenced by human capital. Rather than simply eliminating the role of workers, AI often changes the tasks workers perform and enables them to complete certain activities more effectively. AI-assisted systems can provide information, generate preliminary analyses, identify errors, summarize large amounts of material, and support complex decision-making. This can allow employees to devote more time to activities requiring judgment, creativity, communication, problem-solving, and interpersonal skills (Alam et al., 2024). Consequently, productivity improvements can emerge from human-AI complementarity rather than technological substitution alone.

Knowledge-intensive occupations appear particularly capable of benefiting from AI assistance when workers understand how to use AI effectively. Professionals in areas such as finance, engineering, education, research, consulting, healthcare administration, and business management can use AI tools to accelerate information processing and routine analytical tasks. For example, an analyst may use AI to organize and examine large datasets while retaining responsibility for interpreting results and making strategic recommendations. Similarly, an engineer may use AI-assisted design tools to evaluate multiple alternatives more rapidly while applying professional judgment to determine which solution is technically appropriate. These examples indicate that AI can expand individual productive capacity when workers possess the skills required to supervise and critically evaluate AI outputs.

At the same time, the findings indicate that AI increases the importance of digital literacy, analytical reasoning, communication, adaptability, and problem-solving skills. Workers who lack these capabilities may find it more difficult to benefit from AI or may face greater risks of displacement. This creates an important distinction between AI adoption and AI-enabled productivity enhancement: the technology provides potential capabilities, but human capital determines how effectively those capabilities are converted into economic value. Previous studies on technological change have similarly emphasized that productivity improvements depend on complementary skills and organizational capabilities (Hossain, 2021, 2022).

The evidence therefore supports a shift from viewing human capital solely as a source of technical knowledge toward understanding it as a foundation for effective human-AI collaboration. Workers increasingly need to know not only how to operate digital tools but also how to evaluate their accuracy, identify limitations, formulate appropriate questions, interpret outputs, and make decisions based on multiple sources of information. Continuous investment in education and workplace training is consequently essential for ensuring that AI contributes to broad-based productivity growth rather than producing productivity gains concentrated among a small group of technologically advanced workers and firms.

3.2 Artificial Intelligence and Employment Dynamics

3.2.1 Job Displacement and Automation Effects

The reviewed literature indicates that AI has the potential to displace some forms of employment, particularly where occupational activities consist heavily of predictable, repetitive, and codifiable tasks. AI-enabled automation can perform activities involving data entry, document processing, basic classification, routine customer inquiries, standardized analysis, and other structured tasks with increasing speed and consistency (Filippucci, 2024). Administrative and clerical occupations may therefore experience greater exposure to automation than occupations requiring extensive interpersonal interaction, physical adaptability, complex judgment, or creative problem-solving.

However, the evidence suggests that it is more appropriate to examine tasks within occupations rather than assume that entire occupations will disappear. Most occupations consist of multiple activities, only some of which can be automated effectively (Hossain et al., 2023; Habib et al., 2024). For example, AI may automate parts of an accountant's data-processing activities while leaving interpretation, client communication, strategic advice, and professional judgment largely dependent on human workers. Similarly, customer-service employees may use AI to handle routine inquiries while concentrating on complicated cases requiring empathy and negotiation. Consequently, technological exposure does not necessarily translate directly into complete occupational replacement.

The extent of displacement also varies across industries and countries. Highly digitized sectors with standardized processes may experience faster automation, while sectors characterized by complex physical environments or extensive interpersonal interaction may experience slower substitution. Differences in labor costs, technological infrastructure, regulations, and access to AI systems further influence adoption rates. The findings therefore challenge the view that AI will inevitably produce universal mass unemployment. Instead, the evidence points toward a more complex process in which some tasks disappear, others are redesigned, and new tasks emerge (Habib et al., 2024; Hossain et al., 2026).

Nevertheless, the possibility of significant short- and medium-term disruption should not be underestimated. Workers whose existing skills are closely tied to automatable activities may experience difficulty transitioning into new roles, particularly when training opportunities are limited. Job displacement can also occur faster than workers and institutions can adjust, creating periods of unemployment or reduced earnings even when new employment opportunities eventually emerge. Thus, the employment consequences of AI depend not only on technological capabilities but also on the speed and quality of labor-market adjustment.

3.2.2 Job Creation, Task Transformation, and New Occupations

Alongside displacement, the findings show substantial potential for AI to create employment through the emergence of new tasks, occupations, industries, and business models. The expansion of AI generates demand for professionals involved in AI development, data management, system integration, model evaluation, cybersecurity, technology management, and AI governance (Hossain et al., 2026). At the same time, AI can create indirect employment by enabling the development of new products and services and by increasing productivity, which may expand output and stimulate demand for labor elsewhere in the economy.

The transformation of existing occupations is particularly significant. Rather than replacing workers completely, AI often changes the composition of their tasks. A marketing professional, for example, may use generative AI to produce initial content ideas while spending more time on strategy, audience analysis, brand management, and evaluation. In software development, AI can assist with routine coding and debugging activities while developers concentrate more heavily on system architecture, requirements, testing, and problem-solving. Similar task transformations can occur in finance, education, research, design, logistics, and other knowledge-intensive sectors (Hossain & Alasa, 2024a,b).

The emergence of new occupations is also likely to extend beyond highly technical AI development roles (Ho, 2026). Organizations increasingly require personnel who can translate business needs into AI applications, monitor automated systems, evaluate AI-generated outputs, manage data quality, assess risks, and ensure responsible use. This creates opportunities for hybrid occupations that combine domain-specific knowledge with AI and digital competencies. For example, organizations may require professionals who understand both financial processes and AI-based risk systems or both educational practice and AI-supported learning technologies.

The findings therefore suggest that the overall employment effect of AI cannot be determined simply by counting jobs directly eliminated by automation. Employment creation, productivity-induced demand, occupational transformation, and the development of entirely new activities must also be considered. The net outcome will depend on the relative speed of these processes. If new tasks and industries expand rapidly enough, AI can contribute to employment growth despite substantial automation. If automation occurs more rapidly than new opportunities emerge, however, particular groups of workers may experience prolonged labor-market difficulties.

3.2.3 Reskilling, Labor Market Adjustment, and Employment Transitions

The evidence strongly identifies reskilling and continuous learning as central mechanisms for managing AI-driven labor-market change. As the task composition of jobs changes, workers need opportunities to acquire new technical and transferable skills. Digital literacy, data interpretation, analytical thinking, communication, creativity, problem-solving, and adaptability are increasingly important because they allow workers to complement AI systems rather than compete directly with them on tasks that machines can perform efficiently.

The ability to adjust, however, differs substantially across workers, firms, industries, and countries. Workers with higher levels of education and stronger digital skills may have greater opportunities to move into complementary occupations, whereas workers whose jobs contain large proportions of routine tasks may face more significant adjustment challenges. Firms with substantial training budgets can retrain employees internally, while smaller organizations may have fewer resources for structured workforce development. Similarly, countries with strong education systems, digital infrastructure, labor-market institutions, and social-protection mechanisms are likely to have greater capacity to manage technological transitions than countries where these systems remain limited.

Workplace training is therefore an important component of successful AI adoption. Organizations that introduce AI while simultaneously investing in employee development may be better positioned to achieve productivity gains without generating unnecessary workforce disruption. Employees who understand how AI systems function and how their responsibilities are changing can participate more effectively in technology implementation. This can also reduce resistance to technological change and improve the likelihood that AI will be used as a complement to human expertise.

The findings further suggest that education systems must adapt to a labor market in which specific technical skills can become outdated relatively quickly. Traditional education that focuses exclusively on acquiring fixed occupational knowledge may be insufficient in an environment characterized by rapid technological change.

Lifelong learning, modular training, vocational education, workplace-based learning, and accessible digital training can provide mechanisms through which workers continuously update their capabilities (Korinek, 2021). Partnerships among governments, educational institutions, employers, and technology providers are particularly important for ensuring that training programs correspond to emerging labor-market needs.

Overall, the evidence indicates that AI-driven employment transitions should be understood as a process of reallocation and transformation, rather than simply job destruction. Productivity gains from AI can support economic growth and create new employment opportunities, but these benefits are unlikely to be distributed automatically or evenly. Workers and firms with greater access to skills, capital, infrastructure, and training are likely to adapt more successfully. Consequently, effective reskilling policies, inclusive education systems, organizational investment in human capital, and supportive labor-market institutions are essential for translating the productivity potential of AI into broad-based economic benefits. The interaction between these productivity and employment effects also provides an important foundation for understanding the study's broader concern with income and economic inequality, since unequal access to AI capabilities may determine which firms, workers, and countries capture the largest share of the resulting economic gains.

3.3 Artificial Intelligence and Income Inequality

The review indicates that the relationship between artificial intelligence (AI) and income inequality is complex and depends substantially on the nature of technological adoption, labor-market institutions, access to skills, and ownership of productive assets. AI can generate substantial productivity gains and create new employment opportunities, but these benefits are not automatically distributed equally across workers, firms, regions, or countries. The evidence reviewed suggests that AI is particularly capable of changing the relative returns to different types of labor and capital. Workers with advanced digital, analytical, managerial, and AI-related capabilities are generally better positioned to benefit from AI adoption, while workers performing highly routine and predictable tasks may face greater pressure from automation. At the same time, AI can increase the productivity of less-skilled workers when it functions as an assistive technology rather than a substitute for human labor. Consequently, the distributional effects of AI depend not only on whether jobs are created or displaced, but also on who has access to AI tools, who controls AI-related capital, and how productivity gains are distributed.

3.3.1 AI and Wage Inequality

The findings show that AI adoption can widen wage differences when it disproportionately increases the productivity and bargaining power of highly skilled workers. Employees with expertise in data science, software development, engineering, advanced analytics, AI system management, and strategic decision-making can command wage premiums because their skills are complementary to AI technologies. For example, a financial analyst who can effectively use AI for forecasting, risk assessment, and data interpretation may perform substantially more complex analyses within the same amount of time. Similarly, healthcare professionals who use AI-assisted diagnostic systems may process information more efficiently while retaining responsibility for clinical judgment (Islam et al, 2025). These examples demonstrate that AI does not necessarily replace skilled workers; in many circumstances, it increases the value of workers who can effectively integrate technology with specialized knowledge.

The review also finds evidence that AI is particularly relevant to the transformation of routine cognitive and administrative tasks. Activities such as data entry, standardized reporting, basic document processing, scheduling, and repetitive customer-service interactions can increasingly be performed or supported by AI systems. Medium-skilled workers whose occupations contain a large proportion of such tasks may therefore experience greater restructuring pressures than workers performing highly interpersonal, creative, or complex problem-solving activities. However, substitution is not inevitable. Workers who receive appropriate training can transition from routine task execution toward roles involving supervision, interpretation, quality control, customer interaction, and AI-assisted decision-making.

The effects on low-skilled workers are similarly mixed. In some occupations, AI-powered automation can reduce demand for repetitive manual or service tasks, potentially suppressing wages or employment opportunities. In other situations, AI can provide workers with relatively limited formal training with tools that improve their performance. For instance, an AI-assisted system can help a new employee respond to customer inquiries, diagnose basic equipment problems, or follow complex operational procedures. This suggests that AI may reduce some traditional skill barriers by embedding knowledge within technological systems. The overall effect on wage inequality therefore depends on whether AI primarily operates as a substitute for workers or as a complement that expands their capabilities.

Previous research on skill-biased technological change provides an important basis for interpreting these findings. Earlier technological transformations tended to increase the relative demand for workers with complementary skills while reducing demand for certain routine occupations. AI extends this process because its capabilities increasingly encompass tasks previously associated with cognitive rather than purely physical work (Sood, 2024). Nevertheless, the reviewed evidence suggests that AI may also produce a new form of task-based inequality in which workers possessing AI-related competencies receive wage premiums while workers unable to access training or technological resources become increasingly disadvantaged. Thus, the critical issue is not simply the number of jobs affected by AI but the changing distribution of productivity and earning capacity across occupational groups.

3.3.2 AI, Capital Ownership, and Distribution of Economic Gains

A major finding of the review is that the distribution of AI-related economic gains depends strongly on ownership and control of AI-related capital. AI systems require substantial investments in computing infrastructure, data, software, intellectual property, specialized talent, and research and development. Firms that control these assets can capture significant portions of the productivity gains generated by AI. This creates a potential divergence between productivity growth and the distribution of income, particularly where technological ownership is concentrated among a relatively small number of large firms (Hemal et al., 2025; Saha et al., 2026).

Large technology companies provide a clear example of this dynamic. Firms with extensive datasets, computing capacity, proprietary algorithms, cloud infrastructure, and specialized AI researchers possess advantages that smaller competitors may find difficult to reproduce. AI can therefore reinforce economies of scale and network effects, allowing technologically advanced firms to expand their market position while reducing the relative competitiveness of firms with limited access to capital and advanced infrastructure. The resulting concentration of economic power can affect not only corporate profits but also the distribution of income between capital owners and labor (Hossain et al., 2024; Ayrin et al., 2025).

The review nevertheless indicates that AI-generated productivity gains can benefit workers when institutional arrangements allow productivity improvements to translate into higher wages, improved working conditions, employment expansion, or investment in human capital. The extent to which workers share in these gains depends on factors such as collective bargaining arrangements, labor-market competition, minimum-wage policies, taxation, corporate governance, and the degree of competition within product markets. Where workers have weak bargaining power, productivity gains may be captured primarily through higher profits and returns to capital rather than corresponding increases in labor income. AI may consequently contribute to a broader shift in the distribution of economic gains toward owners of technology, intellectual property, data, and financial capital. However, this outcome is not technologically predetermined. Policies that promote competition, wider access to digital technologies, employee participation, entrepreneurship, and investment in public technological infrastructure can broaden the distribution of AI-related benefits. The evidence therefore supports the view that inequality arising from AI is partly a question of institutional design and ownership structures rather than an unavoidable consequence of technological progress.

3.3.3 Digital Divide, Regional Inequality, and Unequal AI Adoption

The review identifies unequal access to digital infrastructure, skills, finance, and technological capabilities as a major factor determining the distributional effects of AI. Developed economies generally possess stronger broadband infrastructure, greater computing capacity, larger pools of skilled workers, stronger research institutions, and greater access to venture and corporate investment. Developing economies, particularly those with limited electricity reliability, inadequate connectivity, low levels of digital literacy, and restricted access to investment capital, may face greater barriers to AI adoption. As a result, the productivity benefits of AI may initially be concentrated in countries and regions that are already technologically advanced (Alam et al., 2025; Saha et al., 2026).

Similar inequalities occur within countries. Large firms typically possess greater financial resources and specialized personnel to experiment with and integrate AI than small and medium-sized enterprises. Large urban centers also tend to have stronger digital infrastructure, universities, technology firms, and skilled labor markets than rural and peripheral areas. For example, an urban financial-services firm may have access to cloud computing, AI specialists, and digital data systems, while a small rural enterprise may struggle with basic connectivity and financing. Such differences can create cumulative advantages in which already productive regions adopt AI more rapidly and subsequently attract additional investment and skilled workers (Yusuf et al., 2025; Hemal et al., 2025). The findings suggest that unequal AI adoption can therefore reinforce existing regional and international inequalities. Regions that successfully integrate AI into manufacturing, finance, healthcare, education, agriculture, and professional services may experience faster productivity growth, while regions lacking infrastructure and skills may fall further behind. However, AI also has potential to reduce geographic inequalities when combined with appropriate infrastructure. Remote education, telemedicine, digital financial services, precision agriculture, and AI-supported public services can extend specialized knowledge to underserved areas. The extent to which this potential is realized depends on affordability, connectivity, local skills, institutional capacity, and the design of AI applications.

3.4 Macroeconomic and Structural Effects of Artificial Intelligence

3.4.1 AI and Aggregate Economic Growth

The reviewed evidence indicates that AI has significant potential to increase aggregate economic growth through productivity improvements, capital formation, innovation, and the creation of new products and services. At the firm level, AI can reduce production costs, improve forecasting, automate repetitive activities, increase the speed of decision-making, and support more efficient allocation of resources. When these improvements are adopted across large parts of an economy, they can raise total factor productivity and increase potential output. AI-driven growth, however, is unlikely to occur automatically or immediately. The economic impact depends on complementary investments in organizational restructuring, worker training, digital infrastructure, data systems, and physical capital. A firm may acquire an advanced AI system without obtaining substantial productivity gains if employees lack the skills to use it effectively or if existing organizational processes are incompatible with the technology. This finding is consistent with earlier technological transformations in which major productivity benefits emerged only after firms reorganized production and developed complementary innovations (Alam et al., 2025).

The review further indicates that AI can stimulate investment and innovation by lowering the cost of research, experimentation, information processing, and product development. In sectors such as pharmaceuticals, engineering, finance, and software development, AI can accelerate activities that previously required considerable amounts of human time. New markets may consequently emerge around AI applications, cloud computing, data services, robotics, cybersecurity, AI consulting, and specialized software. These developments can generate additional economic activity beyond the productivity gains achieved through automation. Nevertheless, the macroeconomic impact depends on the balance between productivity-enhancing effects and adjustment costs. Displaced workers may experience temporary unemployment or declining earnings, while firms may incur significant costs when adopting new technologies (Abbas Khan, 2024). If labor-market transitions are slow or concentrated geographically, the short-term social costs can be substantial even when long-term output increases. Thus, the evidence supports a positive long-term growth potential for AI but emphasizes that the magnitude and distribution of this growth depend on complementary economic and institutional conditions.

3.4.2 Sectoral Transformation and Structural Change

The findings demonstrate that AI is transforming economic structures differently across sectors because the composition of tasks, data availability, capital intensity, and opportunities for automation vary considerably. In manufacturing, AI is increasingly associated with predictive maintenance, quality inspection, industrial robotics, demand forecasting, and production optimization. These applications can reduce downtime, improve product quality, and increase production efficiency while changing the occupational composition of factories toward more technical, supervisory, and maintenance-oriented roles (Sami et al., 2026).

In finance, AI is widely applicable to fraud detection, credit assessment, risk management, customer service, financial forecasting, and algorithmic decision support. These applications can increase processing speed and improve the capacity to analyze large volumes of financial information. However, they also reduce the need for certain routine administrative activities and increase demand for professionals capable of managing technological systems, interpreting outputs, and addressing regulatory and ethical risks.

Healthcare represents another important area of transformation. AI can support medical imaging, clinical decision-making, patient monitoring, drug discovery, and administrative processes. Rather than completely replacing healthcare professionals, many applications function as decision-support tools (Saha et al., 2025a,b). This can increase professional productivity while creating new requirements for digital competencies and oversight. Education is similarly affected through adaptive learning, automated feedback, administrative automation, and personalized educational resources. At the same time, teachers remain important for motivation, social interaction, contextual judgment, and the development of broader competencies.

Agriculture can benefit from AI through precision farming, crop monitoring, weather forecasting, disease detection, irrigation optimization, and agricultural market analysis. Such applications are particularly important for improving resource efficiency and climate resilience, although adoption may be constrained by connectivity, affordability, farm size, and farmers' digital skills. Transportation is being transformed through route optimization, intelligent logistics, driver-assistance systems, and increasingly automated operations. Professional services, including accounting, consulting, legal services, marketing, and research, are also experiencing changes as AI performs or assists with information-intensive tasks (Tanvir et al., 2024; Alam et al., 2023).

Overall, the findings suggest that AI is contributing to structural change rather than simply eliminating employment. Some occupations decline, others expand, and entirely new occupational categories emerge. The competitive advantage of firms increasingly depends on their capacity to combine human expertise with AI capabilities. Economies that successfully manage these structural transitions are likely to experience greater productivity and competitiveness, whereas economies unable to adapt their skills and institutions may experience persistent adjustment problems.

3.4.3 AI Adoption Across Developed and Developing Economies

The comparative findings show substantial differences in the capacity of developed and developing economies to benefit from AI. Developed economies generally possess stronger digital infrastructure, greater research and development capacity, higher levels of tertiary education, deeper financial markets, and more mature technology ecosystems. These characteristics allow them to adopt AI more rapidly and integrate it into sophisticated production systems. They are also more capable of producing AI technologies rather than simply consuming technologies developed elsewhere.

Developing economies face a more heterogeneous situation. Some countries possess strong technology sectors, growing digital economies, and highly skilled labor forces and can therefore participate actively in AI development. Others face substantial constraints related to electricity supply, broadband connectivity, computing infrastructure, financing, data availability, education, and institutional capacity. These differences mean that the economic consequences of AI will not be uniform across developing countries (Yusuf et al., 2024).

The findings also suggest that developing economies may benefit from AI through technology diffusion without necessarily reproducing all the stages of technological development experienced by advanced economies. AI-powered mobile financial services, agricultural advisory systems, digital healthcare, educational platforms, and automated business services can provide relatively low-cost access to capabilities that were previously concentrated in major urban or industrial centers. However, dependence on foreign AI technologies can also create challenges related to data ownership, technological dependence, intellectual property, cybersecurity, and the outflow of economic value (Rahman et al., 2025; Hossain et al., 2026).

Institutional quality is therefore a critical determinant of AI outcomes. Countries with effective regulatory institutions, reliable infrastructure, strong education systems, competitive markets, and supportive innovation policies are better positioned to transform AI investment into broad-based economic development. The evidence consequently suggests that AI should be treated not simply as a technology policy issue but as part of a wider development strategy involving infrastructure, education, investment, institutions, and productive-sector transformation.

3.5 Policy Implications and Strategies for Inclusive AI-Driven Growth

3.5.1 Education, Skills Development, and Workforce Resilience

The findings strongly emphasize human capital development as one of the most important mechanisms for ensuring that AI contributes to inclusive economic growth. Since AI changes the tasks performed within occupations, workers require opportunities to develop both technical and complementary human skills. Digital literacy should therefore become a foundational component of education, while more advanced programs should develop competencies in data analysis, programming, AI applications, cybersecurity, digital management, and technological problem-solving (Alam et al., 2023; Sami et al., 2026).

Vocational and technical education also requires adaptation. Training institutions should increasingly cooperate with employers to identify emerging occupational requirements and develop curricula that correspond to changing workplace conditions. For workers already employed, reskilling and upskilling programs can help them transition from routine tasks toward roles involving AI supervision, interpretation, maintenance, quality assurance, and human-centered services. Lifelong learning is particularly important because AI technologies are developing rapidly, meaning that a single period of education at the beginning of a person's career may no longer provide sufficient skills throughout working life.

The evidence further indicates that education policy should not focus exclusively on advanced AI specialists. Broad-based digital competence is equally important because AI will affect workers across manufacturing, agriculture, healthcare, education, retail, finance, government, and professional services. Policies that provide affordable access to training can reduce the risk that AI creates a sharp divide between technologically capable workers and those excluded from emerging opportunities.

3.5.2 Inclusive AI Policies, Social Protection, and Labor Market Institutions

The review indicates that governments have an important role in managing the distributional consequences of AI. Because technological adoption can create both winners and losers, social protection systems need to provide support during periods of employment transition. Unemployment assistance, employment services, retraining support, wage insurance mechanisms where appropriate, and targeted assistance for displaced workers can reduce the social costs associated with technological restructuring (Hossain et al., 2026).

Active labor-market policies are particularly important because passive income support alone may not provide workers with pathways into emerging occupations. Governments can facilitate job matching, subsidize training, support apprenticeships, and encourage employers to invest in employee development. Labor-market institutions should also ensure that productivity improvements do not systematically weaken workers' bargaining positions. Effective labor standards, fair remuneration, occupational protections, and mechanisms for worker participation can help ensure that productivity gains are shared more broadly (Sami et al., 2024).

At the same time, regulation should avoid unnecessarily restricting beneficial innovation. Excessively rigid rules may discourage investment and experimentation, particularly in developing economies where technological adoption is already limited. The evidence therefore favors balanced regulatory frameworks that address risks such as discrimination, privacy violations, unsafe automated decisions, and excessive concentration while maintaining sufficient flexibility for responsible innovation (Rahman et al., 2025).

Competition policy is another important consideration. Where AI markets become highly concentrated, a small number of firms may control critical computing infrastructure, data resources, platforms, or intellectual property. Policies promoting competitive markets, interoperability, transparency, and fair access to essential digital infrastructure can reduce excessive concentration and broaden opportunities for smaller firms and entrepreneurs.

3.5.3 Strategies for Sustainable and Equitable AI-Driven Economic Growth

The overall findings suggest that AI can become a powerful driver of productivity, innovation, and long-term economic growth, but its benefits will not automatically be inclusive. A sustainable AI-driven growth strategy should therefore combine technological adoption with investment in people, infrastructure, institutions, and equitable access. Governments should prioritize reliable electricity and broadband connectivity, affordable digital services, modern education systems, research capacity, and financing mechanisms that enable smaller businesses and underserved communities to adopt productive technologies (Sami et al., 2026).

Businesses also have an important responsibility to adopt AI in ways that complement rather than unnecessarily displace workers. Organizations can redesign jobs around human-AI collaboration, provide employees with relevant training, and establish mechanisms for monitoring the effects of automation on employment and working conditions. Educational institutions should continuously update curricula in response to technological change, while research institutions can contribute to locally appropriate AI solutions that address national and regional development challenges (Hossain et al., 2026). For developing economies in particular, international cooperation can help reduce technological disparities through knowledge transfer, infrastructure investment, research partnerships, capacity building, and responsible access to AI technologies. Such cooperation can enable countries with limited resources to benefit from AI without becoming entirely dependent on external technological systems (Islam, 2025; Ayrin et al., 2025). Public and private investment should also encourage AI applications in areas with broad social returns, including healthcare, agriculture, education, environmental management, and public administration.

Ultimately, the review demonstrates that the economic impact of AI is shaped as much by institutional and policy choices as by technological capabilities. AI can increase productivity, create new industries, improve services, and raise potential output, but it can also intensify wage disparities, concentrate economic power, and widen digital and regional divides when access to technology and skills is unequal. An inclusive strategy therefore requires a coordinated approach in which governments establish enabling institutions and social protections, businesses invest responsibly in AI and workers, educational institutions develop adaptable skills, and communities gain affordable access to digital infrastructure. Under these conditions, AI can contribute not only to higher economic growth but also to a more productive, resilient, and broadly shared development process.

4. Conclusion

This review concludes that artificial intelligence (AI) has significant potential to reshape economic growth through its effects on productivity, employment, and income distribution. The evidence indicates that AI can enhance productivity by automating routine activities, improving decision-making, optimizing resource allocation, and enabling innovation across sectors; however, the magnitude of these gains depends on complementary investments in skills, digital infrastructure, organizational capabilities, and institutional capacity. At the same time, AI is transforming employment by displacing some routine and highly automatable tasks while creating new occupations and increasing demand for advanced technical, analytical, and interpersonal skills. These changes may generate transitional unemployment and widen skill-based disparities if workers and institutions are unable to adapt. The review further shows that AI can contribute to income inequality when productivity gains and economic returns are concentrated among highly skilled workers, technology-intensive firms, and capital owners, although appropriate policies can broaden access to its benefits. Overall, AI should therefore be viewed not simply as a technological innovation but as a major structural force whose economic outcomes depend on how effectively governments, businesses, and educational institutions manage technological adoption. Policies emphasizing inclusive digital infrastructure, education and reskilling, social protection, competition, and equitable access to AI technologies will be essential for ensuring that AI-driven productivity improvements translate into sustainable and broadly shared economic growth.

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