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Artificial Intelligence Techniques in Economic Analysis

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ABSTRACT

This paper provides an overview of the existing literature on the use of artificial intelligence (AI) in various fields, including economics, finance, mining, manufacturing, and innovation. The paper identifies the drivers and effects of AI deployment in the context of innovation and highlights the challenges and opportunities that arise from the use of AI. The studies reviewed in this paper cover various topics related to forecasting, including the impact of AI on professional skills, hybrid forecasting techniques for predicting commodity prices, and novel deep reinforcement learning algorithms for crude oil price forecasting. The paper's contribution lies in its systematic and comprehensive approach to reviewing the literature, which allows for a better understanding of the impact of AI on various fields and the identification of strategies to address the challenges that arise from its deployment.

KEYWORDS

Artificial Intelligence, Economic Analysis, Machine Learning, Natural Language Processing, Deep Learning, Neural Networks, Forecasting, Predictive Analytics

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1. Introduction

1.1. Background and motivation

The use of artificial intelligence (AI) has become increasingly popular in various fields, including finance, economics, mining, and organizational sectors. AI has the ability to minimize cognitive strain or automate jobs now carried out by humans, leading to increased productivity and efficiency. However, the rapid changes brought about by AI also have large implications for organizations and workers, as it can lead to job losses and require the implementation of measures and strategies to retrain workers (Morandini et al., 2023). In the finance and economics field, AI has been used to solve investment problems concerning the stochastic nature of investment return (Rutkauskas et al., 2021). In mining, Sustainable Development Goals (SDGs) were enacted by various companies such as mining companies around the world, and the degree of importance of the seventeen SDGs on sustainable mining has been investigated using a rough sets based decision making approach (Deveci et al., 2022). In organizational sectors, the restructuring of professional skills by AI has been investigated, and strategies to upskill or reskill workers have been identified (Morandini et al., 2023). In the field of forecasting, quantitative methods have been successful in producing baseline forecasts of time series, but they do not forecast the timing or impact of special events such as promotions or strikes (Nikolopoulos, 2010). Forecasters prefer to use their own judgment for adjusting for forthcoming special events, but human efficiency in such tasks has been found to be deficient. Therefore, an expert method that combines the strengths of regression and AI has been proposed (Nikolopoulos, 2010). The use of AI in various fields has led to the need for innovation in management, and ethical leadership has been found to bring benefits for employees and employers and increase the level of productivity and profits of companies (Baboshkin and Uandykova, 2021). However, some results of investigations in that area have suggested that ethical leadership could also have negative consequences of human behavior. Overall, the use of AI has brought about both opportunities and challenges in various fields, and research has been conducted to investigate its impact and identify strategies to address the challenges.

1.2. Aims, Novelty and Contribution

The aim of this paper is to provide a comprehensive overview of the existing literature on the use of AI in various fields, including finance, economics, mining, and organizational sectors. The paper aims to identify the antecedents and consequences of AI deployment in the context of innovation and to highlight the challenges and opportunities that arise from the use of AI.

The paper also offers a current summary of the literature on the application of AI to different areas of economics that is integrated into an interpretive framework, allowing for the decoupling of the primary drivers and effects of AI in the context of innovation.

This paper contributes to the body of knowledge by providing an overview of the existing literature on the use of AI in various fields. The paper identifies the drivers and effects of AI deployment in the context of innovation and highlights the challenges and opportunities that arise from the use of AI. The paper also identifies research directions for further investigation in relation to different types of innovation, which allows for a better understanding of the impact of AI on various fields and the identification of strategies to address the challenges that arise from its deployment.

2. AI in Economics

2.1. Overview of Artificial Intelligence in Economic Analysis

AI has become an increasingly popular tool in economic analysis, with applications in forecasting economic indicators, modeling complex economic systems, predictive analytics, decision making, trading, and investment management. 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. Machine learning (ML) is a popular AI technique used in economic analysis, which is particularly suited for problems of prediction (Zapata and Mukhopadhyay, 2022). ML models are not designed for parameter estimation and inference, but they address problems of prediction by modeling nonlinearity (Ali et al., 2023) and improving out-of-sample prediction. Recent advances in ML have led to the development of more efficient computation methods for regularization, which have expanded the econometric frontiers in asset pricing (Zapata and Mukhopadhyay, 2022).

Natural language processing (NLP) is another AI technique used in economic analysis, which involves the analysis of human language to extract meaning and insights from text data. NLP has been used to analyze consumer sentiments and to identify trends in economic news and reports (Hajek and Novotny, 2022; Yadav et al., 2021).

Deep learning is a subset of ML that involves the use of neural networks with multiple layers to learn complex patterns in data. Deep learning has been used in economic analysis to improve the accuracy of economic forecasting and to model complex economic systems (Ali et al., 2023).

Neural networks are another AI technique used in economic analysis, which are designed to simulate the behavior of the human brain. Neural networks have been used to model complex economic systems and to predict financial and raw material markets (Liu et al., 2021; Lv et al., 2022; Puka and Lamasz, 2020).

2.2. AI Techniques in Economic Analysis

AI techniques have been applied in various fields of economic analysis, including forecasting economic indicators, modeling complex economic systems, predictive analytics, decision making, trading, and investment management. 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).

AI techniques have been used to forecast economic indicators such as GDP, inflation, and unemployment rates. For example, machine learning algorithms have been used to predict 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). Deep learning algorithms have been used to forecast macroeconomic variables such as GDP and inflation (Sun et al., 2019). AI techniques have been used to model complex economic systems such as financial markets and supply chains (Bahoo et al., 2023; Bourke, 2019). Neural networks have been used to model the behavior of financial markets and to predict stock prices. Deep learning algorithms have been used to model supply chain networks and to optimize inventory management (Bolton et al., 2018).

AI techniques have been used for predictive analytics and decision making in various economic sectors. Natural language processing (NLP) has been used to analyze consumer sentiments and to identify trends in economic news and reports. Machine learning algorithms have been used to predict customer behavior and to optimize marketing strategies (Bourke, 2019). Expert systems have been used to support decision making in investment management.

AI techniques have been used in trading and investment management to improve the accuracy of investment decisions and to reduce risk. Machine learning algorithms have been used to identify patterns in financial data and to predict stock prices (Ruiz-Real et al., 2021). Neural networks have been used to develop trading strategies and to optimize portfolio management.

The applications of AI techniques in economic analysis have brought about both opportunities and challenges, and research has been conducted to investigate their impact and identify strategies to address the challenges.

2.3. Illustrative example

One real-world example of the application of AI techniques in economic analysis is the use of machine learning algorithms to predict stock prices. In recent years, machine learning algorithms have been used to predict the stock prices of companies, which is a critical task in investment management and financial decision making. One such case study is the work done by Behera et al. (Behera et al., 2020), which proposes machine learning models for predicting stock prices using real-time streaming data from various sources. The authors use the distributed platform, Spark, to analyze data from two sources, Google Finance and Twitter API. The proposed model is based on a distributed architecture known as Lambda architecture and is found to be more accurate than other models, with support vector regression having the best accuracy. The study highlights the potential of using real-time streaming data for stock prediction and the importance of developing scalable and fault-tolerant models for this purpose. The results of this study demonstrate the potential of AI techniques in predicting stock prices. By accurately predicting stock prices, investors and financial institutions can make more informed investment decisions and manage their portfolios more effectively. However, it is important to note that this study is a proof-of-concept and further research is needed to validate the results on a larger dataset and in a real-world setting.

2.4. 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.

2.4.1. 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).

2.5. 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.

2.6. Future research directions

The application of AI techniques in economic analysis has shown promising results, but there are still several limitations and challenges that need to be addressed. In this section, we will elaborate on future research directions as follows:

- One of the key challenges of applying AI techniques in economic analysis is the lack of interpretability and explainability of AI models. Researchers and practitioners need to focus on developing AI models that are explainable and interpretable, which can increase their trust and adoption.
- Incorporating domain knowledge into AI models can improve their accuracy and interpretability. Future research should focus on developing approaches that combine domain knowledge with AI techniques to improve economic analysis.

- AI models are susceptible to adversarial attacks and noise in the data. Future research should focus on developing robust AI models that are resistant to adversarial attacks and can handle noisy data.

3. Conclusion and Future Work

In this paper, we explored the efficiency and effectiveness of AI techniques in economic analysis. We conducted a comprehensive literature review on the applications of AI in economic analysis and identified the most used techniques and their respective advantages and limitations. We then applied these techniques to various economic problems, such as forecasting economic indicators, predicting financial markets, and analyzing consumer sentiments, and evaluated their performance using various metrics. Our results showed that AI techniques can improve the accuracy and efficiency of economic analysis in many cases, especially when dealing with large and complex datasets. However, we also found that AI methods have their own limitations, such as the need for high-quality and abundant data, interpretability and explainability concerns, and ethical considerations related to bias and discrimination.

This study makes several contributions to the field of economic analysis. First, it provides a comprehensive review of the existing literature on the applications of AI in economic analysis, which can serve as a valuable resource for researchers and practitioners interested in this topic. Second, it identifies the most commonly used AI techniques and evaluates their performance in various economic problems, which can help guide future research and applications. Our research also has several practical implications. For example, our findings suggest that AI techniques can be useful in predicting financial market trends and consumer behavior, which can inform investment and marketing decisions. Additionally, our results highlight the importance of data quality and interpretability in the application of AI to economic analysis, which can help practitioners avoid potential pitfalls and ethical concerns.

This study has some limitations that should be acknowledged. First, our evaluation was limited to a few specific economic problems and datasets, and thus our results may not generalize to other contexts. Second, the interpretability and explainability of some AI techniques, such as deep learning and neural networks, were not thoroughly analyzed, which is an important area for future research. In terms of future work, there are several avenues for further investigation. First, more research is needed to explore the interpretability and explainability of AI techniques in economic analysis, which can help increase their trust and adoption by practitioners. Second, more attention should be paid to the ethical considerations related to the use of AI in economic analysis, such as bias and discrimination, and strategies should be developed to mitigate these risks. Finally, there is a need for more comparative studies that evaluate the performance of different AI techniques in economic analysis, which can help identify the most effective approaches for specific problems and contexts.

In conclusion, this study shows that AI techniques have the potential to improve the efficiency and effectiveness of economic analysis, but their successful application requires careful consideration of data quality, interpretability, and ethical considerations. Our findings provide valuable insights and directions for future research and applications in this field.

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Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

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