The Application of Artificial Intelligence in economics: A review of current trends and future directions

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Abstract: *Artificial Intelligence is fundamentally reshaping the practice and mission of economics, creating massive opportunities to augment analytical capacity, increase predictive accuracy, and steer policy decision-making. The present study provides a systematic survey on the trends and trajectories of AI in modern economics, covering both its methodologies, various domain-specific applications as well as potential advantages and challenges. This paper includes Key AI subfields such as ML, DL, NLP and RL (reinforcement learning), but especially also Causal AI due to its advantages of dealing with vast, complex, often unstructured economic data. The report calls attention to the role AI is playing in transforming economic forecasting, shaping behavioral economics, improving econometric models and enhancing public policy such as monetary policy, social programs and climate change mitigation. Although AI offers potential advances in efficiency, speed, and the discovery of finer patterns, its embedding comes with Head 1 3 important challenges concerning data quality, model interpretability, and algorithmic bias. The future of AI in economics will be characterized by the emergence of hybrid econometric-AI models, more long-term macroeconomic applications and further focus on interdisciplinary collaboration as well as robust governance structures for fair and responsible deployment.*

Keywords: Artificial Intelligence, AI and economic modelling, chatbots in education, economic analysis, economics education, economics teaching, students learning outcomes

INTRODUCTION

The advent and fast development of artificial intelligence (AI), in particular generative AI (Gen AI) is revolutionizing several fields, the discipline of economics is not an exception as it has benefited from it.economics (Ahamefula, Anum, & Megwa, 2018). The rapid development of digital technologies has also fundamentally changed how people interact with computers, tablets and mobile phones, as well as daily routines and methods to increase performance (Omokhabi, 2021). It possesses a growing influence, as numerous instruments and patterns impact society lifestyle and work styles (Omokhabi, 2023). Artificial intelligence has in recent years become a disruptive technology used in various fields including education (Ojokheta & Omokhabi, 2023) and healthcare (Omokhabi, Erumi, Omilani, & Omokhabi, 2025) and now the teaching and learning of economics.

AI is a catchall term for a wide range of technologies engineered to help machines perceive, interpret and act. These capabilities have unparalleled prospects in dealing with complex problems, improving forecast precision, augmenting decision-making and accelerating economic expansion (Ahamefula, et al, 2018). AI can help economists to control their activities that make tasks easier. As technology continues to evolve, mental health is a relevant element in determining how people process stress and emotions and make reasonable choices (Omokhabi, 2025).

The global “AI revolution” is driven by striking increases in the level of private AI investment, most notably in the US, and to a lesser extent China (Anum et al. 2023). The dimension of this technology driven transformation is destined to expand and shift job roles and the place of labor across all economies (Ahamefula, et al, 2018). The incorporation of AI into the house of economic science is not just a few limited technical improvements; but rather, it’s nothing less than an economic shock – another industrial revolution and whose potential transformation of human affairs we can pick up from previous rounds. Indeed AI has the power to shift the frontiers of production possibilities of economies and result in large rearrangement of labor and capital (Ahamefula, et al, 2018). The systemic effect this is generating, seem to be increasingly at the center of contemporary economic debate: including economists like Daron Acemoglu who focuses on the social distribution of what these innovation powers “produce” (Anum et al, 2023). The possibility of AI in several sectors (economics sector inclusive) makes it seem exciting but the double-edgedness behind AI is such that as much as it seems to be very excitedly interesting, its broader implications (as a whole) on economies and societies are quite intricate and unspecific (Ahamefula, et al, 2018).

This inherent uncertainty also relates to the long-run consequences for labor market dynamics, including labour income, wealth inequality and the influence on the natural rate of interest whereby productivity gains might push that up whilst increasing equality may pull it down (Ahamefula, et al., 2018). That being where an ambitious exploration of AI in economics will have to tread when discussing this thorny trade-off of the particular way that AI has potential to disrupt equilibrium, but that we do need discussions filled with ambiguity and contrasts that must be stewed on. In summary, this report aims to offer a coherent picture about the recent and future trends in AI and its applications in economics by highlighting the methodological roots of AI applications in economics, some of its application domains, advantages and disadvantages, and emerging areas for research trajectory.

Research Questions

1. What are the core AI methodologies and their economic application?
2. What are the diverse applications of AI across economic domains?
3. What are the benefits of AI applications in economics?
4. What are the challenges of AI applications in economics?
5. What are the future directions in AI integration in economics?

Methodology

In this study, Systematic Literature Review (SLR) was employed for the assessment of AI integration into economics teaching and learning and application which is expected to be deemed appropriate for the use in this paper due to - it being a method that follows an open and rigorous process that can be replicated. Major databases, peer review journals and articles, conference papers were systematically reviewed. The search was narrowed to articles published between 2016 and 2024 (the time frame during which AI applications in education and economics gained critical mass and global momentum). The following key terms were used to search: Artificial intelligence in economics education, AI in economics teaching, AI and student learning outcomes, AI in higher education economics, Adaptive AI learning system, Chatbots in education.

The studies considered were those published 2016 - 2024, written in English language and relevant to AI for teaching&learning or economics teaching⁄econ/mic-related performance. These papers could be empirical or conceptual/review articles. Grey literature not peer‑reviewed or published in the English language were also excluded. We also excluded studies that are not related to economics or education, or are duplicate.

A search of the main databases such as Scopus, web of science, Google scholar and researchgate was run and various articles were found. The title and abstract of the articles were screened for relevance, their full text were also considered according to the inclusion and exclusion criteria then relevant studies emerged to be included in the review. Each extracted article was reviewed in terms of objectives, methodological quality, contribution to the knowledge body and focus on AI integration in economics. Empirical papers such as Dabingaya (2022), Ding (2023) and Emmanouil (2024) were also included for their insights on AI-supported learning, and conceptualisation/review papers such as Chassignol et al. (2008), Chen (2022) and Mircea (2023) were left with respect to their theoretical framework. Locally related studies (Ahamefula et al., 2018; Anum, 2023) were also incorporated to reflect the African viewpoint of AI integration in economics education. Thematic synthesis was followed to assimilate bibliographic descriptions, teaching/learning outcomes of AI application type, benefits and challenges as well as future pathways. These empirical pieces (e.g., Thompson et al. 2023, Shahzad et al. 2024) were contrasted with conceptually-oriented examinations (Prodanova et al., 2019; Mustak et al., 2021), reflecting on potential trends, opportunities and constraints associated with AI incorporation in economics education.

Expected Outcomes

The objective of this paper is to provide an in-depth view about the successful application of AI in economic teaching & learning. This work will demonstrate the AI applications for economics and their impact on advances in AI based economic systems and agents. The study will show interventions that work and that are needed if economics is to progress. The research will also demonstrate AI in action for research and development work aimed at economics.

This research will serve researchers, academicians and economics teachers, policy makers, technologist developers or whoever is interested in economics.. In the end we are able to declare a recommendation of AI for economic applications. The research will uncover opportunities and obstacles to marrying AI with economics. This article will also propose the future direction of incorporating AI with economic functions in education.

Results and Discussions

Foundational AI Methodologies for Economic Analysis

The use of artificial intelligence in economics is supported by several core methodologies that provide distinct features for analyzing complex economic phenomena. These methodologies include Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Reinforcement Learning (RL), and, increasingly, Causal AI.

Artificial Intelligence (AI) has ML, which is at the core of AI whereby economics employs large, diverse datasets to bring out latent structure and enable markets to respond in real-time (Chassignol, Khoroshavin, Klimova and Bilyatdinova, 2018). Quantitative finance has extensively adopted ML techniques for algorithmic trading, risk management, portfolio optimization and economic activity forecasting (Chen, Y. 2022). ML applications can analyze millions of data points that come from a wide variety of sources such as financial markets, social media posts, and economic indicators, from which trends or anomalies in the economic data can be detected (Chassignol et al 2018). Common ML algorithms that have been used for prediction of economic events are: Autoregressive Integrated Moving Average (ARIMA), Linear Regression, Logistic Regression, Decision Tree and Random Forest, Support Vector Machine and k-nearest views.

ML “has become the heart of AI”; economics uses diverse large datasets “to uncover latent structure and to enable markets to react to new challenges in real time” (Chassignol et al., 2018 Khoroshavin,et al.>Klimova & Bilyatdinova). ML methods are widely used in quantitative finance for carrying out algorithmic trading, risk management, portfolio optimization and economic activity prediction (Chen, Y. 2022). For example, ML applications can now at scale analyze millions of data points that are generated from a range of sources including financial markets, social media posts and economic indicators, which in turn can be used to surface patterns or potential anomalies such as within economic data (Chassignol et al 2018). Popular ML algorithms applied for prediction of economic events are: Autoregressive integrated moving average (ARIMA), linear regression, logistic regression, decision tree and random forest, support vector machine and k-nearest views.

The natural language processing (NLP) technology has been used in extracting economic information from unstructured textual sources such as news articles, social media and company reports (Chassignol et al., 2018). The public opinion and market sentiment is also research subject to the sentiment analysis that is in the domain of NLP. Utilization of such non-conventional qualitative data enriches predictive economic models that cannot digest the qualitative information under econometric modeling (Chassignol, et al 2018).

Reinforcement Learning (RL) and its recent form Deep Reinforcement Learning (DRL), is a sub-branch of ML where agents learn how to take successive decisions over time in a dynamic environment under uncertainty so as to optimize cumulative reward. DRL combines RL with deep neural networks, which allows agents to learn and solve problems that are high-dimensional and complicated (Chen, Y., 2022). Applications in real life include portfolio selection, auction design, macroeconomic policy simulation and even constructing fully automatic trading systems (Chen Y., 2022). Recently RL and DRL have been also adapted to economic, financial, and marketing studies. Thus, although ML and DL can perform predictive economic forecasting and the detection of latent structure in big data, a key development in the application of AI to economics is the emergence from prediction to understanding underlying causal mechanisms. This is the crossroad where Causal AI emerges. Classical machine learning usually generates correlations and spurious relationships that can make the results non-generalizable (Emmanouil C., 2024). In contrast, CAI allows AI to answer 'why' responses - If I do X, what will happen? - and can perform causal simulations of possible interventions including sound explainable peeling back the layers of how AI systems have generated such responses, as opposed to considering only statistical associations (Emmanouil C., 2024). This is a vital matter for policy making due to the fact that policy makers would like to know why and not just what will happen concerning economic occurrences. The emergence of Causal AI, and the concept of "hybrid methods" - relating new technologies such as AI with classical econometrics – represents the very first step towards a future in which technology will no longer replace economic theory but supplement and expand its domains (Chassignol et al 2018)). We thus collectively forecast data-maximal and theory-based forecasts, to allow for a broader consideration of economic planning and policy-making (Chassignol et al., 2018).

A structured overview of these foundational methodologies, including their specific utility in economic research and practice, is presented in Table 1, which summarizes their key characteristics and applications.

Table 1: Core AI Methodologies and Their Economic Applications

AI Methodology	Key Characteristics/Capabilities	Specific Economic Applications	Relevant Data Sources
Machine Learning (ML)	Pattern recognition, large dataset processing, real-time adaptation, predictive modeling.	Economic forecasting (GDP, inflation), risk management, portfolio optimization, algorithmic trading, consumer behavior prediction.	Financial markets data, economic indicators, social media, sales data, historical prices
Deep Learning (DL)	Multi-layered neural networks, complex non-linear pattern identification, handling noisy data.	Financial market prediction (stock, foreign exchange), behavioral finance, complex economic dynamics modeling, image-based economic analysis.	High-frequency financial data, consumer behavior data, business sentiment indicators, satellite imagery
Natural Language Processing (NLP)	Text analysis, sentiment extraction, understanding human language.	Sentiment analysis in financial markets, analysis of news streams, economic reports, social media for market trends and public opinion.	News articles, social media posts, corporate earnings calls, policy documents
Reinforcement Learning (RL)/Deep Reinforcement Learning (DRL)	Sequential decision-making, optimal policy learning through trial-and-error, maximizing cumulative rewards.	Algorithmic trading systems, portfolio optimization, auction design, macroeconomic policy simulation, resource allocation.	Market data, simulated economic environments, policy outcomes
Causal AI	Causal inference, answering "why" questions, simulating interventions, explainable decision-making.	Personalized causal effects, policy evaluation, structural modeling, understanding underlying economic mechanisms, mitigating human biases.	Experimental data, observational data with confounders, policy intervention data

3. Diverse Applications of AI across Economic Domains

The widespread applications of AI have witnessed it being integrated into various economic sectors, quickly transforming typical approaches to analysis, forecasting, and policymaking.

3.1. Improving Economic Forecasting / Predictive Analytics

AI is a breakthrough in predictive economic forecasting as it provides better accuracy, speed and flexibility than traditionally used methods (Chassignol, et al 2018). In addition, another key benefit to AI platforms is the predictive capability in real-time allowing it to repeatedly consume data and always offer fresh insights into discerning phenomena such as when weather models are able to receive updates rather than updating every few hours for example (Chassignol, et al 2018). These can analyse millions of data points across disciplines such as financial markets, social media, economic indicators and even the weather in order to search out patterns and anomalies (Chassignol et al., 2018). This also pertains to exercising the unstructured sources of data such as sentiment and news streams on social media that are not easy for conventional econometric models to take advantage of (Dabingaya, M. 2022).

AI use has a strong effect on prediction effectiveness – ability of AI to find non-obvious correlations, real-time processing and Adjustments to market changes (Mustak, Salminen., Plé, L & Wirtz, J. 2021). Taken together, all these translate into real gains for the companies in terms of better inventory management and demand forecast as well as reduced costs of doing business (Mustak, et al., 2021). AI can even economically mimic economic conditions, predicting recessions, many a time years before they occur, and this is just going to get stronger as models and data become robust (Prodanova, et al.,. 2019). Applications Predicting GDP (Gross National Product) Growth, Sentiment Analysis of Financial Markets, Stock price and Commodity Price Forecasting (Prodanova, et al. 2019). AI models provide so much more flexibility to play with data and take into account multiple variables that can be estimated without the constraint of time and complexity in terms imposed by traditional models (Enachescu, et al. 2025). Discovering non-linear relationships and complex patterns in data that usually it can be out of reach to traditional econometric methodologies, you can do this as well thanks to the ability of AI models to process such a huge dataset within those speeds, data volumes, and speed rates far higher than what humans are capable upon (Chassignol et al. 2018).

3.2. Advancing Behavioral Economics and Consumer Insights

The marriage of AI and behavioral economics is an exciting new frontier in research. Behavioral economics uses learnings from psychology, sociology and neuro-science to traditional economic thinking on how people make decisions when in complex situations within an economic domain (Ezekoka, Isiozor & Anum 2016). AI on the other hand is concerned with developing machines that can exhibit human-like intelligent behaviour like reasoning, problem solving and decision making (Ezekoka, et al. 2016).

The majority of this interventionist literature in the field deals with consumer behavior and customer reactions, such as behavioral game theory, neuroeconomics, and decision-making under uncertainty. The approach is mainly based on machine learning and deep learning tools (Costache, 2025). In particular AI algorithms have been investigated for predicting consumer behaviour, forecasting stock prices within financial markets as part of behavioural finance, and developing interventions to reduce or remove human bias in decision making. Other uses of AI bring forecasting down to earth through behavioural simulations and explore potential market dynamics akin to how relevant economic, regulatory and behavioural factors could play out in markets (Petcu et al. 2025). This application of AI results in new avenues for the capabilities of behavioral economists to examine and analyze complex economic systems.

3.3. Revolutionizing Econometrics and Causal Inference

Artificial Intelligence (AI) has found its applications in Econometrics such as new advanced predictive modeling, automating data analysis and decision making among others (Ezekoka, et al. 2016). The area has seen further progress with the use of AI and machine learning models, particularly Gradient Boosting Machines (GBMs) and Causal Forests which is to provide causal inference for individuals(Mircea, M. 2023). Causal inference is about more than the econometric estimates of ATE, which largely fail to show differences (from heterogeneous individual response) in response to treatment. AI also discloses uneven treatment by individuals, permitting comparison of how people respond to the same economic therapy (Mircea, M. 2023). Second, AI can capture more complex causal structures than classical linear regression and econometric models.

Causal AI could be a game changer in this area. It offers the capability to respond at any preferred why-question counterfactual (both scheduled and individual causal inference), while also replicating one's own or some other intervention in data-supported answers that offer better, more appropriate, replicable explanation than can casual inference due to matters of decision making that is substantial, underground causation may predicate for implementation the stop-and-go algorithm; direct causes or any merely instrumental triggers of artificial l did less than a year ago' justifications.Explanations turn out only three years from now nested under adjacency entailment following Emmanouil.et al.,2024). There are many reasons for policy analysis to be concerned with an accurate estimation of heterogeneous (or personalised) responses. In response to social problems, policymakers should be sensitive to heterogeneous effects in constructing more targeted and equitable responses,7 as opposed to simple one-size-fits-all solutions (Mircea, M. 2023).
Identifying that individuals of one type, for example young or low income and education, responds very differently to interventions relative to others highlights the potential value of personalized causal inference in real world policy (Ezekoka et al., 2016).

3.4. Leasing Public Policy and Resource Allocation

AI has a major consequence on public policy and resource allocation, as it provides new mechanisms for governance and addressing social issues.

Monetary Policy: The use of AI in the economy has implications for the monetary policy of central banks. As they affect macroeconomic conditions (e.g., productivity growth, income inequality), AI can indirectly influence the monetary stance and have its impact on transmission of monetary policy to the economy:There are two ways in which AI could affect the balance of risks in that regard. For example, faster productivity growth associated with AI may imply a higher natural interest rate as well, meaning that both the natural-rate and monetary-policy rates consistent with price stability could be correspondingly elevated. However, if the AI leads to inequalities through faster job displacement and sluggish job creation or if it contributes to a "digitization of poverty", this can put downward pressure on n (Anum, 2023). In any event, investment in AI remains very low, even in the US.

Social Programs and Resource Allocation: Machine learning and AI are used to develop simulation models that facilitate governance decisions and encourage citizens participation in their control using interactive portals (Shahzad, M. F. et al. 2024). It allows governments to monitor and analyze social trends, so they may respond quickly to these changes and the associated socio-economic crises (i.e., pandemics, natural disasters) using AI systems (Shahzad et al. 2024). Specific examples include the use of social media big data to un- cover patterns and trends among large populations (Shahzad, et al., 2019), enabling more evidence-based policy creation or resource allocation based on need. 2024). Machine learning models can predict economic or social crises like increased unemployment, and health emergencies; it enables the government agents to intervene with predictive information in time and reduces the negative effect of these events (Shahzad et al. 2024). AI is also used to define community requirements in enabling resource allocation for higher efficiency, ensuring that social support and aid are delivered more promptly to targeted populations (**Shahzad, et al. 2024).** Furthermore, AI can be used to enhance the health care by gaining AI preventive personalized recommendations and early disease markers and reduce bias in rank order expressions of discrimination using social context data to uncover biases in employment, education decisions,htm and other social institutions applications of machine learning (Shahzad et al. 2024).

Climate Change Modeling: And AI is very useful about climate change models and the economics of them if one shares them from a sustainable development perspective. AI aids in the integration of diverse data sources, such as meteorological, geophysical sources as well as economic sources to enable evaluating climate change effects on levels of production, trading of productions at international level and cost of capital (Dabingaya, 2022). AI can also be applied to identify climate trends (**Dabingaya, 202**2) by using artificial neural networks and satellite images to detect developments in natural resources such as timber or deforestation. Third, environmental costs may be estimated through AI, as it is not only possible to analyze complex relations between greenhouse gas emissions and economic effects of greenhouse gas emissions (directly: crop yield or indirectly: road infrastructure) using AI (Dabingaya, 2022).

Taken together, these apps represent an important shift to smaller, more current and personalized economic analysis. The fact that AI is capable of quickly analyzing enormous data and discovering the hidden pattern empowers us to have a detailed level view on individual's', people are not treated as samples. For instance, instead of estimating the GDP for a country we could predict e.g., the way some clients will behave or human feelings from social media at a certain time (Chassignol et al. 2018). This level of specificity can enable very targeted intervention and policy, instead of a broad-brush, one-size-fits-all intervention. These real-time, timely updating and quick training data models for responding to crisis individually or collectively, mark a shift in the way economic/public policy and governance in general are planned and implemented -- from crisis management to proactivity/adaptive governance (Chassignol et al. 2018) with significant ramifications for enhancing economic stability and sustainable development.

4. Key Benefits of AI Integration in Economics

To bring artificial intelligence into an economic analysis and decision making environment has several significant advantages that it is obviously going to raise the bar in multiple dimensions.

One popular advantage is the accuracy and timeliness with which economic forecasting AI"s perform analysis in real time (Mustak, et al 2021). Overall, the AI can calculate precision because it is analyzing voluminous data and recognizing multidimensional trends in real time (Chassignol et al. 2018). AI, unlike traditional economic predictions with systematic models that rely on infrequent updates and may have a lag time to address desired solutions, introduces enhanced accuracy, speed and flexibility in the analysis of multi-dimensional economic data. AI can forever take "live data" from engagement sources, and spectate on updates now. This again results in easier financial stability, lesser risks circuitry and banks-deliverable-processing effectiveness for prediction of banking institutions and stock markets (Prodanova,, et al. 2019). For the business, the business value of the AI forecast is to give insights about demand characteristics for better planning and preparation into how to manage either upward or downward demand trends (Mustak, et al. 2021).

Another great strength of AI lies in working with massive, complicated and unstructured data sets. Artificial Intelligence is so fast, it is capable of manipulating big amounts of data and at the speed far faster than a human can do that. It can also link extensive data sets coming from different sources, including real-time financial transactions, consumer behavior and social networks responses, macroeconomic variables or news, and even satellite images of location as (Chassignol, et al. 2018). This is very disruptive because it has the power to extract complex patterns and non-linear relationships that are usually considered a priori impossible like in a traditional econometric model (Barbulescu et al., 2025). This is why the impact of AI isn't just better economic analysis; it's that data constructs and the scale of data that may be put into economic models actually changes what can be calculated. Ai is bringing in a completely new way of judging economic behavior – forming the basis for "Big Data Economics." All of these advances enable scientists and researchers to spot behaviors in holistic, real-time ways that are easier than ever before. In economic analysis, it has the potential of capturing economic response in a more timely and comprehensive fashion than imposed by the confines of pre-configured or time-series data that have traditionally been applied systematically in decades past.

After all, AI significantly affects decision making and performance. The use of AI technologies infuses the decision-making process into all aspects of the economic policy cycle, from agenda-setting to evaluation (Prodanova, et al 2019). They permit companies to make long-term, strategic decisions concerning supply chain, efficiencies, stocks and expenses (Mustak, et al 2021). By modelling scenarios and testing hypothetical outcomes, executives can make decisions based on established circumstances and expedite decision-making processes (Mustak, et al 2021). AI also makes possible automation of data analysis and decision making into processes and decisions than the application of these traditional processes in various sectors leading to efficiency as well as innovation among other two factors (Ezekoka, et al 2016). All of this adds up to an accumulated capability advantage that represents a strategic asset which is valuable to any organization or government that can use it. AI tools offer viable avenues to identify early signals of a recession, gain the strategic advantage in decision-making and effect permissive policy changes towards successful force response. proactive decision-making and risk management (Chassignol et al 2018). Thus AI moves the economic analysis from a traditional way of description or just pure prediction toward strategic foresight and competitive advantage as its an instrument for decision makers, changing deeply the logic of economy.

5. Challenges and Ethical Considerations

While the promise is great, the broader application of AI in economics raises important challenges and considerations about the ethics of using these tools in a responsible and equitable manner.

Data quality, data access and privacy are considered major concerns. The reasons for the success of AI applications are based on high quality data as well as systems integration (Mustak, et al (2021). The data capacity of the AI models is limited and its applicability/ effectiveness depends on whether such datasets are complete as well as being accurate (Prodanova, et al, 2019). Data protection is also an ethical and practical issue; especially in the case of AI systems that are known to ingest large volumes of personal data (like social media data), which may inadvertently infringe privacy, consent, and autonomy of citizens (Dergaa, Chamari, Żmijewski & Saad 2023). Reasonable data protection mechanisms should be built at all stages in AI development.

Another big challenge is explainability of AI models, which is more commonly known as the "black box" issue. AI models, in particular deep learning models, are nontrivial and difficult to understand directly so as to interpret the results that AI throws up. In economic analysis, having a correct forecast is not enough in itself; economists and policy makers want to know how the variables are interrelated so that they can try to determine what the best policies to pursue actually are (Dabingaya 2022). T The black-box nature of AI's decision making is obviously a classic weakness in economic forecasting (Prodanova, et al 2019). To meet this challenge, there is a need to evolve Explainable AI (XAI) techniques, that can provide some useful potential insights which are also explainable in nature so as towards the establishment of trust in the process of decision making through AI and thereby facilitating action or better decision making by users (Dabingaya et al., 2022).

Algorithmic bias, fairness, and accountability are arguably some of the most profound ethical questions about AI. AI tools can also embed and reproduce 'real-world' bias and discrimination from historical datasets, to help generate new forms of inequality in society (Ahamefula, et al 2018) and could be hostile to the lived experience of marginalized groups. AI bias will be the term used to describe algorithms that make systematic biased decisions due to training on biased historical data, harming some social groups (Dabingaya, 2022). For example, AI credit scoring models can reproduce systematic bias in the past that results in more difficult access to credit for people living in underserved communities like Black and Latino (or African American and Hispanic) applicants having lower chance of accessing credit or being assigned higher risk scores compared to white applicants with the same financial profile (Thompson et al., 2023). A historical demographic lending data set being used to tune AI response systems, may be patterned for historic lending patterns that reinforce existing socially stigmatized decisions regarding lending. One example is how often a tradeoff between maximising predictions (or predictive accuracy) and fairness may look like in an AI model that for financial institutions follows the profit over social value – where a moral dilemma can arise, representing some of the issues behind 'fairness by design. In this, "fairness by design" offers a timely caveat that ethics must be embedded in the development and deployment of AI applied to economic domains, with fairness not an add-on after it has been deployed.

There are also numerous practical challenges, related to digital infrastructure and staff readiness beyond implementation. Importantly, other emerging and developing economies will have to build the right digital infrastructure and skills to fully tap AI's benefits (Dabingaya, 2022). Although there are possibilities for AI application in the public sector, only the developed countries will be able to take advantage of them-this emphasises crucial importance for AI inclusion and sustainability across all groups and sectors (Prodanova et al. 2019). The performance requirements and skills/programming obstacles are also major limitations for their adoption (Dabingaya, 2022). A suitable governance regime, the investment in digital infrastructure, up and reskilling of workforce and adequate global partnerships will be required for fair and sustainable development and integration of AI (Prodanova et al. 2019). One more thing to consider is the balance between predictive capacity induced by AI systems/technologies under a “black box” regime, and not being able to trust, understand or justify these models from a public interest viewpoint with regard to debt/equity decisions in the financial sector – most notably in sensitive applications such as credit scoring or public financing.

The essential advantages and disadvantages of AI integration in economics are summarized in Table 2.

Table 2: Benefits and Challenges of AI in Economics

Category	Aspect	Description	Relevant Data Sources
Benefits	**Forecasting Accuracy**	Significantly improved precision, real-time updates, and adaptability in complex economic data analysis.	
	Data Processing	Capacity to analyze vast volumes of diverse, complex, and unstructured datasets (e.g., social media, satellite imagery).	
	Decision-Making	Enhanced strategic and operational decision-making, improved efficiency, and ability to simulate scenarios for optimal outcomes.	
	Proactive Policy	Enables swift response to economic changes and crises, shifting from reactive to proactive governance.	
Challenges	**Data Quality & Privacy**	High data demands, issues with data quality, and significant concerns regarding privacy violations from mass data collection.	
	Interpretability	"Black box" nature of complex AI models, making it difficult to explain causal relationships and build trust in decisions.	
	Algorithmic Bias	Perpetuation of historical biases from training data, leading to discriminatory outcomes and exacerbating existing inequalities.	
	Implementation Hurdles	High computational demands, need for robust digital infrastructure, and challenges in workforce reskilling and adaptation.	

6. Future Directions and Emerging Research Frontiers

The future of AI in economics reveals the potential for promising and burgeoning areas within research that will change how this discipline operates. One way forward is to develop hybrid AI-econometric models. It is becoming increasingly evident that the direction of travel is to harness the best vessels in more inclined orthodox econometric model space- for example, linear regressions and perhaps soldier still Vector Autoregression (VAR) that offer both interpretability and theoretical underpinning alongside enhanced Ai or machine learning techniques such as deep neural networks, random forests and gradient boosting which are able to model complex, non-linear relationships (Dabingaya, 2022). the motivation behind hybridising econometric and machine learning methods is to benefit from better prediction accuracy, provided the estimation of such relationships is based on new non-linearities introduced by machine learning; but without losing its interpretability through avoiding technological functions which catch the classical economic theory) (Enachescu, 2024).

Recent developments in modeling literature around neural layers and econometric constraints into neural networks suggest the hybrid approach may well become commonplace across economics disciplines (Dabingaya, 2022). Integrating AI with traditional economic theories and approaches may provide new study direction in the future of forecasting; AI might act as an assistant instrument to enhance human capacity rather than replace human expertise (Chassignol, et al. 2018). This is a step toward `human-in-the-loop' AI for economic governance in that the AI does more sophisticated analysis and prediction, but humans assign ultimate responsibility (interpreting the results themselves --matching it to their theoretical knowledge, including ethical commitments) which is important for trust and recursive self-checking of responsible use in high-stakes economic environments (Costache et al. 2024).

There is also increasing interest in whether AI might help longer-term macroeconomic and climate policy. AI has generally been designed for the short-term market-based and market-analytic use; however, AI is also increasingly promising for macroeconomic long-term planning, especially in the light of demographic changes over the world, reorganization of plenty of modes of production because of robotizations and automations, as well as climate policy developments (Chassignol et al. 2018). First, macroeconomic AI models can possibly do a better job of capturing the interacting and non-linear couplings among numerous different variables and they may be able to work with larger data sets potentially having access to large statistical datasets, social media post information, or satellite data etc. (Chassignol et al. 2018). This facility helps policymakers, by allowing better and faster forecasts of ultimately long-run movements in economic activity or inflation or the labor market, to design policies more efficiently.

The role of AI in the modeling of climate change and its economic impact will also grow steadily, helping to design optimal public policies and to support sustainable growth. This implies a significant and very meaningful extension in the capabilities of AI applied to economics from narrow financial or market optimization to broader (non-financial) society-level problems and challenges, like poverty or unemployment or education or healthcare, also long-run phenomena (Thompson, et al 2023). This trend emphasizes AI's potential as a tool for sustainable development and inclusive growth, which calls for a more comprehensive and transdisciplinary comprehension and applications of such types of AI technologies.

As I mentioned earlier, the causal AI method (CAI) will continue to be a key frontier of innovation in the future. CAIs will retain banking significance as an approach to more up front addressing "why" questions and, on top of that, be in a position to use a causal perspective toward understanding the effects of interventions. CAI will be an important way of making good robust consequential decisions, with explanations, in the area of economics (Thompson, et al 2023). The use of CAI for the EBP personalized causal inference is already paving the way via potentiality with these techniques to amalgamate and implement as part of decision-making in producing efficient causally-informed policy interventions.

Last but not least, interdisciplinarity and good governance are indispensable. Hence, the successful implementation of AI is possible based on a stabilization to fair standards and regulations, increased visibility, and approach to global data equity (Prodanova et al. 2019). There will also be requirements for active governance, continued investment into digital infrastructure, re-skilling the work-force holistically and engaging countries in order to achieve equitable and sustainable integration of AI within economies (Prodanova et al. 2019). It is documented in literature, and consequently there might be more potential for interdisciplinary work among researchers from the field of behavioral economics and AI. The field also needs to champion an interdisciplinary approach to economic research and supplement AI with time-tested traditional methods for developing fresh solutions to the challenges of today's economy. Research going forward in the AI and behavioral economics nexus should also consider what is ethical about AI that incorporates behavioral insights as tools for decision-making. Given that bias, privacy and accountability in AI applications has been found by past literature to be a focal issue the creation of robust ethical frameworks is going to have to be implemented (Thompson, et al 2023).

Conclusion and Recommendations

We therefore know that AI is a game changer and it's transforming the world of economic analysis, forecasting and policy. "Artificial intelligence has evolved beyond clear technical improvements to provide nuanced understandings of complex, non-linear relations and personalized economic impacts. Indeed, AI - especially machine learning and deep learning, natural language processing (NLP), and reinforcement learning - has enhanced the accuracy, speed, and in some cases even real-time analytic capabilities upon which economists have traditionally depended. It facilitates the analysis of large amounts of data, which may be heterogeneous and unstructured, allowing individual economic "facts" to be assessed in a richer and more powerful way than it was previously possible; enabling policy-makers to intervene before waiting for occurrence of phenomena.

All the same, careful use of AI in economics will have to be aware of several daunting challenges. Despite the promising reality of AI, ethical dilemmas still exist in its application (Ajiye & Omokhabi, 2025). It is thus important that data quality, availability, and privacy are guaranteed, because the level of AI results relies on a solid data-driven input being used. The issue of the "black box" and opaque nature of complex AI models demand greater focus on interpretability, or possibly the development of Explainable AI (XAI) standards for trustworthiness and policy application.

It is evident that Artificial Intelligence is disruptive and redefining business as well as the world of economic analysis, forecasting and policy formulation. AI has shifted from rudimentary enhancements of tech capabilities to nuanced patterns such as non-linear relationships and micro-economic impacts. AI has become more accurate, faster, and even gained real-time analytical capability that economists have traditionally depended on, especially in machine learning, deep learning, natural language processing and reinforcement learning. It allows us to process vast, heterogeneous and sometimes unstructured data sets in a more powerful and comprehensive manner, thus advancing our understanding of economic behaviors and making possible policy interventions that are more proactive than reactive.

However, the considered use of AI in economics must be aware of several major impediments. Despite the advantages of AI some ethical problems arise when using it (Ajiye & Omokhabi, 2025). Thus, it is essential for the quality provision and assured privacy of data as AI output tool largely focus on strong data driven input. The "black box" issue and opacity of complex AI models, would seem to require further focus on interpretability, even moving toward the development of Explainable AI (XAI) standards for reliability and policy formation.

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