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# The Transformative Impact of Artificial Intelligence (AI) on Economic Sector

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## ABSTRACT

This study explores the economic implications of Artificial Intelligence (AI), focusing on its potential to enhance productivity and economic growth. A qualitative approach analyzes existing online data on AI, economic growth, employment, and income inequality. The research acknowledges the uncertainties surrounding AI's long-term trajectory but highlights its potential for job creation alongside automation-driven displacement. While the dominant impact remains unclear, existing literature suggests a potential rise in income inequality due to automation cost reductions. Public policy interventions are emphasized to address potential job losses, with proposals including workforce training, universal basic income, and robot taxes. Given the early stage of AI development, substantial uncertainty surrounds its influence on future economic growth, employment, and income inequality. However, as AI advances, research on its economic implications is expected to intensify, focusing on optimal policy design to manage these disruptive effects. The goal is to ensure society benefits from AI while assisting individuals in adapting to this evolving technology. A comprehensive understanding of AI's economic consequences is crucial for shaping policies that promote inclusive growth and minimize potential downsides.

**Keywords:** Artificial Intelligence; Economic Growth; Employment; Income Inequality; Job Automation

## INTRODUCTION

The continuous evolution of artificial intelligence (AI) has emerged as a central focal point in the realm of economic considerations, prompting economists to articulate perennial concerns regarding the repercussions of technological progress on economic landscapes. Throughout history, noteworthy technological advancements have invariably coincided with remarkable upswings in productivity. The resonance of these concerns has intensified in the contemporary era, particularly with the advent of AI—a cutting-edge technology that relentlessly redefines and reshapes the economic paradigm. It is playing an increasingly important role in business and tourism (Wiyatno & Do, 2021; Nasution & Rahmawati, 2021; Madan et al., 2022)

The origins of this transformative journey can be traced back to the surge in AI research during the 1940s and 1950s, culminating in the landmark Dartmouth Conference of 1956. This pivotal event formally inaugurated the AI field, crystallizing itsfoundational principles. Dr. John McCarthy's seminal definition of AI as "the science and engineering of making intelligent machines" during the conference laid the conceptual groundwork that continues to shape subsequent AI developments.

In the present context, the trajectory of AI is propelled by recent breakthroughs in big data, technology, and algorithms, marking the commencement of a new zenith in AI development. Forecasts bolster the expectation that AI will progress at an accelerated pace, heralding the promise of significant scientific and technological breakthroughs with profound ramifications for both the economy and human society. As the researchers delve deeper into AI's implications for the economy, income inequality, employment, and other pivotal themes, there is a growing recognition of the imperative need to comprehend and harness the vast potential of AI. Furthermore, the impact of AI and deep learning technologies on the dissemination of economic ideas and other essential concepts is emerging as a critical area of study, paving the way for a more comprehensive understanding of AI's multifaceted influence.

This paper delves into the economic ramifications of AI, with a specific focus on its potential to enhance productivity and stimulate economic growth. By systematically reviewing existing research, the aim is to understand how AI can contribute to a more efficient and prosperous economic landscape. This analysis will explore how AI technologies can potentially streamline processes, optimize resource allocation, and ultimately lead to a more productive and growing economy.

## LITERATURE REVIEW

The impact of AI on economic dynamics is a multifaceted subject that scholars explore through economic growth models. Hanson (2001), for instance, utilizes neoclassical models, assuming that technology either complements or replaceshuman labor. This perspective, however, might underestimate the transformative effects of AI by not accounting for the potential creation of new jobs. In response to this limitation, Acemoglu and Restrepo (2019) introduce a task-based model that considers the endogeneity of the number of tasks. Their approach recognizes the dual nature of automation—acting as both a substitution, reducing labor demand, and a productivity enhancer, replacing labor with more cost-effective capital.

Empirical research, guided by these theoretical frameworks, has burgeoned with the availability of data and advanced models. Studies predominantly focus on specific AI sectors, like computer capital and industrial robots, using various metrics to measure productivity. Notably, Brynjolfsson and Hitt's (2003) analysis of stock data from 527 US businesses indicates a positive short-term impact of computerization on productivity, with potential long-term contributions. Similarly, works by Acemoglu & Restrepo (2020), Graetz (2020), and Kromann & Sørensen (2019) underscore the positive influence of automation, particularly in the context of industrial robots. However, there's a notable gap in empirical evidence regarding the influence of AI on economic growth in underdeveloped nations. This gap highlights the necessity for future research to expand data collection efforts in developing countries and diverse industries to create a more comprehensive understanding of AI's global economic implications.

## RESEARCH METHOD

This research employs a qualitative research methodology, signifying a deliberate choice to delve into the nuances of the impact of AI on economic parameters. The primary approach involves the systematic collection and analysis of existing qualitative data accessible on the internet, focusing on keywords like AI, Economic Growth, Employment, and Income Inequality.

The study seeks to draw insights from a diverse array of online sources, ranging from academic articles and reports to case studies and expert analyses. By leveraging the extensive information available on the internet, the research aims to uncover intricate patterns, discern trends, and reveal qualitative nuances associated with the intricate interplay between AI and economic facets such as growth, employment dynamics, and income distribution.

Content analysis serves as a key tool in this endeavor, allowing for a meticulous examination of relevant literature and reports. This analytical approach is instrumental in providing a comprehensive overview of the qualitative dimensions of AI's impact on these economic parameters.

While the absence of direct surveys and interviews may limit the depth of personal perspectives, the reliance on existing qualitative data enables a more expansive exploration of the discourse surrounding AI and its multifaceted implications. This chosen methodology aligns seamlessly with the overarching goal of capturing the qualitative intricacies of the relationship between AI and critical economic variables, contributing to a more profound understanding of the societal implications arising from the advancements in AI, grounded in readily available information from diverse online sources.

## RESULTS

### The Influence of AI on Workforce Employment

The rapid evolution of AI is significantly reducing automation costs, leading to the substitution of human labor by machines. The historical debate on the impact of technological advancements on employment reveals a dual effect. On one hand, technological progress enhances labor productivity but may limit job opportunities by displacing some workers. Scholars like Schumpeter argue that while innovations boost demand initially, subsequent process innovations can decrease labor demand and increase unemployment. On the other hand, technological growth creates jobs through expanded manufacturing scales. The academic community is divided on the significance of these opposing consequences. Unlike past revolutions, AI introduces unprecedented speed, scope, and depth, automating non-routine tasks through machine learning. Ongoing research focuses on AI's risk of job automation, its broader influence on employment, and the structural shifts in job dynamics.

#### *The Peril of Job Automation*

The continual decline in computer prices has precipitated an accelerated replacement of routine activities by computers, resulting in the automation of an increasing array of jobs. Notably, the trajectory of AI development is expanding the scope of automated occupations beyond traditional routine tasks, raising concerns about the potential ramifications for the workforce. Various studies have delved into the nuanced complexities of job automation risks, with researchers employing diverse methodologies to assess the vulnerability of jobs to technological displacement.

A seminal study by Frey and Osborne (2017), utilizing the O-NET database, pioneered an assessment of 702 jobs in the United States, predicting their susceptibility to computerization. Their approach, employing a probabilistic classification algorithm, identified nine skill attributes deemed less prone to automation. Shockingly, their findings suggested that nearly half of US employment, classified as high risk, could be highly automated. However, this approach faced scrutiny from Arntz et al. (2016), who criticized its focus on jobs rather than labor activities, potentially overestimating the extent of future job automation.

Arntz et al. (2016) proposed a task-based methodology, addressing the variability of tasks across occupations, and used real job task data from the PIACC database across 21 OECD nations. Their results painted a more conservative picture, indicating a mere 9% likelihood of job automation based on work tasks. This underscores the importance of considering not only the technological adoption process but also the adaptive capacity of workers and the creation of new job opportunities resulting from technological changes.

It is crucial to recognize that the risk of job automation, as highlighted in these studies, does not necessarily equate to actual job losses. Several factors contribute to this nuanced landscape, including the slow pace of technological adoption, the adaptability of workers to new technologies, and the potential for technological changes to create new employment avenues. In this complex ecosystem, understanding how AI influences jobs requires a multifaceted examination that considers various economic and social factors.

### *AI and Work-Life Balance*

Theoretical models project that the impact of computers and automation on the job market operates through two primary channels: augmenting human labor and enhancing the efficiency of specific workforce tasks. The augmentation aspect suggests that technology could complement human skills, potentially increasing overall productivity. On the flip side, efficiency improvements imply the automation of routine tasks, which could lead to job displacement in traditional sectors. Task-based models introduce a nuanced perspective by emphasizing that while certain jobs may be lost to automation, the simultaneous creation of new roles may offset the overall impact on employment.

Delving into the theoretical literature provides qualitative insights into the intricate mechanisms through which AI influences employment. These models offer conceptual frameworks to understand how technological advancements like AI might reshape the labor market. In tandem, empirical research adopts a quantitative approach, leveraging historical data to scrutinize the real-world impact of AI on specific sectors. Studies often zero in on particular domains such as industrial robotics or computing capital, leading to diverse conclusions about the net effect on employment. For instance, while some studies find minimal overall impact, others suggest significant reductions in employment-population ratios in response to increased robot use.

The complexity of AI's influence on labor employment becomes apparent when considering various factors, including the diverse levels of AI development and technological diversity across different regions. The interplay between theoretical predictions and empirical findings underscores the need for a comprehensive understanding of how AI shapes the dynamics of the contemporary job market.

### The Influence of AI on Workforce Composition

The impact of AI on employment is a subject of ongoing debate, and its consequences are not uniform across industries and skill levels. One notable concern raised by scholars is the phenomenon of job polarization, where intermediate-skilled workers face displacement due to the implementation of AI and automation technologies. This trend results in a divergence between high-skilled industries and low-skilled service sectors, both of which experience employment growth, while the middle-skilled workforce encounters challenges.

Researchers have conducted studies identifying tasks that are inherently challenging to automate. These tasks often involve abstract work requiring problem-solving skills and manual labor that necessitates environmental adaptation and interpersonal skills. Job polarization arises as these tasks tend to be dispersed at different extremes of the skill spectrum. The historical and contemporary growth of labor-substituting technologies, as theorized by Feng and Graetz (2015), further contributes to this phenomenon. They argue that automation becomes more feasible for jobs with lower training requirements, leading to a shift in labor towards highly complex or natural occupations with minimal training demands.

The polarization of jobs reflects a broader shift in the nature of work and the types of skills in demand. As automation targets routine and repetitive tasks, high-skilled occupations that involve creativity, critical thinking, and complex problem-solving see increased demand. Conversely, low-skilled service sectors, which often require a human touch and interpersonal skills, also experience growth. The middle-skilled workforce, however, faces challenges as their tasks are more susceptible to automation.

In summary, the impact of AI on employment is complex and varies across skill levels and industries. Job polarization is a significant concern, with the displacement of middle-skilled workers being a prominent feature. The ability to automate certain tasks, coupled with historical trends in labor-substituting technologies, contributes to this polarization, emphasizing the need for a nuanced understanding of the evolving job market in the age of AI. Policymakers, educators, and industries must adapt to these changes to ensure a balanced and inclusive workforce.

**The Impact of AI on Income Inequality**

The rise of AI and automation, while contributing to economic development and increased wealth, has also sparked concerns among economists regarding the potential escalation of income inequality. Notably, economists, including Autor et al. (2006), have highlighted that if technology renders a segment of the workforce redundant, the primary economic challenge shifts from scarcity to distribution. This underscores the idea that the impact of AI on employment and income distribution is a critical aspect of economic discourse.

Several mechanisms contribute to the influence of AI on economic inequality. According to Berg et al. (2018), two primary factors drive the current growth in inequality. First, as robotics become less expensive, there is an increase in production per person, leading to a rise in the capital share of total income. Second, there is a progressive increase in wages for skilled work and skilled labor, while wages for low-skilled labor decline, deepening the pay disparity (Berg et al., 2018). The interplay between skilled individuals and robots, along with other factors, plays a crucial role in determining the magnitude of inequality.

Numerous studies delve into the process and effects of AI or automation on income inequality, examining it from various angles. One perspective involves the reduction of the labor income share, highlighting how automation can impact the distribution of earnings between capital and labor. Another perspective focuses on the increase in the capital income share, emphasizing the role of technology in reshaping the economic landscape. Lastly, researchers explore the expansion of labor pay disparity, studying how advancements in AI and automation disproportionately affect different skill levels, further exacerbating income inequality. Understanding these dynamics is crucial for developing effective policies that address the social and economic implications of AI.

### The Influence of AI on Capital and Labor Income Distribution

The impact of AI on income inequality has become a central concern among economists as technological advancements reshape the dynamics of the labor market. In reality, the distribution of capital is inherently more unequal than that of labor, with a disproportionate concentration of capital in the hands of a select few individuals. As AI and automation continue to evolve, there is a growing consensus that the proportion of capital in the production process will increase, leading to a widening gap in income distribution.

One key aspect explored by economists like Hansen (2013) is the relationship between wage growth and the fair compensation of labor by capital owners. According to neoclassical economic development models, if workers receive a fair share of labor compensation, wages are expected to rise with economic development. However, if capitalists disproportionately receive a larger share of labor compensation, wages may fall faster than the declining costs of computer technology, exacerbating income inequality.

DeCanio (2016) delves into the potential effects of broad AI deployment on wages, employing a model that integrates labor, machines, and conventional capital. The study suggests that the impact of AI on income inequality depends on the aggregate production relations and the replacement connection between human and machine labor. The uncertain distribution of returns to robotic capital across the population poses challenges in predicting the overall outcome on wages and inequality.

Benzell et al. (2021) take a different approach by utilizing a two-stage overlapping generation model (OLG) that includes high-skilled and low-skilled individuals. Their hypothesis emphasizes the comparative advantages of high-skilled individuals in analytical activities and low-skilled workers in interpersonal tasks. The study projects that advances in robot productivity may disproportionately benefit the capital-owning generation, leading to a rise in the proportion of intangibles in national income over time, ultimately contributing to a decline in labor share and wage decline, potentially impoverishing future generations.

Brynjolfsson and Hitt (2003) further emphasize the potential role of higher returns to capital as a driver of AI-induced income inequality. Their findings underscore the imbalance that can arise in the distribution of benefits from AI advancements, potentially widening the wealth gap. As technological progress accelerates, the intricate interplay between AI, capital, and labor becomes increasingly complex, demanding careful consideration and proactive policy responses to mitigate the potential negative impacts on income distribution and societal well-being.

### The Impact of AI on Income Inequality Across Labor Markets

The transformative impact of AI on the employment landscape extends beyond mere job displacement; it fundamentally reshapes the relative pay share of low- and medium-skilled workers. Lankisch et al. (2017) contribute to this discourse by incorporating automation capital as a factor of production into an endogenous economic growth model. Their assumption that low-skilled workers are more susceptible to automation than their high-skilled counterparts forms the basis for analyzing the repercussions of automation on the wages of these distinct skill groups. Notably, the study reveals that automation diminishes the actual earnings of low-skilled laborers, contributing to an increase in the skill premium and, consequently, exacerbating income inequality.

Acemoglu and Autor (2011) delve into the broader consequences of automation, emphasizing the steady decline in both the positions and earnings of the middle class. His findings suggest a correlation between pay polarization and job polarization, indicating a dual impact on the workforce. Dauth et al. (2017) extend this line of inquiry by suggesting that the rise in the use of industrial robots disproportionately affects intermediate-skilled workers, resulting in significant income losses. Intriguingly, these losses are not attributed to job displacement but rather stem from a decline in existing employment earnings, highlighting the nuanced ways in which AI influences the economic landscape.

Challenging common assumptions, Acemoglu and Restrepo (2018) question the prevailing belief that highly skilled professionals are immune to machine replacement due to their reliance on soft skills such as judgment and problem-solving. Acknowledging the evolving capabilities of AI, the researchers incorporate low-skilled and high-skilled automation into their model. This distinction refers to occupations that can be performed by machines instead of unskilled laborers and acknowledges the potential displacement of high-skilled employment by AI. The study introduces the concept that the final product is a composite of consecutive jobs, each of which can be executed by machines or laborers with varying degrees of competence.

The research employs a task-based model to explore how automation affects the prices of labor and capital. Despite the aggregate uncertainty surrounding the overall impact of automation on wages, a clear pattern emerges: low-skilled automation consistently amplifies wage inequality, while high-skilled automation tends to mitigate wage disparity. This insight underscores the complex interplay between technological advancements and income distribution, highlighting the need for nuanced policy responses to address the disparate effects on different segments of the workforce. As AI continues to evolve, understanding these dynamics becomes crucial for crafting inclusive economic policies that navigate the challenges posed by automation.

## The Diverse Effect of AI on Disparities in Income

### *Income Inequality in Stages*

The varying rates of growth at different stages of AI and the gradual evolution of the economy lead to fluctuations in the influence of AI on income inequality during periods of economic growth. By integrating automation into the horizontal innovation growth model, Hémous and Olsen (2021) demonstrated a three-stage economic development process: in the initial stage, low-skilled wages and automation are lower, while income inequality and the labor share remain relatively stable. In the second phase, the levels of automation and the skill premium both grow proportionally. In the third stage, the percentage of automated goods begins to stabilize, and the salaries of low-skilled laborers expand at a slower rate than those of high-skilled labor.

Utilizing task-based models, Acemoglu and Restrepo (2019) showed that automation and the concurrent development of new activities have distinct consequences for inequality. Automation increases inequality in the short and medium term, and the introduction of new tasks exacerbates disparity in the short term. However, in the long run, as activities become more standardized, low-skilled work becomes more productive, limiting the growth of inequality.

In the analysis by Hémous and Olsen (2021), the early stage of economic development is characterized by low wages for low-skilled workers and high levels of automation, yet income inequality remains stable. In the second stage, with proportional growth in automation and the skill premium, income inequality begins to increase. In the third stage, although the percentage of automated goods stabilizes, the wages of low-skilled workers grow at a slower rate than those of high-skilled workers, contributing to an expanding income gap.

Acemoglu and Restrepo's (2019) study emphasizes that while automation and the introduction of new tasks may increase inequality in the short term, in the long run, the standardization of activities can help reduce the gap between high-skilled and low-skilled workers. Through this understanding of the stages of economic growth, we can better formulate economic policies that respond to the challenges of inequality arising from technological developments like AI.

***Income Inequality between Regions***

The issue of income inequality extends beyond the individual strata of the population and significantly influences disparages between regions. Berger and Frey's (2016) research reveals that the surge in income inequality within different segments of the population has broader consequences, contributing to a widening gap between regions. Notably, the concentration of high-skilled workers in urban centers, where new jobs are created, exacerbates this regional disparity. Interestingly, even though these cities may experience job losses or replacements, the overall economic inequality across regions continues to escalate. The uneven distribution of economic opportunities and resources among cities intensifies, further fueling regional income disparities.

Alonso et al. (2022) argue that the substitution of unskilled labor in emerging nations by robots will result in a reduction of relative wages in these nations, thereby altering the global distribution of production. The advent of industrial automation makes labor replacement more cost-effective, gradually diminishing the cost advantage that low-wage countries once possessed. Consequently, wealthier nations may opt to relocate their production to automated plants situated close to their domestic markets. This shift marks a significant transformation in the dynamics of global production, potentially concentrating economic activities in more advanced economies.

Furthermore, technological advancements in industrialization imply a diminishing role for manufacturing jobs in the future. Low-income nations, which historically relied on labor migration from agriculture to high-paying urban factory work for rapid growth, may find this path less accessible. The traditional trajectory of economic development, characterized by industrialization and the associated surge in employment, is evolving. With automation reducing the demand for manual labor, particularly in manufacturing, low-income nations face the challenge of redefining their growth strategies.

The global landscape is undergoing a profound shift as economic dynamics evolve, reshaping the traditional patterns of production and employment. As high-skilled workers concentrate in urban centers and automation transforms the nature of labor, addressing regional income inequality becomes a complex and multifaceted challenge. Policymakers must grapple with the implications of these changes, developing strategies that not only mitigate disparities between regions but also foster inclusive growth in a technologically advancing world. The future trajectory of global economic development hinges on the ability to navigate these shifts effectively, ensuring that the benefits of progress are distributed equitably across nations and regions.

## Public Policy

### *Relevant Suggestions for Public Policy to Lessen the Impact of AI on the Job Market*

The increasing impact of AI on employment patterns gives rise to worries regarding possible job losses and economic inequality. Despite the potential for heightened productivity and economic expansion, AI's swift and extensive transformations surpass the adaptability observed in previous technological revolutions. This poses a challenge for policymakers who must formulate effective strategies to alleviate adverse effects on low- and middle-skilled workers. Scholars stress the importance of implementing public policy measures urgently, highlighting the need to devise methods for generating shared wealth and preserving social welfare to guarantee the ongoing adoption and advancement of AI technology.

### *The Importance of Public Policy*

Throughout the course of history, significant technological advancements have consistently transformed societal structures and economic systems. The resulting shifts in the economy often necessitate government intervention to alleviate adverse outcomes. Drawing parallels to the changes in U.S. agriculture during the 19th and early 20th centuries, the text underscores how rapid technological advancements can lead to unemployment, diminished well-being, and economic downturns. Government initiatives, such as Keynesian economic policies and social welfare programs, played a vital role in addressing these challenges. Insights from 19th-century Britain underscore the significance of public policies in reducing income disparity following the Industrial Revolution. With the acceleration of artificial intelligence (AI) development, the text highlights the imperative for government-led strategies to manage the potential impact on employment and income distribution. The authors advocate for effective public policies, including progressive taxation and social support, to ensure a more equitable distribution of AI benefits, fostering overall well-being and preventing increased inequality.

### *Public Policy Advice*

Confronted with the possible adverse outcomes of AI, scholarly works explore the advantages and disadvantages of several policy tools, with the most commonly discussed ones being: improving education and training for workers, implementing a universal basic income policy, and imposing taxes on robots.

#### *Strengthening Education and Training for Workers*

The emergence of AI has the potential to result in unemployment among individuals with low and middle-level skills. However, addressing this issue by providing enhanced training and readiness for disadvantaged workers could aid in their reemployment and counteract the negative trajectory. This necessitates a heightened focus on vocational retraining and the development of proactive and adaptable personnel. Governments play a pivotal role in this process by actively promoting the acquisition of new skills, retraining workers for effective AI utilization, and facilitating smoother job transitions in the ever-evolving technological landscape. Numerous studies underscore the significance of improving education and workforce training to mitigate the impact of AI. Scholars like Glaeser et al. advocate targeted investments in education and workforce training, particularly for low- and middle-skilled workers. Thierer et al. emphasize the societal value of job-oriented training to make positions less susceptible to automation. In the era of globalization, specialized technical skills are considered crucial, highlighting the need for primary and secondary education to emphasize mathematics, science, and communication, and for higher education to benefit economically disadvantaged groups. Emphasizing the alignment of classroom instruction with labor market demands, higher education mechanisms should aim to train individuals with specialized skills while nurturing managers, professionals, and entrepreneurs.

Despite these endeavors, challenges persist for low- and medium-skilled employees seeking to re-enter the job market through training. Arntz et al. (2016) acknowledge the difficulty faced by less educated workers in regaining a comparative advantage, particularly in the face of rapid technological change. Bessen (2015) underscores the slow and challenging nature of acquiring new skills for regular employees, emphasizing the crucial role of institutional and cultural support in facilitating effective social change.

*Implementing a Universal Basic Income Policy*

Introducing a Universal Basic Income (UBI) policy is considered a practical approach to address the escalating impact of automation propelled by AI and robotics. This idea, stemming from Friedman's 1962 (in Preiss, 2015) proposal for a "negative income tax," entails providing regular, unconditional payments to all citizens from the government. Unlike conventional welfare systems, UBI offers fixed and unconditional transfers that individuals can use for any purpose. While automation contributes to societal wealth, UBI ensures a reasonable quality of life for everyone, including those without employment. Despite ongoing debates, proponents assert that UBI can sustain consumption levels, diminish unemployment, alleviate poverty and inequality, stimulate corporate activity, and yield various social benefits such as gender equality, improved work-life balance, enhanced job quality, and better preparation for economic instability. However, challenges arise regarding funding, meeting residents' essential needs, and aligning with existing welfare policies. The substantial cost and potential impact on workforce participation present significant barriers to the widespread adoption of UBI, necessitating careful consideration. Currently, no national policy has fully implemented a Universal Basic Income due to these complexities.

*Tax on Robots*

Substantial investments are needed to enhance training for low- and middle-skilled workers and implement a universal basic income program. However, the rise of automation technologies poses a threat to government revenue, largely derived from the existing tax system. To address this challenge, Abbott and Bogenschneider (2018) propose a strategy for taxing robots, advocating for a neutral approach that treats robot and human labor taxes equally, without providing deductions for automation. This approach aims to slow down the introduction of automation, allowing workers time to transition to new occupations and generating income for a universal basic income.

The theoretical research supporting robot taxation suggests that the decline in automation costs, under the current tax structure, could worsen income inequality. Rebelo et al. (2019) propose taxing robots and offering a one-time tax refund to mitigate the inequality caused by automation. Gasteiger and Prettner's (2022) study using the OLG model supports the idea of taxing robots, suggesting it could increase capital and production per capita. However, they emphasize the need for global adoption to prevent the migration of capital to countries that do not tax robots.

Despite these arguments, critics like Atkinson (2019) caution that taxing robots may negatively impact societal well-being by hindering technological growth in the robotics field. The loss of production due to high robot taxes could outweigh the collected tax amount. Rebelo et al. (2019) also note that taxing robots may be inappropriate in a fully automated economy, where employees are no longer required to work, as it may influence production decisions without reducing income disparity. Deciding whether to tax robots is a complex issue with potential implications for economic growth and societal welfare.

## DISCUSSION

The rise of AI raises concerns about income distribution between capital and labor, potentially leading to job displacement and a decline in labor income shares. Simultaneously, AI owners may benefit from increased capital income. Policymakers closely monitor these dynamics to address potential inequalities.

AI's impact on income distribution involves a twofold transformation. Cost-effective AI technologies boost production efficiency, increasing the capital share of income. However, this also leads to rising wages for skilled work and declining wages for low-skilled labor, intensifying income disparities. This dynamic shift in income distribution necessitates thoughtful policy considerations to navigate the evolving economic landscape shaped by AI.

The growing income inequality within population segments widens the gap between regions, as highlighted by research from Berger and Frey (2016). Internal income disparities, coupled with the concentration of high-skilled workers in urban areas, contribute to increased inequality between regions. The global impact, emphasized by Alonso et al. (2022), suggests that the substitution of unskilled labor in emerging nations by robots could reshape the worldwide distribution of production. These findings underscore the interconnected nature of income inequality, influencing regional and global economic dynamics. Policymakers must address these challenges to foster more equitable economic development and global prosperity.

## CONCLUSION

The studies delve into the pathways through which AI influences economic development, employing neoclassical growth models, task-based models, or empirical research to verify its effects. Despite uncertainties about AI's trajectory toward singularity, scholars acknowledge its potential to create new jobs while also causing labor substitution. However, a consensus on the dominance of either impact has not been reached, with the outcome potentially contingent on market conditions. Existing literature predominantly suggests that the decrease in automation costs may temporarily raise income inequality, primarily through a decline in the labor income share and an increase in the wage gap between different labor groups.

Against this backdrop, various sources emphasize the critical need to establish appropriate public policies to address potential job losses caused by AI. Proposed policies include enhancing workforce education and training, implementing universal basic income, and taxing robots as measures to mitigate the adverse effects on unemployment and economic inequality. The economic ramifications of AI represent a pivotal subject, recognizing that AI technology is still in its early developmental stages and widespread adoption. Substantial uncertainty surrounds its influence on future economic growth, employment scale and structure, and income inequality.

Looking ahead, anticipating that AI's impact will intensify, it is expected that scholars will further fortify research on the economic implications of AI. This includes discussions on formulating optimal policies to mitigate the substantial impacts brought about by technological changes. The goal is to ensure that society at large can reap the benefits ushered in by AI, while simultaneously assisting individuals in effectively coping with the transformative impact of this evolving technology. As AI continues to progress, a comprehensive understanding of its economic effects will be crucial for shaping policies that foster inclusive growth and minimize potential negative consequences.

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## DECLARATION OF CONFLICTING INTERESTS
I declare that there are no conflicting interests associated with the information and content presented in this text. I affirm that this work has been conducted with integrity and in an unbiased manner. No financial or personal relationships with individuals or organizations have influenced the objective presentation of information.

In the event of any potential conflicts of interest arising in the future, I commit to promptly disclosing such conflicts and taking appropriate measures to ensure transparency and maintain the integrity of the information presented. This declaration is made in the interest of maintaining credibility and upholding ethical standards in scholarly and informational endeavors.

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