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Artificial Intelligence Driven Computing Methods in Economic Modeling: History, Current Trends and Future Perspectives

Faheema Gul [1], Muhammad Asif Zahoor Raja [2*], Adiqa Kausar Kiani [3]

ABSTRACT

The rapid evolution of artificial intelligence and computational technologies has substantially renovated economic research, enabling the exploration of increasingly complex systems characterized by nonlinearity, uncertainty and large-scale data. Simultaneously, mathematical modeling continues to be a fundamental tool for interpreting economic behavior, optimizing resource allocation, forecasting market dynamics, and supporting policy production. This review provides a broad examination of the introduction of mathematical modeling in economics and the incorporation of mathematical models and artificial intelligence within the domain of economics. A systemic literature survey was done using the Web of Science database. The reviewed literature was classified according to economic application spheres, mathematical modeling approaches and AI methodologies. The bibliometric analysis underscores a significant growing convergence of economics, mathematics and computational intelligence. This paper connects key research trends, evolving interdisciplinary directions and current challenges related to interpretability, model integration and uncertainty quantification. Overall, this study establishes the concept that the alliance of mathematical modeling and artificial intelligence is reforming the modern economic research and provides substantial opportunities for developing more precise, adaptive and data driven economic systems.

Key words: Economic theory, Microeconomics, Macroeconomics, Market Forecasting, Mathematical modeling, Artificial Intelligence, Revenue optimization

1. INTRODUCTION

Traditional economic theories were reliant on linear relationships of indices, troughs and peaks in market values, and perfect rationality; these were completely based on restrictive assumptions to maintain mathematical tractability. Until a few past decades, these traditional theories were implemented successfully due to their ease of use and simplicity.

However, as global markets observed spikes in volume while generating huge data with nonlinear characteristics, these traditional analytical prototypes failed to capture sudden systemic crises, emergent market behaviors, and sudden qualitative/quantitative shifts. Moreover, handling large amounts of available data posed a challenging situation for traditional techniques. To address these limitations, the research community in the field of economics experienced and went through an extensive paradigm shift, including nonlinear modeling, adoption of advanced numerical methods, and forecasting unknown numbers according to the provision of relationships. To provide a robust base in this theoretical stream, the fundamental concepts and definitions are presented below.

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[1] PhD Scholar, Graduate School of Engineering Science and Technology, National Yunlin University of Science and Technology, Taiwan, R.O.C.

[2*] Professor (corresponding author), Graduate School of Engineering Science and Technology, National Yunlin University of Science and Technology, Taiwan, R.O.C. (email: rajamaz@yuntech.edu.tw)

[3] Professor, Future Technology Research Center, National Yunlin University of Science and Technology, Taiwan, R.O.C.

1.2 Fundamental concepts

1.2.1 Economics

Economics is the social science that studies how individuals, corporations, societies and governments allocate sparse resources to fulfill unlimited needs and wants. It seeks to understand the production, spending and allocation of goods and services, as well as the procedures that influence decision-making under resource restrictions [1] [2]. Economics is generally divided into microeconomics, which focuses on personal economic agents and markets, and macroeconomics, which investigates combined phenomena such as economic development, unemployment, inflation and domestic income [3].

1.2.2 Econometrics

The branch of economics that employs mathematical, statistical, and computational techniques on economic data to analyze economic theories, assess relationships among variables, and make forecasts [4, 5]. By merging economic theory with experimental observations, econometrics enables researchers to quantify economic activities and evaluate the effects of policies and market subtleties [6].

1.2.3 Mathematical model in Economics

Mathematical modeling implies the devising of economic phenomena using mathematical equations, differential equations, optimization frameworks, stochastic processes, game theory and other arithmetical techniques [7]. These models give simplified

illustrations of real-world economic schemes and enable researchers to analyze financial dynamics, markets, policy interventions, resource allocation and economic forecasting under various constraints and assumptions [8]. Mathematical models can explain complex relations in a systematic and rigorous manner [9].

1.2.4 Artificial intelligence

Artificial intelligence is a field of computer science referred to the advancement of systems capable of execution of tasks that typically need human intelligence, including learning, pattern recognition, intellect, prediction, and decision-making [10]. AI contains a wide range of computational systems such as machine learning, neural networks, deep learning, expert systems and evolutionary algorithms. Unlike traditional approaches, AI systems can automatically capture patterns from big datasets and adapt their behavior based on understanding [11].

1.2.5 Machine Learning/ AI in economics

Machine learning is a subset of artificial intelligence that focuses on making algorithms capable of learning patterns from information and making predictions without being overtly programmed. In economics, it has emerged as a strong technique for forecasting, policy evaluation, classification, risk assessment, portfolio management, behavioral analysis and demand prediction. The increasing availability of large-scale financial and economic datasets has increased the adoption of machine learning approaches in both practical and academic research applications.

1.2.6 Integration of Mathematical modeling and artificial intelligence into economics

Although mathematical modeling and artificial intelligence belonging to different scientific groups, they are progressively being integrated to address complex problems. Mathematical models provide theoretical structure, analytical insights, and interpretability, whereas AI techniques present powerful data-driven capabilities for controlling high-dimensional data, nonlinear relationships, and uncertain environments. The conjunction of these approaches has enabled the advancement of economic financial modeling, forecasting, resources allocation, market design, policy analysis and decision support systems. Consequently, the integration of mathematical modeling and AI represents one of the most significant methodological advances in contemporary economic research.

1.3 Necessity to shift from conventional Economics towards/ Literature gap

1.3.1 Limitations of adhering to traditional Economics

The mathematical modeling of both micro and macroeconomic systems has undergone major changes over the past two centuries [12] while the evolution of this shift is based on three basic imperatives; first, the near impossibility of conducting experimentations due to logistical and ethical restrictions. Second, the substantial increase in empirical accuracy of mathematical formulation over time, and lastly, the epistemic reality that the rigorous scientific status is achieved by economic inquiry only when grounded in quantitative references [13, 14] . A critical bottleneck appearing at this stage is; what is the reason behind shifting from standard mathematical calculus to a multivariate economics model. The answer to this question is the range of relevant variables including hundreds of heterogenous agents that affect an economic model exponentially but can't be described by standard mathematical calculus. Another reason is the discontinuities in economic systems such as market crashes, interest rate flashes and regulatory threshold changes, where classical calculus fails to supply feasible vectors.

1.3.2 Shifting from Analytical to Numerical methods

Contemporary economic models are characterized by complex dynamic interactions and non-linearity due to infusion of heterogeneous agents. Economic system experienced a paradigm shift by switching from conventional to high-performance computational handling [15]. Economists faced, prior to this shift, strict restrictions posed by analytical solutions. The economists abandoned three basic assumptions due to exponential increase in computational power. First conventional macroeconomic considering the whole sector as one identical entity to keep mathematics tractable, making it a reliant on 'Representative Agent' assumption [16-18]. Second important assumption of classical math is that the economic functions possess infinite computing capacity to predict future paths. Instead, numerical simulations came up with more practical and realistic concept of bounded rationality [19, 20]. Third major assumption considered by analytical techniques is linearized continuous state of equilibrium, while real economies have dynamic stochastic general equilibrium can be best described by numerical methodologies [21].

1.3.3 Big data and AI infusion in Economics

Modern economic systems are no longer simple and aggregated , instead it has transformed into a decentralized and massively dispersed digital ecosystem that carries vast information flows about supply chain friction, real-time market shifts, consumers' behavior and behavior of the global financial markets, high-frequency transactions and many other features [22]. The structural complexity of modern economy resulted in a avalanche of data that conventional econometric tools may not handle. Consequently, like many other social sectors, economy has also grasped and exerted ML/AI due to its present rapidly evolving nature of handling big data [23]. Various branches of economy have apropos gain grounding of AI to optimize microeconmic decision-making and macroeconmic forecasting. AI models converts this multi-dimensional big data into this multi-dimensional big data into workable economic assessments and provide economic insights[24]. On the other hand, AI has the potential to analyze extensive datasets of behavioral economics and identify the hidden trends in consumer decision-making [25]. This analysis enables companies with outstanding potential to anticipate consumer behavior and preferences. These features necessitate present economy to incorporate AI for innovation and guarantee effective decision making. To contextualize the transition from traditional techniques that dealt economy towards state of the art intelligent models, the gradual evolution can be presented as illustrated in Figure 1. It graphs the development from early closed-form analytical constraints through initially adapted computational estimation and heterogenous simulation frameworks and ending in contemporary nonlinear artificial intelligence standard techniques built for high dimensional big data economic environments.

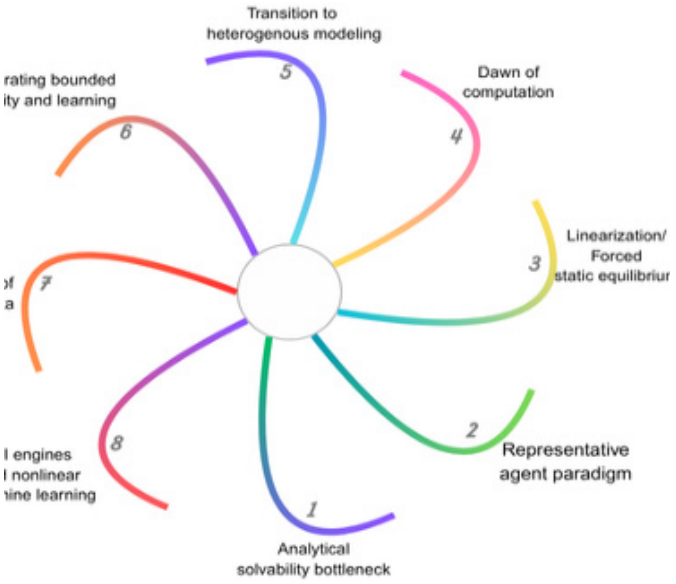


Fig. 1 The computational evolution of economic theory: from analytical ability to intelligent characterization

The figure shows that the journey begins at age of pen and paper and converted to a representative agent model that simplified macroeconomic sections into a uniform multivariable equation system solved manually. This age traversed to age of linearization that smoothened the complex dynamics into flat states. Discipline of linearization sought a change into numerical approximations during the rise of computational power. However transitioning into heterogenous agent modeling successfully abandoned the previous assumptions based computational strategies. Introducing the era of large information rendered the classical heterogenous regression models obsolete due to velocity and volume of modern digital footprints. To better handle this big data, AI engines were utilized to steer the economy wholly dependent over accurate, automated and remotely operated structures.

The remaining paper is organized as follows: Section II discusses the research methodology, research questions and the relevant articles selected for analysis. Section III answers the research questions. Section IV provides insights about integration of AI in economy and section V have the concluding remarks of this study.

2. METHODOLOGY/ LITERATURE SEARCH

The following segment of this review deliberately states the process of selecting the topic/ point of discussion (Economics, Mathematical model and Artificial Intelligence). A comprehensive review of the presently available literature organizes a solid base for any research endeavor. Researchers can develop an explicit view of the existing state of research level within a specific field. Such analysis provides major research developments, help identify effective theories and pointing out knowledge gaps, while discussing challenges and problems faced previously. Additionally, a review paper provides diverse comparisons and findings, providing the readers with a broader landscape of research. Keeping the above in view, this section presents a thorough view of the applicability of mathematical modeling and artificial intelligence in the field of economics with their pros and cons discussed in the sub sections.

The systematic search was initialized by exploring Web of Science (WoS), a digital repository containing extensive research articles known on 26/05/2026,. The search originated by setting three distinct combinations of queries, using primary and added/ secondary terms respectively; i.e., 1) Economics and Modeling, 2) Economics and Numerical and 3) Economics and Artificial Intelligence in Topics. This paper is economics-centered study thus we apply this term as the main key term while considering the various physical systems and structural frameworks that have been represented by some mathematical model to show how these systems and the assumed variables are interconnected. Since Economics is an important field of social sciences, effective mathematical modeling of economy is the need of hour for social development, hence the authors are interested in highlighting how systemic models are reliant on numerical solutions, quantitative foundations and basic mathematical calculations. Although mathematical models of economy are known to be based on different assumptions and considered as not perfect, still the research in this field requires models. The model presented by Francois Quesnay [26] on social economy is regarded as 1st ever model in this field. Some other well-known economics models are Leontief dynamic Model on Input-Output Economics [27], Keynesian model, treating economy as a single element [28] [29], Samuelson-Hicks model to interpret Trade Cycle Theory [30], Solow model [31] to study nonlinearity of small-sector, Walrasian model [32] for defining consumer-demand function, Neumann Model [33] and Goodwin Model [34] etc., used for operational forecasting of economic phenomenon. Research proves the mathematical model as effective tool to study economics or indirect study of economic processes.

Economic affairs like every other practical field is also embracing AI for sustainable operations to overcome fixed assumed agents and hyper-rational activations. Using adaptive learning better captures the algorithmic states transformation as compared to standard economic mathematical models. To know the impact of current trends to adapt artificial intelligence by different fields, this study is inquisitive to show the influence of intelligent data driven frameworks in the selected area of interest. Secondly, the purpose of choosing these auxiliary key terms to mirror the shifts in prototype economics computation over the recent decades. Inclusion of modeling. A pertinent question here may arise in the minds of readers is ‘why these keys terms and why not other broader terms like ‘digitalization’ and ‘computing’ and ‘technology’ etc. The answer is to avoid highly generalized terms in order to minimize systematic noise while maintaining a search precision. Chronological evolution of technology is also a stimulant behind choosing these key words, so that they combinedly capture a thorough spectrum of advancements experienced by the field of computational economics. We observe how complex economic systems are being represented by mathematical models and prominent researchers forwarded their traditional numerical approaches to solve these models, while ‘Artificial Intelligence’ maps the applicability of state-of-the-art data-driven techniques to these traditional approaches.

To see the temporal evolution of peer-reviewed publications for last five years (from 2021 to 2026) that also outlines the distribution of interdisciplinary intersection of ‘economics’, ‘mathematical model’ and ‘artificial intelligence’. A generic view of figure 2 reveals a overwhelming surge in research output, particularly in the year 2026. This growth indicates that the assimilation of artificial intelligence into economic mathematical modeling has transformed from emerging corner into a mainstream research template. IEEE dominating this scenario by reaching approximately 80 publications this year, highlighting the algorithmic and technical basis of AI-driven economics are heavily fastened with

engineering and computational frameworks. Springer Nature and Elsevier, being traditional economic publishing banks, shows almost similar structural growth trajectories while Wiley and MDPI form a tertiary tier if high-volume output increases annually.

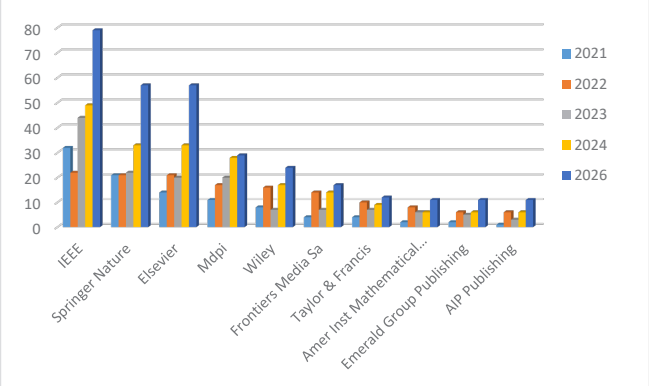


Fig. 2 Analysis of the distribution of publications on interdisciplinary studies for the year 2021-2026

The execution of search queries yielded a large number of raw articles. The first set of search queries retrieved 4353 documents while the second and third set of key terms returned 2616 and 1825 number of research articles respectively. 53 articles were found in available literature while the three key terms (economics+ model+ artificial intelligence) were combinedly searched.

This fundamental query containing significant number of irrelevant articles that were beyond the scope of this paper. Search is refined by exclusion procedure to filter out irrelevant articles/ documents to establish a highly focused study by removing "Open publisher-invited reviews", "early access" and "Book chapters". In next step, we narrowed our search by selecting "English" as language of the drafts. Ultimately, we had 40 articles for final study. Figure 3 provides the above-mentioned strategy pictorially.

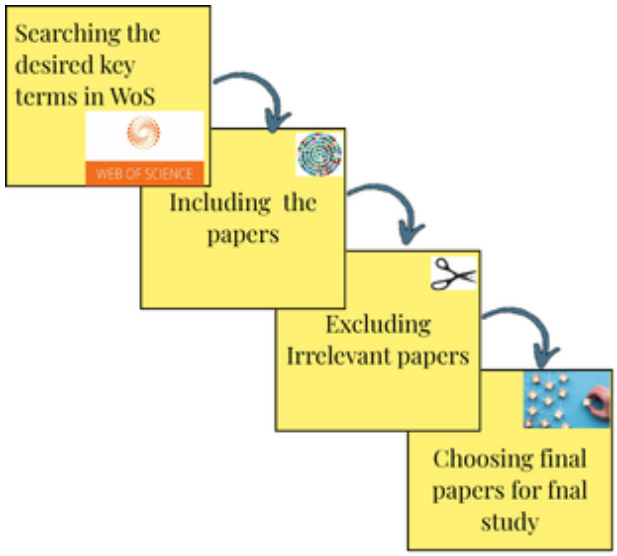


Fig. 3 Stepwise paper selection process

Figure 4 below provides a comprehensive survey of leading research institutions, to evaluate and understand the institutional and geographical distribution driving mathematical models/architectures in economics.

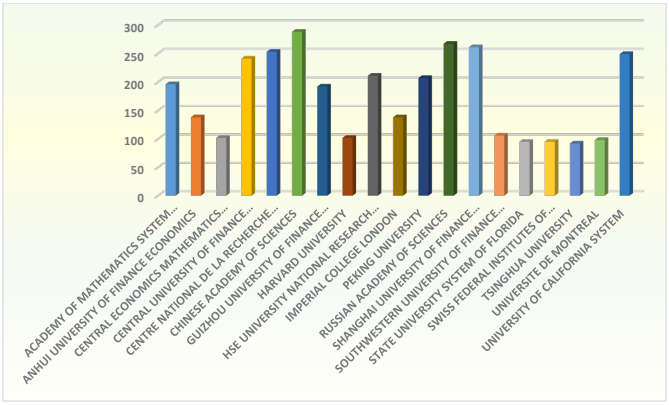


Fig. 4 Survey of affiliations working on mathematical modeling in economics

The survey presented above highlights a sheer concentration of research in Chinese, Russian and American academia.

The Chinese academy of Sciences emerged as the topmost global contributor, approaching nearly 300 publications. This output is closely reflected by finance-focused institutions within the same region, such as the Shanghai University of Finance and Economics. The dense clustering proves a coordinated push and state-backed support to move financial and econometric research into large scale computational platforms. Analyzing the behavior of communities outside the Asian centers particularly western communities in the similar context, the University of California system and the Russian Academy of Sciences show noticeable productivity, taking 250 number of publications. This contribution highlights that actual bulk of macroeconomic modeling implementation is limited to some national academies and public university net.

Donut chart in Figure 5, provides a measure of individual productivity within the sphere of economics+ mathematical model. A fractional contribution analysis is detailed in this figure showing a collaborative and healthy research ecosystem characterized by high parity among its top tier authors, rather than a single individual monopolizing this space. Authors Xu CJ and Wang SY occupy the two leading investigators in this environment, placing them at the central technical anchors of this area, while the remaining volume of this systemic research is shared among core fecund researchers. A significant segment of the profile is ascribed to consortium entries/ groups of networks, international laboratories where individual authorship is decentralized into international institutional groups.

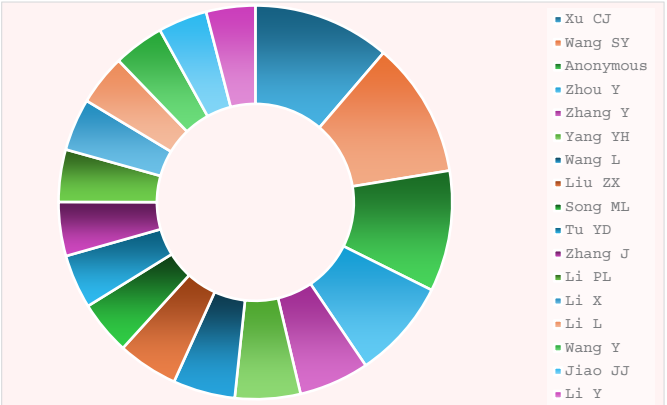


Fig. 5 Number of publications per author economics +math model

The line graph given in Figure 6, demonstrates a multi-phase trajectory in the adoption of artificial intelligence (AI) and machine learning (ML) techniques to clarify the trend of frameworks within economic modeling from 2012 till this year. The data reveals a dramatic structural transition, moving from a lengthy incubation period into a phase of aggressive, steep acceleration.

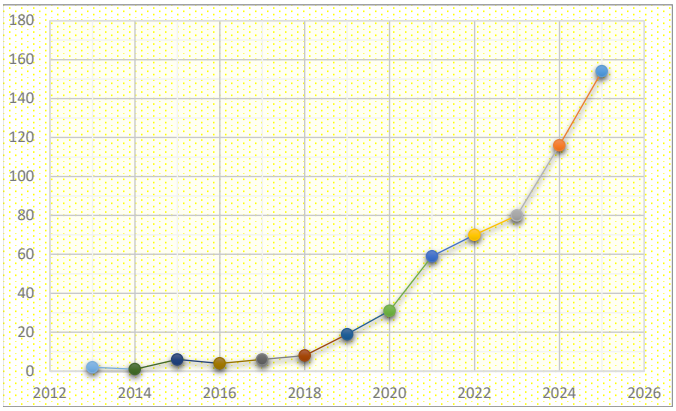


Fig. 6 Year wise introduction of AI/ML in economics

The conceptual incubation phase lying over the window of 2012 to 2018, the integration of AI techniques within economy remained practically negligible. During this period, mainstream economics apprehended machine learning doubtful, remained attached to the traditional parametric econometrics. This baseline drift indicates significant institutional inertia. The initial notable step taken in 2018. Number of publications broke past its dormant era, going to 20 papers in the next year and reaching 30 papers in 2020. This variation points coincides with the expanded availability of machine learning libraries (such as PyTorch and TensorFlow) and the preliminary academic proof-of-concepts showing that nonlinear complex algorithms could considerably outperform conventional regressions in processing big data sets. An exponential growth in converting to intelligent mechanism can be observed post 2020. The publications volume rapidly scaled from roughly 60 paper and reached almost 80 in 2023. This expansion burst in next two years, jumping roughly to155 publications in 2025.

While evaluating the above figures collectively, these metrics prove that computational evolution is rapidly accelerating on world level while seeking a algorithmic transition towards data-driven forecasting and approximation establishing themselves as the SOTA methodology for economic analysis.

2.2 Research questions

The authors aimed to address following research questions.

Q1. What is the current operational scope of AI applications contemporary economics modeling?

Q2. What are the basic computational and methodological constraints, challenges and issues faced in successful deployment of AI in economics?

Q3. What type of analytical frameworks and metrics can be helpful to enhance accuracy of predictive validity?

Economic systems based on mathematical models analyzed by AI/ML algorithms can interpret and recognize the complex patterns in the economic markets. These patterns are based on correlations between various economic variables such as market prices, consumers' spending, and other macroeconomic indicators. AI models evaluate big data to point out potential malfunctions, risks, recommend solutions and predict outcomes.

2.3 Analysis of the selected papers

A thorough review of the final 53 papers reveals that representing dynamics of economy in terms mathematical models provide sustainable solutions and make it simpler for incorporation of intelligent models. A design for economic framework suggested in [35] that integrate engineering and economic analysis for effective evaluation of process and material trade-off. The authors show using various case studies that overall operating costs can be reduced. IndLog is a form of Inductive Logic programming (ILP) introduced by Camacho.R in [36] having the ability to handle complex hypothesis spaces across miscellaneous application domains. Salient features of IndLog including language level search, distributed computer support and statistical validation approaches making it an effective methodology in multi-relational and numerical environments. Successful application in various fields such as economics, engineering, time series modeling and life sciences proves its effectiveness. Valença M et al. provides a comparison of Periodic Autoregressive Moving Average Model with Neural Networks in their study [37] and to verify the better performance of intelligent model while using these models for economy of hydroelectric power industry. Results obtained demonstrate the predictive accuracy of intelligent techniques over classical autoregressive models while treating such nonlinear dynamical projects. Similarly, using fuzzy neural networks for solving System of Fuzzy Differential Equations applicable in various fields of economics and engineering related, is presented as an efficient tool [38]. The model shows a versatile nature when applied in numerous applications. Prohibitively Complex Forecast (PCF) forwarded by Dohnal M. [39] shows that PCF provides a relatively viable mathematical technique capture complex socio-technical interactions as compared to traditional econometrics. Making structural modifications in previous integrated inventory model, the authors introduced a multi-tiered lot size-dependent framework [40]. The model presents a dynamic progression in the optimization of integrated inventory economics. Ahmed et. al [41] by integrating Stochastc Volatility Models from economics with Ornstein-Uhlenbeck process, solved a latent state estimation numerically. The basic advantage of this interdisciplinary approach is its capability to mathematically pick up both short and long-term decay This dynamic tracking approach provides a substantial advantage over conventional deterministic or static metrics. The study [42] proposed a hybrid technique combining adaptive kernel density estimation (AKDE), GRU and CNN for predicting probabilistic electricity forecasting deregulated markets. By combining residential load and wind speed predictions, this hybrid model effectively captured price dynamics, highlighting importance in economics. The authors [43] developed a mathematical technique for pricing strategy in social networks while taking congestion factors and network effects into account along with simultaneous pricing methods. It is elaborated that dynamic pricing schemes substantially enhanced the revenue of network operators and users experience as compared to traditional pricing. This scheme emphasizes the role of computational methods in digital economics. A contract-theoretic mathematical framework in mobile networks [44] for data reward design under asymmetric information is proposed by Z. Xiong et al to prove how incentive-compatible optimization may balance user engagement and advertiser revenue. In [45], multi-agent consensus theory based distributed economic model is suggested for microgrids prone to cyberattacks. Similarly, the authors in [46] formulates profit sharing and cooperation problem between communities and prosumers energy storage using distributed optimization methods and Nash bargaining theory to ensure privacy and compatibility.

Fractional analysis have the potential to incorporate past terms of a model. Feng et al., introduced a fractional evolutionary algorithm in their study [47], is a model that incorporates memory effects for user-focused network selection in diverse networks, proving balance and stability while showing improved cumulative utility under dynamics of memory. The authors developed a framework for fresh data trading under Age of Information (AoI) [48], where subscription-based and time-dependent pricing schemes are analyzed through both finite and infinite-horizon optimization models. An economic dispatch architecture using cloud-edge AI framework [49] is presented for microgrids. This architecture enables the system to make real time decisions.

The authors in [50] also suggested an AI technique for economic load dispatch in microgrids, while training the ML models on previous optimal dispatch decisions manage energy in real time under renewable power generation and load variations. In order to model sponsored content services in mobile networks, the authors in [51], developed a Stackelberg game combined with contract theory. The salient features reported are optimized framework for sponsorship, pricing and user demand under irregular information. The study presented by Kiani et al., [52], discusses the application intelligent Bayesian Regularization (BR) NN model for solving mathematical model environmental mathematical systems. Accuracy of solving complex environmental and economic models is proven by the results given in the study. [53], presented an efficient tool decision-making issues in economics. This study develops a numerical framework for solving fuzzy nonlinear equations using triangular fuzzy numbers. Another similar study, encouraging mathematical modeling of uncertainty through fuzzy FDEs presented by [54], where the authors employed fractional differential transform to get analytical solutions. This methodology is applicable in different optimization and economics problems. Overall, the above-mentioned studies unanimously highlight the growing convergence of mathematical modeling (game theory, optimization, contract theory and control) and artificial intelligence schemes in addressing economic issues and uncertainties. Additional applications of these techniques are resource allocation, economic load dispatch and uncertainty quantification etc.

Stochastic emission-aware economic dispatch under carbon taxation was investigated in [55] using chance-constrained and distributed robust optimization techniques. The results demonstrate that these models bring a fruitful balance between economic costs, system reliability and environmental constraints in a renewable power system. Three-stage Stackelberg game was introduced by authors in [56] to analyze mobile data trading markets. The analysis monitors the user subscription choices, operator pricing and trading decisions. The work presented by Shoaib et al., [57] applies to a hybrid intelligent model incorporating NN, SQP and GA for solving COVID-19 SIR model. This study highlights the applicability of AI in computational methods. In order to address the uncertain behavior of the renewable power sources, the study [58] proposes an intelligent hybrid forecasting model that combines wavelet transform, isolated forest, quantile regression and categorical boosting for probabilistic and deterministic wind power prediction. The accurate forecasting supports the applicability of AI in supporting decisions in energy management and forecasting performance of renewable resources. In contrast, the authors in [59], provides a basis for mathematical foundation of modeling uncertainty through fuzzy FDEs, offering analytical solutions so that they may be utilized in the field of optimization and economics. Similarly, [60] contributes to present AI-based neuro-stochastic Bayesian model that can approximate nonlinear financial systems while interacting with macroeconomics. These studies also illustrate the roles of stochastic modeling, mathematical optimization and economics related challenges.

A mathematical framework was developed in [61] based on utility for prediction markets, elaborating how risk preferences, trade beliefs and information aggregation mutually decide market equilibrium prices. The authors in [62] presented a commodity price forecasting method, 1-dimensional convolutional Neural Network (1D-CNN) specifically for copper price prediction. The analysis of results indicated that deep learning intelligent models are able to capture long-term price variations accurately and present a reliable technique for market members and a policymaker in resource and energy economics. An l1/l2 fractional regularization technique introduced in [63] for sparse portfolio optimization within the framework of mean-variance. The proposed model integrates efficient numerical algorithms with mathematical optimization to improve out-of-sample investment and portfolio sparsity while sustaining desired return levels. The work presented in [64] introduces an evolutionary algorithm integrated economic model for forecasting and regulating chaotic economic phenomena. The proposed technique shows how AI-aided control methods can improve the predictability of expectations of economic agents and stabilize irregular market behavior. By evaluating the impact of solar power forecasting on green hydrogen production costs, the authors in [65] highlight the economic value of ML techniques in renewable power systems. A comprehensive analysis of XGBoost, LSTM and SVR is presented to show that forecasting by using AI technology can help improve efficiency of operational decisions and investment and reduce economic uncertainty. Overall analysis of the studies discussed above illustrates the necessity and applicability of mathematical modeling and optimization techniques for improved economy. Further, the growing trends of integration of AI in financial decisions, economic forecasting and market designs for a sustainable economic system.

2.4 Comprehensive review table

Table 1 below presents different economic models and their merits and demerits.

Ref	Year	Economic domain	Mathematical model	AI technique	Main objective
35	1998	Process analysis	KB numerical analysis	-	Production and operational cost
36	2004	Modeling		ILP	Solving complex hypothesis
37	2013	Economics of engineering	Differential equations	Fuzzy system	Solving complex models
39	2016	Macroeconomics	-	Prohibitively Complex Forecast (PCF)	capture complex socio-technical interactions
40	2017	Inventory	multi-tiered lot size-dependent framework	-	Reducing inventory time

Ref	Year	Economic domain	Mathematical model	AI technique	Main objective
41	2017	Financial economics	Stochastic Volatility Models from economics with Ornstein-Uhlenbeck process	-	Capture the volatility of market
42	2019	Electricity domains	AKDE	CNN-GRU	Electricity price forecasting
43	2019	Wireless economics	Dynamic pricing model	-	Revenue optimization
44	2020	Revenue	Contract theoretic model		Compatibility optimization
45	2020	Microgrids economy	Consensus theory	Multi agent system (MAS)	Revenue optimization and Cyber attacks
46	2020	Energy economics	Nash bargaining, ADMM		Energy sharing optimization
47	2020	Telecommunications	Fractional evolutionary algorithm		Network selection
48	2021	Data economics	Dynamic optimization		Fresh data pricing
50	2021	Smart grids	Economic dispatch	Machine learning	Real-time dispatch
51	2020	Mobile services	Stackelberg + contract game		Sponsored contract pricing
52	2021	Environmental economics	Differential equations	Bayesian neural networks	Environment economic modeling
53	2021	Economics under uncertainty	Fuzzy nonlinear equations		Numerical solution
54	2022	Mathematical economics	Fractional differential equations		Uncertainty modeling
55	2021	Energy economics	Optimization		Carbon-tax dispatch
56	2020	Telecommunications economics	Stackelberg game		Data trading markets
58	2023	Energy forecasting	Quantile regression	CatBoost, Wavelets	Wind power forecasting
60	2025	Financial economics	Chaotic differential systems	Neuro-stochastic Bayesian network	Financial dynamics
61	2025	Prediction markets	Utility theory		Market equilibrium analysis
62	2024	Commodity economics		1D-CNN	Copper price forecasting
63	2024	Portfolio optimization	l_1/l_2 regularization, ADMM		Sparse portfolio selection
64	2025	Macroeconomics	OLG model	Evolutionary algorithm	Chaos control
65	2025	Hydrogen economics	Cost modeling	XGBoost, SVR, LSTM	Cost optimization

Figure 7. conceptualize the taxonomy of AI branches applied within the economic analysis. This figure illustrates a non-hierarchical relationship of the given subfields of AI with economics, suggesting their modular application in model economic decision making and forecasting etc. The widespread implementation of AI in distinct forms positions it as an ecosystem of methodological approaches to address different aspects of model's complexity, data-driven inference and optimization.

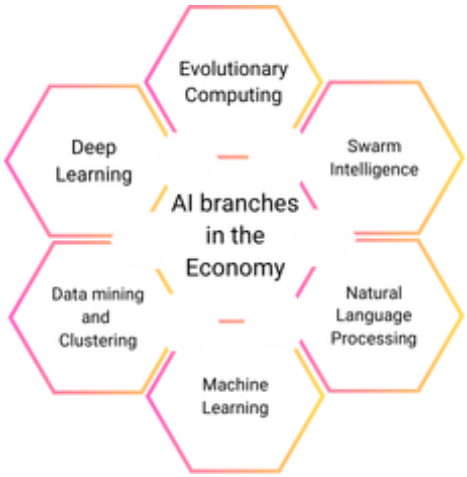


Fig. 7 Branches of AI applied in economics

3. ADDRESSING THE RESEARCH QUERIES

Based on the reviewed literature and relevant studies discussed in the preceding sections, the three core research questions are answered and synthesized below.

3.1 Answer to research question 1

Artificial intelligence is added into the economy primarily as a high-dimensional computational function that automates mundane tasks, pushes corporate productivity, enhances predictive analytics and optimizes logistics. Systematically, its integration has developed across numerous distinct frameworks:

3.1.1 Handling fuzzy and unstructured data

In environments characterized by operational uncertainty, Fuzzy Neural Networks (FNNs) are trained on a combination of crisp and fuzzy data vectors. By employing the Universal Approximation Method (UAM) and modifying fuzzy weights via specialized cost functions, these networks solve systems of fuzzy differential equations (SFDEs) near uncertain initial loci.

3.1.2 Continuous-Time state estimation

Human engagement, concentration and hidden behavioral traits are modeled dynamically by integrating physics-inspired

Stochastic Volatility Models, mathematically solved via particle filters to provide real-time follow-up metrics.

3.1.3 Dynamic Inventory and distribution system

Algorithmic alterations allow AI models to manage stochastic demand by handling logistic friction such as flexible transportation times and twofold safety stock threshold as active optimization decision variables.

3.1.4 Qualitative reasoning and trend modeling

Under acute shortage of information, where numerical constants are mathematically unobtainable or extraneous, AI qualitative tools replaces classical ordinary differential equations with Equationless Heuristics (EHEs). This mechanism streamlines a multidimensional, complex, socio-technical relations into readable trend-based scenarios (increasing, decreasing, constant or volatile trends).

3.2 Answer to the research question 2

Although the AI has exceptional transformation power, still it faces significant socio-ethical, systemic and computational obstructions while employed in the field of social sciences.

3.2.1 Socio-economic equity and Disruption

High velocity intelligent automation threatens widespread potential wage reduction, economic displacement and job losses across services sectors and industry, causing a risk of impairing systemic wealth inequality.

3.2.2 Data vulnerabilities (Bias, noise and accuracy)

AI systems rely on past data during training process. In this data is incomplete, outdated of having biased terms, the systems automatically generate unfair, inaccurate and skewed responses. Additionally, the complexity of global market introduces unknown and unwanted external factors (such as negative media shocks, corporate reforms and financial storms) where conventional training data fails to capture.

3.2.3 Invariability of Human behavior

Human behavioral response is beyond the scope of AI as they can not anticipate how humans will respond to sudden policy adjustments or economic crises, leading to training errors where the human interaction fluctuates abruptly.

Data security and privacy: Since deep learning algorithms ingest huge personal and industrial information/ data, they cause severe data vulnerability to malware and malicious manipulation. Regulating these systems is extremely difficult due to their complex, dynamic and the resistance of applying legal frameworks across various global jurisdictions.

3.2.4 Complexity of calculation

To achieve high accuracy in economic computation and forecasting needs multidimensional large data from fragmented sources. These inputs necessitate immense expensive computing capability for processing that acts as a steep barrier.

3.3 Answer to research question 3

Evaluating the effectiveness of AI models needs to change the direction from using stiff static metrics to multi-level resilient frameworks that assess both computational behavior and real-world applicability: 3.3.1 Model robustness and intra-market generalization: Assessment criteria to check the efficiency of algorithms includes testing its resilience across various, highly volatile financial landscapes to make sure that the models are not fit to a single market regime or representing only a specific financial landscape.

3.3.2 Scenario density optimization: Performance of an adopted AI model can be measured by its ability to mitigate the "curse of dimensionality". For example, an expert-knowledge-driven EHE system is efficient if it could condense a massive, seemingly unmanageable solution spaces to a compressed and usable subset of high probability paths.

3.3.3 Explainability and comprehensive risk management: Since deep learning models function as black boxes, their explainability is a critical metric of their efficiency. Actual optimization demands building transparent risk management user interfaces that allow human policy-makers to understand, audit and believe the algorithmic logic behind economic decisions.

3.4 Conclusion

This paper discusses modeling and reviews different mathematical models and infusion of AI in economic systems, creating a structural foundation for understanding modern day economy. The paper does not include all but some of them which are more frequently used and practiced widely. The authors endeavors to prepare a base to know how quantitative tools can be utilized to overcome the conventional analytical tools to achieve volatile dynamics of contemporary global economics. Moreover, this work maps an intersection of economic models and intelligent state-of-the-art mechanism, providing insights to researchers working in this frame of reference.

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