

AI and Machine Learning-Driven Innovations in Macroeconomics

Hong Tao¹, Liqian Huang² and Yiheng Zhao²

¹ School of Business, Xianda College of Economics and Humanities, Shanghai International Studies University, Shanghai 200083, China

² School of Data Science, Xianda College of Economics and Humanities, Shanghai International Studies University, Shanghai 200083, China

Abstract: With the rapid development of Artificial Intelligence (AI) and Machine Learning (ML) technologies, the research methods and practices in macroeconomics are undergoing profound transformations. Traditional economic analysis methods often rely on historical data and empirical models, facing challenges such as data lag, information asymmetry, and insufficient predictive accuracy. The introduction of AI and ML has provided new approaches and tools for economic research, demonstrating wide application prospects, particularly in the construction of novel economic indicators, economic forecasting, policy analysis, and financial market analysis. This paper reviews the current status and future trends of AI and ML applications in macroeconomics, with a focus on the use of alternative data in constructing economic indicators, the integration of machine learning with traditional economic forecasting models, the potential and challenges of large language models in economic policy analysis, and the application of machine learning in financial market analysis.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Macroeconomics, Economic Forecasting, Novel Economic Indicators, Economic Policy Analysis, Financial Market Analysis.

1. Introduction

In recent years, with the rapid development of Artificial Intelligence (AI) and Machine Learning (ML) technologies, traditional research methods in macroeconomics are undergoing unprecedented transformations. Economics, as a discipline that studies the allocation and optimization of societal resources, has traditionally relied on data analysis and model construction to guide decision-making and forecasting. However, conventional economic models, when dealing with complex economic phenomena, often face limitations such as data acquisition delays, information asymmetry, and overly simplified model assumptions, resulting in suboptimal performance in addressing complex economic systems, forecasting accuracy, and real-time decision support [1]. The introduction of AI and ML not only provides new possibilities for addressing these traditional issues but also opens new avenues for macroeconomic research through their powerful data processing and pattern recognition capabilities [2].

The application of AI and ML in macroeconomics is not merely to replace traditional quantitative analysis methods, but rather to complement them, forming a new framework for economic analysis. AI technologies, particularly deep learning, big data analytics, and natural language processing, can reveal complex relationships and patterns hidden within traditional economic data through large-scale data analysis and mining [3]. Machine learning models can self-learn and adjust parameters, thereby continuously improving the prediction accuracy and the generalization ability of models. These advantages make AI and ML indispensable tools in economic research, especially in a rapidly changing and information-overloaded economic environment, where the benefits of AI technologies become even more pronounced.

Traditional economic analysis typically relies on historical statistical data and conventional econometric models, using these models to predict macroeconomic trends such as GDP growth forecasts and inflation rate predictions. However, these models often suffer from delays, static assumptions, and

insufficient accuracy when dealing with dynamic and complex economic systems. With the advancement of technologies such as the internet, big data, and the Internet of Things, traditional economic research faces new challenges and opportunities. In particular, alternative data sources (such as social media data, news texts, online transaction data, and nighttime light data) have provided rich, non-traditional data for economic analysis. AI and ML technologies can effectively leverage these data sources to construct more real-time and accurate new economic indicators. In this context, the integration of traditional economic analysis methods with AI/ML technologies has become a research hotspot in both academia and practice in recent years.

In the early stages, the application of AI and machine learning in macroeconomics primarily focused on forecasting and modeling. As research has progressed, more scholars are focusing on how AI technologies can enhance the accuracy and real-time capabilities of economic models. Specifically, machine learning in economic forecasting includes not only parameter optimization of traditional economic models but also the exploration of nonlinear relationships through big data and deep learning models [4]. Additionally, with the development of natural language processing technologies, the emergence of large language models (such as GPT-2, BERT, etc.) has made text analysis an emerging field in economic research [5]. By analyzing text data from sources like news, financial reports, and policy documents, AI can assist economists in capturing policy changes, market sentiment, and other unstructured information, thereby enhancing the comprehensiveness and precision of forecasts [6].

In recent years, financial market analysis has become an increasingly important area of macroeconomic research, integrating AI and machine learning technologies. Issues such as volatility forecasting, risk management, and high-frequency trading strategy optimization in financial markets have greatly benefited from the widespread application of AI and machine learning. Through deep learning of large-scale financial data, AI technologies can identify market patterns

that traditional analytical methods fail to capture, providing more accurate market predictions. In high-frequency trading, reinforcement learning models have been employed for strategy optimization, enabling responses to the rapid changes and complexities of financial markets. AI and machine learning also provide more dynamic and refined perspectives for financial risk analysis, helping to achieve early warnings of market fluctuations and risks.

2. Construction and Application of New Economic Indicators

With the rapid advancement of information technology, traditional macroeconomic indicators are gradually revealing certain limitations when analyzing and forecasting economic phenomena. Traditional economic analysis relies on government-published statistical data, such as GDP, CPI, and others, which, while providing a foundation for economic decision-making, are typically delayed and fail to reflect the real-time fluctuations of the economy. To address this issue, both academia and industry have gradually expanded their focus to non-traditional data sources, using the powerful analytical capabilities of AI and machine learning to construct new economic indicators. These new indicators not only compensate for the shortcomings of traditional economic metrics but also offer more comprehensive, immediate, and sensitive economic insights.

2.1. The Rise of Alternative Data in Constructing Economic Indicators

Alternative data refers to non-governmental statistical data, usually sourced from the internet, social media, sensor networks, and other channels. These data include news texts, online prices, nightlight data, shipping data, and more. They are characterized by high frequency, large volumes, and diversity, offering superior real-time capabilities compared to traditional economic data. With the advancement of computational power and big data technologies, alternative data has gradually become an important supplement to macroeconomic analysis.

News texts, social media information, and other online data can reflect real-time market sentiment and changes in expectations, which often occur before official economic data is released. Through Natural Language Processing (NLP) technologies, researchers can extract valuable information about market dynamics, consumer behavior, and government policies from vast amounts of news reports and social media content to construct economically predictive indicators. For instance, researchers have successfully predicted retail sales trends by analyzing sentiment and discussion frequency on social media. Nightlight data, as an alternative data source, collects changes in the intensity of nighttime light on Earth's surface via satellite imagery. This data can effectively reflect the strength of regional economic activity, particularly in developing countries lacking comprehensive economic statistics.

In addition, online prices, commodity inventories, and transaction data can provide real-time indications of supply-demand changes in commodity markets. These data not only fill the lag in traditional macroeconomic indicators but also offer multi-dimensional economic signals. Through machine learning algorithms, scholars can integrate these heterogeneous data sources to generate new economic indices, which can be used for economic forecasting and policy

analysis. Therefore, the application of alternative data provides a fresh perspective for constructing new economic indicators and accelerates the digital transformation of macroeconomics.

2.2. Deep Learning and the Construction of New Indicators

Deep learning, as a powerful data processing tool, has shown tremendous potential in constructing new economic indicators due to its automatic feature extraction and efficient pattern recognition capabilities. By combining big data analysis, deep learning can process vast amounts of complex unstructured data, such as satellite images, Automatic Identification System (AIS) data for ships, climate data, and others. These data typically contain useful economic signals but are large in volume and structurally complex, making it difficult for traditional methods to efficiently extract valuable economic insights.

Satellite imagery, as a crucial non-traditional data source, can provide detailed information about the Earth's surface on a global scale. By using deep convolutional neural networks (CNNs) and other deep learning models, researchers can analyze land use changes, urbanization processes, agricultural production, and other factors, constructing indicators closely related to economic activities. For example, satellite images reflecting changes in farmland, urban expansion, and nighttime light intensity have been used to predict economic growth, consumption trends, and regional development levels. The real-time nature and high spatial resolution of these indicators make them a powerful supplement to traditional macroeconomic metrics.

AIS data for ships is another important alternative data source, especially valuable in global trade and international economic research. The AIS system provides real-time shipping activity data globally, including ship positions, course, speed, and more. By applying deep learning algorithms, researchers can convert this shipping data into economic indicators reflecting international trade activities. Studies have found that AIS data is closely related to global economic trade activities, production, and consumption patterns. Real-time analysis of this data through deep learning models can provide strong support for short-term global economic forecasts and changes in trade patterns.

3. Applications of Machine Learning in Economic Forecasting

With advancements in data acquisition technology and computational power, machine learning has gradually become one of the key tools in economics, especially in economic forecasting. Traditional economic forecasting models, such as linear regression and time series analysis, often face limitations when dealing with complex, nonlinear, and high-dimensional data. In contrast, machine learning algorithms, particularly deep learning techniques, can effectively handle large-scale, nonlinear, and highly complex economic data, offering significant improvements in prediction accuracy.

3.1. Complementarity Between Machine Learning and Traditional Econometric Models

In economic forecasting research, traditional econometric models are often used to establish theoretical frameworks for economic relationships, from which data analysis and

predictions are derived. However, these models typically assume linear or predetermined relationships between economic variables, which can lead to overly simplified assumptions and insufficient forecasting accuracy when faced with complex economic phenomena. The introduction of machine learning provides an effective supplement to the limitations of traditional economic models. Machine learning methods, with their adaptive learning and automatic feature extraction capabilities, can identify complex nonlinear relationships from large amounts of historical data, thereby improving prediction accuracy.

For example, machine learning algorithms like Support Vector Machines (SVM), Random Forests, and XGBoost can discover latent relationships between variables without predefined assumptions. These methods not only handle large datasets but also identify deeper patterns that traditional models may miss. Thus, the integration of machine learning with traditional econometric models not only enhances flexibility but also significantly improves the accuracy of predictions. In practice, the complementarity between machine learning and traditional models has become a key approach to improving economic forecasting performance.

By combining traditional econometric methods with machine learning models, researchers can fully leverage the strengths of both. On one hand, traditional models provide a clear economic theoretical framework that helps us understand relationships between variables; on the other hand, machine learning algorithms, through a data-driven approach, reveal more complex interactions and hidden patterns. This diversified model combination allows economic forecasting to maintain theoretical rigor while adapting better to the evolving complexities of economic phenomena.

3.2. Potential Applications of Deep Learning and Large Language Models in Economic Forecasting

With the continued development of deep learning technologies, particularly the emergence of advanced models such as large language models (e.g., GPT series), a new technological revolution is unfolding in economic forecasting. Deep learning, especially neural network-based models, has strong data learning capabilities, enabling it to handle large amounts of data and complex patterns that traditional methods cannot manage. Its wide application across image, text, and time-series data provides new perspectives and methods for economic forecasting.

Large language models (e.g., GPT-2, GPT-3) are deep neural network models trained on vast amounts of text data. These models use natural language understanding and generation techniques to capture economic trends and signals hidden in economic news, policy interpretations, corporate reports, social media discussions, and more. In economic forecasting, traditional macroeconomic indicators are often lagging and narrow, whereas large language models can analyze real-time news, policy changes, and public opinion dynamics to provide a timely and precise supplement to predictions. For instance, research has shown that sentiment analysis of financial market news using large language models can improve short-term stock market, foreign exchange, and commodity price forecasts. Moreover, large language models can interpret company earnings reports and market analysis, extracting valuable information about industry trends and economic growth potential, thus supporting economic policy formulation.

Another promising application of deep learning lies in time series forecasting. Time series data, which is common in economics, includes stock market indices, commodity prices, GDP growth rates, and more. While traditional time series methods (such as ARIMA models) are effective for simple linear relationships, they often fall short when dealing with complex nonlinear dynamics. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks in deep learning are highly effective at capturing long- and short-term dependencies in time series data, offering a significant advantage in economic forecasting. By training on vast amounts of historical data, deep learning models can identify complex nonlinear patterns, thus improving prediction accuracy.

Additionally, ensemble learning methods (such as deep ensemble neural networks) have found wide applications in economic forecasting. Ensemble learning combines the predictions of multiple models, improving the stability and accuracy of overall predictions. Especially in large-scale data environments, ensemble learning mitigates the shortcomings of individual models, reduces overfitting risks, and enhances the generalization ability of prediction results.

4. The Role of Machine Learning in Economic Policy Impact Analysis

In macroeconomics, the implementation of economic policies plays a crucial role in influencing markets, industries, and the overall economic system. Traditional economic analysis methods often rely on theoretical models and regression analysis, assuming specific relationships between economic variables to predict policy effects. However, these traditional methods often fall short when dealing with complex economic environments, dynamic policy impacts, and diverse data. In this context, machine learning techniques have shown tremendous potential, enabling automated analysis of vast amounts of data, revealing the real impact of economic policies, and helping policymakers make more precise decisions.

4.1. Model Explanation and Policy Variable Analysis

One of the key advantages of machine learning lies in its ability to handle complex datasets, especially in terms of model interpretability. Traditional economic methods often rely on structured equations and fixed assumptions, which make it difficult to capture nonlinear relationships and interactions among multiple variables comprehensively. In contrast, machine learning algorithms, such as decision trees, random forests, and support vector machines, can automatically identify key features in the data and provide model interpretability. This characteristic offers new insights for economic policy analysis, helping researchers better understand how policy variables affect different aspects of the economic system.

For example, by using SHAP values (Shapley additive explanations), researchers can interpret the contribution of each feature to the predictions made by machine learning models. In economic policy analysis, SHAP values can help reveal which economic variables have the greatest impact on policy implementation outcomes, thus providing a basis for policy adjustments. For instance, when evaluating the impact of tax policies on the consumer market, SHAP values can indicate how factors such as consumption propensity, income

levels, and consumer confidence contribute to the policy's effect. This method is more intuitive than traditional regression analysis and can handle more complex multivariable interactions.

Furthermore, machine learning models can identify latent factors that traditional economic analysis methods might overlook. For instance, hidden social behavior patterns, psychological expectations, or market sentiment may be ignored in conventional analysis frameworks, but machine learning can capture these micro-level insights effectively through big data processing. Thus, machine learning not only provides a tool for model interpretation but also offers policymakers a more comprehensive and in-depth understanding of economic dynamics.

4.2. Causal Inference and Machine Learning

Causal inference has always been a central issue in economic policy analysis. Traditional econometrics methods analyze causal relationships through assumptions and model tests; however, these methods often rely on strong assumptions and are susceptible to biases when dealing with complex data. Machine learning, particularly when integrated with causal inference theory, has shown broad application potential. As the field of causal inference continues to develop, techniques such as random forest regression, difference-in-differences, and regression discontinuity design have been increasingly incorporated into machine learning models, driving innovation in causal inference analysis.

Through causal inference frameworks, machine learning can help researchers uncover the causal effects of policy interventions from large datasets. For example, comparing pre- and post-policy implementation data, or analyzing differences between treatment and control groups, are common methods in causal inference. Machine learning models can leverage these methods to accurately quantify the specific impact of policy changes on markets or society. More importantly, machine learning can handle the effects of multiple variables, nonlinear relationships, and dynamic changes, overcoming the limitations of traditional causal inference models in complex situations.

Additionally, machine learning can identify the heterogeneity of policy effects—i.e., how different regions, groups, or economic entities respond differently to the same policy. This capability is difficult to achieve with traditional econometrics, as these methods often assume that effects are uniform across all units. Machine learning, by processing large-scale heterogeneous data, can reveal how different policy interventions affect various economic actors. This is crucial for developing more personalized policies and regional strategies. For example, in regions with significant income inequality or imbalanced industry development, machine learning can help identify these disparities and optimize policy design accordingly.

The combination of causal inference and machine learning can also promote the development of policy simulation and prediction. In practical applications, policymakers often wish to simulate the effects of different policy scenarios to choose the best course of action. Machine learning's flexibility allows policy simulations to not only address linear models used in traditional economics but also to incorporate more complex dynamic changes and diverse policy effects. In this way, machine learning improves the accuracy of causal inference while enabling policymakers to make more scientifically grounded and rational decisions in dynamic and complex

economic environments.

5. Applications of Machine Learning in Financial Analysis

With the increasing complexity of global financial markets and the dramatic growth of data, traditional financial analysis methods are gradually revealing their limitations in handling large-scale, high-dimensional data and dynamic market changes. Machine learning, with its powerful data processing and self-optimization capabilities, has become a crucial tool in modern financial analysis. Machine learning can not only help analysts uncover potential patterns and trends from vast amounts of data but also provide more accurate predictions and decision support in real-time environments. As financial markets continue to evolve, the application of machine learning in areas such as financial risk management, portfolio optimization, and market trend forecasting is transforming the traditional financial analysis framework.

5.1. Financial Market Forecasting and Machine Learning

The volatility and nonlinear characteristics of financial markets present challenges for traditional statistical analysis methods when predicting market trends. For example, in stock market forecasting, traditional regression analysis methods typically assume that the data is linear, ignoring market noise and complex dynamic relationships. However, market data is highly nonlinear and often influenced by factors such as investor sentiment and policy changes, which are difficult to quantify and are often not effectively captured by traditional models.

Machine learning, especially algorithms such as deep learning, support vector machines (SVM), and random forests, can uncover complex patterns by learning from large volumes of historical market data. Deep learning, for instance, can capture underlying relationships in the data through multi-layer nonlinear mappings, improving the accuracy of market trend predictions. Additionally, time series prediction models like Long Short-Term Memory (LSTM) networks are particularly adept at handling the temporal characteristics inherent in financial data and are widely used for predicting stock prices, exchange rates, and commodity prices.

Machine learning techniques are not limited to stock market forecasting; they are also widely applied across other financial markets such as bond markets, foreign exchange markets, and cryptocurrency markets. In these areas, machine learning models can process and analyze market data in real-time, quickly adjusting predictions to respond to fast-changing market conditions. The advantage of machine learning in market trend forecasting lies primarily in its ability to model nonlinear relationships and its self-learning capability for complex data patterns, helping investors make more accurate judgments in a volatile and dynamic market environment.

5.2. Risk Management and Machine Learning

Financial risk management is one of the core tasks for financial institutions such as banks, insurance companies, and investment firms. Traditional risk management methods, such as Value-at-Risk (VaR) and Conditional VaR, while useful in certain contexts, rely on model assumptions and often fail to fully capture market nonlinearities and complexities. With the rapid development of markets and continuous financial

innovation, traditional methods have proven inadequate in dealing with sudden events and nonlinear risks.

Machine learning has shown immense potential in financial risk management. By constructing machine learning models based on historical data, financial institutions can more accurately identify and predict potential market risks. For example, using algorithms like support vector machines, random forests, and XGBoost, financial institutions can detect credit risks and market risks from historical trading data. In credit risk management, machine learning can analyze customer credit history, consumption behavior, and socio-economic data to provide more accurate credit scores, which in turn optimize lending decisions and risk control.

Moreover, machine learning can assist financial institutions in real-time risk monitoring within dynamic market environments. By using dynamic optimization algorithms like reinforcement learning, financial institutions can quickly adjust their risk management strategies when market conditions change, thereby ensuring returns while minimizing potential risks. Compared to traditional risk management methods, machine learning offers greater flexibility to adapt to market changes, providing more precise risk assessment and prediction capabilities.

6. Applications and Prospects of Large Language Models in Macroeconomic Work

With the rapid advancement of natural language processing (NLP) technology, large language models (such as GPT-2, GPT-3, etc.) have demonstrated immense potential across various fields, especially in macroeconomics. Large language models are not only capable of processing massive text data but can also effectively generate language, perform semantic analysis, and reason, offering new solutions in many traditional economic tasks. Their potential applications span across automatic report generation, intelligent tutoring, economic data analysis, and policy forecasting, providing substantial support for research and decision-making in macroeconomics.

6.1. Application Exploration and Potential Value

In macroeconomic research and practice, data analysis and report generation are common and critical tasks. One important application of large language models is the automatic generation of economic analysis reports. This process requires in-depth data understanding and efficient text generation. Traditionally, economists and researchers need to spend a significant amount of time organizing data, performing statistical analyses, and writing reports. However, with the help of large language models, this process can be greatly simplified. By inputting relevant data and research questions, the model can automatically generate logically coherent and semantically clear reports, thus improving work efficiency and reducing the burden of manual writing. Furthermore, the model can generate reports for various scenarios in a short time, adapting to diverse needs.

Another significant application of large language models is in the field of intelligent tutoring. Since economics involves numerous complex concepts and theories, students and researchers often encounter various questions during their learning and research processes. Traditional learning methods usually rely on teacher-student interactions or static textbooks,

whereas large language models can provide real-time intelligent Q&A support. By training, the model can understand the basic theories of economics, policy analysis, and data processing methods, showcasing substantial advantages in assisting students with answering questions, offering academic support, and guiding research work. Its application is not limited to classroom education but can also extend to supporting researchers in data analysis, model construction, and other tasks, making it a valuable tool in academic research.

Moreover, large language models can play a crucial role in economic data analysis. Economic research often relies on massive textual data such as policy documents, economic reports, and news articles. Large language models can perform semantic understanding and sentiment analysis on these textual data, extracting key information and trends to help researchers identify potential economic phenomena. For instance, by analyzing news reports and social media comments, sentiment analysis can evaluate public attitudes toward certain economic policies, providing policymakers with more precise decision-making support. At the same time, large language models can analyze vast amounts of historical data to forecast future economic trends, providing forward-looking insights for macroeconomic decision-making.

6.2. Challenges and Future Directions

Although large language models have enormous potential in macroeconomics, several challenges still need to be addressed in their development. First, the model's reasoning ability and data integrity are significant issues. While large language models excel at generating language, they often lack sufficient accuracy and depth when handling complex reasoning tasks. In macroeconomics, many economic phenomena are highly complex and uncertain, and simple models may fail to accurately capture such complexity. Therefore, improving the accuracy of large language models in reasoning, analysis, and decision-making is a key direction for future development.

Second, the quality and availability of data are also important factors limiting the application of large language models. In macroeconomics, the accuracy, comprehensiveness, and timeliness of data are critical for economic analysis. However, since large language models rely on vast amounts of training data, the quality of the data input can significantly impact the results. Especially when data is missing or contains noise, the predictions and analyses generated by the model may become biased. Ensuring the quality of data used by models and optimizing algorithms to reduce the impact of data inaccuracies on results are crucial areas for future research.

Furthermore, as the scale and capabilities of these models continue to expand, issues related to computational costs and energy consumption are becoming pressing challenges. Training and deploying large-scale language models require significant computational resources, and in the context of growing global environmental concerns and energy consumption pressures, improving model computational efficiency and reducing energy consumption will be critical considerations for the future of large language models.

Looking ahead, large language models have a broad development prospect in macroeconomics. As technology advances, the reasoning capabilities and accuracy of models will continually improve, and their applications in economic forecasting, policy analysis, and market monitoring will

become more widespread. Additionally, interdisciplinary integration and innovation will open up new directions for the application of large language models. For instance, combining technologies like image recognition and reinforcement learning can further enhance the model's intelligence, enabling it to tackle more complex and dynamic economic issues. Moreover, as data protection and privacy concerns become increasingly important, ensuring data security and protecting user privacy will also be a key issue in the application of large language models in macroeconomics.

7. Conclusion

With the continuous development of artificial intelligence (AI) and machine learning (ML) technologies, their applications in macroeconomics have shown immense potential, bringing profound transformations across various fields. By complementing and innovating traditional economic analysis methods, AI and machine learning are gradually breaking the limitations of conventional economics, providing more accurate and efficient tools for economic research. In the construction of new economic indicators, economic forecasting, and policy analysis, AI and machine learning not only improve the precision and timeliness of analyses but also offer unprecedented data processing capabilities and analytical methods for macroeconomic researchers.

This paper first explores the construction and application of new economic indicators, especially in the context of combining alternative data and deep learning techniques. These innovations in economic indicators help fill the gaps in traditional data and improve the real-time nature and informational value of economic monitoring. With the emergence of big data such as satellite imagery and ship AIS data, the integration of deep learning allows us to capture subtle microeconomic changes in economic activities, providing more accurate tools for economic monitoring and forecasting. Through deep data mining and intelligent analysis, the field of macroeconomic analysis has been significantly expanded, offering policymakers and economic researchers more precise decision-making support.

Secondly, the application of machine learning in economic forecasting demonstrates its essential complementary role to traditional econometric models. Machine learning methods are better equipped to handle large-scale, complex economic data, overcoming the limitations of traditional models in addressing non-linear relationships and high-dimensional data. By complementing machine learning with traditional econometric models, the accuracy of economic predictions can be enhanced, especially in predicting complex economic phenomena such as economic fluctuations and financial crises. In particular, deep learning and large language models have significant potential in economic forecasting, not only improving prediction accuracy but also facilitating the effective integration and analysis of multidimensional economic information.

In the analysis of economic policy impacts, the application of machine learning provides new methodologies for policymaking. Through explanatory analyses of machine learning models, the mechanisms through which economic policies affect outcomes become clearer. With support from interpretability methods like SHAP values, we can more

precisely identify which policy variables have decisive impacts on economic results. Moreover, the combination of causal inference and machine learning enhances the ability to conduct heterogeneous analysis in policy research, allowing for a deeper understanding of how policy interventions perform in different economic environments. This, in turn, provides a scientific basis for policy optimization.

In financial analysis, AI and machine learning applications also offer robust tools for market risk assessment, portfolio optimization, and financial product pricing. By processing vast amounts of financial data, machine learning can reveal underlying market risks and volatility trends, assisting investors and financial institutions in making more informed decisions. Furthermore, the application of deep learning techniques in financial time series analysis, price forecasting, and credit risk evaluation significantly enhances the accuracy and timeliness of analyses.

The application of large language models in macroeconomics is also showing new trends. The exploration of automated report generation, intelligent tutoring, and sentiment analysis highlights the vast potential of large language models in improving work efficiency, optimizing decision-making processes, and enhancing academic research. However, challenges still remain, including the models' reasoning abilities, data integrity, and computational resource consumption. These challenges require ongoing optimization of algorithms and the improvement of computational efficiency to expand their range of applications.

Future research should focus on improving the transparency and explainability of machine learning and deep learning models, addressing biases arising from incomplete or noisy data, and considering ways to reduce resource consumption during model training. As model algorithms continue to improve, AI technology will have an even deeper impact on macroeconomics, driving innovation and development in both economic theory and practice.

Acknowledgements

This research was funded by the 2024 Annual School-level Research Project of Shanghai International Studies University, Xian Da College of Economics and Humanities (Grant No. A3107.24.1801.2410)

References

- [1] Brynjolfsson E, McAfee A. The second machine age: Work, progress, and prosperity in a time of brilliant technologies [M]. WW Norton & company, 2014.
- [2] Chui M, Francisco S. Artificial intelligence the next digital frontier [J]. McKinsey and Company Global Institute, 2017, 47(3.6): 6-8.
- [3] Mullainathan S, Spiess J. Machine learning: an applied econometric approach [J]. Journal of Economic Perspectives, 2017, 31(2): 87-106.
- [4] John Lu Z Q. The elements of statistical learning: data mining, inference, and prediction [J]. 2010.
- [5] Devlin J. Bert: Pre-training of deep bidirectional transformers for language understanding [J]. arXiv preprint arXiv: 1810.04805, 2018.
- [6] Loughran T, McDonald B. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks [J]. The Journal of finance, 2011, 66(1): 35-65.