

The Economics of Artificial Intelligence: A Bibliometric Review

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Abstract. Artificial intelligence (AI) has rapidly evolved from a futuristic concept to a robust technology transforming our world. This research explores the economic impacts of AI by analyzing a decade of academic literature from 2015 to 2024. Using a quantitative method called bibliometric analysis, this study maps out the key themes and influential works that have shaped our understanding of AI's economic role. The findings reveal that AI transforms work by reallocating tasks, creating new roles, and complementing human skills rather than just replacing them. Key research areas that have emerged include the importance of building trust in AI systems, utilizing machine learning for improved economic forecasting, and applying AI to address complex societal challenges such as sustainable urban development and supply chain optimization. The study also highlights a growing focus on the ethical dimensions of AI, including fairness and data privacy. This paper concludes that the central question is not whether AI will change our economy, but how we can guide its development. The path forward requires a proactive approach that fosters an environment where AI complements human ingenuity and its benefits are shared widely and equitably across society. This involves creating policies that support lifelong learning, encourage the development of human-centric AI, and ensure that technological progress translates into broad-based prosperity.

Keywords: Artificial intelligence; Bibliometric analysis; Human capital; Economics; Sustainability; Technology

1.0 Introduction

Artificial intelligence (AI) has rapidly transitioned from a theoretical concept to a robust and pervasive technology reshaping the global landscape. This transformative wave, fueled by breakthroughs in machine learning, deep learning, and computational power, fundamentally alters industries, societies, and daily human experiences. According to Rashid and Kausik (2024), AI systems are now integral to various aspects of daily life, including personalized consumer recommendations, medical diagnostics, autonomous transportation, and complex financial modeling. The technology's expanding capabilities create unprecedented opportunities for innovation and efficiency across virtually every sector. As its integration deepens, AI is increasingly recognized as a tool and a general-purpose technology with the potential to redefine economic and social structures (Aldoseri et al., 2024). The sheer scale and speed of this technological diffusion have sparked intense interest and debate among academics, policymakers, and industry leaders worldwide. Consequently, understanding the multifaceted implications of AI has become one of the most critical intellectual challenges of our time.

AI is a game-changer for economics, questioning many accepted theories and models. AI affects core economic variables such as employment, productivity, and growth due to its capacity as a powerful automation and predictive tool. For example, Gao and Feng (2023) analyzed the influences of AI-enhanced technology on employment and asked whether it would generate mass unemployment or create new opportunities and roles. Moreover, AI data is transformed into a new economic asset that challenges traditional understandings of capital, focusing research on how technology influences firm strategy, competition, and market dynamics (Johnson et al., 2022). Navigating the AI revolution implies understanding the economic dynamics, opportunities, and risks. In the quest to understand the relationship between economic outcomes and technological progress, the economics of artificial intelligence has emerged as a vibrant field offering significant insights.

A substantial body of literature in artificial intelligence economics already exists, leading to several branches of study. Much of the early literature, such as Acemoglu and Restrepo (2019), focuses on the macroeconomic consequences, particularly the balance between the displacement and productivity effects of automation. These studies increasingly rely on theoretical models to examine how AI-driven automation reallocates tasks between humans and machines, with consequences for wages and the labor share of income. An important line of research examining the impact of AI on firm-level and aggregate productivity was surveyed by Czarnitzki et al. (2023), who also investigated the conditions under which these benefits are realized. The study examined how firms adopt AI technologies and the impact of these technologies on innovativeness and operational efficiency. This body of work has contributed to fundamental knowledge that AI is an important catalyst for economic change. The broad consensus seems that AI has vast potential for productivity gains, but its overall effects on labor markets are complex and depend on institutional and policy responses.

Indeed, the microeconomic implications of artificial intelligence and its macroeconomic effects have been extensively studied in a comprehensive academic literature. Krakowski (2025) provided an attractive prism to consider the impact of AI on market dynamics and business strategy, characterizing it as a reduction in the cost of prediction. This perspective has motivated research on the effects of AI on business decision-making, the development of new business models, and the evolution of competitive dynamics. Another essential area for research is the function of data. Ownership, privacy, and network effects fueled by data may lead to monopoly "winner-takes-all" markets dominated by a few tech titans, as Rong (2022) discussed. The distributional effects of AI, including its adverse impacts on income and wealth inequality, are also receiving considerable attention in a growing body of literature, as noted by Skare et al. (2024). This article analyses the distribution of AI's benefits between owners of capital, workers, and consumers. These diverse microeconomic studies give a broad view of how AI disrupts markets and economic relationships in complicated ways.

Despite a burgeoning body of literature, the rapid, fragmented growth of research on the economics of AI poses a challenge. While individual reviews on specific subtopics exist, a comprehensive, quantitative mapping of the field's intellectual structure is absent. This gap makes it difficult for researchers to systematically identify foundational studies, emerging trends, and underexplored areas. While prior studies examined AI in specific sectoral contexts, few provide a comprehensive bibliometric mapping of the overarching economic literature on AI. This research gap hinders a clear understanding of how intellectual discourse has been formed and where it is headed.

The primary objective of this study is to address the identified research gap by conducting a comprehensive bibliometric analysis of the economics of artificial intelligence literature. This research aims to systematically map the intellectual structure, thematic evolution, and collaborative patterns within this rapidly expanding academic domain. A bibliometric analysis is the most suitable methodology because it employs quantitative methods to analyze large volumes of scholarly publications, offering an objective, replicable overview of a field's development. By examining citation networks and keyword co-occurrences, this approach can uncover key research themes, influential papers, and intellectual connections that are not readily apparent in traditional qualitative reviews. This study will therefore provide a macroscopic "map" of the field, highlighting its foundational pillars and most active research frontiers. Ultimately, this analysis is necessary to consolidate existing knowledge, provide a structured guide for scholars and policymakers, and illuminate promising avenues for future research in this critically important area.

2.0 Methodology

The study employs quantitative bibliometric analysis to systematically map the literature on the economics of artificial intelligence. Bibliometric analysis employs statistical and mathematical techniques to analyze large datasets of published research, allowing for the objective measurement of publication patterns, authorship networks, and thematic developments (Passas, 2024). Its quantitative orientation provides clear metrics for evaluating the growth, impact, and collaboration trends of AI economics. This approach is well-suited to capturing the field's interdisciplinary and rapidly evolving nature. Only journal articles indexed in Scopus between 2015 and 2024 were included for this study to ensure up-to-date coverage. The inclusion criteria further restricted the dataset to works classified under business, economics, development, or management, and originating from Scopus-listed open-access journals.

The Scopus database was the sole data source used for this analysis, due to its rich metadata and broad inclusion of peer-reviewed literature. Kim (2025) indicates that precise filtering by publication year, domain, and access type is enabled by Scopus's advanced indexing and classification. The reliable tracking of citations makes the database suitable for mapping research influence and collaboration. Finally, common keyword pairs indicating new themes would be identified through co-word analysis to reveal the underlying conceptual structure of the investigation. Collaboration patterns will be examined using complementary co-occurrence analysis, focusing on authors, institutions, and countries. When integrated, these methods provide a multi-dimensional view of network dynamics and thematic evolution in AI economics research. Network mapping and the visualization of bibliometric data were performed using VOSviewer. The research clusters and their correlations are readily apparent in VOSviewer's high-quality, user-friendly maps generated from co-occurrence matrices. Density visualization highlights regions of high scholarly activity, while clustering algorithms automatically group similar keywords and papers. Some map construction parameters, such as minimum penalty values for node movement and attraction/repulsion forces, were modified to enhance readability and legibility. The network maps generated informed the interpretation of key knowledge clusters and new research areas. We exported outputs in figure format to ensure final-paper-ready quality for all visuals.

3.0 Results and Discussion

3.1 Co-Citation Analysis

Table 1 presents the top ten most co-cited papers as identified by the Co-Citation analysis, ranked by the strength of the link in total. Of the 140,296 cited references retrieved from the database, 60 meet the minimum requirement of 60 cited references. The threshold was adjusted several times until strong, uniformly distributed clusters were obtained, and the optimal visualization was achieved. The representation can be too complex or too simple if the threshold is too high or too low. Meanwhile, the total link strength indicates the total strength of the links between an article and other articles in the sample analyzed.

Table 1. Top 10 Documents with the Highest Co-Citation and Total Link Strength

Documents	Citation	Total Link Strength
Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. <i>American Economic Review</i> , 108(6), 1488-1542.	96	266
Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. <i>Journal of Political Economy</i> , 128(6), 2188-2244.	114	260
Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In <i>Handbook of Labor Economics</i> (Vol. 4, pp. 1043-1171). Elsevier.	90	240
Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. <i>Journal of Economic Perspectives</i> , 33(2), 3-30.	81	214
Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. <i>Journal of Economic Perspectives</i> , 29(3), 3-30.	114	211
Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. <i>The Quarterly Journal Of Economics</i> , 118(4), 1279-1333.	97	210
Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis.	89	194
Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. <i>American Economic Review</i> , 103(5), 1553-1597.	74	159
Ajzen, I. (1991). The theory of planned behavior. <i>Organizational Behavior and Human Decision Processes</i> , 50(2), 179-211.	44	136
Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. <i>Economics Letters</i> , 159, 157-160.	241	129

Figure 1 shows the network structure in the co-citation analysis. Based on the network visualization, co-citation

analysis produces three distinct clusters. Each cluster is labeled and characterized based on representative publications, as interpreted by the researcher, in accordance with their inductive understanding of the three clusters.

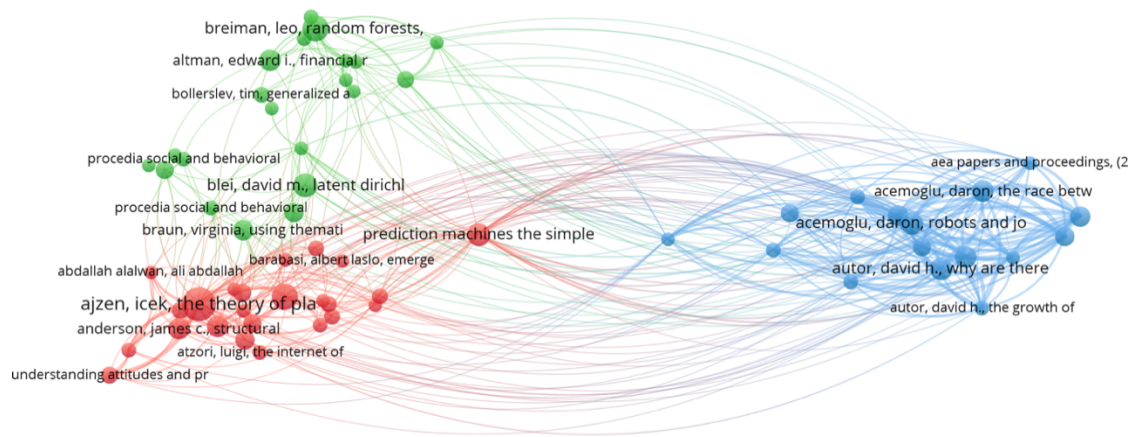


Figure 1. Co-Citation Analysis of Big Data Analytics on the Economics of Artificial Intelligence

Cluster 1 (Red) represents a thread between the design of innovation ecosystems, trust dynamics, and human behavior in AI adoption. By using trust constructs to explain the adoption of mobile banking, Alalwan et al. (2017) build on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and demonstrate that social influence and perceived trust drive technology use behavior in financial contexts. Meanwhile, Acquisti et al. (2015) show in their study of the privacy paradox that individuals trade their personal information for convenience despite what they say. This tension is particularly relevant in the context of AI, which leverages user data for predictive services. This is followed by Adner and Kapoor's (2010) ecosystem lens, which shifts the gaze from individual companies to networks and demonstrates how value creation in later generations of AI is configured through interdependencies among technology providers, complementors, and adopters. These studies help pave the way for trust-aware integrative AI deployments in modern smart cities or digital finance ecosystems by revealing how AI trajectories at the early stage, from micro-level behavioral intentions and risk perceptions to macro-level structural interrelations.

Cluster 2 (Green) shows the maturation of analytical techniques and interpretability, with methodological quality and transparency encompassing AI research. Arrieta et al. (2020) categorize different means of strengthening the accountability and trustworthiness of automated decisions by peering into the "black box" of complex models. Meanwhile, Athey and Imbens (2019) link machine learning to economics to explain how flexible algorithms, including uplift models and causal inference, enable economists to use big data without sacrificing identification. Instead, methods such as those proposed by Chen and Guestrin (2016) parallelize the structure learning to be efficiently applied to large-scale data, such as rice trading or e-commerce. Their work exemplifies high-performance boosting techniques that span a significant parameter space and are effectively becoming learners' default choice in predictive tasks across marketing and finance research applications.

Cluster 3 (Blue) highlights the impact of automation and AI on labor markets and growth regimes. To shift the conversation away from technology-induced unemployment, automation reallocates tasks, devalues routine jobs, and generates new complementary occupations (Acemoglu & Restrepo, 2019). A somewhat more nuanced opposing viewpoint comes from Arntz, Gregory, and Zierahn (2017), who find evidence that conventional task-based models understate firm-specific re-allocations of work, overpromoting automation risks. While the long-run macroeconomic implications are addressed by Aghion, Jones, and Jones (2017), who argue that AI-enabled innovation can positively affect growth but at the cost of distributional issues as returns to skill rise. These contributions illuminate a fluid "race between man and machine," where institutional, policy, and upskilling responses will determine whether artificial intelligence widens inequality or enhances prosperity.

3.2-Co-Word Analysis

Table 2 summarizes the top 15 co-occurring keywords, along with their counts and total link strength. The co-word analysis applies to the same database. From the 64,645 keywords, 354 met the minimum of 60 occurrences, resulting in 5 clusters.

Table 2. Top 15 Keywords in the Co-Occurrence of Keywords Analysis

Ranking	Keyword	Occurrences	Total Link Strength
1	Sustainability	1444	6871
2	Artificial Intelligence	1724	5601
3	Decision Making	1059	5128
4	Sustainable Development	954	4863
5	Machine Learning	1250	4345
6	Innovation	882	3771
7	China	786	3596
8	Covid-19	970	3345
9	Algorithm	431	2120
10	Optimization	482	2017
11	Supply Chain Management	394	1924
12	Human	326	1867
13	Literature Review	378	1859
14	Numerical Model	344	1853
15	Forecasting	423	1716

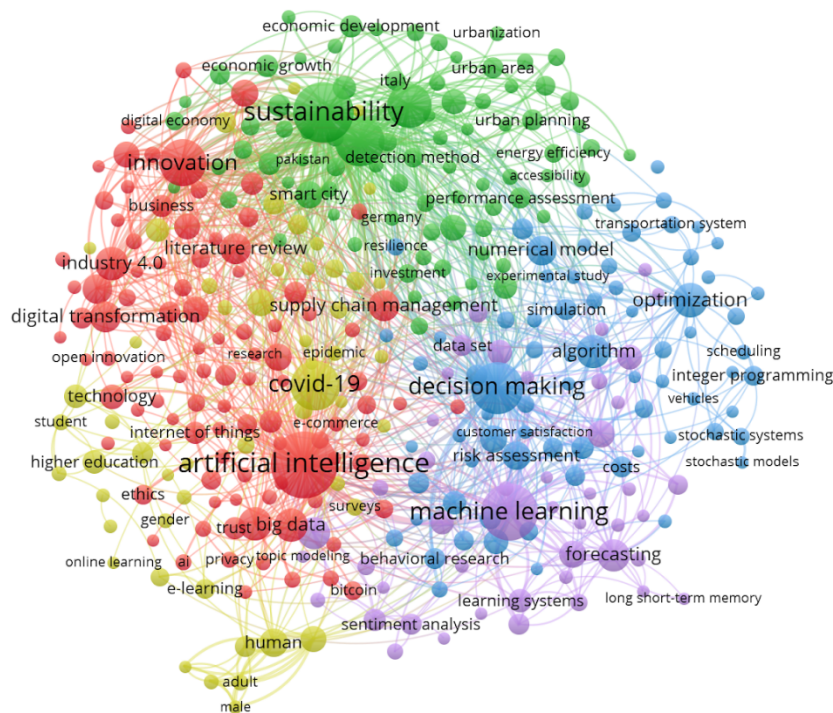


Figure 2. Co-Word Analysis of Big Data Analytics on the Economics of Artificial Intelligence

Cluster 1 (Red) focuses on the central research topic of bridging AI, business strategy, and macroeconomic change, and can be observed in the largest node of AI. There is, of course, a strong interplay among Industry 4.0, digital transformation, and innovation, suggesting an important topic: AI as a general-purpose technology that dramatically changes the rules of production and the makeup of the economy. Scholars in this area study how advances propelled by AI boost productivity, open new markets, and remake entire industries. From a microeconomic perspective, business is the study of how companies use AI to optimize operations, gain competitive advantage, and launch new businesses. That a Covid-19 mention was made is particularly revealing, as it represents an acknowledgement of a significant body of recent research that describes how the

pandemic has ushered in a digital transformation, forcing companies to implement AI and other technologies. Hence, they could deal with economic shocks and adapt to market realities.

Cluster 2 (Green) focuses on sustainability and economic development, applying AI to urgent societal and policy-related economic challenges. This subject examines how AI can serve as a tool for long-term economic planning and the public interest, beyond profitability at the level of individual firms. Supply chain optimization is a key application area where AI techniques are deployed to streamline operations, reduce waste, and balance logistics—all of which aid environmental and economic sustainability goals. The strong associations with smart cities, urban planning, and urban areas show that the studied domain of urban economics is widely considered. To build more livable and economically vibrant cities, research in this cluster study examines how AI can control intricate urban systems, including monitoring public utilities and traffic flow to improve energy efficiency. The term performance assessment is significant because it points to research aimed at quantifying the economic and social rewards of investing in AI-powered systems. That means developing metrics to measure resilience, sustainability, and overall improvements in economic health.

Cluster 3 (Purple), which focuses on using machine learning to answer fundamental economic questions of choice and prediction, represents our discipline's quantitative and methodological nucleus. The primary focus is decision-making under uncertainty (a core of economic theory). Classic keyword forecasting is widely used in econometrics, where commercial services and researchers aim to make better forecasts of economic variables such as inflation, consumer demand, and stock prices than conventional statistical methods can achieve. It is also closely associated with finance and business analytics via keyword risk assessment, in which machine learning models are developed to determine credit, fraud, and investment portfolio risks. Including microeconomic concepts, such as costs and consumer satisfaction, gives evidence to research lines that analyze how companies use machine learning for optimal pricing, customized marketing, and improved operational efficiency.

Cluster 4 (Blue) highlights AI's computationally complex, operations-research-oriented subfield. The top four keywords (numerical model or model, simulation, optimization, algorithm) relate to research on complex resource allocation problems. These discussions are more concerned with developing specialized computational techniques to achieve computational efficiency at the microeconomic level than with generic economic theory. An excellent example is the very strong sub-cluster in the transportation system, including scheduling, vehicles, and integer programming. We can solve one of these textbook classes of problems with AI and machine learning algorithms. Moreover, stochastic models exist, and a stochastic system is important because it shows how this field addresses uncertainty in the real world. These are not models of perfect information, but rather AI that can search for the best plans in an uncertain, shifting landscape. This is essential for both realistic operational and economic forecasts.

Cluster 5 (Yellow) probes labor economics, education, and ethics. This cluster shifts the focus from technology and models to the impact of AI on people and society. AI effects on human capital are a central topic, as is the intimate association between online and e-learning. This area of research explores how AI-powered educational technologies are transforming how students and workers develop skills. It explores the economic whys and hows of these innovative learning models and the role they could play in addressing the skills gaps caused by automation. There is also the question of AI governance and societal approval. Trust, big data, ethics, and privacy are prominent in a burgeoning body of work on the financial consequences of algorithmic bias, data security, and public trust. These papers argue that ethical AI will be the key to unlocking AI's full economic potential.

On the other hand, important contributions on the distributional impacts of AI are underscored by their use of demographic keywords, such as 'male' and 'gender'. Academy researchers also investigate whether AI technologies exacerbate or mitigate existing economic inequalities. For instance, they explore algorithmic bias in hiring or how automation impacts demographic groups unequally.

Table 3 provides a brief overview of the top research on the economics of artificial intelligence. It presents the paper's objective, primary findings, and suggestions for future researchers and studies.

Table 3. Summary of Key Papers

Authors	Objective	Findings	Suggestions for Future Work
Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. <i>American Economic Review</i> , 108(6), 1488-1542.	To model how automation (which displaces labor) and the creation of new, complex tasks (which reinstates labor) interact to affect growth, employment, and the labor share of income.	Automation can reduce labor's share of income and wages, but this is counteracted by a "reinstatement effect" from new tasks where labor has a comparative advantage. Stagnant wages can result if the creation of new tasks is too slow relative to the pace of automation.	Investigate the factors that drive the creation of new tasks. Explore policies that could encourage the development of labor-complementing technologies rather than just labor-replacing ones.
Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. <i>Journal of Political Economy</i> , 128(6), 2188-2244.	To empirically measure the impact of the adoption of industrial robots on local employment and wages in the U.S. from 1990 to 2007.	Increased exposure to industrial robots in a local economy significantly reduced employment and wages. The paper estimates that one additional robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%.	Analyze the aggregate, economy-wide effects of robots beyond local labor markets. Study the impact of other automation technologies like AI and examine adjustment mechanisms in non-manufacturing sectors.
Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In <i>Handbook of Labor Economics</i> (Vol. 4, pp. 1043-1171). Elsevier.	To propose a task-based framework to understand better how technology, skills, and globalization affect the labor market, as an alternative to the standard model of skill-biased technological change.	The task-based model better explains job polarization (the hollowing out of middle-skill jobs). It shows that technology often replaces labor in routine tasks while complementing labor in non-routine tasks, increasing demand at both the high-skill (abstract) and low-skill (manual) ends.	Develop more direct and robust measures of the task content of jobs. Further distinguish empirically between different types of technological change (e.g., routine-replacing vs. skill-enhancing).
Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. <i>Journal of Economic Perspectives</i> , 33(2), 3-30.	To provide a clear framework explaining the dual impact of automation on labor markets: the negative displacement effect and the positive reinstatement effect through new task creation.	While automation has a strong labor-displacing effect, this is not the full story. The creation of new tasks reinstates labor into the production process. The overall impact on labor demand depends on the balance between these two competing forces.	Conduct more empirical research to identify the creation of new tasks in the economy and understand the factors that determine whether technological innovation is primarily labor-displacing or labor-reinstating.
Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. <i>Journal of Economic Perspectives</i> , 29(3), 3-30.	To explain the paradox of why, despite centuries of automation, technology has not led to mass unemployment.	Automation eliminates jobs but not work. It substitutes for routine tasks but complements non-routine tasks requiring problem-solving, creativity, and adaptability. It also creates new work through economic growth and increased demand for various services.	Analyze how modern AI might be different from past technologies, especially its potential to automate non-routine cognitive tasks. Consider policy responses to help workers adapt and ensure the benefits of automation are shared broadly.
Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. <i>The Quarterly Journal of Economics</i> , 118(4), 1279-1333.	To empirically test whether the rapid adoption of computers has shifted labor demand by substituting for routine tasks and complementing non-routine analytical and interactive tasks.	Computerization is strongly associated with a decline in the share of routine tasks (both manual and cognitive) and an increase in the share of non-routine tasks. This task-shifting explains a significant portion of the rising demand for college-educated workers.	Extend the analysis to newer technologies that have emerged since the widespread adoption of the personal computer. More directly link the observed task shifts to changes in wage inequality.
Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis.	To estimate the percentage of jobs at high risk of automation in 21 OECD countries using a task-based approach, arguing that it is more accurate than an	On average, only 9% of jobs in the surveyed OECD countries are at high risk of automation. This is much lower than the 47% estimate for the U.S. from studies using an occupation-based method, as many jobs	Improve the measurement of job tasks and the mapping of technological capabilities to these tasks. Analyze how firm-level characteristics and worker heterogeneity affect the adoption of automation.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. <i>American Economic Review</i> , 103(5), 1553–1597.	occupation-based approach. To link the computerization of middle-skill jobs to the simultaneous growth of low-skill, in-person service jobs, thereby explaining a key component of job polarization.	contain a substantial share of hard-to-automate tasks. Workers displaced from routine, middle-skill jobs by technology reallocate their labor to low-skill service occupations. This influx of labor supply into the service sector leads to employment growth in those jobs but also puts downward pressure on their wages.	Investigate the long-term career prospects and wage trajectories for workers in these growing low-skill service jobs. Explore how changing consumption patterns contribute to demand for these services.
Ajzen, I. (1991). The theory of planned behavior. <i>Organizational Behavior and Human Decision Processes</i> , 50(2), 179–211.	To propose the Theory of Planned Behavior (TPB), a model for predicting and explaining human behavior based on attitudes, subjective norms, and perceived behavioral control.	An individual's intention to perform a behavior is the best predictor of that behavior. This intention is shaped by three factors: their attitude toward the behavior, the subjective norms (perceived social pressure), and their perceived behavioral control (their belief in their ability to perform it).	Apply the model to a broader array of health, social, and consumer behaviors. Refine the measurement of the theory's core constructs and better understand the links between background beliefs and the main predictors.
Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. <i>Economics Letters</i> , 159, 157–160.	To refine their earlier (2016) work and reinforce the argument that a task-based approach is superior to an occupation-based one for assessing automation risks.	The paper confirms that occupation-based estimates overstate the risk of automation because they overlook the variety of tasks within jobs. It also shows that individual worker characteristics, such as education and on-the-job training, significantly influence the automatability of their job.	Investigate how labor market institutions (e.g., unions, minimum wage laws) and firm-level decisions mediate the actual impact of potential automation on employment outcomes.

Redefining the frame of reference from an occupation-based to a task-based approach to understand the impact of technology on the labor market is one significant theme that emerges from this compiled research. Many crucial papers note that automation substitutes certain, often monotonous tasks within jobs rather than eliminating them. According to the work of Autor, Levy, and Murnane (2003), on computerization, non-routine analytical and interactive skills were in greater demand while routine tasks declined. The concept is used to explain the phenomenon of job polarization, in which demand for high-skill abstract jobs and low-skill mechanical jobs rises while the middle hollows out; developed by Acemoglu and Autor (2011), it helps them to muse about how lagging relative skill supply accounts for wages that seem inexplicably high given factors like returns to education. The move from an occupation-based to a task-based approach to understanding the effects of technology on labor markets is one of the major themes that characterizes the research assembled. Some significant documents concur that automation is a partial, not a total, replacement of routine tasks in commonly performed jobs.

On the other hand, some papers present specific empirical findings and methodological criticism, whereas most focus on the theoretical underpinnings of labor market changes. For instance, Acemoglu and Restrepo (2020) find that the introduction of industrial robots in U.S. labor markets from 1990 to 2007 led to sharp declines in employment and wages. This provides concrete evidence of the robust displacement effect in a specific ecology. Arntz et al.'s (2017) alternative study is methodologically oriented and argues that occupation-based estimates of automation risk are subject to a proportion of contact error. By looking at tasks rather than jobs, they estimate that only 9% of jobs in Organisation for Economic Co-operation and Development (OECD) countries are at high risk of automation, a figure that is more conservative than previous estimates. This may contrast with much of the social sciences, where the psychologist Ajzen's (1991) Theory of Planned Behavior, which predicts human action and intention, diverges somewhat from more straightforward economic analysis. This could be used in studies of technology adoption behavior, but it does not directly examine the economics of AI.

Overall, the principal contribution of this research is its collective reframing of the automation debate, shifting it from a story about mass unemployment to an appreciation of the more multifaceted nature of task displacement, job polarization, and labor reinstatement. The main policy takeaway is that addressing employee transitions and reducing wage inequality created by the hollowing out of the middle job market may be more pressing than any

job shortage. A common understanding of the future research agenda is also emerging. Academics often call for more empirical work to measure and characterize the creation of new tasks, examine the economic effects of emerging technologies such as artificial intelligence (AI) beyond local market failures, and explore how modern AI might differ from past technologies in automating non-routine cognitive tasks. To ensure that the monetary gains of AI are more equitably distributed, it is also recognized that policies that might actively favor the production of labor-complementary technologies should be explored.

4.0 Conclusion

This bibliometric analysis reveals that research on the economics of AI has evolved from a narrow focus on job displacement to a multifaceted examination of task reallocation, ethical governance, and sustainable development. The intellectual core of the field has shifted from a binary view of job destruction toward a more sophisticated, task-based framework that sees automation as a force that complements and reshapes human labor. The research landscape demonstrates a dynamic interplay between technological innovation, its strategic implementation in key sectors like supply chain management, and its application to pressing societal challenges.

Ultimately, the analysis confirms that the critical question is not whether AI will change the economy, but how its development can be guided to produce broadly shared prosperity. The interdependence of the research clusters—from machine learning's predictive power to its labor market impacts and ethical dimensions—underscores that technological progress is inseparable from its human context. As AI becomes more embedded in our economic systems, the field is correctly broadening its focus to include governance, equity, and societal resilience. This marks a proactive shift toward shaping a future where AI-driven growth is sustainable and inclusive. This study's limitations include its reliance on the Scopus database and a specific ten-year timeframe, which may exclude influential works from other sources or periods.

For researchers, the key takeaway is the need for more interdisciplinary collaboration. Scholars focused on algorithmic optimization should work with those examining labor market transitions and ethical governance to ensure efficiency gains do not come at a prohibitive social cost. For policymakers, the priority must be to create an innovation ecosystem that favors human-complementary AI. This requires investing in lifelong learning platforms to help the workforce adapt, establishing clear regulatory frameworks that build public trust, and ensuring the economic benefits of AI are distributed fairly across society.

5.0 Contributions of Authors

The sole author is responsible for the paper's idea, construction, and writing.

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7.0 Conflict of Interests

There are no reported conflicts of interest.

8.0 Acknowledgment

None.

9.0 References

- Acemoglu, D., & Autor, D. (2011). Skills, tasks, and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4(Part B), 1043–1171. [https://doi.org/10.1016/s0169-7218\(11\)02410-5](https://doi.org/10.1016/s0169-7218(11)02410-5)
- Acemoglu, D., & Azar, P. (2017). Endogenous production networks. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3083542>
- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488–1542.
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188–2244. <https://doi.org/10.1086/705716>
- Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science*, 347(6221), 509–514. <https://doi.org/10.1126/science.aaa1465>
- Adner, R., & Kapoor, R. (2010). Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management Journal*, 31(3), 306–333. <https://doi.org/10.1002/smj.821>
- Aghion, P., Jones, B., & Jones, C. (2017). Artificial intelligence and economic growth. <https://tinyurl.com/2ryf43p5>
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, 37(3), 99–110. <https://doi.org/10.1787/5f129h56dvq7-en>
- Aldoseri, A., Khalifa, K. N. A., & Hamouda, A. M. (2024). AI-Powered innovation in digital transformation: Key pillars and industry impact. *Sustainability*, 16(5), 1790. mdp. <https://www.mdpi.com/2071-1050/16/5/1790>
- Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries. *OECD Social, Employment and Migration Working Papers*, 189(189). <https://doi.org/10.1787/5f129h56dvq7-en>
- Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159(159), 157–160. <https://doi.org/10.1016/j.econlet.2017.07.001>
- Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bannetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial

- intelligence (XAI): Concepts, taxonomies, opportunities, and challenges toward responsible AI. *Information Fusion*, 58(1), 82–115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11(1), 685–725. <https://doi.org/10.1146/annurev-economics-080217-053433>
- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>
- Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5), 1553–1597.
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333.
- Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD'16*, 1(1), 785–794. <https://doi.org/10.1145/2939672.2939785>
- Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, 211, 188–205. <https://doi.org/10.1016/j.jebo.2023.05.008>
- Gao, X., & Feng, H. (2023). AI-Driven productivity gains: Artificial intelligence and firm productivity. *Sustainability*, 15(11), 8934–8934. <https://doi.org/10.3390/su15118934>
- Johnson, P. C., Laurell, C., Ots, M., & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change*, 179(179), 121636. <https://doi.org/10.1016/j.techfore.2022.121636>
- Kim, E. (2025). Does publisher volume matter? A cross-sectional analysis of Scopus journal publishing patterns. *Publications*, 13(2), 17. <https://doi.org/10.3390/publications13020017>
- Krakowski, S. (2025). Human-AI agency in the age of generative AI. *Information and Organization*, 35(1), 100560. <https://doi.org/10.1016/j.infoandorg.2025.100560>
- Passas, I. (2024). Bibliometric analysis: The main steps. *Encyclopedia*, 4(2), 1014–1025. <https://doi.org/10.3390/encyclopedia4020065>
- Rashid, A. B., & Kausik, A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, 7(100277), 100277–100277. <https://doi.org/10.1016/j.hybadv.2024.100277>
- Rong, K. (2022). Research agenda for the digital economy: An IBCDE framework. *Journal of Digital Economy*, 1(1). <https://doi.org/10.1016/j.jdec.2022.08.004>
- Skare, M., Gavurova, B., & Blažević Burić, S. (2024). Artificial intelligence and wealth inequality: A comprehensive empirical exploration of socioeconomic implications. *Technology in Society*, 79, 102719. <https://doi.org/10.1016/j.techsoc.2024.102719>