Applications of Artificial Intelligence in Economic Analysis

Dr. Velu Suresh Kumar

Associate Professor & Head, PG & Research Department of Economics
H.H. The Rajah's College (Autonomous), Pudukkottai - 622 001 Tamil Nadu, India

Abstract: Accurate economic forecasting is crucial for economists and policy makers, as it allows them to make informed decisions about issues such as monetary policy, fiscal policy, and business strategy. In recent years, artificial intelligence (AI) has emerged as a powerful tool for economic forecasting, as it is able to analyze large amounts of data quickly and accurately and identify patterns and relationships that may be difficult for humans to see. However, the application of AI in economic forecasting also presents challenges and it is also important to carefully consider the ethical implications of using AI in economic decision making, and to ensure that it is used in a responsible and transparent manner.

Keywords: Artificial Intelligence, Machine Learning, Natural Language Processing, Deep Learning, Neural Networks, Forecasting.

INTRODUCTION

In this era, the business environment is dynamic and unstable due to several forces, such as technological dependence, increased customer expectations, pandemics, and war (Mediavilla *et al.*, 2022). Consequently, businesses must respond quickly to market changes and unexpected events to stay competitive. Applications of information and communication technologies (ICT) assist organizations in making appropriate decisions and developing effective strategies to manage and control unanticipated effects. They assist organizations in dealing with supply chain issues caused by the increased movement of goods and data in the supply chain (Huddiniah & Mahendrawathi, 2019). As a result of the ICT revolution, many predictions and management tools based on Artificial Intelligence (AI) have been released, allowing enterprises to record large amounts of data and robust information (Rafael González Perea *et al.*, 2019).

AI has been widely used in various fields, such as engineering, sciences, banking, finance, economics, tourism, and healthcare. AI is the simulation of human intelligence using software-coded heuristics (Frankenfield, 2023). AI is the primary innovation for creating intelligent machines that mimic human behavior and perform various tasks (Annor *et al.*, 2019). AI is better suited for complex input-output relationships (Raza & Khosravi, 2015). Thanks to AI, manufacturers can effectively obtain upstream and downstream product information to make precise product predictions and decisions (Fu & Chien, 2019). AI modelling is being created for intelligent tourism platforms to accurately predict tourism choice behavior patterns (Doborjeh *et al.*, 2022). Thus, AI-based techniques have significantly contributed to the evolution of various sectors, industries, and supply chains.

AI has been applied in various fields of economic analysis, including economic forecasting, modeling complex economic systems, predictive analytics, decision making, trading, and investment management. Economic forecasting is the process of attempting to predict future conditions of the economy using a combination of indicators. The primary economic indicators include inflation, interest rates, industrial production, consumer confidence, worker productivity, retail sales, and unemployment rates.

Governments and businesses use forecasts for long-term planning, such as infrastructure development and urban planning. Governments rely on economic forecasts in setting fiscal and monetary policies. For example, if a recession is predicated, the government might implement expansionary fiscal policies to stimulate the economy (Tejvan Pettinger, 2015). Businesses rely on economic forecasts to make investment decisions, plan production, and manage resources effectively. Investors use economic forecasts to predict market trends and make informed decisions about buying or selling assets. Economic forecasts influence consumer behavior, affecting their spending and saving patterns based on expected

economic conditions. The use of AI in economic analysis has been driven by the need to improve the accuracy and efficiency of economic forecasting and decision making (Liu *et al*., 2023; Rutkauskas *et al*., 2021).

Accurate forecasting brings many positive effects and benefits. It helps in anticipating market trends and economic conditions. Accurate forecasts enable efficient use of resources by aligning production, inventory, and staffing levels with expected demand. This reduces waste and improves operational efficiency. Reliable forecasts build confidence among investors, consumers, and business. On the other hand, inaccurate predictions can lead to overproduction or under production, resulting in wasted resources, excess inventory, or unmet demand. It also leads to inefficient investments, resource misallocation and strategic errors. Investors, consumers, and businesses may lose confidence in the economic environment, leading to reduced spending, investment and overall economic activity.

For all the reasons mentioned above, precise demand forecasting is vital. Therefore, selecting a reliable forecasting method is indispensable. Different forecast techniques and applications have been proposed and developed based on AI (Aburto & Weber, 2007; Chen *et al*., 2015; Khashei & Bijari, 2011; Kilimci *et al*., 2019; Mediavilla *et al*., 2022). Nevertheless, choosing the optimal AI methods can be challenging due to lots of methods. In addition, each method has its drawbacks and strengths.

Evolution of Forecasting Techniques

Forecasting is the first stage of demand management - a vital supply chain management process (Crum & Palmatier, 2003). Predictions help balance demand and supply at the customer level and utility planning (Bot *et al*., 2020). Demand variability is one of the main variables utilized for calculating the safety stock held by a firm for handling stock-out circumstances caused by fluctuations in supply and demand (Jaipuria & Mahapatra, 2021). Thus, forecasting accuracy is critical in efficient supply chain management and, ultimately, in firm success. Accurate demand forecasting improves supply chain performance (Mobarakeh *et al*., 2017; Moroff *et al*., 2021; Nguyen *et al*., 2021). As a result, many demand forecasting techniques have been developed and proposed.

Managers and researchers have employed different techniques to forecast. They can be categorized into qualitative and quantitative methods (Hofmann & Rutschmann, 2018; İfraz *et al*., 2023; Moroff *et al*., 2021). Qualitative methods are used when the available data is insufficient for a quantitative analysis or when qualitative information is likely to improve forecast accuracy. Expert opinions or knowledge of special events are examples of qualitative methods. In contrast, quantitative methods analyzed historical data (time series) or specific relationships between system elements (causal models).

Time series methods can be classified into traditional and modern methods. Besides, modern methods can be regarded as AI methods. AI methods can train large amounts of data, nonlinear trends, and complex data. For example, autoregressive integrated moving average (ARIMA) and ARIMA with exogenous factors (ARIMAX) are traditional methods that work well with linear data but have data limitations. In contrast, long short-term memory (LSTM) is an AI method that performs well with nonlinear and complex data (Kantasa-ard *et al*., 2021; Narayanan *et al*., 2023; Nguyen *et al*., 2021). As a result, much research has proved that AI methods perform better than traditional ones (Kantasa-ard *et al*., 2021; Nguyen *et al*., 2021; Soltani *et al*., 2022). Therefore, AI forecasting techniques play vital roles in dealing with complex data and boosting forecasting accuracy.

AI Techniques in Economic Analysis

Machine Learning Algorithms

Machine learning algorithms have become increasingly important in economic forecasting due to their ability to handle large datasets and capture complex patterns. Here are some key machine learning techniques used in economic forecasting (Trinh Nguyen, 2023):

•	Artificial Neural Networks (ANNs): ANNs can model non-linear relationships and interactions between variables, making them suitable for capturing complex economic dynamics.

•	Long Short-Term Memory Networks (LSTMs): A type of recurrent neural network (RNN) that excels at learning long-term dependencies in sequential data, making them ideal for time series forecasting. This model is commonly used to predict

economic indicators such as GDP growth and stock prices.

- Random Forests: An ensemble learning method that combines multiple decision trees to improve prediction accuracy and robustness. It is effective for both classification and regression tasks.

- Support Vector Regression (SVR): SVR is useful for predicting continuous outcomes and can handle high-dimensional data, making it suitable for economic forecasting.

- K-Nearest Neighbors (KNN): A simple, non-parametric method that predicts the value of a variable based on the values of its nearest neighbors.

- Gradient Boosting Machines (GBMs): GBMs build models sequentially, each new model correcting errors made by the previous ones. It is highly effective for improving prediction accuracy.

- Elastic Net: This algorithm was originally proposed by Zou and Hastie in 2005 and is a combination of the ridge and least absolute shrinkage and selection operator (LASSO) regressions. Both approaches are forms of penalized regressions, a method to improve Ordinary Least Squares (OLS) regressions by performing dimension reduction and/or variable selection when dealing with large datasets with multiple, possibly correlated regressors (Jin-Kyu Jung *et al*., 2018).

- Decision Trees: It is a supervised machine learning algorithm used for both classification and regression tasks. It works by splitting the dataset into subsets based on the value of input features. This process is repeated recursively, creating a tree-like structure.

These algorithms have been applied to various economic forecasting tasks, such as predicting GDP growth, inflation rates, and the direction of the stock market and to forecast the price of commodities such as oil and gold (Nikolopoulos, 2010) or copper (Zhang *et al*., 2021; Ruiz-Real *et al*., 2021). Machine learning algorithms have been used to predict customer behavior and to optimize marketing strategies (Bourke, 2019).

Deep Learning Algorithms

Deep learning algorithm models have shown significant improvements in forecasting accuracy and are widely applied in various economic subfields, including financial markets, macroeconomics and business administration. Here are some key deep learning approaches used in economic forecasting:

- Recurrent Neural Networks (RNNs): These are particularly useful for time series forecasting due to their ability to maintain temporal dependencies (Zheng, Y *et al*, 2023).

- Convolutional Neural Networks (CNNs): While traditionally used in image processing, CNNs have been adapted for economic forecasting by capturing spatial dependencies in data. This model is effective in identifying patterns in financial time series (Yang Dexiang *et al*, 2023).

- Generative Adversarial Networks (GANs): GANs are used to generate synthetic data that can help improve the robustness of forecasting models. This model is particularly useful in scenarios where historical data is limited (Cheng Zhang *et al*, 2023).

- Deep Reinforcement Learning (DRL): DRL is applied in economic forecasting to optimize decision-making processes. This model is used to portfolio management and trading strategies to predict market movements and make informed investment decisions (Zheng, Y *et al*, 2023).

- Hybrid Models: Combining traditional statistical methods with machine learning techniques to leverage the strengths of both approaches.

Challenges and Limitations of AI in Economic Analysis

While the use of AI techniques in economic analysis has brought about many opportunities, it has also raised several challenges and limitations. Some of the key challenges and limitations are discussed below:

One of the main challenges of using AI in economic analysis is the quality and availability of data. AI models require large amounts of high-quality data to train and make accurate predictions. However, economic data is often incomplete, inconsistent, and subject to measurement errors. This can lead to biased or inaccurate predictions and limit the effectiveness of AI models (Wang and Strong, 1996).

Another challenge of using AI in economic analysis is the interpretability and explainability of AI models (Owens *et al*., 2022). AI models are often complex and difficult to interpret, making it challenging to understand how they arrive at their predictions. This can limit the ability of economists to use AI models to inform policy decisions and to understand the underlying economic mechanisms.

AI models can also be subject to bias (Zhang *et al*., 2021) and ethical considerations, which can have significant implications for economic analysis. For example, AI models may be biased against certain groups of people or may perpetuate existing inequalities in the economy. This can lead to unfair or discriminatory outcomes and limit the effectiveness of AI models in economic analysis.

Strengths and Weaknesses of AI Methods

AI methods have several strengths and weaknesses when applied to economic analysis. Some of the key strengths and weaknesses are discussed below. The strengths can be summarized as follows:

• Improved Accuracy: AI methods can improve the accuracy of economic forecasting and decision making by modeling complex patterns in data.

• Efficiency: AI methods can process large amounts of data quickly and efficiently, allowing for faster and more accurate predictions.

• Flexibility: AI methods can be applied to a wide range of economic problems, including forecasting, modelling, and decision making.

• Nonlinear Modeling: AI methods can model nonlinear relationships between economic variables, which can improve the accuracy of predictions (Zapata and Mukhopadhyay, 2022).

The weaknesses can be summarized as follows:
• Data Quality and Availability: AI methods require large amounts of high-quality data to make accurate predictions, and economic data is often incomplete, inconsistent, and subject to measurement errors.

• Interpretability and Explainability: AI models can be complex and difficult to interpret, making it challenging to understand how they arrive at their predictions.

• Bias and Ethical Considerations: AI models can be subject to bias and ethical considerations, which can have significant implications for economic analysis.

• Overfitting: AI models can be prone to overfitting, which occurs when the model is too complex and fits the training data too closely, leading to poor performance on new data (Zapata and Mukhopadhyay, 2022)

Ethical Considerations and Biases of AI in Economic Analysis

AI models have the potential to revolutionize economic analysis, but they also present ethical considerations and potential biases that need to be addressed. These ethical considerations arise from the fact that AI models learn from historical data and are only as good as the data they are trained on. If the data contains biases or reflects historical discrimination, the AI models will replicate these biases and discriminate in their predictions and recommendations.

One of the most significant ethical considerations in AI models is bias (Von Zahn *et al*., 2021). Bias can be defined as the presence of systematic errors or inaccuracies in the data that cause an AI model to make incorrect predictions or recommendations. Bias can be introduced in various ways, such as sampling bias, measurement bias, or data preprocessing bias. For example, if an AI model is trained on historical data that reflects past discrimination against a certain group, such as women or minorities, it may replicate this discrimination and perpetuate it in its predictions and recommendations. In economic analysis, bias in AI models can have significant implications. For example, if an AI model used to predict creditworthiness or loan approvals is biased against certain groups, such as minorities or low-income individuals, it can perpetuate the cycle of poverty and discrimination. Similarly, if an AI model used for investment management is biased towards certain industries or companies, it can lead to inefficient allocation of resources and market distortions.

To address these ethical considerations and potential biases in AI models, several approaches can be taken. First, data quality and preprocessing should be carefully considered to ensure that the data used to train AI models is unbiased and representative of the population. Second, transparency and interpretability

of AI models should be improved to enable stakeholders to understand how AI models make decisions and detect potential biases. Third, diversity and inclusion should be prioritized in the development and deployment of AI models to avoid discrimination and ensure that AI models reflect the diversity of the population they serve.

CONCLUSION

In conclusion, AI can be a valuable tool for economic forecasting, as it is able to process large amounts of data quickly and accurately and identify patterns and relationships that may be difficult for humans to see. AI-powered economic forecasting has the potential to improve the accuracy and timeliness of economic forecasts, and to assist economists and policy makers in making more informed decisions.

However, it is important to recognize that AI is not a substitute for human judgment and decision making. It should be used as a tool to assist with economic forecasting, rather than replacing human expertise and judgment entirely. There are also challenges and limitations to using AI for economic forecasting, such as the dependence on high-quality data and the difficulty in understanding complex economic phenomena.

Looking to the future, there is potential for the development of more advanced machine learning algorithms and the availability of more high-quality data, which could further enhance the accuracy and usefulness of AI-powered economic forecasting. However, it will be important to carefully consider the ethical implications of using AI in economic decision making, and to ensure that it is used in a responsible and transparent manner.

REFERENCE

[1] Aburto, L., & Weber, R. (2007). Improved Supply Chain Management based on Hybrid Demand Forecasts. Applied Soft Computing Journal, 7(1), pp. 136-144. https://doi.org/10.1016/j.asoc.2005.06.001

[2] Bot, K., Ruano, A., & Ruano, M. G. (2020). Forecasting Electricity Demand in Households using Moga-designed Artificial Neural Networks. IFAC-PapersOnLine, 53(2), pp. 8225-8230. https://doi.org/10.1016/j.ifacol.2020.12.1985

[3] Bourke, E. (2019). Smart Production Systems in Industry 4.0: Sustainable Supply Chain Management, Cognitive Decision-Making Algorithms, and Dynamic Manufacturing Processes. Journal of Self-Governance and Management Economics, 7(2):25-30. https://doi.org/10.22381/JSME7220194

[4] Chen, Y., Yang, Y., Liu, C., Li, C., & Li, L. (2015). A Hybrid Application Algorithm based on the Support Vector Machine and Artificial Intelligence: An Example of Electric Load Forecasting. Applied Mathematical Modelling, 39(9): 2617-2632.
https://doi.org/10.1016/j.apm.2014.10.065

[5] Cheng Zhang et al, 2023, Deep Learning Models for Price Forecasting of Financial Time Series: A Review of Recent Advantages: 2020-2022, WIRES Data Mining and Knowledge Discovery, 14(1).
https://doi.org/10.1002/widm.1519

[6] Crum, C., & Palmatier, G. E. (2003). Demand Management Best Practices: Process, Principles, and Collaboration. Boca Raton, FL: J. Ross Publishing.
http://books.google.at/books?id=6l3iWbGM-54C

[7] Doborjeh, Z., Hemmington, N., Doborjeh, M., & Kasabov, N. (2022). Artificial intelligence: A Systematic Review of Methods and Applications in Hospitality and Tourism. International Journal of Contemporary Hospitality Management, 34(3): 1154-1176.
https://doi.org/10.1108/IJCHM-06-2021-0767

[8] Frankenfield, J. (2023). Artificial Intelligence: What It Is and How It Is Used. https://www.investopedia.com/terms/a/artificial-intelligence-ai.asp

[9] Fu, W., & Chien, C.-F. (2019). UNISON Data-driven Intermittent Demand Forecast Framework to Empower Supply Chain Resilience and an Empirical Study in Electronics Distribution. Computers & Industrial Engineering, 135, pp. 940-949.
https://doi.org/https://doi.org/10.1016/j.cie.2019.07.002

[10] González Perea, Rafael, Camacho Poyato, E., Montesinos, P., & Rodríguez Díaz, J. A. (2019). Optimisation of Water Demand Forecasting by Artificial Intelligence with Short Data Sets. Biosystems Engineering, 177, pp. 59-66.
https://doi.org/10.1016/j.biosystemseng.2018.03.011

[11] Hofmann, E., & Rutschmann, E. (2018). Big Data Analytics and Demand Forecasting in Supply Chains: A Conceptual Analysis. International Journal of Logistics Management, 29(2): 739-766. https://doi.org/10.1108/IJLM-04-2017-0088

[12] Huddiniah, E. R., & Mahendrawathi, E. R. (2019). Product Variety, Supply Chain Complexity and the Needs for Information Technology: A Framework based on Literature Review. Operations and Supply Chain Management, 12(4): 245-255. https://doi.org/10.31387/oscm0390247

[13] İfraz, M., Aktepe, A., Ersöz, S., & Çetinyokuş, T. (2023). Demand Forecasting of Spare Parts with Regression and Machine Learning Methods: Application in a Bus Fleet. Journal of Engineering Research, 11(2), 100057. https://doi.org/10.1016/j.jer.2023.100057

[14] Jaipuria, S., & Mahapatra, S. S. (2021). A Hybrid Forecasting Technique to Deal with Heteroskedastic Demand in a Supply Chain. Operations and Supply Chain Management, 14(2): 123-132. https://doi.org/10.31387/oscm0450291

[15] Jin-Kyu Jung, Manasa Patnam, and Anna Ter-Martirosyan (2018). An Algorithmic Crystal Ball: Forecasts based on Machine Learning. IMF Working Paper No. 18/230. https://www.imf.org/en/Publications/WP/Issues/2018/11/01/An-Algorithmic-Crystal-Ball-Forecasts-based-on-Machine-Learning-46288

[16] Kantasa-ard, A., Nouiri, M., Bekrar, A., Ait el cadi, A., & Sallez, Y. (2021). Machine Learning for Demand Forecasting in the Physical Internet: A Case Study of Agricultural Products in Thailand. International Journal of Production Research, 59(24): 7491-7515.

[17] https://doi.org/10.1080/00207543.2020.1844332

[18] Khashei, M., & Bijari, M. (2011). A Novel Hybridization of Artificial Neural Networks and ARIMA Models for Time Series Forecasting. Applied Soft Computing Journal, 11(2): 2664- 2675. https://doi.org/10.1016/j.asoc.2010.10.015

[19] Kilimci, Z. H., Akyuz, A. O., Uysal, M., Akyokus, S., Uysal, M. O., Atak Bulbul, B., Ekmis, M. A., & Silva, T. C. (2019). An Improved Demand Forecasting Model using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain. Complexity, 2019. https://doi.org/10.1155/2019/9067367

[20] Liu, W., Wang, C., Li, Y., Liu, Y & Huang, K. (2021). Ensemble Forecasting for Product Futures Prices Using Variational Mode Decomposition and Artificial Neural Networks. Chaos, Solitons and Fractals, 146. https://doi.org/10.1016/j.chaos.2021.110822

[21] Mediavilla, M. A., Dietrich, F., & Palm, D. (2022). Review and Analysis of Artificial Intelligence Methods for Demand Forecasting in Supply Chain Management. Procedia CIRP, 107(March): 1126-1131. https://doi.org/10.1016/j.procir.2022.05.119

[22] Mobarakeh, N. A., Shahzad, M. K., Baboli, A., & Tonadre, R. (2017). Improved Forecasts for Uncertain and Unpredictable Spare Parts Demand in Business Aircraft's with Bootstrap Method. IFAC-PapersOnLine, 50(1): 15241-15246. https://doi.org/10.1016/j.ifacol.2017.08.2379

[23] Moroff, N. U., Kurt, E., & Kamphues, J. (2021). Machine Learning and Statistics: A Study for Assessing Innovative Demand Forecasting Models. Procedia Computer Science, 180(2019): 40-49. https://doi.org/10.1016/j.procs.2021.01.127

[24] Moritz Von Zahn, Stefan Feuerriegel, & Niklas Kuehl. (2021). The Cost of Fairness in AI: Evidence from E-Commerce. Business & Information Systems Engineering, 64(3):335-348, September 2021. https://doi.org/10.1007/s12599-021-00716-w.

[25] Nikolopoulos, K. (2010). Forecasting With Quantitative Methods: The Impact of Special Events in Time Series. Applied Economics, 42(8):947-955. https://doi.org/10.1080/00036840701721042

[26] Nguyen, T. T. H., Bekrar, A., Le, T. M., & Abed, M. (2021). The Effect of Machine Learning Demand Forecasting on Supply Chain Performance - The Case Study of Coffee in Vietnam. In H. M. Le Thi, H.A., Pham Dinh, T., Le (Ed.), Lecture Notes in Networks and Systems, Vol. 363. (pp. 247-259). Springer, Cham. https://doi.org/https://doi.org/10.1007/978-3-030-92666-3

[27] Owens, E., Sheehan, B., Mullins, M., Cunneen, M., Ressel, J., & Castignani, G. (2022). Explainable Artificial Intelligence (Xai) in

Insurance. Risks, 10(12), 2022. https://doi.org/10.3390/risks10120230

[28] Raza, M. Q., & Khosravi, A. (2015). A Review on Artificial Intelligence based Load Demand Forecasting Techniques for Smart Grid and Buildings. Renewable and Sustainable Energy Reviews, 50, pp. 1352-1372. https://doi.org/10.1016/j.rser.2015.04.065

[29] Richard Y. Wang and Diane M. Strong (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. Journal of Management Information Systems, 12(4):5-33, March 1996.

[30] https://doi.org/10.1080/07421222.1996.11518 099.

[31] Rutkauskas, A. V., Stasytyte, V & Martinkute-Kauliene, R. (2021). Seeking the Investment Portfolio Efficiency Applying the Artificial Intelligence. Transformations in Business and Economics, 20(3):259-277.

[32] Soltani, M., Farahmand, M., & Pourghaderi, A. R. (2022). Machine Learning-based Demand Forecasting in Cancer Palliative Care Home Hospitalization. Journal of Biomedical Informatics, 130(June 2021), 104075. https://doi.org/10.1016/j.jbi.2022.104075

[33] Tejvan Pettinger, 2015: What is the importance of economic forecasts? https://www.economicshelp.org/blog/1976/eco nomics/importance-of-economic-forecasts/

[34] Trinh Nguyen, 2023: A Comprehensive Guide to Machine Learning Forecasting. https://www.neurond.com/blog/machine-learning-forecasting

[35] Yang Dexiang, Mu Shengdong, Yunjie Liu, Gu Jijian and Lien Chaolung (2023), An Improved Deep-Learning-Based Financial Market Forecasting Model in the Digital Economy. Mathematics 2023, 11(6), 1466. https://doi.org/10.3390/math11061466

[36] Yuanhang Zheng, Zeshui Xu & Anran Xiao (2023), Deep Learning in Economics: A Systematic and Critical Review. Artificial Intelligence Review, 56, 9497-9539. https://doi.org/10.1007/s10462-022-10272-8

[37] Zapata H. O. & Mukhopadhyay, S. (2022). A Bibliometric Analysis of Machine Learning Econometrics in Asset Pricing. Journal of Risk and Financial Management, 15(11). https://doi.org/10.3390/jrfm15110535

[38] Zhang, H., Nguyen, H., Bui, X., Pradhan, B., Mai, N. & Vu, D. (2021). Proposing Two Novel Hybrid Intelligence Models For Forecasting Copper Price Based On Extreme Learning Machine And Meta-Heuristic Algorithms. Resources Policy, 73. https://doi.org/10.1016/j.resourpol.2021.10219 5