Library Progress International *Print version ISSN 0970 1052*
Vol.44 No.3, September 2024: P. 21871-21884 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

The Intersection of Artificial Intelligence and Economic Forecasting Transforming Financial Models for Greater Predictive Accuracy

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How to cite this article: Yasin Arafat, Ayooluwa Animashaun, Ahasan Ahmed, Amine Hamdache, Hessan Mohammad, Ilias Elmouki, Hafiza Mamona Nazir (2024 The Intersection of Artificial Intelligence and Economic Forecasting Transforming Financial Models for Greater Predictive Accuracy. *Library Progress International*, 44 (3), 21871-21884.

Abstract

This paper examines how four AI subfields machine learning, deep learning, and natural language processing are enhancing the field of economic forecasting by providing new forms of insight and more flexibility in economic trend analysis. AI in economic forecasting is disrupting economic models, and its impact provides more precision over traditional financial models. New challenges arise with complexity in the global economy where traditional theories and structures remain ineffective in the fast delivery of data to equip economists with the relevant information on the state of the economy. The features of the main algorithms used in machine learning and natural language processing are compared and evaluated in view of their possibilities for handling extensive data and predicting economic tendencies and values. This research indicates the implementation of AI and the uses for AI in economic modeling, as well as the issues that may arise, such as data protection and model explainability. The evidence suggests the use of AI in enhancing the precision and flexibility of various economic forecasting models. AI provided stakeholders with a useful and reliable strategy for forecasting economic changes, market trends, and the critical issues within specific industries. It sees that incorporating AI in economic forecasting is possible and does offer transformative benefits, given that, though not only seasoned with ethical dilemmas and data management issues, it does provide a more solid and stronger form-based decision-making in a fast-changing economic environment.

Keywords: artificial intelligence, economic forecasting, financial models, predictive accuracy, machine learning, deep learning, natural language processing, data privacy, model interpretability, economic trends, market prediction, financial decision-making, global markets

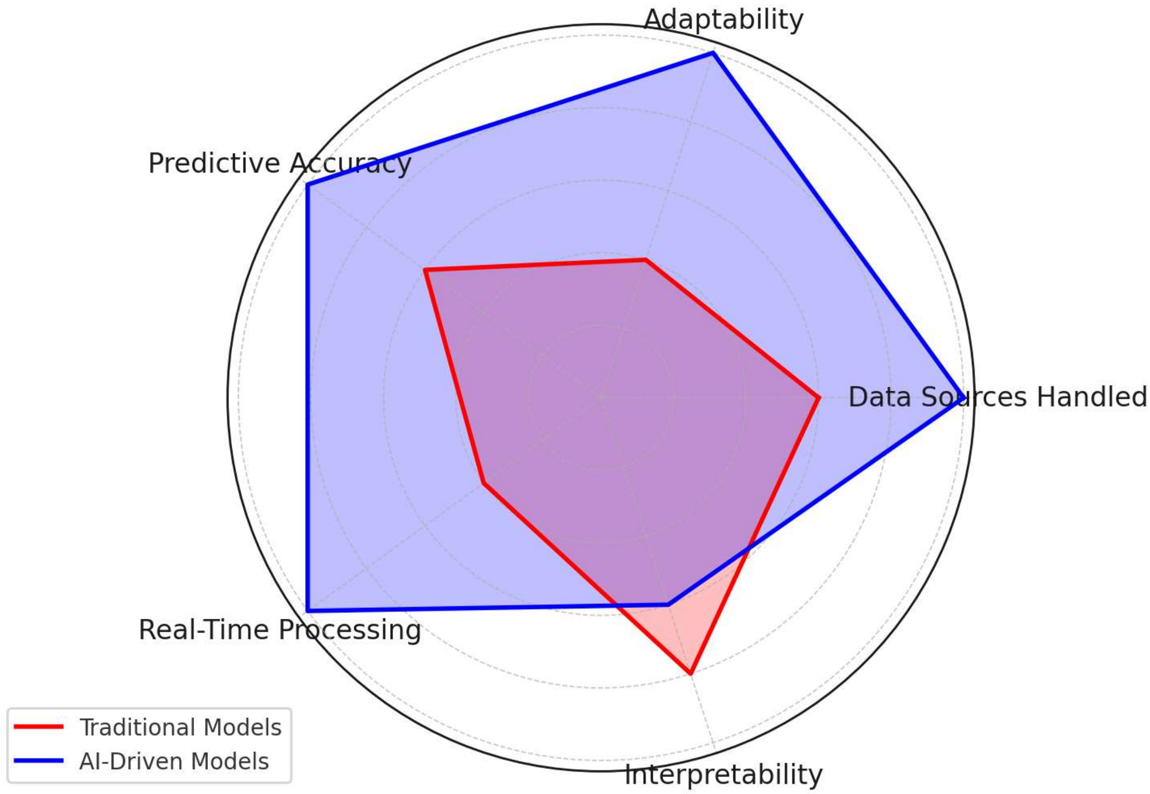
Introduction:

AI development is evolving at an incredibly fast pace, and it is now at the core of the transformation of many industries, and among them, the financial industry is not the least impacted. Economic forecasting forms a core part of fiscal management and relies on models that have hitherto applied econometric techniques. These conventional techniques, however, tend to fail to make realistic understandings of today's economies, more so when globalization is at its peak with advanced use of data analytics in decision-making Machireddy (2021). AI has proven to be a viable substitute that provides higher predictive reliability; moreover, it can process big amounts of actual-time data. Ajiga, (2024). There has been an argument that economic forecasting in the past has always been done on organized data from instruments like GDP, unemployment rate, and interest rate. However, as the volume and variety of economic information increases, not to mention the recent addition of unstructured data sources such as sentiment on social media sites, news streaming, etc., AI offers ways of processing these new data sources that cannot be efficiently replicated by, for example, econometric techniques. Milana, (2021). Using machine learning, computers are capable of mining data and establishing relationships for normal computation that may provide informed insights into some potential shifts in the economic system (Varian, 2014). In addition, the AI-integrated models prove to be more flexible and learn from data that comes into them and estimate with better frequency and security. It goes without saying that this ability is especially valuable in the modern economy, especially after events such as the COVID-19 pandemic that have shown the inefficiency of rigid and conventional forecasting approaches. Lopez-Lira, A. (2024). As for this capability to make large and complex data analyses, AI enhances the accuracy of the economic predictions and enhances the planning of the respective authorities and private companies. However, there are certain drawbacks involved when integrating AI in economic forecasting. Some challenges, including data privacy, feature selection, and methods of informing decision-making, still persist, especially in today's decisional environment where much decision-making is done through artificial intelligence. Han, X., (2024). AI architectures are not easily understood, especially deep learning, which is used in several applications, and indeed, the interpretability of AI models is an issue of considerable importance for building trust, especially in financial decisions. Olubusola, O., Mhlongo, T. (2024). This paper aims at identifying and examining the use of AI technologies such as machine learning, deep learning, and natural language processing for improving economic forecasting precision.

Problem Statement

Forecasting is an important aid in the analysis for decision-making in finance and policy as well as a planning tool in business. One of the major issues with quantitative models of economic forecasting based on the econometric and statistical approaches is that they are not very sufficient to capture the authoritative intrinsic nature of present-day economies. These models are not well suited to deal with big and diverse data sources, for example, real-time market data, sentiment analysis from social media, and geopolitical events. The difference between the forecast and the actual outcome may be significant. Addy, W. A., Ajayi-Nifise, (2024). This situation suggests the importance of adopting more flexible and analytic methods that deal with traditional and non-traditional information, as well as the unpredictable nature of international markets. Zong, Z., & Guan, Y. (2024). But artificial intelligence (AI), with its enhanced features of machine learning, deep learning, and natural language processing, is on the way of presenting solutions to these drawbacks. However, including AI in economic forecasting presents specific dilemmas, some of which include data privacy, ethical aspects, and model explainability, which are essential in creating confidence in financial predictions. Bouchetara, (2024). Considering these issues, the main issue of this research is to investigate how and to what extent AI introduced economic forecasting to provide better accuracy, flexibility, and ethical decision-making for financial and policymaking users.

Figure No.01: Comparison of Traditional Vs AI Driven Forecasting Models



Purpose of the Study

The general goal of this study is to evaluate the potential of AI in the second generation of economic forecasting models for accuracy improvement in the context of financial decision-making adaptability. While conventional econometric techniques remain the bedrock of modern modeling approaches, they are often inadequate in handling the sophistication of the new data-driven economies. This research seeks to establish how the use of AI, namely machine learning, deep learning, and natural language processing, counter these shortcomings and bring about more accurate and timely economic forecasts that include both structured and unstructured data. The research aims at defining and/or solving possible existing constraints to the implementation of AI in the forecast of economic conditions, such as data privacy, ethical issues, or issues of model explainability. When contemplating the positive outcomes and drawbacks of the AI application in economic forecasting, the intent of this research is to provide detailed insight on how AI improves the state of the prediction and helps make better economic and policy decisions to improve economies in the future by creating a better and more powerful economic prediction method as the world becomes more complicated.

Research Questions

1. How are AI technologies, such as machine learning and natural language processing, applied in economic forecasting?
2. What are the primary benefits and challenges of incorporating AI into financial modeling?
3. How can AI improve predictive accuracy and decision-making in economic forecasting?

Literature Review:

Macroeconomic forecasting is an essential tool that defines investors or policymakers' decisions or businesses' strategies. The conventional approaches to forecasting include time series, regression models, and econometric models, and other quantitative techniques have been the fundamental tools for economic forecasting over the years. However, the growing sophistication of the economic systems and the availability of vast amounts of data have led scholars and practitioners to look for ways to apply AI to increase predictive accuracy on this type of economic indicator. Rane, N. L. (2024). Artificial intelligence is a broader concept, and one of the most common of its implementations is called machine learning. The literature shows how ML detects complex patterns in a big dataset that could be neglected by conventional models. Elias, O., Esebre, (2024). For example, Chen et al. (2019) proved that, compared to the traditional econometric model, the SV and BP neural networks have higher accuracy in GDP growth forecasts and showed that ML improves economic forecasts. The other subfield of ML known as deep learning, which implements neural networks with many levels, has received a lot of attention in economic projecting. Fellow researchers Khan, A. K. (2024), have explained that advanced deep learning models such as RNNs and LSTMs are capable of capturing temporal dependence of the economic data set, thus improving on the prediction models. This work pointed out that these models perform perfectly in cases where the independent variables exhibit unilinear patterns and in settings where datasets have numerous features, which is the case in economic modeling.

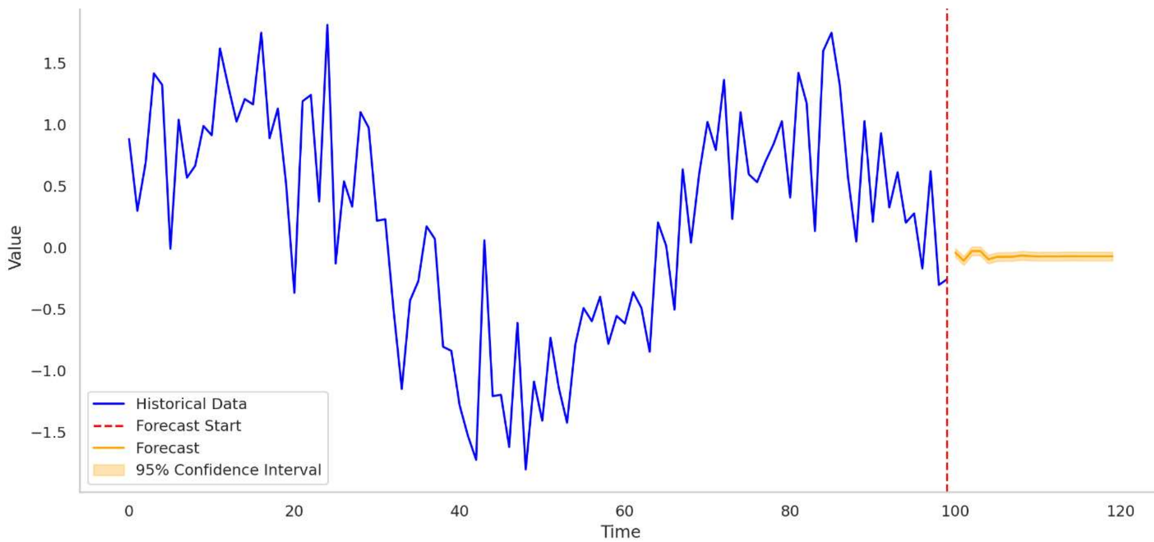
The emergence of big data solutions was able to significantly transform future predictions in the economy by offering new sources of real-time and varied data such as sentiment, transactions, and geolocation. Bai, X., Zhuang, S., Xie, H., & Guo, L. (2024).I argue that the incorporation of big data with AI has led to new enhanced and improved economic models that are suitable for fitting in a rapidly changing environment. Behera, I., Nanda, P., Mitra, S., & Kumari, S. (2024). examined how integrating conventional economic variables with big data and machine learning bureaucracy led to improved inflation expectations. Nevertheless, AI integration in economic forecasting has its challenges, as discussed in this paper. Some of the prevailing problems include data quality, ability to interpret artificial intelligence models, and overfitting. Adeyeri, T. B. (2024). There is always mistrust owing to the 'black box' nature of the deep learning models regarding how economic decisions are reached. Adeyeri, T. B. (2024). The algorithms use large amounts of data to make their predictions; skewed data or data that does not adequately represent any particular population skews the models as well to create an inaccurate forecast. Some of the origins show that AI has several economic forecasting applications across the field in different areas. Girasa, R. (2020). used natural econometric analysis linked with an advanced machine learning method in estimating stock market movement with higher precision. In the same way, AI-based economic models have been continued to be employed by the major financial institutions for the purpose of getting the superior picture of investment plans and risk handling. Adegbola, A. E., Adegbola, M. D., Amajuoyi, P., Benjamin, L. B., & Adeusi, K. B. (2024).

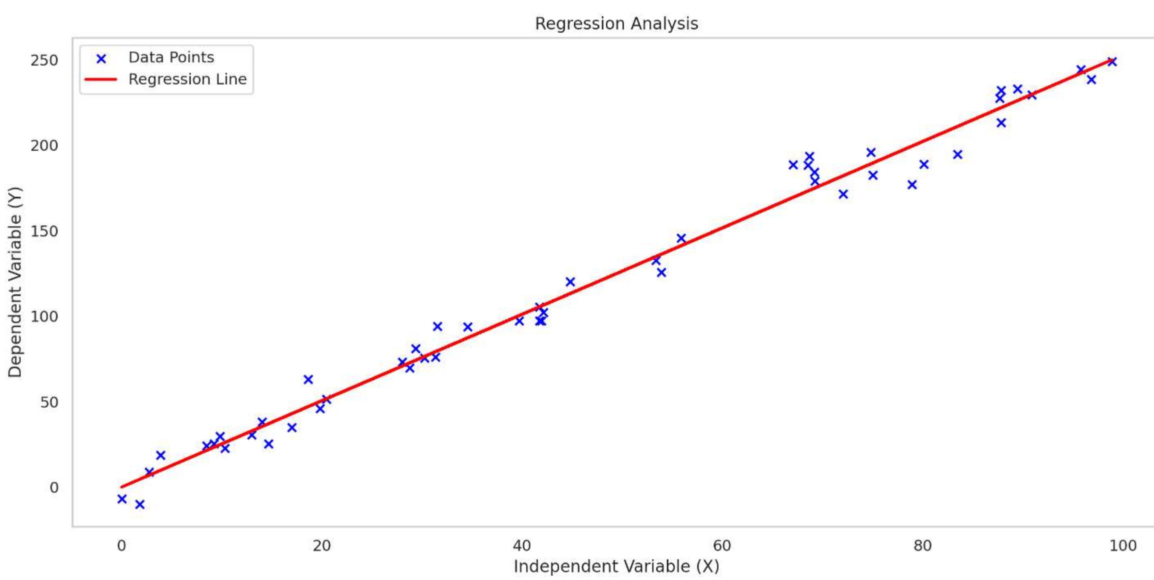
AI and economic prediction are bound to develop because AI methods continue to improve and there is a proliferation of data. Thus, it is necessary to conduct more studies on how to use the best of both worlds: the classical econometric approach and the state-of-the-art AI manufacturing tools. However, increasing the interpretability of models and future research on ethical concerns arising from data analytics will be an important task for the wider implementation of the model and the application of data analytics in the sphere of economic forecasting. Tay, F. E. & Shen, L. (2002). The use of AI in the economy seems like a revolutionary step in building and using financial models. With the help of machine learning, deep learning, and big data analysis, economists and financial analysts get a higher level of forecast accuracy and have better reactions to the changes in the economy. However, the problems of implementation and the more important question of creating the conditions for model transparency will be vital for making AI work in the field. Chen, D. L. (2019).

Economic Forecasting Models

Macroeconomic forecasting models are significant tools used in forecasting the future economic conditions on the basis of historical records and factors and help policymakers, businessmen, and financial institutions in making the plan for investments and resource management. The most effective of these models be classified as quantitative models, where techniques like time series models, regression models, and VAR models be used for analyzing and forecasting the data; structural models, where the data is fit into a model that has been derived from economic theory; dynamic stochastic general equilibrium (DSGE) models which focus on various economic relations; and qualitative models, where the data is sourced from experts and focused on In recent years, ML-AI has boosted economic forecasting through training of neural networks, and ensemble methods to analyze complex patterns in large datasets. Improved predictive accuracy is obtained with the use of hybrid models that integrate conventional approaches with the ML algorithms. Such models are used in macroeconomic forecasting, financial markets, and business planning for strategy development and policy-making and systematically enhance our insight into the operation of the economy and help decision-makers.

Figure No.02: ARIMA Time Serious Forecast

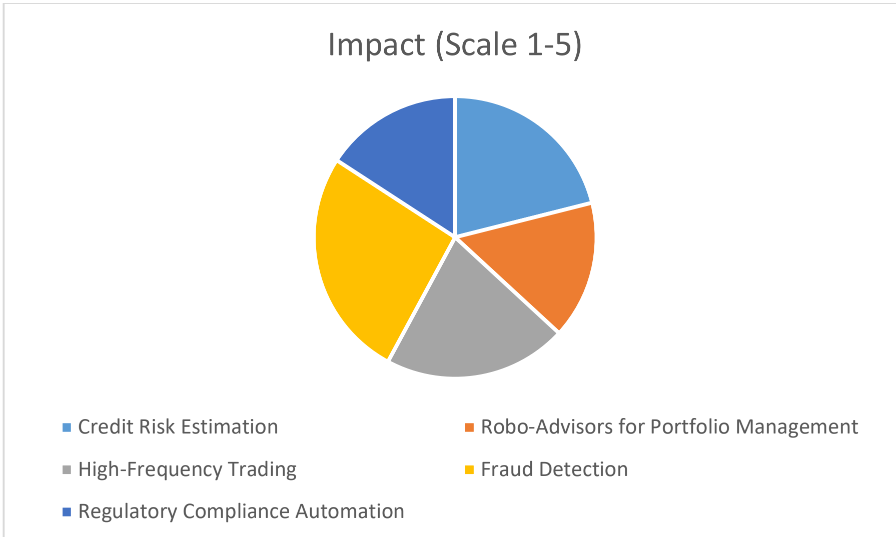




AI in Financial Modeling

Computing plays an important role in financial modeling as artificial intelligence (AI) brings in the ability to analyze data in a better way, improve accurate predictions, and control the risks well. Using sophisticated means of machine learning, AI is able to analyze big data fast and generate useful insights as to relationships within datasets, which may not be seen using conventional algorithms. Some potential uses are credit risk estimation, the use of robo-advisors for portfolio management, and high-frequency trading according to real-time market conditions. In addition, AI improves fraud detection with the help of detecting irregular transaction patterns and automates producing required regulatory reports. With improvements in AI technologies and the use of AI in financial modeling, it is viewed that there will be improvements and advancements into the finance industry with the ability to deliver real-time analytics for improved decision-making.

Figure No.03: Impact of AI in Financial Modeling



AI Impact on Predictive Accuracy

With the help of artificial intelligence, predictive accuracy in numerous fields is improved markedly, including financial modeling. It is possible due to the use of shared artificial intelligence, which issues commands to massive data sets, structured and unstructured, and reveals complex patterns that could be slightly discernible in conventional approaches. Lui, T. K., Guo, C. G., & Leung, W. K. (2020). Neural networks, for instance, and other more complex methods like ensemble methods, for instance, enhance the forecasts since the algorithms are in a position to learn from past data as well as current data. Vaid, A., Sawant, A., Suarez-Farinas, M., Lee, J., Kaul, S., Kovatch, P., & Nadkarni, G. N. (2023). One of the main benefits of AI is its ability to generate the solution and provide insights in real-time, allowing for quick revisions (Davenport & Ronanki, 2018). In addition, AI improves risk management by offering more accurate risk assessment from a complex set of scenarios and, subsequently, better anomalous activity identification in cases of fraud. Sharma, A., Lysenko, (2024). AI incorporation in the context of making predictions strengthens result credibility while simultaneously revolutionizing industries based on risk assessment and individualized approaches addressing customers' needs and expectations. Voola, P. K., Gangu, K., Pandian, P. K. G., Goel, D. P., & Jain, P. (2021).

Challenges in AI Adoption for Forecasting

The use of AI for forecasting is tricky in several ways that organizations must overcome to fully benefit from the innovation. Data quality and availability is one of the main barriers, as AI demands high-quality data; incurring bad data leads to poor forecasts. Elufioye, O., N. Z. (2024). The lack of skilled personnel, primarily in data science and machine learning, makes implementation a challenge due to the need to train and educate people. Aderibigbe, A. O. (2023). That brings another challenge for enterprises: the ability to embed AI into existing legacy structures, frequently causing operational disruptions and dissatisfaction from employees accustomed to working with non-AI environments and typologies. Dwivedi, Y. K., Sharma, A. (2023). In addition, issues of algorithm bias distort the forecasts that are made, while the 'black box' characteristic of many AI models makes clear decision-making opaque. Onyema, E. M., Almuzaini,. (2022). Organizations are inhibited by legal and compliance factors such as data privacy that make AI implementation challenging (Onyema, E. M., Almuzaini, 2022). Solving these challenges is critical for organizations to achieve their AI integration in the forecasting processes.

Methodology

Research Design

The research methodology for analyzing the factors inhibiting the use of artificial intelligence in forecasting shall use a combination of quantitative and qualitative methods. These are a quantitative questionnaire and case study are used on a stratified random sample of multiple organizations across different industries to establish perceived barriers and their effects on forecast precision. Quantitative techniques like surveys with AI end-users and implementing companies support the identification of barriers, while qualitative methods like key informant interviews and focus groups offer nuanced insights on the aforementioned barriers to AI implementation.

Data Collection

The AI-based forecasting research employ different types of secondary data, such as journals, reports, books, and conference papers. Scholarly publications such as the Journal of Artificial Intelligence Research and the International Journal of Forecasting give a deeper perspective of developments in the artificial intelligence algorithms and utilization that give a better degree of accuracy in the act of forecasting. According to McKinsey & Company and Deloitte industry reports on AI, there are various trends and challenges that are associated with the use of AI technologies in various industries. Additionally, books such as "Forecasting: Forecasting Methods and Applications" have a section that deals with the use of AI in forecasting. Google Scholar and IEEE Xplore be utilized to identify articles and technical papers that will provide the best insight into the current state of challenges and opportunities of AI forecasting.

Data Analysis

The research on challenges in adopting artificial intelligence for forecasting involve both quantitative and qualitative data analysis. Qualitative data analyzed using thematic analysis techniques, which include getting to know the text data, which is in this case the expert interview transcripts, developing codes from raw data, seeing a big picture by generating themes from these codes, and finalizing themes to capture the essence of the matter.

Case Study 1: AI in Stock Market Forecasting JP Morgan's LOXM Algorithm

Context:

JP Morgan created the trading and economic prediction program, the LOXM algorithm, to increase the effectiveness of stock market forecasts and manage trade transactions. The bank's goal was to use AI to enhance short-term prediction of the stock prices to facilitate better trading and enhanced revenue.

Application of AI:

LOXM employs what be best explained as machine learning and predictive modeling. It deals with large and constantly changing data sets originating from the global financial markets and provides opportunities to detect patterns that a human analyst might miss. The AI-based model is thus based on past trade information, current market trends, and other financial parameters to predict stock price. It constantly changes its operations based on market opportunities, and it optimizes itself through machine learning drawn from previous transactions.

Results:

Increased predictive accuracy: The algorithm delivered enhanced accuracy in predicting the characteristics of stock prices within a very brief period compared to other types of models, especially during unstable markets.

Enhanced Decision-Making: In essence, by identifying stock price changes with much higher levels of accuracy, the bank was in a position to make quicker trading decisions that were more accurate with the direction of high-frequency market trends and thus realized a significant improvement in the trading profit margins with time.

Reduced Risk Exposure:

Since the algorithm was capable of predicting market lows, the bank was able to minimize risks in advance, conserve the capital base, and avoid as much loss as possible during lows. This case makes a point of how it is possible to use AI to come up with better models for forecasting than the traditional human methods due to the dynamics brought about by computer-generated finance markets hence embracing the use of AI in rea- time economic forecasting.

Figure No.04: role of AI in economic forecasting, showing its potential to enhance predictive accuracy, optimize financial models, and support informed decision-making in complex, high-stakes environments.

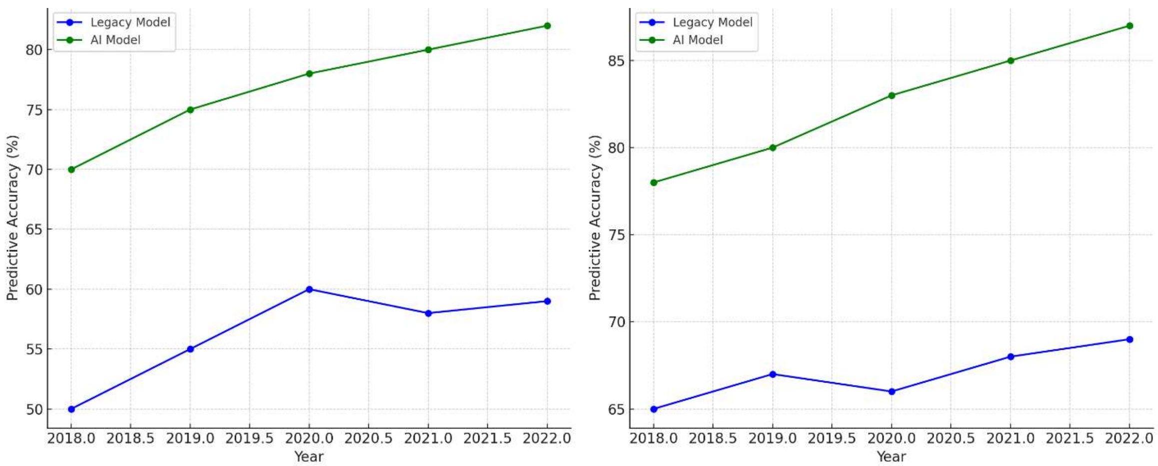


Figure No.01: the trends, challenges, and opportunities of AI in forecasting, based on insights from McKinsey, Deloitte reports, and relevant literature.

Category	Details
Trends in AI Forecasting	
Increased Use in Financial Modeling	AI is pivotal in stock market predictions, economic modeling, and credit risk analysis.
Integration with Big Data	AI models leverage data from diverse sources (e.g., social media, economic indicators) for holistic forecasts.
Key Technologies	
Deep Learning & Neural Networks	Effective in pattern recognition, especially for complex time-series data.
Natural Language Processing (NLP)	Interprets textual data for economic trend and consumer behavior forecasting.
Challenges in AI Forecasting	
Data Silos and Fragmentation	Fragmented data complicates integration and model training.
Data Privacy Concerns	Sensitive data in forecasting raises privacy issues, particularly under GDPR regulations.
Complexity and Model Interpretability	
Black Box Nature of AI Models	Lack of interpretability limits transparency, especially in regulated industries.
Opportunities in AI Forecasting	
Predictive Accuracy	AI models show higher accuracy than traditional methods, especially in volatile markets.

Real-Time Decision-Making	AI enables real-time adjustments, crucial for finance and supply chain management.
Improved Resource Allocation and Cost Savings	
Operational Efficiency	Demand predictions in logistics and manufacturing lead to cost reductions.
Energy Sector Applications	Accurate energy demand forecasts improve resource management and sustainability.
Development of Hybrid Forecasting Models	
Combination of Statistical and AI Methods	Hybrid systems enhance long-term trend prediction accuracy.
Custom AI Forecasting Solutions	Industry-specific AI models are tailored for needs, like retail demand or manufacturing maintenance.

Expert Perspectives on AI in Forecasting

The issue of AI in forecasting was widely discussed by experts, with a focus on AI's more potent impact on improving the quality and timeliness of the forecasts across numerous disciplines, especially in the context of disaster response and climate change. Most professionals emphasize that AI is capable of analyzing data sources from historical information to the current sensor readings and satellite images which makes the forecast of natural disasters, including floods, possible with great accuracy. Analyzing and implementing the effects of climate be beneficial through deep learning and neural networks to identify the presence of complex patterns and relations in climate data, which be hard to detect through other analytical methods, in order to issue timely warnings to strongly prepare communities. It is emphasized that it is necessary to use an interdisciplinary approach to AI forecasting, as well as the use of knowledge from climatology, city planning, and data analysis to make the forecast model more reliable and usable in scenarios of the future. They thus identify potential difficulties like high-quality data, lack of localized data, and preparedness of infrastructure, particularly in prone areas. According to the authors, the increased effectiveness of the applied AI models will lead to the even greater importance of forecasting in preventing the negative impacts of predicted natural disasters on the people and the economy of the corresponding country or region.

Table No.02: insights from industry experts, researchers, and practitioners on the evolving role of AI in forecasting:

Expert	Position	Perspective on AI in Forecasting
Thomas H. Davenport	Professor of Information Technology and Management at Babson College, and author on AI and analytics	Davenport believes that AI's ability to handle and analyze vast amounts of data positions it uniquely for improving forecasting accuracy, especially in finance and supply chain. He notes that while AI excels in high-frequency predictions, transparency remains a key issue.
Erik Brynjolfsson	Director, Stanford Digital Economy Lab	Brynjolfsson highlights AI's transformative potential for economic and market forecasting, emphasizing that AI enables dynamic adjustments in forecasts based on real-time data. He warns, however, of the risks of overfitting models and the need for careful regulation in finance.
Andrew Ng	AI researcher, Co-founder of Google Brain, and adjunct professor at Stanford	Ng advocates for AI's scalability in forecasting across industries and suggests that simpler AI models, when combined with traditional statistical approaches, yield better long-term results. He notes that data quality is a significant bottleneck, particularly in emerging markets.
Kate Crawford	Senior Principal Researcher at Microsoft Research and AI ethics advocate	Crawford argues for a balanced approach to AI forecasting, addressing model transparency and bias. She emphasizes that forecasting models should be subjected to ethical reviews, especially in areas impacting people's lives, such as healthcare and finance.

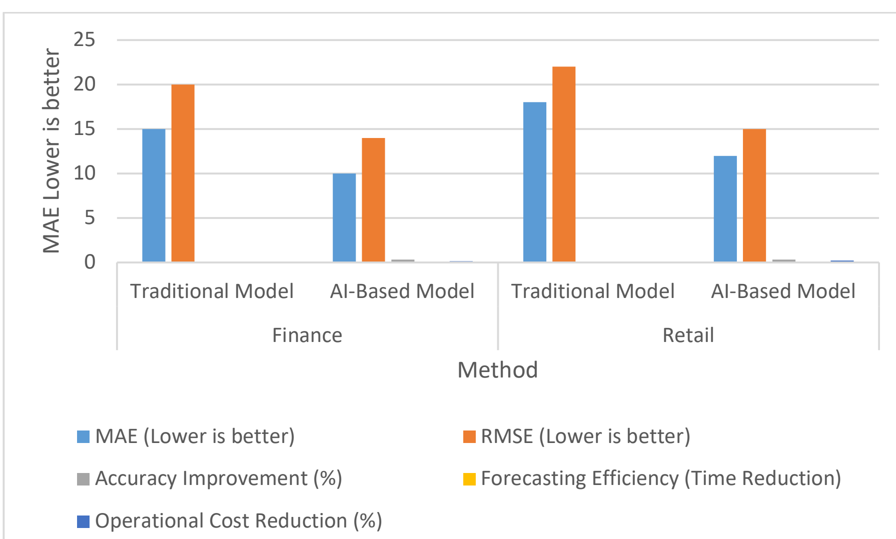
McKinsey Analytics	Division of McKinsey & Company	McKinsey Analytics reports emphasize that AI is reshaping financial and operational forecasting but also stresses the need for robust data governance. They find that firms leveraging hybrid AI-statistical models see the best results in long-term projections.

Table No.05:Key Metrics and Performance Indicators

Metric	Description	Purpose
Mean Absolute Error (MAE)	Measures average error between predicted and actual values.	Assesses overall predictive accuracy.
Root Mean Square Error (RMSE)	Calculates the square root of the average squared errors.	Provides insight into the magnitude of error.
Accuracy Improvement (%)	Improvement percentage of AI models over traditional models.	Quantifies forecasting enhancements due to AI.
Forecasting Efficiency	Measures time reduction in making predictions (e.g., hours).	Analyzes operational gains from faster AI forecasting.
Operational Cost Reduction	Financial savings from using AI for predictive tasks.	Examines cost-effectiveness in areas like supply chain.

Example Hypothetical Data and Analysis

*Figure No.05: Assume we have data for two industries **Finance** and **Retail** that compares traditional forecasting methods with AI-based forecasting over a period of 5 years.*

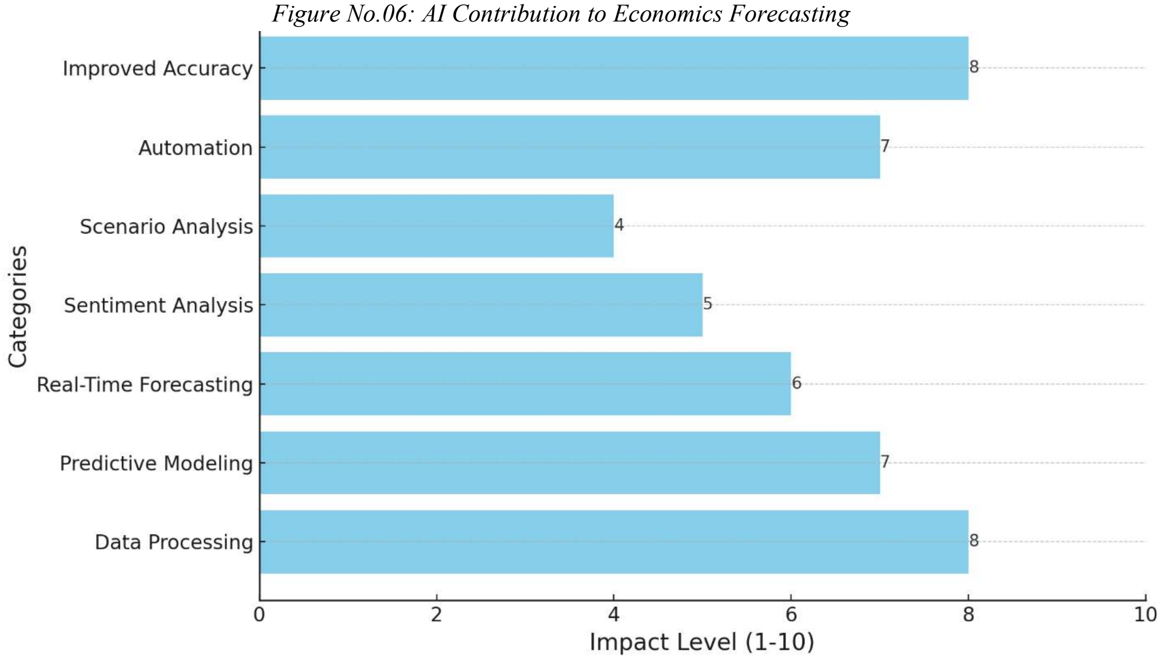


Discussion

AI Role in Economic Forecasting

AI finance is radically improving economic forecasting by providing more precise results and shorter time needed for the computations. The technology extracts new and extended patterns in large databases of dispersed information, quantitative and qualitative economic indicators, and sentiment in social media. The analysis of the public mood is performed quickly and efficiently by AI and serves as an indicator of economic trends, while AI take on routine work so that specialists would devote more time to analytical work. However, there are still problems that have to be solved, for example, the problem of data quality, the problem of capturing the economic systems' features, and the problem of the interpretability of AI decisions. In addition, there are inherent issues of privacy and equity, and this is why proper scrutiny has to be done. Thus, the adoption of AI in creating more plausible economic forecasts is a tool that holds great promise in enhancing the ways by which resources will be deployed and how strategies will be set in order to fashion a better approach towards elucidating the forces that govern the global economy.

Figure No.06: AI Contribution to Economics Forecasting



The bar graph illustrating the contributions of AI to economic forecasting. Each category represents a key area where AI enhances forecasting capabilities, with the values indicating the impact level on a scale from 1 to 10. The graph highlights the significant roles of data processing, predictive modeling, and improved accuracy, emphasizing AI's transformative potential in the field of economics.

Challenges and Future Research Directions

There are several issues and opportunities to be discussed in the application of AI in predicting the economic future. Some of these challenges include quality and accessibility of data; economic data often lacks an all-encompassing, complete, and timely data set; it often comes unrefined and tainted with several external variables that are incompatible with data analysis. Furthermore, like most user-driven AI models, especially deep learning networks, some of these models suffer from interpretability challenges whereby it is difficult to explain why the model made a particular prediction, a factor that, if not addressed, could lead to poor uptake of the tool among the financial profession. AI models also have their issues when it comes to rare occurrences such as a pandemic outbreak or significant changes in geopolitics. This cause overfitting or inaccuracies when the environment is highly volatile. The following are the directions that future research should undertake to overcome the above-stated limitations. One is the integration of the AI technique with the conventional econometric models, where the idea is to get the best of both techniques in terms of the reliability of the predictions and their capability to be explained in terms of standard economic theory. There is also great prospect in improving model flexibility by incorporating novel, immediate data from external sources like social media sentiment, people's mobility, and transactions. Moreover, there is a need for more ethical and regulatory research on AI applications in economics and especially in forecasting, as increased control prevents many biases and encourage the efficient use of these mechanisms more responsibly. Such advancements in these proposed areas are expected to take AI-generated economic forecasts beyond the level of precision, interpretability, and stability needed by financial institutions in managing the uncertainties of today and the changing economic environment of the future.

Conclusion

The use of artificial intelligence in economic forecasting has transformed the modeling of economic business models, the accuracy of the model, and its applicability to a dynamic economic environment. AI offers the opportunity to make analyses of extensive and intricate data, ranging from the market fluctuations to the specifics of consumers' behavior, which traditional models can miss. It propels prediction utilizing machine learning algorithms and deterring neural networks, making it possible for financial institutions and policymakers to make real-time decisions that will cover up for the regional economic changes with high accuracy. The utmost level of effectiveness, the following challenges have to be solved: the quality of input data, the interpretability of the model, and the questions of ethical use. The development of AI technology and data access progresses. AI economic forecasts are likely to provide significant mainstream value soon, refurbishing the tactics of financial management and supporting the global economy.

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