



Economy and empirical research perspectives towards Artificial Intelligence: A deep dive investigative exploration analysis

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Abstract

The transformative potential of Artificial Intelligence (AI) has sparked significant interest across economic and empirical research domains, inspiring investigations into its impacts on productivity, labor markets, economic growth, and policy adaptation. This study offers a comprehensive analysis of AI's economic implications, focusing on its integration into diverse sectors and its measurable effects on economic performance. Through a multi-dimensional approach, we explore AI's role in enhancing productivity and efficiency, reshaping workforce dynamics, and influencing the distribution of economic benefits. Supported by recent empirical studies and quantitative analyses, this research highlights AI's capacity to drive innovation while examining its challenges, such as labor displacement, income inequality, and skill gaps. Case studies and data-driven insights provide evidence of AI's role in fostering new economic models, underscoring its dual potential to stimulate growth and exacerbate disparities. Furthermore, the study delves into the evolving landscape of policy responses, analyzing how different regulatory frameworks influence AI's integration and impact across economies. By offering nuanced perspectives on AI's transformative effects, this investigation identifies key trends and areas requiring further research, including the long-term implications for developing economies and global inequality. The findings aim to equip policymakers, researchers, and industry leaders with evidence-based insights to navigate AI's complexities, ensuring sustainable and inclusive economic advancement in an AI-driven future.

Keywords: Artificial intelligence, Economic growth, Economic models, Economic paradigms, Economics science, Economy, Empirical research perspectives.

JEL Classification: A10; A12; B00; B52; C10; C69; C80; D02; D91; E27.

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Contribution of this paper to the literature

This study uniquely integrates economic and empirical research perspectives to analyze AI's dual impact on productivity and inequality, supported by case studies and quantitative insights. It bridges gaps in existing available knowledge by emphasizing AI-driven policy implications and proposing sustainable frameworks for equitable economic growth in an AI-dominated landscape.

1. Introduction

The rapid evolution of Artificial Intelligence (AI) has fundamentally altered the technological and economic landscapes, introducing new paradigms across industries, economies, and society as a whole (Kianpour, Kowalski, & Overby, 2021; King, 2018). As AI advances in capability and complexity, its applications are permeating diverse sectors—from finance and healthcare to manufacturing and services—each harnessing AI's capacity to automate tasks, derive insights, and enhance decision-making. This integration has brought about significant economic shifts, prompting an urgent need to understand and analyze the empirical impacts AI is exerting on economic growth, labor markets, productivity, and inequality.

The implications of AI for economic performance are multifaceted. AI-driven innovations have the potential to boost productivity, reduce operational costs, and unlock new avenues for economic growth (Becker, 1974, 1991; Hanushek & Wößmann, 2007). However, these benefits come with substantial challenges, especially concerning workforce displacement, the reshaping of labor demand, and the polarization of job opportunities. AI's transformative power raises questions about the future of work and the equitable distribution of economic benefits, highlighting the critical need for policy adaptations that can mitigate adverse effects and ensure sustainable economic progress. Empirical research is instrumental in addressing these questions, offering data-driven insights into how AI affects macroeconomic indicators and sector-specific dynamics. Studies to date reveal both positive and negative outcomes; while some sectors experience unprecedented efficiency gains, others face disruptions due to job reallocation and shifting skill demands. These empirical findings are crucial for informing policy measures, enabling stakeholders to devise strategies that promote AI adoption while protecting against economic inequalities. This study provides a comprehensive exploration of the economic and empirical research perspectives on AI, presenting an in-depth analysis of its impact on productivity, labor dynamics, and policy. Through an evaluation of case studies, economic models, and empirical research, we aim to offer a nuanced understanding of how AI is reshaping economic structures and driving the need for new economic models. By identifying gaps in the current research and areas requiring policy attention, this study seeks to support researchers, policymakers, and industry leaders in fostering an AI-integrated economy that aligns technological advancement with equitable growth.

2. Methods and Experimental Analysis

This study employs a multi-dimensional, empirical approach to examine the economic impacts and implications of Artificial Intelligence (AI) adoption across various sectors. The methodology combines a rigorous investigative available knowledge exploration, data analysis, and case study examination to explore the direct and indirect economic effects of AI on productivity, labor markets, and policy formation. Through these methods, the study aims to construct a comprehensive understanding of AI's evolving role in economic systems, highlighting both positive advancements and potential challenges.

The first phase of the methodology involves an extensive available knowledge exploration analysis, which serves as a foundation for the analysis of AI's economic impact. This investigation systematically examines research articles, economic reports, and industry studies published within the last decade to capture the contemporary discourse on AI's transformative potential. Special emphasis is placed on peer-reviewed studies that offer quantitative insights into AI's contributions to economic growth, productivity, and labor reallocation. By critically analyzing these sources, we aim to identify common findings, emerging trends, and research gaps that will guide the empirical analysis in later phases. The second phase incorporates a quantitative analysis of economic data related to AI adoption. Publicly available datasets from sources such as the World Bank, International Labour Organization, and various AI industry reports provide empirical data on economic indicators including Gross Domestic Product (GDP) growth, productivity levels, labor force participation, and industry-specific performance metrics. Econometric models are employed to analyze the correlation between AI adoption rates and these economic indicators, enabling an assessment of AI's direct impact on economic performance. The analysis also evaluates sectoral shifts and workforce trends to understand how AI-driven automation and augmentation affect labor demand and job quality across industries. This quantitative approach provides an evidence-based perspective on the economic ramifications of AI at both macro and micro levels. In the third phase, case studies of selected industries, including finance, healthcare, and manufacturing, are conducted to provide a contextualized understanding of AI's impact in real-world settings. These sectors were chosen due to their high degree of AI adoption and their significance to the economy. For each case study, data from industry reports, company financial statements, and news sources are synthesized to examine specific instances of AI application, focusing on productivity gains, cost reduction, and labor adjustments. By analyzing these practical examples, we aim to capture the nuanced effects of AI across different economic sectors and provide insights into the sector-specific challenges and opportunities presented by AI technologies. Finally, the study employs a policy analysis framework to evaluate the effectiveness of current policies in managing AI's economic impacts. This involves a review of AI-related policies and regulatory documents from several leading economies, including the United States, the European Union, and China. The analysis examines how different policy approaches address AI's potential to disrupt labor markets, influence wage structures, and alter economic inequalities. This policy review not only identifies best practices but also highlights areas where policy innovation is necessary to support an equitable and sustainable AI-driven economy.

Together, these methods form a cohesive approach that blends qualitative and quantitative analyses to assess the economic and empirical research perspectives on AI. The multi-phase methodology allows for a well-rounded investigation that considers both theoretical insights and practical applications, ultimately offering a comprehensive view of AI's economic implications and providing recommendations for future research and policy development.

3. Background Research and Investigative Exploration for Available Knowledge

Economics is a social science focused on studying the production, distribution, and consumption of goods and services, as well as the behaviors and interactions of economic agents. The discipline is divided into two main branches: microeconomics, which examines the basic elements within an economy such as individual agents (households, firms, buyers, and sellers) and their interactions, and macroeconomics, which views economies as systems and analyzes larger phenomena like production, inflation, economic growth, and the influence of public policies (Kianpour et al., 2021; King, 2018).

Economics is also categorized by various distinctions, such as between positive economics, which describes "what is," and normative economics, which explores "what ought to be." Other distinctions exist between theoretical and applied economics, rational and behavioral economics, and mainstream versus heterodox economics. Beyond its traditional boundaries, economic analysis is applied across diverse fields, including finance, health care, engineering, government, crime, education, and environmental studies (Becker, 1974, 1991; Hanushek & Wößmann, 2007).

Historically, economics was known as "*political economy*," but by the late 19th century, the term "*economics*" became common. Originating from the Greek word *oikonomia*—meaning "*household management*"—the discipline evolved to study how resources are managed, whether for a household, state, or society. Early economists like Adam Smith defined economics in terms of wealth creation and distribution, focusing on how societies achieve prosperity. Jean-Baptiste Say emphasized the science of production, distribution, and consumption, while Thomas Carlyle famously called it "*the dismal science*" for its often-pessimistic outlook (Bertholet, 2021; Blaug, 2017; Towards, 2011).

Later economists provided definitions that reflect the discipline's evolving focus. Alfred Marshall described economics as the study of people in their "*ordinary business of life*," while Lionel Robbins defined it as a science examining human behavior in light of limited resources and competing ends. Robbins' definition is widely accepted for focusing on the influence of scarcity, yet it has faced criticism for being too broad. Some argue that the definition has expanded economics into areas that were traditionally outside its domain, such as the analysis of non-market behaviors (Bertholet & Kapossy, 2023; O'Driscoll & Rizzo, 2014). This expansion has been championed by economists like Gary Becker, who applied economic principles to new social areas, viewing economics as a methodology rather than a specific subject matter.

However, critics like Ha-Joon Chang argue that limiting economics to a single approach, such as rational-choice modeling, risks defining it as a "*theory of everything*" and diverging from the traditional subject-based focus common to other sciences. These debates reflect an ongoing discussion about whether economics should be defined by its methodology or its subject matter, showing the discipline's dynamic and interdisciplinary nature (Cameron, 1993; Cordato, 1980; Julie, 2016).

The history of economic thought covers the evolution of economic theories, tracing how societies have conceptualized and organized resources, production, and distribution through time. This development is categorized into several key eras (Aghion, Akcigit, Cagé, & Kerr, 2016; Baker & Rafter, 2022; Bird, 2015; Boring & Zignago, 2018; Camerer, 2017; Department International Monetary Fund Monetary and Capital Markets, 2023; Goldfarb & Tucker, 2017; Hengel & Phythian-Adams, 2022; Human Development Reports, 2019; Jahan, 2012; Neves, Afonso, & Silva, 2016; Trapeznikova, 2019; Ventura, 2022; Walker, 1878).

3.1. From Antiquity through the Physiocrats

Early economic ideas can be traced to ancient thinkers like Hesiod, often considered the "*first economist*" for his insights on resource distribution in household management. Greek thinkers like Xenophon also influenced economic terminology with works like *Oeconomicus*, where "*economy*" originally referred to household management rather than broader economic systems. In the 16th and 17th centuries, two influential schools of thought emerged: Mercantilism and Physiocracy. Mercantilists, focused on national wealth through gold and silver accumulation, advocated for trade surplus strategies by exporting goods and limiting imports. Physiocrats, however, argued that true wealth was derived from agriculture, and they proposed policies that would allow minimal government interference in the economy (*Laissez-faire*).

3.2. Classical Political Economy

Smith (1776) is often cited as the foundational work of modern economics, marking economics as a distinct field. Smith introduced the idea of the "*invisible hand*," suggesting that self-interested actions inadvertently promote societal good, and he emphasized specialization and division of labor. David Ricardo further expanded on Smith's work by explaining income distribution among landowners, laborers, and capitalists, introducing the principle of comparative advantage, which supports free trade based on cost efficiencies. Thomas Malthus offered a counterview with his population theory, predicting that population growth would outstrip food supply, leading to poverty. Meanwhile, John Stuart Mill distinguished between market efficiency in resource allocation and income distribution, opening discussions about potential societal interventions.

3.3. Marxian Economics

Karl Marx developed a critical response to classical economics, highlighting class struggles within capitalist economies. In *Das Kapital*, he presented the labor theory of value, asserting that labor is exploited as capitalists reap surplus value generated by workers.

3.4. Neoclassical Economics

In the late 19th century, neoclassical economics emerged, popularized by economists like Alfred Marshall. This school emphasized marginal utility and supply-demand dynamics in determining value, moving away from the labor theory of value. Neoclassicals analyzed individual and household behavior, with economics focusing on choices under scarcity, an approach that Lionel Robbins formalized as studying "*human behavior as a relationship between ends and scarce means*." Neoclassical economics integrated mathematical methods, which enabled systematic models and econometric analysis, and influenced both microeconomic theory and Keynesian macroeconomics in the 20th century.

3.5. Keynesian Economics

Keynes (1936) introduced concepts that fundamentally reshaped economic thought, focusing on national income and employment levels. Keynes argued that in certain situations, free markets cannot self-correct during periods of low demand, and advocated for government intervention to manage economic stability. This framework laid the foundation for contemporary macroeconomics and influenced policies on economic stabilization, employment, and growth. These various schools, each responding to the challenges of their times, have cumulatively advanced the field, influencing modern economic policy, international trade, and approaches to managing economic cycles. The methodology of economic research relies on both theoretical and empirical approaches, with significant sub-disciplines and techniques used to build and test economic theories. Here's an overview of these research methodologies and their applications.

3.6. Theoretical Research

Theoretical economics focuses on developing models and frameworks to understand economic behaviors and predict economic outcomes (Aghion et al., 2016; Aghion, Jones, & Jones, 2017; Baldwin, 2019; Bird, 2015; Boring & Zignago, 2018; Camerer, 2017; Goldfarb & Tucker, 2017; Hengel & Phythian-Adams, 2022; Human Development Reports, 2019; Misuraca, Barcevičius, & Codagnone, 2020; Neves et al., 2016; Nguyen & Doytch, 2022; Qin, Xu, Wang, & Skare, 2024; Rogerson, Hankins, Nettel, & Rahim, 2022; Sachs, 2023; Samuelson, 2016; Trabelsi, 2024; Trapeznikova, 2019; Yang, 2022; Zhao, Gao, & Sun, 2022). This involves creating simplified assumptions that reduce complex real-world scenarios into manageable variables, allowing economists to explore relationships, make predictions, and stimulate additional research.

3.6.1. Microeconomic Theory

- Key Concepts: Microeconomic theories revolve around supply and demand, rational choice, opportunity cost, utility, and market structures.
- Market Structures: Economists categorize markets into structures like perfect competition, monopoly, and oligopoly, each with distinct dynamics and implications for price and output control.
- Production and Efficiency: In microeconomic models, production functions and cost efficiencies play a crucial role, including concepts like opportunity cost and the production-possibility frontier (PPF), which helps illustrate scarcity and efficiency.

3.6.2. Macroeconomic Theory

- Traditional macroeconomic models analyze aggregate variables such as GDP, inflation, and unemployment rates, often linking these to underlying microeconomic foundations to create a holistic view of economic activities on a national or global scale.
- General Equilibrium Theory: This theory seeks to explain the interplay across various markets, assuming that all factors are interdependent and that markets will reach an equilibrium state over time.

3.6.3. Mathematical Economics

- Role of Mathematics: Mathematical economics uses mathematical tools to represent theories, enhancing precision in the formulation of hypotheses and enabling a more robust analysis of economic relationships. Theorems, as described in works like Paul Samuelson's *Foundations of Economic Analysis*, can be tested empirically to verify or refute economic theories.

3.7. Empirical Research

Empirical research in economics involves testing hypotheses through data analysis, often employing econometrics, which uses statistical methods to analyze economic data. Empirical research aims to confirm or refute theoretical models by observing actual economic behaviors and outcomes (Aghion et al., 2016; Aghion et al., 2017; Akhtar, 2024c; Baker & Rafter, 2022; Baldwin, 2019; Behrendt, Peter, & Zimmermann, 2020; Boring & Zignago, 2018; Camerer, 2017; Cameron, 1993; Department International Monetary Fund Monetary and Capital Markets, 2023; Fang, Cao, & Sun, 2022; Goldfarb & Tucker, 2017; Hengel & Phythian-Adams, 2022; Human Development Reports, 2019; Jahan, 2012; Konieczny, 2023; McDowell & Vetter, 2023; Misuraca et al., 2020; Neves et al., 2016; Nguyen & Doytch, 2022; O'Driscoll & Rizzo, 2014; Qin et al., 2024; Rogerson et al., 2022; Sachs, 2023; Samuelson, 2016; Tekale, 2024; Trabelsi, 2024; Trapeznikova, 2019; Ventura, 2022; Walker, 1878; Yang, 2022; Yu et al., 2023; Zhao et al., 2022).

3.7.1. Econometrics

- Statistical Analysis: Econometrics uses tools such as regression analysis to test the strength and significance of relationships between variables. For example, it examines the effect of interest rates on inflation or the relationship between education and income.
- Hypothesis Testing: Empirical testing in economics often deals with probabilistic conclusions, where a hypothesis is accepted if it withstands multiple tests rather than being proven definitively. Results are subject to variance based on data sets, experimental conditions, and underlying assumptions.

3.7.2. Experimental Economics

- Controlled Experiments: Experimental economics has advanced the field by conducting scientifically controlled experiments to directly test behavioral assumptions, bridging a gap between theoretical predictions and observed human behavior.
- Behavioral and Neuroeconomics: Studies like those of Daniel Kahneman and Amos Tversky have shown that actual human behavior often deviates from the assumptions of purely rational decision-making. Neuroeconomics further investigates economic decision-making through the lens of cognitive neuroscience.

3.7.3. Natural Experiments

- Natural experiments analyze scenarios where external factors create a quasi-experimental environment, allowing economists to observe the effects of variables without formal control. This method is particularly useful for studying the impact of policy changes or economic shocks on real-world outcomes.

3.8. Microeconomic Concepts and Applications

Microeconomics, as a foundation of economic theory, analyzes how individual agents—such as consumers, firms, and governments—make decisions (Aghion et al., 2016; Aghion et al., 2017; Agrawal, Gans, & Goldfarb, 2019; Akhtar, 2024a, 2024b, 2024c; Baker & Rafter, 2022; Baldwin, 2019; Behrendt et al., 2020; Bertholet & Kaposy, 2023; Bird, 2015; Boring & Zignago, 2018; Camerer, 2017; Cameron, 1993; Cordato, 1980; Department International Monetary Fund Monetary and Capital Markets, 2023; Fang et al., 2022; Goldfarb & Tucker, 2017; Hengel & Phythian-Adams, 2022; Human Development Reports, 2019; Jahan, 2012; Julie, 2016; Konieczny, 2023; McDowell & Vetter, 2023; Misuraca et al., 2020; Neves et al., 2016; Nguyen & Doytch, 2022; O'Driscoll & Rizzo, 2014; Qin et al., 2024; Rogerson et al., 2022; Sachs, 2023; Samuelson, 2016; Tekale, 2024; Trabelsi, 2024; Trapeznikova, 2019; Ventura, 2022; Walker, 1878; Yang, 2022; Yu et al., 2023; Zhao et al., 2022).

3.8.1. Market Interactions

- Price and Quantity: Prices coordinate production and consumption decisions, influenced by supply and demand dynamics. This interaction is foundational in determining market equilibrium in competitive markets, as described in the supply-demand model.
- Imperfect Competition: Real-world markets often do not align with perfect competition; thus, concepts of monopoly, oligopoly, and monopolistic competition offer insights into pricing and output decisions by firms with market power.

3.8.2. Production and Cost

- Inputs and Outputs: Production involves converting inputs (labor, capital, and natural resources) into outputs (goods and services). Efficiency in production, as measured by concepts like Pareto efficiency and illustrated by the production-possibility frontier (PPF), represents the optimal use of resources within an economy.

3.8.3. Specialization and Trade

- Comparative Advantage: Specialization allows economies to benefit from trade by producing goods in which they have a comparative advantage. This principle underlies the theory of gains from trade, suggesting that economies can achieve higher output and utility levels through specialization and trade.
- Global Trade Patterns: Specialization leads to diverse trade patterns, where nations engage in producing goods with lower opportunity costs, resulting in greater global efficiency and increased income levels.

Economics utilizes a combination of theoretical models and empirical testing to study complex economic systems. The integration of theory with quantitative methods and experimental approaches has allowed economics to advance both as a social science and as a discipline with increasing alignment to scientific rigor, particularly through empirical validation and behavioral insights. By combining microeconomic and macroeconomic perspectives, economic research seeks to offer comprehensive insights into resource allocation, market dynamics, and societal welfare. Uncertainty and game theory play a significant role in economic decision-making, where uncertainty refers to unpredictable outcomes that can be quantifiable as risk.

This concept underlies various fields within economics, affecting household behavior, capital markets, and communications. To model such uncertainty, economists often rely on game theory, a branch of applied mathematics analyzing strategic interactions between agents. Game theory's foundational text, by Neumann and Morgenstern (1944) has far-reaching applications beyond economics, influencing fields such as political science, ethics, and evolutionary biology. It allows economists to generalize market dynamics by modeling scenarios with incomplete information and anticipating strategic behavior in competitive contexts, such as wage negotiations and firm behavior within oligopolies.

Market failures are instances where economic assumptions fail, leading to inefficiencies. Examples include information asymmetry, where one party has more knowledge than another, as in the "Market for Lemons" scenario. Externalities also exemplify market failures, where costs or benefits are not reflected in market prices (e.g., pollution as a negative externality). Governments often intervene through taxes, subsidies, or regulations to mitigate these failures. Welfare economics evaluates societal well-being and resource allocation, focusing on how economic activities contribute to social welfare.

Macroeconomics, distinct from microeconomics, studies the economy on a large scale, analyzing aggregates like national income, unemployment, and inflation. It examines the effects of monetary and fiscal policies on economic stability and growth.

Economic growth theory explores factors driving per capita output over time, with research focusing on investment, technology, and population growth. Business cycle theories explain fluctuations in economic activity, influenced by Keynesian and classical approaches. Unemployment, measured as the percentage of job-seeking workers, can be frictional, structural, or cyclical, with Okun's law highlighting the link between output and unemployment rates. Money and monetary policy are central to economic systems, with money acting as a medium of exchange, store of value, and unit of account. Monetary policy, typically managed by central banks, uses tools like interest rate adjustments to stabilize economies.

Economics is a broad discipline that explores a range of issues from public policy to labor dynamics, international trade, and developmental economics. Public economics, for example, examines government activities, such as taxation, spending, and fiscal policies, with a focus on economic efficiency and income distribution.

It also includes welfare economics, which uses microeconomic techniques to determine efficient resource allocation and income distribution, seeking to assess social welfare. International economics studies trade and capital flows across borders, focusing on the impacts of globalization, tariffs, and international finance on exchange rates and economic gains from trade. Labor economics investigates how labor markets operate through the

interactions of workers and employers, analyzing wage patterns, employment, and income. This field examines labor as a distinct factor of production, distinct from land and capital, while also exploring concepts like human capital. Development economics centers on the economic growth and structural changes in low-income countries, where it often incorporates social and political elements to understand poverty and development better. Economics also intersects with fields like law, politics, energy, and sociology. Law and economics apply economic principles to evaluate legal rules and their efficiency, a method pioneered by Ronald Coase. Political economy examines the interplay of economic systems, politics, and law, analyzing how various political and economic systems influence one another. Energy economics addresses issues related to energy supply and demand, integrating concepts like entropy from thermodynamics, while economic sociology examines how social paradigms affect economic phenomena. Influential thinkers in economic sociology include Weber and Simmel (1988) who linked economic behaviors to social norms. The professionalization of economics has seen significant growth, with economists now employed in academia, government, and the private sector. They apply rigorous quantitative methods, including calculus, linear algebra, statistics, and game theory, to analyze complex economic issues. Many economists receive recognition through awards like the Nobel Memorial Prize in Economic Sciences, while women in economics, although historically underrepresented, have increasingly contributed to the field. Prominent figures like Harriet Martineau, Joan Robinson, and recent Nobel laureates such as Esther Duflo and Claudia Goldin highlight the significant impact of women in economics, even as gender representation remains imbalanced in certain areas of the profession.

4. Empirical Research Perspectives

Empirical research is a methodology for acquiring knowledge based on direct or indirect observation and experience, prioritizing empirical evidence over theoretical beliefs. This approach involves systematically collecting and analyzing observable data to answer questions about specific phenomena. Researchers can analyze data in either quantitative or qualitative forms, or sometimes a combination of both, to form conclusions about empirical questions (Aghion et al., 2016; Aghion et al., 2017; Agrawal et al., 2019; Akhtar, 2024a, 2024b, 2024c; Baldwin, 2019; Behrendt et al., 2020; Camerer, 2017; Fang et al., 2022; Goldfarb & Tucker, 2017; Konieczny, 2023; McDowell & Vetter, 2023; Misuraca et al., 2020; Nguyen & Doytch, 2022; Qin et al., 2024; Rogerson et al., 2022; Sachs, 2023; Tekale, 2024; Trabelsi, 2024; Yang, 2022; Yu et al., 2023; Zhao et al., 2022). Typically, empirical research is particularly valued in fields like social sciences and education, where direct laboratory study may not always be feasible. In these disciplines, research often uses mixed-method designs, combining quantitative and qualitative analyses for a more comprehensive understanding of complex issues.

Empirical research often begins with the formation of a research question or hypothesis based on an existing theory. For example, a researcher might hypothesize that listening to music affects memory retention, predicting that those who study with music will recall less information than those who study in silence. The researcher then tests this hypothesis through experimentation, and depending on the outcome, the hypothesis is either supported, rejected, or further refined. This approach aligns with a scientific process in which evidence is collected through observable measures, and results contribute to a theory's validation or prompt adjustments for future tests (Aghion et al., 2016; Aghion et al., 2017; Agrawal et al., 2019; Akhtar, 2024c; Baldwin, 2019; Behrendt et al., 2020; Fang et al., 2022; Konieczny, 2023; McDowell & Vetter, 2023; Misuraca et al., 2020; Nguyen & Doytch, 2022; Qin et al., 2024; Rogerson et al., 2022; Sachs, 2023; Tekale, 2024; Trabelsi, 2024; Yang, 2022; Yu et al., 2023; Zhao et al., 2022). Historically, the term "empirical" traces back to ancient Greek practitioners who relied on observational evidence rather than dogmatic doctrines. Empirical research methods are rooted in the idea that knowledge is derived from sensory experience, forming the basis for empiricism as a philosophy of knowledge. In scientific research, the term specifically refers to data gathered through sensory evidence or calibrated instruments. This reliance on observable data forms the foundation of empirical research, setting it apart from subjective or anecdotal evidence. For instance, temperature measurements taken with a thermometer provide consistent empirical data, unlike subjective impressions of a room's warmth, which can vary between observers (Akhtar, 2024a, 2024b, 2024c; Behrendt et al., 2020; Fang et al., 2022; Konieczny, 2023; McDowell & Vetter, 2023; Qin et al., 2024; Rogerson et al., 2022; Tekale, 2024; Trabelsi, 2024; Yang, 2022; Yu et al., 2023; Zhao et al., 2022). In conducting empirical research, the scientific method emphasizes the careful calibration and standardization of instruments and procedures. This ensures that results can be replicated and judged according to scientific rigor. Empirical research designs include various typologies, such as pre-experimental, experimental, and quasi-experimental designs, with randomized experiments holding a particularly valued place in fields like education.

Statistical analysis is crucial in empirical research to validate or refute hypotheses; methods such as regression, t-tests, chi-square, and Analysis of Variance (ANOVA) help determine the statistical significance of results. While empirical research does not provide absolute proof, it establishes probabilities that support or question the validity of hypotheses.

A major theoretical debate in empirical research centers on empiricism versus rationalism. Empiricists argue that knowledge originates from sensory experience and is fundamentally observational. In contrast, rationalists believe that certain knowledge can exist independently of sensory experience, rooted instead in innate ideas or deductive reasoning. This philosophical divergence influences empirical research by framing how researchers approach questions of knowledge acquisition. Empiricists often challenge rationalist notions of innate knowledge, emphasizing the necessity of observable data as the basis of knowledge, while rationalists posit that some concepts and understanding are derived beyond empirical experience.

De Groot's (1969) empirical cycle further elucidates the empirical research process, consisting of five stages: observation, induction, deduction, testing, and evaluation. This cycle begins with the observation of a phenomenon, leading to the induction of hypotheses that seek to explain it. Deductive reasoning is then used to design experiments that test the hypotheses.

During the testing phase, data is collected, and finally, the evaluation phase interprets these findings to refine or establish a theoretical framework. This iterative process provides a structured method for researchers to engage with empirical questions, continuously refining theories through evidence-based inquiry. To provide a better understanding concerning the matter Figure 1 provides the cycle illustration.

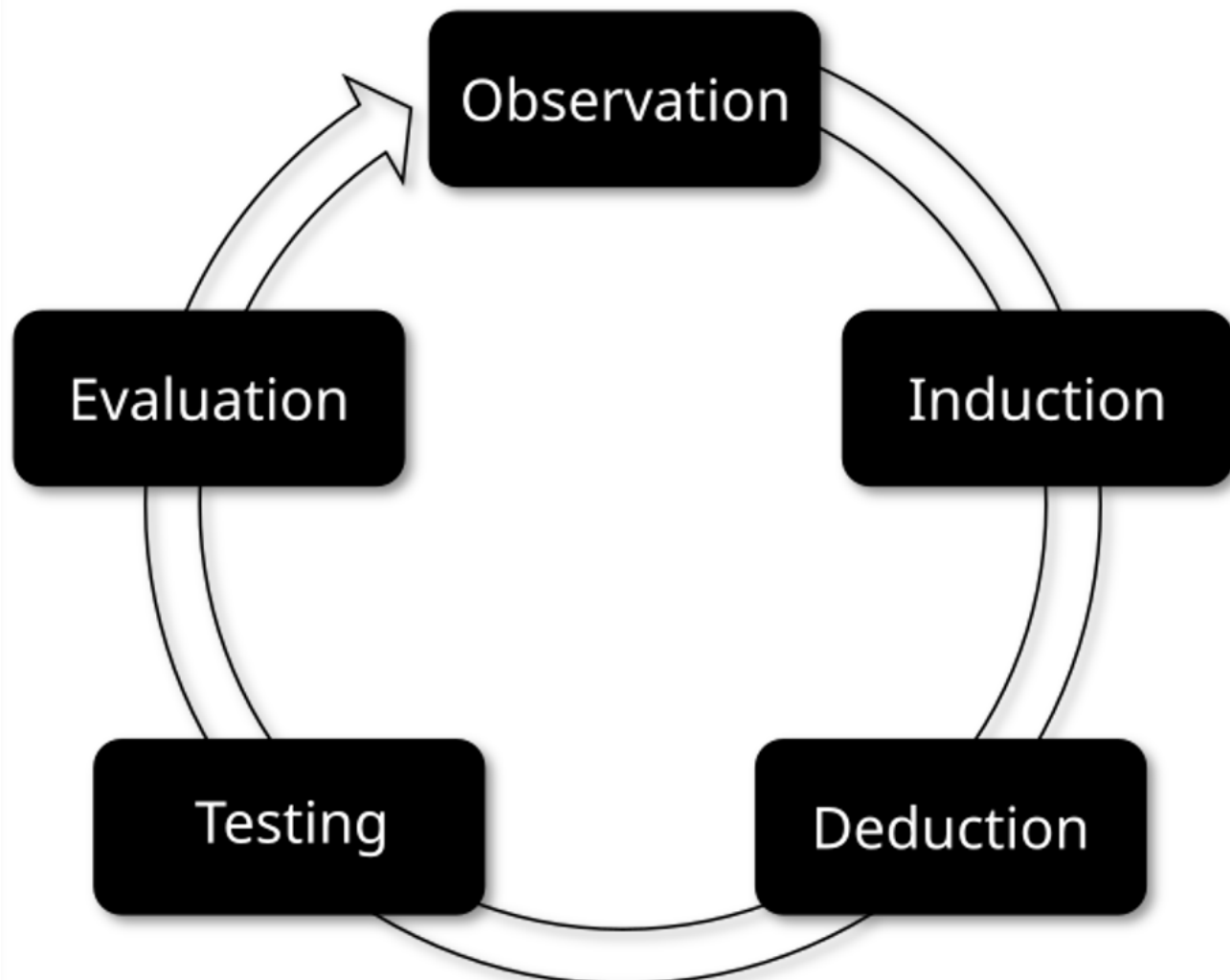


Figure 1. The empirical cycle according to A.D. De Groot.

5. Empirical Research and Analysis: A Deep Dive

Empirical research is a scientific approach that aims to create knowledge about how the world operates by collecting concrete, verifiable evidence. Unlike theoretical research, which relies on models or assumptions, empirical research draws on real-world observations to address questions about how phenomena unfold or interact. This approach builds on the ancient Greek idea of "*empiricism*," which focuses on knowledge acquired through direct experience and sensory observation. Empirical studies seek to reveal general explanations or patterns that hold across various contexts and over time, providing an evidence-based understanding of reality. The core of empirical research lies in its methods, which can be categorized as either qualitative or quantitative. Qualitative methods gather non-numerical data and explore deeper meanings, motivations, or interpretations within a research context. Common qualitative techniques include observations, interviews, case studies, textual analysis, and focus groups. These methods offer rich, descriptive insights into complex issues (Aghion et al., 2016; Aghion et al., 2017; Agrawal et al., 2019; Akhtar, 2024a, 2024b, 2024c; Baldwin, 2019; Behrendt et al., 2020; Bird, 2015; Boring & Zignago, 2018; Camerer, 2017; Fang et al., 2022; Goldfarb & Tucker, 2017; Hengel & Phythian-Adams, 2022; Human Development Reports, 2019; Konieczny, 2023; McDowell & Vetter, 2023; Misuraca et al., 2020; Neves et al., 2016; Nguyen & Doytch, 2022; Qin et al., 2024; Rogerson et al., 2022; Sachs, 2023; Samuelson, 2016; Tekale, 2024; Trabelsi, 2024; Trapeznikova, 2019; Ventura, 2022; Yang, 2022; Yu et al., 2023; Zhao et al., 2022).

For example, observational studies, a subset of qualitative research, involve direct observation of subjects and are commonly used in ethnographic studies. Interviews, another popular qualitative method, provide an in-depth look at individual perspectives, while case studies and textual analysis analyze specific instances or texts to draw broader conclusions.

Quantitative methods, in contrast, collect and analyze numerical data to measure variables such as behavior, preferences, and opinions in a structured format. Common quantitative techniques include surveys, polls, and longitudinal studies. These approaches allow researchers to quantify patterns or trends across larger sample sizes, making it easier to generalize findings. Sometimes, combining qualitative and quantitative methods provides a more comprehensive perspective, as it enables the strengths of both types of data to be leveraged.

Each method has its specific application. Observational studies can yield valuable insights, as exemplified by the famous gravitational wave observation by Abbott and McKinney (2016) which demonstrated the power of quantitative observational research. Interviews capture precise qualitative information, particularly useful in the social sciences and humanities. Case studies delve into specific examples, offering detailed insights that can be applied to similar situations. Textual analysis interprets written content, frequently in the context of social media or other forms of media, and is helpful for understanding public sentiment or cultural patterns.

Lastly, focus groups gather feedback from a selected group on specific topics, often utilized by consumer goods companies to refine product design based on user preferences. Empirical research is essential in advancing knowledge across scientific fields. By distinguishing between qualitative and quantitative approaches and selecting the appropriate methods, empirical research allows scholars to draw conclusions based on tangible, objective evidence. This evidence-driven approach continues to be a cornerstone of modern research, with many empirical studies appearing in prestigious, high-impact journals due to their rigorous methods and influential findings. Quantitative empirical research methods provide a structured, data-driven approach for analyzing and interpreting observations, helping researchers to make informed conclusions. The most common quantitative research

techniques include experiments, surveys, causal-comparative research, cross-sectional studies, longitudinal studies, and correlational research. Each of these methods uniquely serves to collect and assess data in varying contexts. For instance, experiments allow researchers to test hypotheses in controlled environments by adjusting variables, while surveys collect extensive data from target populations, enabling generalizations based on statistical analysis. Causal-comparative research reveals cause-and-effect relationships, whereas cross-sectional studies offer a snapshot view by comparing groups at a single point in time. Longitudinal studies track changes over time, often revealing patterns in subjects' behavior or conditions, and correlational research assesses relationships between variables to identify positive, negative, or neutral correlations.

The process of conducting empirical research involves a systematic approach to ensure rigor and reliability. It starts with establishing the research objective, which involves defining the problem statement, expected outcomes, and potential challenges with resource allocation and scheduling. The next step is a available knowledge exploration analysis, where researchers identify relevant theories and previous studies to ground their research in existing knowledge and frameworks. Then, researchers frame hypotheses, define variables, and determine measurement units, establishing a clear framework for collecting and analyzing data. Selecting an appropriate research design and methodology is crucial, as it affects how data is collected and whether the study will use experimental or observational approaches. After gathering data, the researcher analyzes it quantitatively or qualitatively, supporting or rejecting the hypothesis based on statistical outcomes. The research concludes with a final report that includes findings, limitations, and recommendations for further research, emphasizing originality and credibility by ensuring it is free from plagiarism.

The empirical research cycle, as proposed by De Groot's (1969) formalizes the progression of quantitative research into five key phases: observation, induction, deduction, testing, and evaluation. In the observation phase, an initial idea triggers a hypothesis that can be explored empirically. Induction allows researchers to form a general conclusion from observed data, leading to a hypothesis that guides the research.

Deduction involves reasoning to form specific, testable conclusions, and the testing phase then examines the hypothesis through experiments or statistical analysis. The final phase, evaluation, is vital for interpreting results, acknowledging limitations, and offering directions for future research. This phase consolidates the knowledge gained, ensuring that the research contributes to the wider field and inspires further inquiry by outlining the study's scope and suggesting new variables for continued exploration. The cyclical nature of empirical research reinforces a comprehensive, evidence-based approach to scientific inquiry, enabling consistent advancements in knowledge and understanding.

Empirical research, which has its origins in ancient Greek practice, is a research approach rooted in observation and experimentation, offering a practical way to understand complex phenomena. Distinguished by its reliance on evidence and factual data, empirical research aims to provide verifiable insights into how the world functions, making it a critical tool in modern science and various academic fields. Its methodology can be qualitative—utilizing interviews, case studies, and focus groups to explore themes and experiences—or quantitative, relying on surveys, experiments, and statistical analyses to generate measurable findings. Together, these approaches make empirical research versatile and valuable across disciplines, as it supports hypothesis validation, enhances knowledge, and contributes to theory building.

One of the key strengths of empirical research is its focus on validating existing theories and frameworks through rigorous testing. This method enhances the internal validity of findings by allowing researchers significant control over variables, enabling them to identify and understand gradual changes in the phenomena under study. Because it is based on factual evidence, empirical research is highly authentic, providing dependable data for critical applications, from healthcare advancements to technological innovations. However, the process of gathering such evidence can be challenging; empirical research is often time-consuming, especially in longitudinal studies, and obtaining permission to study sensitive subjects can be difficult. Additionally, interpreting statistical data demands caution, as even experienced researchers can sometimes misinterpret significance levels, leading to potential inaccuracies in findings.

Ethical considerations are integral to empirical research, given its emphasis on human subjects and data-driven results. Researchers are expected to adhere to ethical principles such as informed consent, confidentiality, avoidance of harm, and transparency, ensuring participants' rights are respected and the research's credibility is upheld. Ethical safeguards, such as anonymizing personal data and allowing participants the right to withdraw from studies, are foundational practices that uphold integrity while protecting individual privacy and well-being.

Empirical research's applications are extensive and impactful, ranging from information technology, occupational health, and environmental science to economics, genetics, and infectious disease control. Its methods are also widely used in academic research, notably in theses and dissertations across disciplines like artificial intelligence, urban planning, and marketing. This broad relevance underscores empirical research's role in addressing real-world challenges, from developing medical treatments for new diseases to creating effective environmental policies.

Empirical research is indispensable in modern society. Its structured cycle—comprising observation, hypothesis generation, testing, and evaluation—ensures systematic knowledge-building. By providing a framework for generating accurate, evidence-based knowledge, empirical research enables society to confront complex issues, validate scientific progress, and improve quality of life.

Empirical analysis is an evidence-based approach to research, focusing on information gathered through direct observation or experience. This method is central to scientific research and requires tangible, observable data to substantiate theories. Unlike theoretical approaches that rely on logical deduction, empirical analysis emphasizes collecting verifiable data and testing hypotheses through observable results. This type of research often employs statistical analysis to provide robust support for claims. The term "empirical" is rooted in the Greek word *empeiria*, which means "experience," reflecting its reliance on real-world data.

Empirical analysis is closely tied to the scientific method, involving a cycle that begins with observation and progresses through induction, deduction, testing, and evaluation. This cycle, established by researcher De Groot (1969) ensures a structured and repeatable process. During the observation phase, researchers note phenomena and form initial ideas. In the induction phase, they develop probable explanations or theories based on observed data. Deductive reasoning then leads to testable hypotheses. Testing involves data collection through quantitative and qualitative methods, and results are analyzed to see if they support or refute the hypothesis. Finally, the evaluation

phase synthesizes findings, discussing methodology, limitations, and future research avenues. Empiricism contrasts with rationalism, which seeks truth through logical reasoning without needing observable evidence. While rational approaches develop ideas through logical sequences, empirical approaches validate ideas through data. Both approaches, when used together, produce comprehensive insights that are both logically sound and supported by reality. Empirical analysis can incorporate quantitative methods—focused on measurable, numerical data—and qualitative methods, which capture insights on thoughts, behaviors, and perceptions. The two approaches complement each other, providing both measurable data and deeper understanding.

In information technology and business, empirical analysis plays a crucial role in improving decision-making by uncovering patterns within complex systems and human behavior. Data analytics, for instance, is an empirical process that mines vast datasets for actionable insights, whether related to customer behavior or operational efficiencies. A/B testing, another empirical method, assesses user interaction by presenting different versions of a product to different groups to see which performs better based on metrics like click-through rates. These methods reduce uncertainty and guide more informed choices in IT and business, making empirical analysis an invaluable tool for data-driven fields.

6. Transformations of the Global Economy: Artificial Intelligence (AI) Diversifying Developing Economies

The rapid advance of artificial intelligence (AI) is set to reshape the global economy, bringing both promising opportunities and significant risks (Akhtar, 2024; Akhtar, 2024a, 2024b, 2024c, 2024d; Behrendt et al., 2020; Fang et al., 2022; Konieczny, 2023; McDowell & Vetter, 2023; Qin et al., 2024; Tekale, 2024; Yu et al., 2023). With AI predicted to impact nearly 40% of jobs worldwide, its effects could range from enhancing productivity and boosting global income to replacing jobs and exacerbating inequalities. The net impact is complex and uncertain, requiring a balanced approach from policymakers to harness AI's potential for the betterment of humanity.

AI's impact on labor markets is especially noteworthy, affecting both advanced and emerging economies, though with different intensities. In high-income countries, approximately 60% of jobs may feel AI's influence, with some benefiting from increased productivity as AI augments human tasks.

However, for other roles, AI may perform key job functions, potentially reducing hiring and wage growth. In emerging and low-income nations, AI's effect will be slightly more limited at 40% and 26%, respectively, though these regions face challenges due to limited digital infrastructure and a shortage of skilled workers, which may impede their ability to capitalize on AI advancements. This disparity could further widen economic divides between nations.

Within countries, AI may contribute to rising income inequality. Workers who can effectively leverage AI may experience increased productivity and wages, while those unable to do so may face declining incomes, creating a widening income gap. The potential of AI to complement the skills of high-income earners could drive further gains for this group, while AI-driven productivity boosts for firms may favor high earners through increased capital returns. These trends suggest that, without intervention, AI could deepen socioeconomic divides.

To address these risks, policymakers must act to make the transition to an AI-driven economy more inclusive. Establishing social safety nets and retraining programs is essential to protect vulnerable workers, helping them adapt to new roles in an AI-enhanced landscape. The International Monetary Fund (IMF) has developed an AI Preparedness Index to assist countries in crafting appropriate policies, evaluating readiness in digital infrastructure, human capital, labor market resilience, and regulatory strength. According to the index, advanced economies, such as Singapore, the United States, and Denmark, are better prepared for AI integration than lower-income countries, though gaps remain even among wealthier nations.

In response, advanced economies should focus on furthering AI innovation and developing comprehensive regulatory frameworks to ensure safe and ethical AI usage. Meanwhile, emerging markets must prioritize investments in digital infrastructure and workforce skills to create an AI-ready environment.

By taking these steps, countries can help ensure that AI benefits are more broadly distributed, fostering a prosperous and inclusive AI era for all. Artificial intelligence (AI), as a transformative general-purpose technology, holds immense potential to aid developing economies in achieving economic diversification.

Much like electricity, AI's broad range of applications—from early-stage disease detection to investment planning—redefines the scope of human work, presenting new opportunities for developing nations to enhance their economic resilience and expand their comparative advantages. For many of these economies, diversification beyond a narrow range of exports can create more stable growth paths, providing a buffer against economic shocks similar to how diversified investment portfolios reduce financial risk.

A recent study, *AI Specialization for Pathways of Economic Diversification*, explores how developing countries can leverage AI to foster growth in diverse sectors. By analyzing private investments in AI across 29 specialized categories—such as autonomous vehicles, agri-tech, and robotics—the study constructs a network that links AI specializations with each country's unique comparative advantages in goods and services.

The research introduces the "*product space*" concept, mapping out sectors where countries can potentially excel with AI support. For example, robot automation in AI shows strong connections with manufacturing industries like machinery, metal products, and chemicals, while image recognition AI aligns well with sectors like food processing and e-commerce. The findings suggest tailored strategies for countries to integrate AI into their economic plans. For instance, Mexico could benefit from investments in robot automation to strengthen its metal fabrication sector, while advancements in FinTech could boost its travel services sector. In India, investments in AI-driven agricultural technology could enhance productivity for its farmers, helping the country leverage AI to support critical domestic sectors.

Moreover, the global AI landscape makes it feasible for AI-driven solutions to be designed in one location and deployed globally. An example of this is KUKA Robotics, a German company whose AI-powered industrial robots are used in diverse industries around the world, such as automotive and electronics. The company's use of AI to optimize various stages of production, from manufacturing to recycling, illustrates how AI could underpin economic participation in global value chains. As AI-based services continue to expand, the wealth of nations may increasingly depend on their ability to integrate AI across diverse industries, enabling sustainable and inclusive economic growth.

7. Case Studies Analysis: Impacts of AI in Terms of Economic Development

Artificial intelligence (AI) has become a prevalent part of modern life, shaping both societal optimism and concerns (Aghion et al., 2016; Aghion et al., 2017; Agrawal et al., 2019; Akhtar, 2024a, 2024b, 2024c; Baldwin, 2019; Behrendt et al., 2020; Fang et al., 2022; Konieczny, 2023; McDowell & Vetter, 2023; Misuraca et al., 2020; Nguyen & Doytch, 2022; Qin et al., 2024; Rogerson et al., 2022; Sachs, 2023; Tekale, 2024; Trabelsi, 2024; Yang, 2022; Yu et al., 2023; Zhao et al., 2022). Many see AI as a source of hope, with the potential to boost productivity, drive economic growth, and enhance risk management across industries. However, there are significant fears regarding the disruption AI may cause, including job displacement, required skill retraining, and the exacerbation of digital divides (Bostrom, 2017; Mateu & Pluchart, 2019). A Ipsos (2021) study of 19,504 respondents across 28 countries highlights the anticipated impact of AI on multiple sectors, including education, security, employment, and transport, with each expected to experience considerable changes due to AI in the coming years.

Historically, AI is viewed as part of the "3rd transformation of economic history," following the 19th-century industrial revolution and the 20th-century computing era (Baldwin, 2019). Research by Joseph (1998); Hemous and Olsen (2014); Acemoglu and Pascual (2018) and Aghion et al. (2017) underscores the potential of AI to drive economic growth by substituting labor with capital, which is theoretically limitless. However, these gains could be hindered if competition policies do not evolve in tandem with AI's development. In a Sachs (2023) report, AI is estimated to affect up to 300 million jobs worldwide, automating about 25% of the global labor market, with particularly high impacts expected in administrative, legal, and engineering roles. The report suggests that the adoption of AI could increase labor productivity and potentially raise the global GDP by 7% annually over a decade. While AI is driving technological and organizational advances, it also faces a "crisis of confidence." Its models and algorithms are often perceived as opaque "black boxes" that lack transparency and robustness. However, new approaches based on principles of collective intelligence are emerging to address these concerns and foster greater trust in AI systems (Jean-Claude, 2018). As AI continues to evolve, it promises both remarkable benefits and complex challenges that require careful consideration and balanced policies to optimize its societal impact. Concerning the case studies investigations which provides a very structured analysis of the socio-economic impacts of AI as detailed towards economy. This also captures the multifaceted impact of AI on the economy, skills, technology, risk management, consumption, and sustainability, highlighting both opportunities and challenges as AI transforms modern socio-economic structures. AI has the potential to significantly enhance human decision-making by offering advanced analytics and predictive insights, enabling businesses and governments to make more informed decisions. By reducing the cost of predictive activities, AI can optimize resource allocation, manage risks, and strengthen competitiveness across sectors like healthcare, energy, and retail (Akhtar, 2024a, 2024b, 2024c; Tekale, 2024).

The concept of an "AI economy" relies on both prospective and predictive perspectives. Prospective AI, focused on real-time responses, is useful for immediate decision-making scenarios, while predictive AI leverages historical data to anticipate future trends, aiding in long-term planning and strategic foresight. The two approaches are complementary. Predictive insights help guide prospective actions, while real-time data from prospective AI can refine predictive models, improving accuracy. However, predictive AI faces challenges due to biases in algorithms, especially in fields like predictive justice and marketing, raising concerns about the validity of such predictions. Increased scrutiny from institutions aims to address these limitations to ensure algorithmic fairness and accuracy.

Globally, AI's integration into public services accelerated during the COVID-19 pandemic, yet a divide remains between developed and developing nations. The AI Readiness Index highlights this disparity, ranking countries based on their AI preparedness in government, technology, and data infrastructure. Leading countries like the USA, Singapore, and the UK excel in areas such as AI strategy, digital capacity, and data governance, while emerging technologies and infrastructure development play a significant role in driving AI capabilities. Deploying AI in public services could enhance efficiency and quality, but it requires equipping government employees with the necessary skills and knowledge. Governments must invest in training and hiring AI experts and, simultaneously, be prepared for citizens' demands for transparency, accountability, and ethical use of AI. Civil society organizations advocate for public participation, independent audits, and regulatory frameworks to safeguard citizens' interests and mitigate potential job displacement. By addressing these societal concerns, governments can foster trust, ensuring that AI benefits public service delivery responsibly and equitably. AI is widely regarded as a powerful driver of productivity and economic growth, enhancing efficiency and decision-making by processing vast amounts of data. It holds the potential to generate new products, services, and industries, thereby increasing consumer demand and opening new revenue streams. However, AI's influence may also disrupt economies and societies, creating super firms with potentially adverse effects on the broader economy and widening disparities between developed and developing nations. Ethical and societal concerns, such as biases and inequalities in automated systems, have sparked debates over AI's implications, especially regarding tools like ChatGPT. The economic value of AI primarily stems from productivity gains, improved consumption, and better risk management. Yet, the impact of AI varies across sectors and regions, influenced by factors such as digital infrastructure, AI skills, and access to technology (Akhtar, 2024; Akhtar, 2024a, 2024b, 2024c; Tekale, 2024). Ensuring inclusive and ethical AI use is essential for maximizing its positive impact on economic growth. Research shows that while advanced economies benefit significantly from technology and patents, emerging economies experience a less pronounced effect, indicating an uneven distribution of AI-driven growth. To harness AI responsibly, governments should work closely with academia, industry experts, and other stakeholders (Akhtar, 2024; Akhtar, 2024a, 2024b, 2024c; Behrendt et al., 2020; Fang et al., 2022; Konieczny, 2023; McDowell & Vetter, 2023; Qin et al., 2024; Rogerson et al., 2022; Tekale, 2024; Trabelsi, 2024; Yang, 2022; Yu et al., 2023; Zhao et al., 2022). Public-private partnerships can expedite AI advancements while aligning them with public interest. Once deployed, AI systems require ongoing monitoring and evaluation to address potential biases and mitigate negative societal impacts. Regular assessments enable adjustments that help optimize AI's benefits and minimize its potential risks, ultimately fostering a balanced approach that benefits society as a whole. For further information concerning the matters Table 1 and 2 along with Figures 2 and 3 provides an overview retrospective.

AI's impact on jobs

Most jobs are exposed to AI in advanced economies, with smaller shares in emerging markets and low-income countries.

Employment shares by AI exposure and complementarity

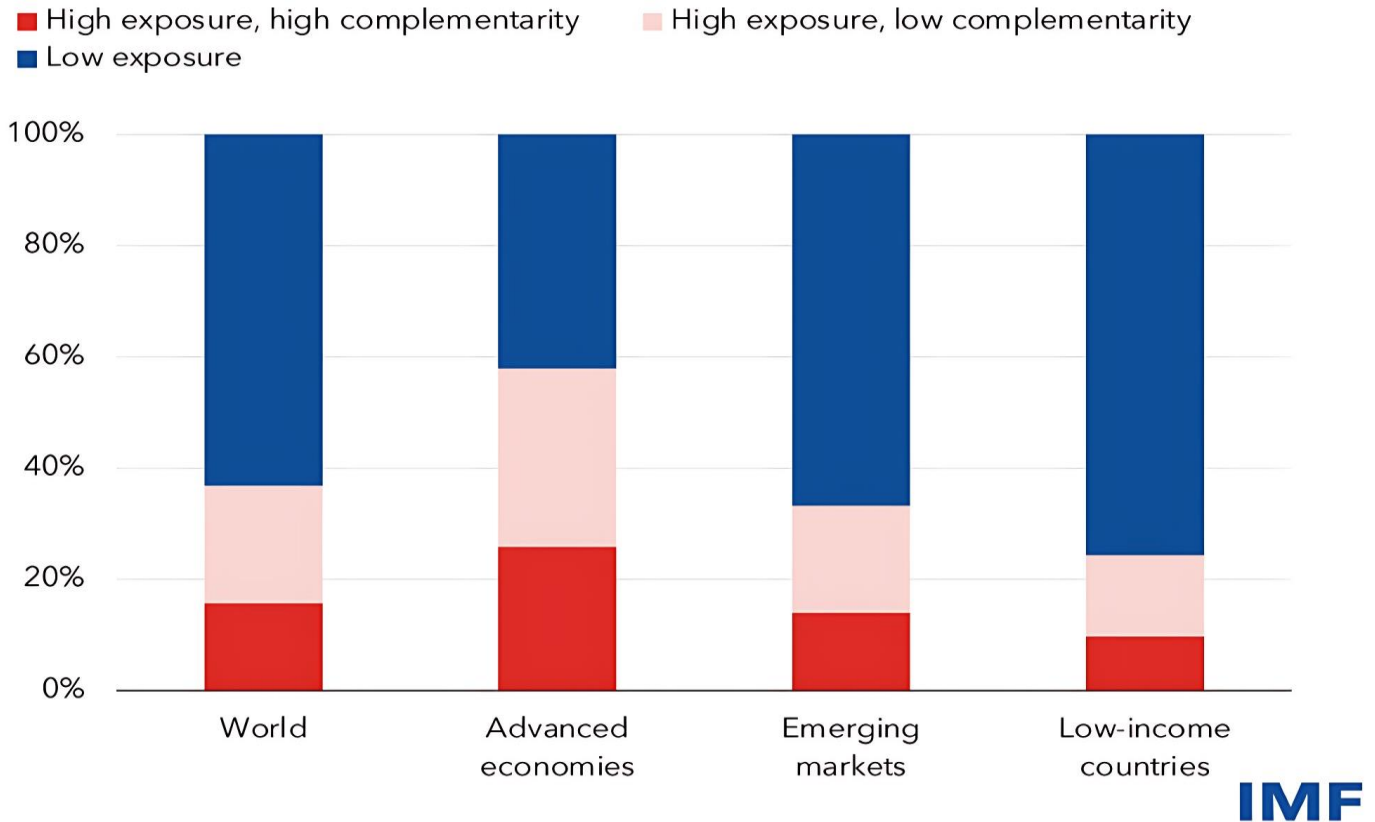


Figure 2. IMF reports 1.

Note: Share of employment within each country group is calculated as the working-age-population-weighted average.

Source: International labour organization (ILO) and IMF staff calculations

Advanced-economy advantage

Wealthier countries often are better equipped for AI adoption.

AI preparedness index and employment share in high-exposure occupations

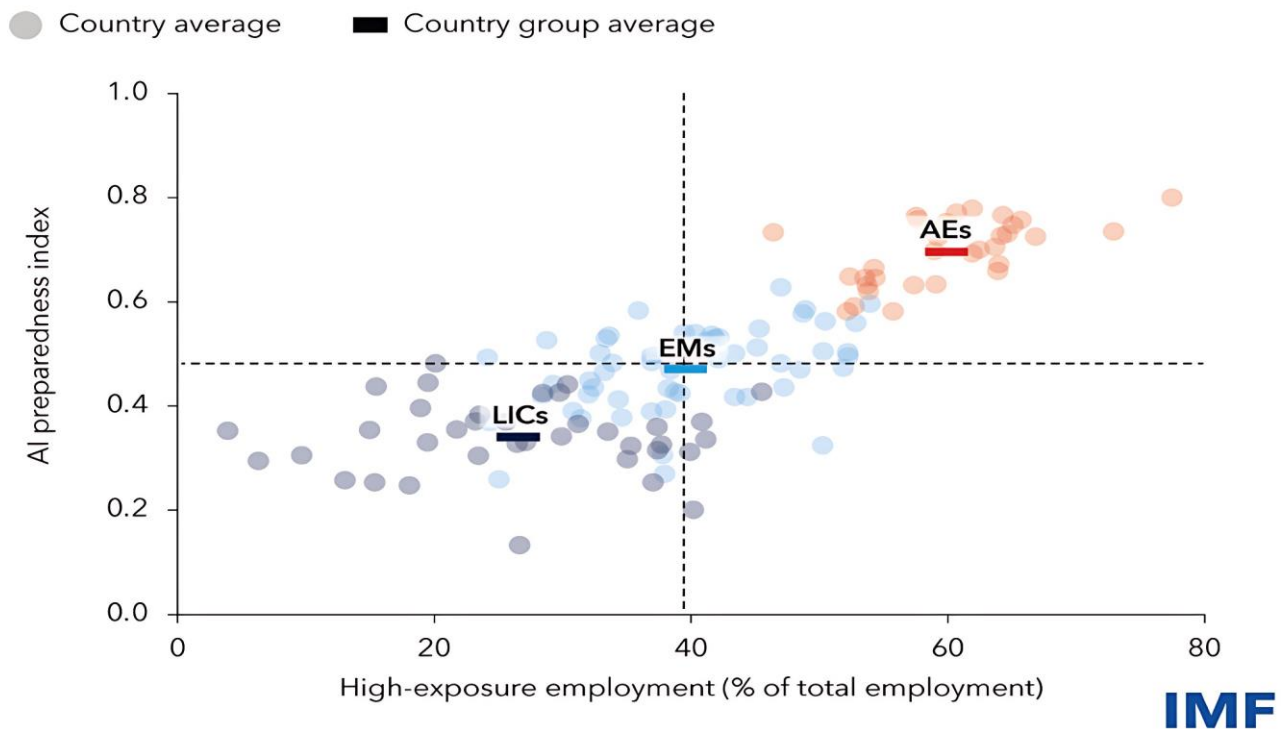


Figure 3. IMF reports 2.

Note: Plot reflects 32 advanced economies, 56 emerging markets economies, and 37 low-income countries. Dotted reference lines are derived from AI preparedness index median values and high-exposure employment.

Color coding

Orange: Represents countries classified as advanced economies (AEs).

Blue: Represents countries classified as emerging market economies (EMEs).

Source: Fraser institute, ILO, international telecommunication union, united nation, universal postal union, world bank, world economic forum, and IMF staff calculations.

Table 1. The top 10 countries who have invested towards AI.

Countries	United States	China	Great Britain	Israel	Canada	India	Germany	France	South Korea	Singapore
Amount invested (Billions of dollars) 2013–2023	248.9	95.1	18.2	10.8	8.8	7.7	7.0	6.6	5.6	4.7

Table 2. The top 20 countries for artificial intelligence (AI) readiness index.

Global position	Countries/Regions	Overall score	Government	Technology sector	Data and infrastructure
1	United States of America	88.16	88.46	83.31	92.71
2	Singapore	82.46	94.88	66.69	85.80
3	United Kingdom	81.25	85.69	67.26	90.81
4	Finland	79.23	88.45	63.85	85.40
5	Netherlands	78.51	80.42	66.17	88.92
6	Sweden	78.16	80.76	67.37	86.36
7	Canada	77.73	84.36	63.75	85.08
8	Germany	77.26	78.04	67.68	86.07
9	Denmark	76.96	83.50	63.24	84.14
10	Republic of Korea	76.55	85.27	58.49	85.89
11	France	76.41	82.10	60.61	86.53
12	Japan	76.18	81.90	59.31	87.32
13	Norway	76.14	84.24	59.25	84.91
14	Australia	75.41	83.79	57.07	85.37
15	China	74.42	83.79	61.33	78.15
16	Luxembourg	73.37	82.67	50.66	86.80
17	Ireland	72.80	74.70	61.11	82.59
18	Taiwan, China	71.98	77.59	59.42	78.92
19	United Arab Emirates	71.60	79.41	53.33	82.05
20	Israel	70.01	64.64	65.87	79.52

8. Results and Findings

This investigative exploration provides an insightful and comprehensive exploration into the intersection of artificial intelligence (AI) and economic theory, framing AI's recent surge as a force poised to redefine traditional economic models. The narrative begins by contextualizing the societal and economic impact of the "rise of AI" through its influence across various sectors, paralleling the transformative effect of the Information Age. This sets the stage for a hypothesis that AI could significantly shift how economic theory is both perceived and applied (Akhtar, 2024; Akhtar, 2024a, 2024b, 2024c; Tekale, 2024). One of the primary objectives delineated within the analysis is to highlight specific domains within economic theory that are experiencing changes due to AI advancements. The exploration dives into techniques from AI that researchers are applying to economics, such as machine learning models for predictive analysis and agent-based simulations for complex market dynamics. Additionally, the analysis aimed to trace academic available knowledge on AI's role in economics, offering a curated, though not exhaustive, overview of significant contributions. The historical background situates the discussion within the evolution of economic thought, tracing the foundational market theories from Adam Smith to the neo-classical refinements of the Industrial Revolution. By presenting the Arrow-Debreu model, the article bridges classical economics with computational frameworks, showcasing how economic equilibria can be formalized through mathematical models and algorithms. This model, widely influential in general equilibrium theory, serves as a conceptual foundation for the broader computational economy. The available knowledge exploration spans early applications of AI in economic models, discussing how concepts like artificial adaptive agents, market design, and multi-agent systems started influencing economic simulations in the 1990s. The focus on agent-based computational economics underscores the shift from single-agent models in traditional AI research to multi-agent interactions that reflect real-world economic systems. These investigations make a compelling case for AI's transformative role in economics, positioning this interdisciplinary convergence as a dynamic field with evolving methodologies and insights. The overall research background—acknowledging some limited formal economics training—adds transparency and frames the investigation as an exploratory study rather than an authoritative economic analysis, enhancing its relevance for readers interested in the broader implications of AI across disciplines. The overview highlights emerging computational methods and stimulates further inquiry into how AI can continue to shape economic theory and practice. Agent-based Computational Economics (ACE) and Artificial Economics provide computational frameworks that enable economists to study the complex dynamics of economic systems in a controlled environment using computer simulations. By modeling economies with interacting agents, researchers can capture the heterogeneous and adaptive nature of real-world economic participants.

8.1. Key Properties of ACE

ACE focuses on five essential characteristics that align well with economic systems.

1. Heterogeneous Agents: Agents are diverse, each with unique states, methods, and data.
2. Dynamic Interactions: Systems evolve as agents interact over time.
3. Strategic Decision-Making: Agents make decisions by considering the past and anticipating future actions.
4. Local Information Processing: Agent's act based on their localized information, rather than global awareness.
5. Reflexive System Influence: Actions of agents affect future states of the system.

This approach also involves many other aspects.

1. Model Setup: Define a population of agents with diverse characteristics.
2. Behavioral Rules: Establish rules that guide agent behavior.
3. Implementation: Translate these rules into code.
4. Validation: Run simulations, calibrate parameters, and compare results with empirical data.

8.2. Agent Representation and Rationality in ACE

A critical consideration in ACE is how to model economic agents. Traditional models often assume rational, utility-maximizing behavior, yet behavioral economics suggests that bounded rationality—where agents have limitations in processing information—may better represent human decision-making. Therefore, ACE models frequently incorporate boundedly rational agents to explore more realistic economic interactions.

8.3. Artificial Economics

Artificial Economics adopts a bottom-up approach, allowing for an explicit representation of agent individuality and interaction. This generative modeling method addresses limitations of classical economics, such as the need for representative agents, by instead representing agents with distinct and evolving characteristics.

The use of machine learning within artificial economics provides new methods for prediction and causal inference, where agents can learn from data, making forecasts based on historical patterns. For a better understanding concerning the matters Table 3 provides further information.

Table 3. Classical vs artificial economics features.

Classical economics features	Artificial economics features
Representative agents	Individual agents with unique attributes
Rationality	Adaptive, learning-based behaviors
Perfect information	Local and asymmetric information
Focus on equilibrium	Emphasis on dynamic, out-of-equilibrium behavior
Determinism	Incorporation of stochastic elements
Top-down analysis	Bottom-up synthesis through agent interactions

8.4. Prediction Markets in ACE and AI

Prediction markets enable agents to trade on the outcome of future events, with market prices reflecting collective beliefs. These markets serve as both a forecasting tool and a mechanism for distributed machine learning.

In such systems, agents can optimize their utility by buying and selling positions based on their beliefs, leading to a probabilistic aggregation of predictions. This approach aligns with ensemble learning methods in AI, where multiple models (agents) are combined to improve prediction accuracy.

8.5. Market-Based Control

In market-based control (MBC), the principles of market dynamics are applied to control systems. Here, economic agents represent various control processes that "trade" resources (e.g., energy, computational power) in a market-like environment to achieve optimized collective behavior. This approach provides flexibility, decentralization, and robustness, which can be advantageous in complex systems requiring adaptive, autonomous decision-making.

ACE and Artificial Economics utilize agent-based modeling and computational simulations to provide richer, more realistic insights into economic phenomena. These fields, combined with AI tools like machine learning, have potential applications in understanding economic systems, improving policy design, and creating adaptive market models that evolve over time based on agent interactions.

The exploration of economic problems through probabilistic models and knowledge representation, a technique that is rooted in probabilistic reasoning under uncertainty, has yet to gain extensive application in economic domains. This approach, exemplified by IBM's Watson system, utilizes a structured ontology—a system that organizes knowledge into objects, properties, and their interrelations. By implementing a medical ontology, Watson was able to process complex and diverse health data, providing diagnostic insights and treatment predictions for patients.

A similar approach holds potential for economic applications where structured data systems could allow AI to analyze vast amounts of financial and social data, leading to more comprehensive economic insights. The potential of probabilistic reasoning and knowledge representation in economic settings is underscored by Dr. David Ferrucci's move to Bridgewater Associates, suggesting active interest in applying such systems in finance.

An examination of the existing available knowledge shows that, while the concept of "ontology" in economics predominantly arises in the field of Philosophy of Economics, it has recently begun to appear in computer science applications. For instance, ontologies have been suggested as models to define fundamental economic entities like goods, money, and value, while other researchers have proposed an ontology for business models. However, skepticism remains around the practicality of using ontologies for modeling complex economic systems, mainly due to concerns about the limitations of language and symbolic representation.

Critics argue that language inherently shapes our perceptions and thought processes, as captured by the Sapir-Whorf hypothesis, suggesting that computer languages may face similar challenges in encapsulating economic realities.

The transition into what some describe as the "Data Age" presents a new phase where data acts as a precursor to knowledge, empowering decision-making across government, business, and personal spheres. The abundance of data generated through individual digital interactions holds transformative potential for economic decision-making and public policy, as the social data revolution provides vast datasets for analysis. As the knowledge economy grows, data-driven insights could reshape business models and social policies, offering new ways to address complex economic issues. For instance, large-scale datasets enable more precise policy-making and economic modeling, but raise questions regarding data privacy and regulation, which future economic models must address to balance utility and privacy.

The historical significance of information in economic theory can be traced to Friedrich von Hayek's seminal work, where he argued that the distributed nature of knowledge limits the feasibility of centralized economic planning. His view laid the groundwork for understanding the economic role of information and the complexities of centralized versus decentralized planning. More recent perspectives, however, suggest that advances in AI and data aggregation could transform these traditional limitations. For example, with enhanced AI tools and reduced data search costs, there may be potential for AI-assisted economic planning. This shift could enable AI to assist or even

partially perform economic planning roles, although such a transition would likely face significant public concern due to fears of excessive AI control over economic and social systems.

Finally, the evolution of AI and its application in economic systems brings to light the ethical implications and public apprehensions surrounding AI autonomy. Experts, including Sir Tim Berners-Lee, highlight the risks of unchecked AI decision-making in areas like finance, where AI systems may autonomously shape markets, potentially creating a layer of economic activity that operates beyond human accountability. While concerns over the singularity and AI autonomy are widespread, current AI research and applications focus largely on more immediate, practical improvements. Consequently, the debate remains open, with a pressing need for clear regulatory frameworks that prioritize human oversight, particularly as AI applications in economics and other societal sectors continue to expand. For a better overview on the matter's [Figures 4, 5, 6 and 7](#) provides an overall visualization of the findings concerning the investigations.

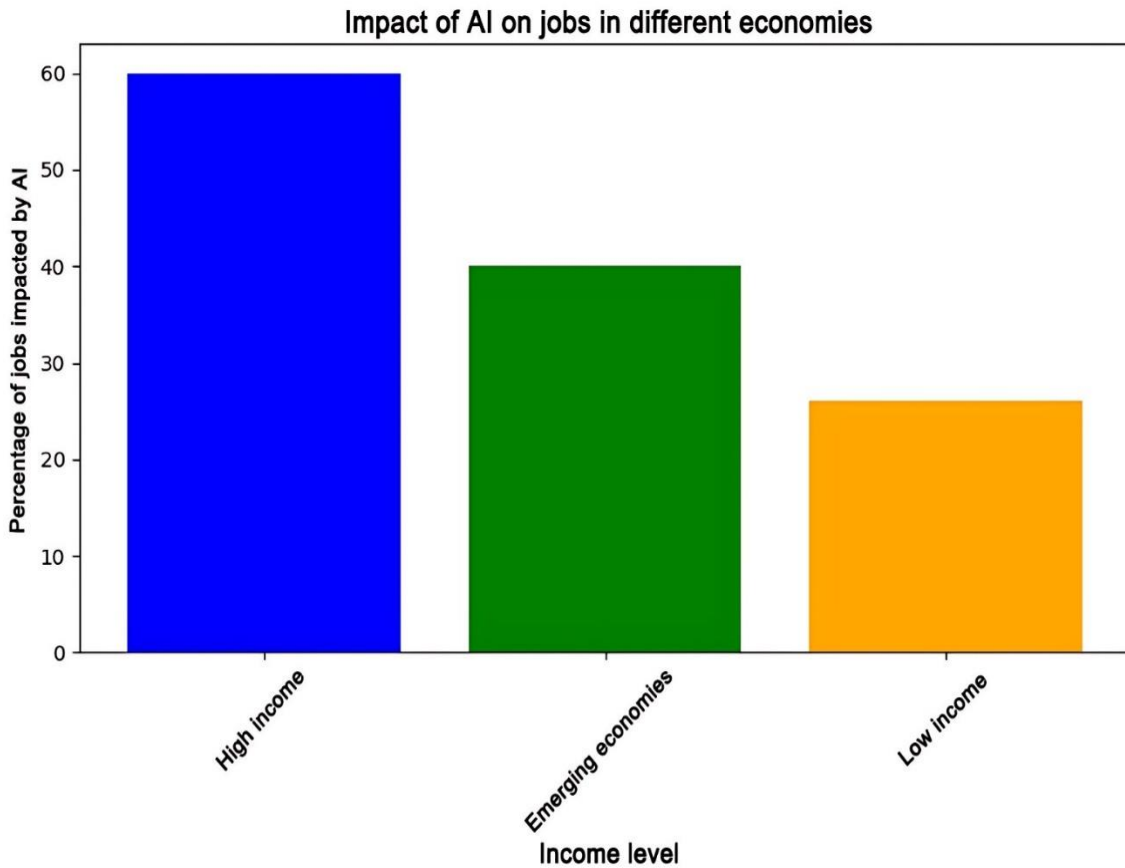


Figure 4. An overview visualization of the research findings 1.

Note: Color coding
 Blue: Represents high income economies
 Green: Represents emerging economies
 Orange: Represents low-income economies

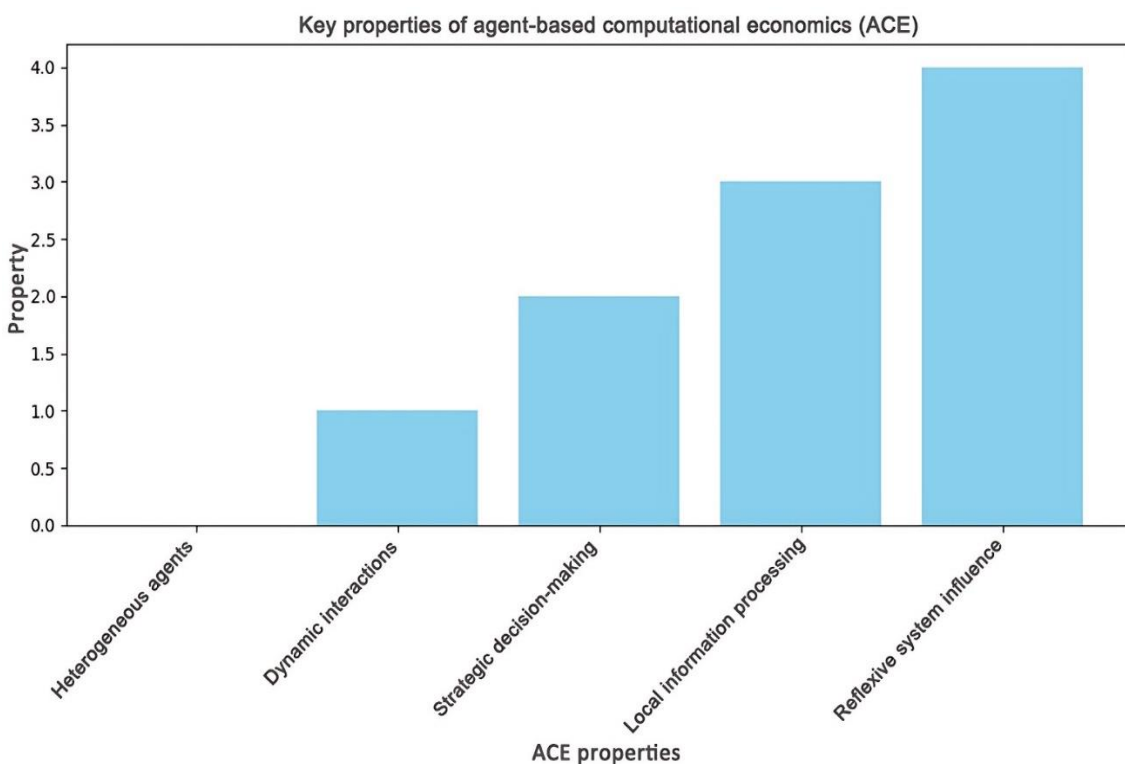


Figure 5. An overview visualization of the research findings 2.

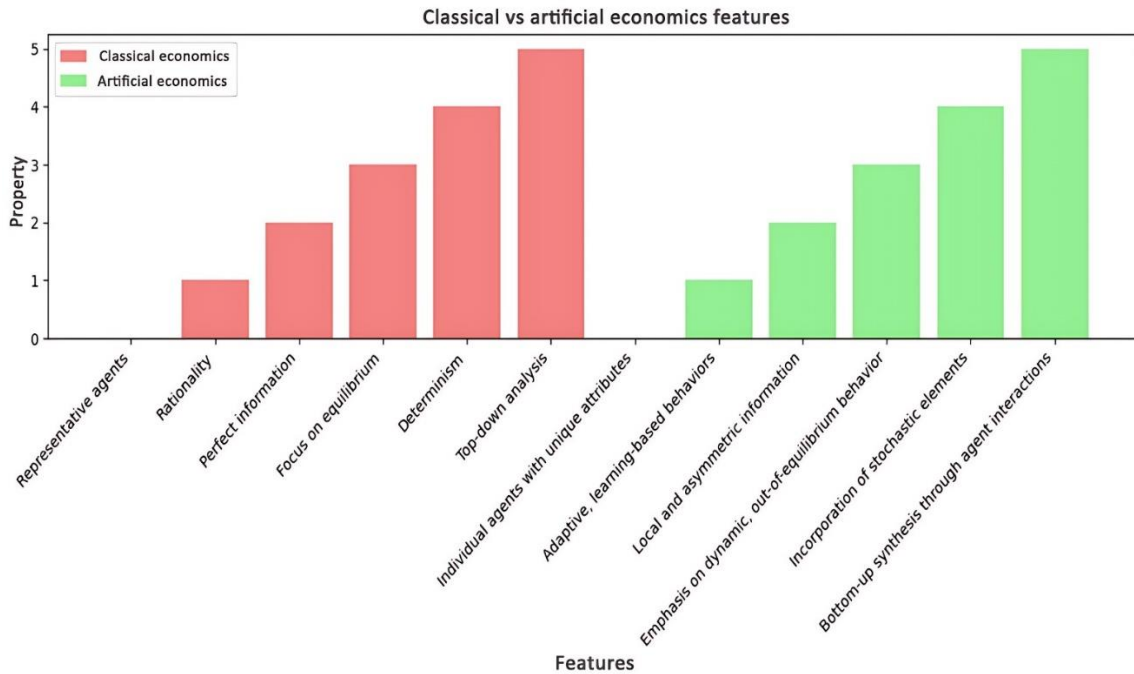


Figure 6. An overview visualization of the research findings 3.

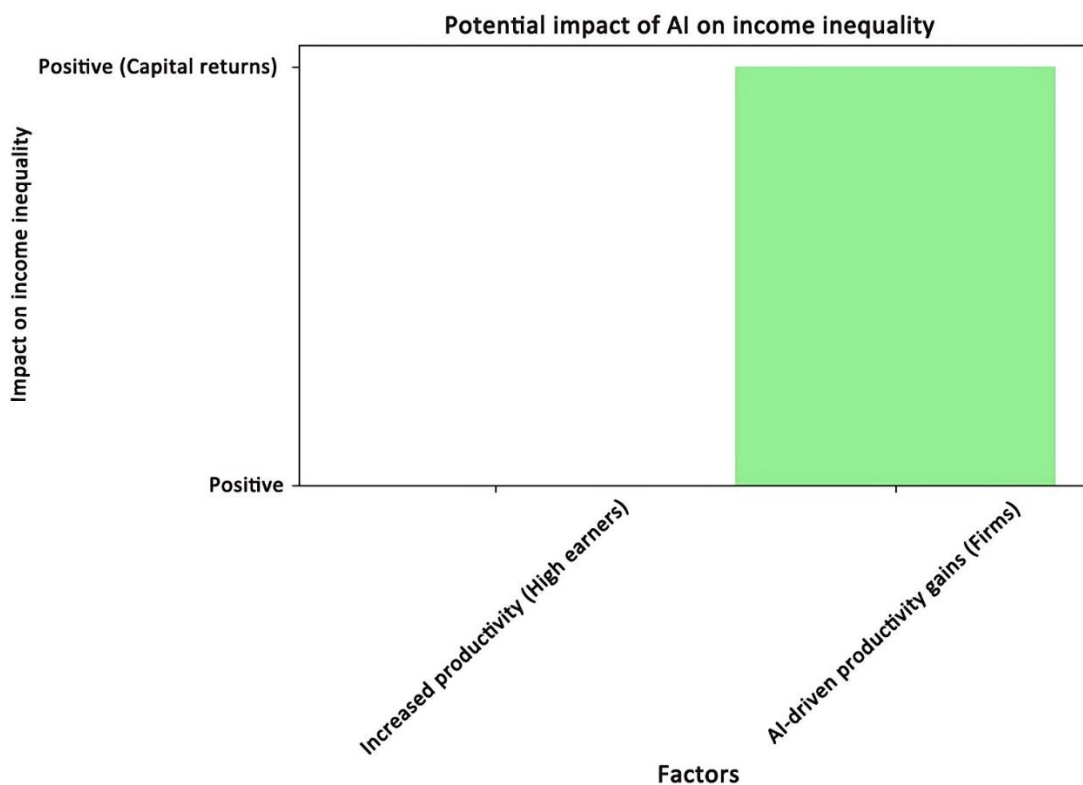


Figure 7. An overview visualization of the research findings 4.

9. Discussions

The analysis reveals a profound economic impact from the accelerated adoption of Artificial Intelligence (AI) across various industries, each of which is characterized by both beneficial advancements and notable challenges. From a macroeconomic standpoint, AI has shown significant potential to drive productivity and economic growth. The findings suggest that AI-enabled automation has led to substantial efficiency gains in sectors such as manufacturing, logistics, and finance. However, this automation also raises concerns about potential displacement of labor, as repetitive and routine tasks become increasingly automated, reshaping workforce dynamics and potentially widening economic inequalities.

One of the most immediate impacts of AI adoption is observed in productivity metrics. Industries that have implemented AI technologies report marked improvements in output efficiency and operational costs. This aligns with empirical data showing a positive correlation between AI adoption and productivity at both firm and industry levels.

However, while productivity increases, the distribution of economic benefits remains uneven. High-skill, high-tech industries are more likely to see gains in productivity and economic output, while industries reliant on lower-skilled labor may face challenges in integrating AI without displacing workers. This disparity highlights a critical need for skill-based workforce development programs and policies aimed at reskilling and upskilling workers to thrive in an AI-enhanced economy.

The empirical analysis of labor markets also reveals an emerging trend in job polarization, where demand for high-skilled roles, such as data scientists and machine learning engineers, is rising, while demand for certain low- and medium-skilled roles declines.

Although AI technology is creating new opportunities and occupations, it is also reshaping traditional jobs, requiring workers to acquire new skill sets. This shift suggests a dual impact on the labor market: on one hand, AI can elevate job quality and create highly skilled positions; on the other hand, it risks deepening existing inequalities if sufficient measures for reskilling the workforce are not adopted. Furthermore, the rise in gig economy roles

associated with AI, such as data labeling and freelance programming, introduces new employment structures that may lack the security and benefits of traditional employment, raising additional socio-economic considerations.

The industry case studies in this analysis illustrate sector-specific dynamics that contribute to a nuanced understanding of AI's economic impact. For example, in healthcare, AI has driven significant advancements in diagnostic accuracy and patient care management, which has led to both cost savings and improved patient outcomes.

However, the integration of AI in healthcare is limited by regulatory and ethical concerns, particularly in data-sensitive environments. Conversely, in the manufacturing sector, AI has facilitated a faster transition to smart factories and autonomous production lines, but these advancements often come at the cost of reduced demand for assembly-line labor. These case studies underscore the importance of industry-specific strategies and policies to support balanced AI adoption that optimizes benefits while mitigating potential harms. The policy analysis suggests that regulatory frameworks are lagging behind the rapid advancements of AI technologies. Currently, policies regarding AI focus primarily on ethical considerations, privacy, and data protection, but less so on economic implications such as job displacement and wage dynamics. The comparison of policy approaches in the United States, European Union, and China reveals distinct strategies. For instance, the European Union has taken a proactive stance on regulating AI with its Artificial Intelligence Act, which places stricter compliance requirements on high-risk AI applications.

In contrast, the United States has adopted a more innovation-friendly approach, favoring minimal regulation to encourage technological growth. Meanwhile, China's approach centers on rapid AI deployment with a focus on economic dominance, albeit with significant state oversight. These different approaches reflect varying national priorities but also highlight the need for a balanced policy framework that both safeguards societal interests and encourages economic growth.

Moreover, this study identifies gaps in the current available knowledge on AI's economic impact, particularly in understanding the long-term effects of AI on wealth distribution and global economic inequalities. While research has largely focused on developed economies, there is a need for deeper investigations into how AI adoption will affect emerging economies. The current economic frameworks used to assess AI's impact may require modifications to account for the technology's rapid evolution, as traditional economic models may not fully capture AI's disruptive potential.

The discussions here underscore the transformative yet complex role of AI in reshaping the economic landscape. The findings highlight AI's capacity to generate substantial economic benefits while also posing challenges related to labor market shifts, industry disruptions, and regulatory adaptation. Policymakers, industry leaders, and educational institutions must work collaboratively to address these challenges, implementing strategies that not only facilitate AI innovation but also foster inclusivity, resilience, and adaptability in the workforce.

This research underscores the importance of an empirical, evidence-based approach to guide responsible AI integration and lays the groundwork for future studies on sustainable AI-driven economic growth.

10. Conclusions

The findings of this research underscore the transformative potential of Artificial Intelligence (AI) within the global economy, highlighting both its substantial benefits and associated challenges. AI's adoption across various industries has spurred significant gains in productivity, operational efficiency, and innovation, illustrating its critical role in driving economic growth and advancing technological capabilities. However, these advancements come with complex socio-economic implications, particularly in the labor market, where the automation of routine tasks poses risks of job displacement and demands new skill requirements. This dual effect, where AI both creates new opportunities and redefines traditional roles, necessitates proactive strategies for workforce development, including targeted reskilling and upskilling programs that equip workers for a changing economy.

A key insight from this study is the uneven distribution of AI's economic impacts, with high-skill sectors and advanced economies experiencing the most substantial gains. As AI continues to reshape industries, it is evident that a well-coordinated response from policymakers, industry leaders, and educational institutions is essential to ensure that the benefits of AI are inclusive and accessible. Developing countries, which often lack the resources for large-scale AI integration, may face challenges in catching up with advanced economies, potentially widening global inequalities.

This reinforces the importance of international cooperation and investment in AI infrastructure and education to promote equitable growth in the AI era. The policy analysis further reveals varying regulatory approaches to AI, reflecting differing national priorities and strategies for balancing innovation with ethical and economic considerations.

For example, the European Union's regulatory framework emphasizes ethical AI deployment with a focus on human rights and data protection, whereas the United States prioritizes innovation with a comparatively minimal regulatory approach. China, meanwhile, seeks economic dominance through rapid AI adoption, often with considerable state oversight.

These contrasting approaches underscore the importance of a balanced regulatory framework that both fosters AI innovation and mitigates its potential risks, including privacy concerns, security vulnerabilities, and socio-economic disparities. Additionally, this study identifies critical gaps in existing literature on the long-term economic impacts of AI, particularly concerning wealth distribution and the effects on emerging economies.

Traditional economic models may fall short in capturing AI's unique, disruptive potential, necessitating updated frameworks that incorporate both the economic gains and social consequences of this technology. Further research in this area will be crucial for developing policies and models that can effectively harness AI's benefits while addressing its broader economic and societal impacts. AI stands at the forefront of an economic revolution that is reshaping industries, job markets, and national policies. Realizing the full potential of AI requires a collaborative approach that includes not only technological innovation but also thoughtful policy-making and investment in human capital.

The results of this research contribute to a deeper understanding of AI's economic implications, offering insights that can guide both national and international strategies for sustainable and inclusive AI-driven economic

growth. By addressing both the opportunities and challenges of AI, this study aims to support a future where AI serves as a catalyst for widespread prosperity, resilience, and equity in the global economy.

References

- Abbott, M. L., & McKinney, J. (2016). *Understanding and applying research design*. John Wiley & Sons, Inc. <https://doi.org/10.1002/9781118647325>.
- Acemoglu, D., & Pascual, R. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488–1542.
- Aghion, P., Akcigit, U., Cagé, J., & Kerr, W. R. (2016). Taxation, corruption, and growth. *European Economic Review*, 86, 24–51. <https://doi.org/10.3386/w21928>
- Aghion, P., Jones, B. F., & Jones, C. I. (2017). *Artificial intelligence and economic growth*. Retrieved from NBER Working Paper No. 23928:
- Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial intelligence: The ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives*, 33(2), 31–50. <https://doi.org/10.1257/jep.33.2.31>
- Akhtar, B. Z. (2024). Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. *Metaverse*, 5(2), 2731. <http://dx.doi.org/10.54517/m.v5i2.2731>
- Akhtar, Z. B. (2024a). The design approach of an artificial intelligent (AI) medical system based on electronic health records (EHR) and priority segmentations. *The Journal of Engineering*, 2024(4), e12381. <https://doi.org/10.1049/tje2.12381>
- Akhtar, Z. B. (2024b). From bard to Gemini: An investigative exploration journey through Google's evolution in conversational AI and generative AI. *Computing and Artificial Intelligence*, 2(1), 1378–1378. <https://doi.org/10.59400/cai.v2i1.1378>
- Akhtar, Z. B. (2024c). Generative artificial intelligence (GAI): From large language models (LLMs) to multimodal applications towards fine tuning of models, implications, investigations. *Computing and Artificial Intelligence*, 3(1), 1498–1498. <https://doi.org/10.59400/cai.v3i1.1498>
- Akhtar, Z. B. (2024d). Unveiling the evolution of generative AI (GAI): A comprehensive and investigative analysis toward LLM models (2021–2024) and beyond. *Journal of Electrical Systems and Information Technology*, 11(1), 22. <https://doi.org/10.1186/s43067-024-00145-1>
- Baker, N., & Rafter, S. (2022). *An international perspective on monetary policy implementation systems | Bulletin–June 2022*. Retrieved from <https://www.rba.gov.au/publications/bulletin/2022/jun/pdf/bulletin-2022-06.pdf#page=54>
- Baldwin, R. (2019). *The globotics upheaval: Globalisation, robotics and the future of work*. London: Weidenfeld & Nicolson.
- Becker, G. S. (1974). Crime and punishment: An economic approach (PDF). In Becker, Gary S.; Landes, William M. (Eds.), *Essays in the Economics of Crime and Punishment*. In (pp. 1–54): National Bureau of Economic Research. <https://www.nber.org/system/files/chapters/c3625/c3625.pdf>.
- Becker, G. S. (1991). *A treatise on the family (Enlarged ed.)*: Harvard University Press. <https://www.hup.harvard.edu/books/9780674906990>.
- Behrendt, S., Peter, F. J., & Zimmermann, D. J. (2020). An encyclopedia for stock markets? Wikipedia searches and stock returns. *International Review of Financial Analysis*, 72, 101563. <https://doi.org/10.1016/j.irfa.2020.101563>
- Bertholet, A. (2021). Constant, Sismondi and Poland. *Annales Benjamin Constant*, 46, 78–81.
- Bertholet, A., & Kapossy, B. (2023). *Physiocracy and Switzerland*. Geneva: Slatkine.
- Bird, M. (2015). *13 women who transformed the world of economics*: World Economic Forum. <https://www.weforum.org/stories/2015/11/13-women-who-transformed-the-world-of-economics/>.
- Blaug, M. (2017). *Economics encyclopædia Britannica*. Retrieved from <https://www.britannica.com/contributor/Mark-Blaug/300>
- Boring, A., & Zignago, S. (2018). *Economics, where are the women?*: Bank of France. <https://www.banque-france.fr/en/publications-and-statistics/publications/economics-where-are-women>.
- Bostrom, N. (2017). *Superintelligence*. Paris: Dunod Edition.
- Camerer, C. F. (2017). *Artificial intelligence and behavioral economics. In Economics of Artificial Intelligence 2017 Oct 5*: University of Chicago Press. <https://www.nber.org/system/files/chapters/c14013/c14013.pdf>.
- Cameron, R. E. (1993). *A concise economic history of the world: From paleolithic times to the present*. USA: Oxford University Press.
- Cordato, R. E. (1980). The austrian theory of efficiency and the role of government. *The Journal of Libertarian Studies*, 4(4), 393–403.
- De Groot, A. D. (1969). *Methodologies* (Vol. 6). Hague: Mouton.
- De Groot's, A. D. (1969). *The empirical cycle in science*. Retrieved from <https://www.degruyter.com/document/doi/10.1515/9783112313121-003/html?lang=en>
- Department International Monetary Fund Monetary and Capital Markets. (2023). *Annual report on exchange arrangements and exchange restrictions 2022*: International Monetary Fund. <https://www.imf.org/en/Publications/Annual-Report-on-Exchange-Arrangements-and-Exchange-Restrictions/Issues/2023/07/26/Annual-Report-on-Exchange-Arrangements-and-Exchange-Restrictions-2022-530144>.
- Fang, Y., Cao, H., & Sun, J. (2022). Impact of artificial intelligence on regional green development under China's environmental decentralization system—based on spatial durbin model and threshold effect. *International Journal of Environmental Research and Public Health*, 19(22), 14776. <https://doi.org/10.3390/ijerph192214776>
- Goldfarb, A., & Tucker, C. (2017). *Digital economics*. Retrieved from Working Paper, No. (23684):
- Hanushek, E. A., & Wößmann, L. (2007). *The role of education quality for economic growth*. Retrieved from World Bank Policy Research Working Paper, No. (4122):
- Hemous, D., & Olsen, M. (2014). The rise of the machines: Automation, horizontal innovation and income inequality. <http://dx.doi.org/10.2139/ssrn.2328774>
- Hengel, E., & Phythian-Adams, S. L. (2022). A historical portrait of female economists' co-authorship networks. *History of Political Economy*, 54(S1), 17–41. <https://doi.org/10.1215/00182702-10085601>
- Human Development Reports. (2019). *Inequality-adjusted human development index (IHDI) archived July 12, 2019, at the Wayback machine*: United Nations Development Programme. <https://hdr.undp.org/inequality-adjusted-human-development-index#/indicies/IHDI>.
- Ipsos. (2021). *Global trends 2021*. Retrieved from <https://www.ipsos.com/sites/default/files/ct/publication/documents/2021-11/ipsos-global-trends-2021-report.pdf>
- Jahan, S. (2012). Inflation targeting: Holding the line. *Finance & Development*, 4, 72–73.
- Jean-Claude, S.-S. (2018). *National assembly*. Retrieved from https://en.wikipedia.org/wiki/Jean-Claude_Servan-Schreiber
- Joseph, Z. (1998). *Workers, machines, and economics growth*. Retrieved from https://josephzeira.weebly.com/uploads/5/7/3/4/57342721/98_qje.pdf
- Julie, A. N. (2016). *Feminist economics. The New Palgrave Dictionary of Economics*. Retrieved from <https://api.taylorfrancis.com/content/books/mono/download?identifierName=doi&identifierValue=10.4324/9781315723570&type=googlepdf>
- Keynes, J. M. (1936). *The general theory of employment, interest and money*. Retrieved from https://www.files.ethz.ch/isn/125515/1366_keynestheoryofemployment.pdf
- Kianpour, M., Kowalski, S. J., & Øverby, H. (2021). Systematically understanding cybersecurity economics: A survey. *Sustainability*, 13(24), 13677. <https://doi.org/10.3390/su132413677>
- King, D. (2018). *Fiscal tiers: The economics of multi-level government*: Routledge. <https://academic.oup.com/ej/article-abstract/95/378/511/5190727>.
- Konieczny, P. (2023). European Wikipedia platforms, sharing economy and national differences in participation: A case study. *Innovation: The European Journal of Social Science Research*, 1–30. <https://doi.org/10.1080/13511610.2023.2195584>
- Mateu, J. B., & Pluchart, J. J. (2019). The economics of artificial intelligence. *Journal of Financial Economics*, 135(3), 257–272. <https://doi.org/10.3917/ecofi.135.0257>
- McDowell, Z. J., & Vetter, M. A. (2023). Rethinking artificial intelligence: Algorithmic bias and ethical issues | The realiation of the commons: Wikidata and the ethics of “free” data. *International Journal of Communication*, 18, 19.
- Misuraca, G., Barcevičius, E., & Codagnone, C. (2020). *Exploring digital government transformation in the EU*. Luxembourg: Publications Office of the European Union.
- Neumann, J. v., & Morgenstern, O. (1944). *Theory of games and economic behavior*. Retrieved from https://en.wikipedia.org/wiki/Theory_of_Games_and_Economic_Behavior

- Neves, P. C., Afonso, Ó., & Silva, S. T. (2016). A meta-analytic reassessment of the effects of inequality on growth. *World Development*, 78, 386-400. <https://doi.org/10.1016/j.worlddev.2015.10.038>
- Nguyen, C. P., & Doytch, N. (2022). The impact of ICT patents on economic growth: An international evidence. *Telecommunications Policy*, 46(5), 102291. <https://doi.org/10.1016/j.telpol.2021.102291>
- O'Driscoll, G. P., & Rizzo, M. J. (2014). What is Austrian economics? In Austrian economics re-examined. In (pp. 19-46): Routledge. <https://library.oapen.org/bitstream/handle/20.500.12657/48514/9781317691365.pdf?sequence=1>.
- Qin, Y., Xu, Z., Wang, X., & Skare, M. (2024). Artificial intelligence and economic development: An evolutionary investigation and systematic review. *Journal of the Knowledge Economy*, 15(1), 1736-1770. <https://doi.org/10.1007/s13132-023-01183-2>
- Rogerson, A., Hankins, E., Nettel, P. F., & Rahim, S. (2022). *Government AI readiness index 2022*. Oxford: Oxford Insights.
- Sachs, G. (2023). The potentially large effects of artificial intelligence on economic growth. *Global Economics Analyst*.
- Samuelson, L. (2016). Game theory in economics and beyond. *Journal of Economic Perspectives*, 30(4), 107-130. <https://doi.org/10.1257/jep.30.4.107>
- Smith, A. (1776). *The wealth of nations*. Retrieved from <https://www.investopedia.com/updates/adam-smith-wealth-of-nations/>
- Tekale, V. (2024). Research paper on the role of the IMF and the world bank in promoting global economic development. Available at SSRN 4850278. <https://doi.org/10.2139/ssrn.4850278>
- Towards. (2011). *Towards a green economy: Pathways to sustainable development and poverty eradication (PDF) (Report)*: United Nations Environment Programme. <https://sustainabledevelopment.un.org/index.php?page=view&type=400&nr=126&menu=35>.
- Trabelsi, M. A. (2024). The impact of corruption on economic growth: A nonlinear evidence. *Journal of Social and Economic Development*, 1-10. <https://doi.org/10.5772/intechopen.108876>
- Trapeznikova, I. (2019). *Methods for measuring income inequality*: IZA World of Labor. <https://wol.iza.org/articles/measuring-income-inequality/long>.
- Ventura, L. (2022). *World wealth distribution and income inequality 2022*: Global Finance Magazine. <https://gfmag.com/features/wealth-distribution-income-inequality/>.
- Walker, F. A. (1878). Money. In (pp. 405). New York: Henry Holt and Company.
- Weber, M., & Simmel, G. (1988). *The sociology of culture*. Retrieved from <https://journals.sagepub.com/doi/abs/10.1111/j.1467-954X.1988.tb02933.x?journalCode=sora>
- Yang, C.-H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy*, 51(6), 104536. <https://doi.org/10.1016/j.respol.2022.104536>
- Yu, C., Moslehpour, M., Tran, T. K., Trung, L. M., Ou, J. P., & Tien, N. H. (2023). Impact of non-renewable energy and natural resources on economic recovery: Empirical evidence from selected developing economies. *Resources Policy*, 80, 103221. <https://doi.org/10.1016/j.resourpol.2022.103221>
- Zhao, P., Gao, Y., & Sun, X. (2022). How does artificial intelligence affect green economic growth?—Evidence from China. *Science of The Total Environment*, 834, 155306. <https://doi.org/10.1016/j.scitotenv.2022.155306>