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Evaluating the Effectiveness of Artificial Intelligence Models in Predicting Economic Indicators: an in-Depth Review

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INFO ARTIKEL	ABSTRAK

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Abstrak: Di era digital saat ini, kecerdasan buatan (artificial intelligence/AI) memainkan peran yang semakin penting dalam analisis ekonomi; namun, efektivitas berbagai model AI dalam memprediksi indikator ekonomi masih memerlukan evaluasi menyeluruh. Penelitian ini bertujuan untuk mengatasi kesenjangan ini dengan menilai efektivitas model AI dalam konteks yang lebih luas melalui pendekatan tinjauan literatur yang sistematis. Penelitian ini mengidentifikasi metode yang efektif dan mengeksplorasi tantangan dan keberhasilan yang terkait dengan implementasinya. Dengan menggunakan pendekatan penelitian kualitatif dan tinjauan literatur sistematis, literatur yang digunakan bersumber dari database pengindeksan seperti Scopus, DOAJ, dan Google Scholar, dengan tanggal publikasi mulai dari tahun 2014 hingga 2024. Hasil evaluasi menunjukkan bahwa model AI, khususnya deep learning dan model hybrid, menawarkan keuntungan yang substansial dibandingkan metode konvensional dalam memprediksi indikator ekonomi. Jaringan syaraf, seperti LSTM dan CNN, unggul dalam menangkap pola temporal dan spasial yang kompleks, sementara model hibrida meningkatkan akurasi prediksi dengan mengintegrasikan berbagai teknik AI. Penggabungan sumber data alternatif, seperti media sosial dan tren penelusuran, memberikan wawasan tambahan di luar data ekonomi tradisional, sehingga memperkaya prediksi. Explainable AI (XAI) semakin mendukung efektivitas model-model ini dengan meningkatkan transparansi dan kepercayaan di antara para pemangku kepentingan. Selain itu, Natural Language Processing (NLP) meningkatkan akurasi prediksi dengan menganalisis sentimen pasar dan berita ekonomi, sehingga menambah konteks yang berharga.

Keywords:
AI Models,
Economic Indicators,
Predictive Analytics,
Systematic Literature Review.

Abstract: *In the current digital era, artificial intelligence (AI) plays an increasingly pivotal role in economic analysis; however, the effectiveness of various AI models in predicting economic indicators still requires thorough evaluation. This research aims to address this gap by assessing the effectiveness of AI models within a broader context through a systematic literature review approach. The study identifies effective methods and explores the challenges and successes associated with their implementation. Employing a qualitative research approach and systematic literature review, the literature used is sourced from indexing databases such as Scopus, DOAJ, and Google Scholar, with publication dates ranging from 2014 to 2024. The evaluation results reveal that AI models, particularly deep learning and hybrid models, offer substantial advantages over conventional methods in predicting economic indicators. Neural networks, such as LSTM and CNN, excel at capturing complex temporal and spatial patterns, while hybrid models enhance predictive accuracy by integrating various AI techniques. The incorporation of alternative data sources, such as social media and search trends, provides additional insights beyond traditional economic data, enriching predictions. Explainable AI (XAI) further supports the effectiveness of these models by increasing transparency and trust among stakeholders. Additionally, Natural Language Processing (NLP) enhances predictive accuracy by analyzing market sentiment and economic news, thereby adding valuable context.*

A. INTRODUCTION

Economic forecasting is crucial in the global economy and public policy as it provides a solid foundation for planning and decision-making. Accurate predictions enable policymakers to identify trends, anticipate crises, and formulate effective policies for economic stability and growth (Drehmann & Juselius, 2014). In an interconnected world, economic forecasting helps countries respond rapidly to changes in international conditions, such as financial market fluctuations and trade dynamics (Cashin et al., 2017). AI plays a significant role in data analysis and economic forecasting, allowing for the identification of patterns not detectable by conventional methods (Iqbal et al., 2020). Through machine learning algorithms and statistical models, AI produces more accurate and reliable predictions, supporting data-driven decision-making.

The use of artificial intelligence (AI) in economics has evolved rapidly since its inception (Ruiz-Real et al., 2021). Initially, AI was applied in a limited capacity to simple predictive models using basic algorithms. As technology and computational capacity advanced, AI was integrated into more complex economic models (Ernst et al., 2019). In the 1990s and 2000s, machine learning techniques and neural networks enabled the processing of large datasets and the identification of subtle patterns. AI was adopted in economic forecasting, financial market analysis, growth projections, and policy evaluation. The increased access to big data and AI's ability to process data from diverse sources have driven this development. Today, AI is widely used by financial institutions, central banks, and governments for more accurate and data-driven economic predictions.

In economic forecasting, various artificial intelligence (AI) models are employed to generate accurate projections. Machine learning models such as linear regression, decision trees, and k-Nearest Neighbors (k-NN) learn from historical data to make predictions without explicit programming (Adeniyi et al., 2016). Deep learning, a subset of machine learning, utilizes artificial neural networks with deep layers (deep neural networks) to handle large and complex data (Najafabadi et al., 2015). Popular deep learning models include long short-term memory (LSTM) and convolutional neural networks (CNN), which are effective in capturing temporal and spatial patterns (Lai et al., 2018). Neural networks also encompass auto-encoders and generative adversarial networks (GANs) (Mescheder et al., 2017). These models are widely used in financial market analysis, inflation forecasting, and credit risk evaluation, supporting data-driven decisions and responsiveness to global economic dynamics.

In evaluating the effectiveness of AI models in economic forecasting, various methods and metrics are used. Common methods include cross-validation and split-sample (Zhang & Yang, 2015). Evaluation metrics commonly used are accuracy, precision, recall, mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared (R^2) (Sofaer et al., 2019) (Reich et al., 2016) (Lolon et al., 2016). (K. Khan et al., 2022) demonstrate that the bagging regressor technique outperforms decision trees and gradient boosting in predicting RAC strength, with a correlation coefficient (R^2) of 0.92 and lower error values (MAE = 4.258; RMSE = 5.693) compared to other techniques.

Recent research evaluates AI techniques in predicting prices and economic indices. (Abidoye et al., 2019) found that Artificial Neural Networks (ANN) outperform Support Vector Machines (SVM) and ARIMA in forecasting property price indices in Hong Kong, with variables such as interest rates and unemployment as significant factors. (Ramírez et al., 2020) identified ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), Genetic Programming (GP), and Support Vector Regression (SVR) as primary methods in predicting economic indicators from data sources including WOS, Scopus, and Google Scholar. (Rampini & Re Cecconi, 2022) reported that ANN has a 5% lower Mean Absolute Error (MAE) compared to XGBoost for predicting house prices in Italy, although accuracy declines for the most expensive houses. (Tang et al., 2020) demonstrated that the Long Short-Term Memory (LSTM) model achieves the best Root Mean Squared Error (RMSE) of 0.43% in predicting stock prices of logistics companies in Hong Kong.

(Chen et al., 2021) propose the AIEM model, which can enhance energy efficiency by up to 97.32% and improve the utilization of renewable energy resources. (Javaid et al., 2022) highlight the role of AI in Industry 4.0, which enhances product consistency, productivity, and reduces costs through the collaboration between robotics and humans, as well as processing IoT data for decision-making and malfunction detection. (Ernst et al., 2019) evaluate the impact of AI on inequality and employment, showing its potential to boost productivity in developing countries and among low-skilled workers, while emphasizing the need for skill policies and digital regulations. (Haleem et al., 2022) assess the role of AI in marketing, including improved data management, user experience personalization, and competitor performance analysis, allowing marketers to target content and channels more effectively.

Research on the effectiveness of AI models in predicting economic indicators reveals significant achievements as well as gaps that need to be addressed. Common methodologies in model evaluation, such as cross-validation, MAE, MSE, and RMSE, have been widely applied. Techniques like bagging regressor have shown superior performance compared to other methods, and ANN has been found to be more effective in predicting property price indices and house prices. LSTM models also exhibit the best results in predicting stock prices. However, there is a gap in the broad and varied application of AI models across different sectors and regions. This research aims to address this gap by evaluating the effectiveness of AI models in a broader context through a systematic literature review approach, identifying effective methods, and exploring the challenges and successes in their implementation.

B. METHOD

In this study, a qualitative research approach using Systematic Literature Review (SLR) is employed to evaluate the effectiveness of artificial intelligence (AI) models in predicting economic indicators. The Problem Formulation begins with identifying gaps in previous research concerning the application of AI models for economic prediction, which drives this study to evaluate these models' effectiveness more comprehensively. Inclusion and Exclusion Criteria are established by selecting articles published within the last 10 years (2014-2024), written in English or Indonesia, and including peer-reviewed journals and conference proceedings that discuss the application of AI models in predicting economic indicators using empirical methods, systematic literature reviews, meta-analyses, or case studies. Articles that are not peer-reviewed, such as editorials or opinion pieces, published before 2014, written in languages other than English, or that do not specifically address AI model applications in economic prediction, are excluded.

Literature Search is conducted using databases such as Scopus, DOAJ, and Google Scholar, with keywords including AI Models, Economic Indicators, and Predictive Analytics. The economic indicators that are commonly predicted by researchers are as per Figure 1.

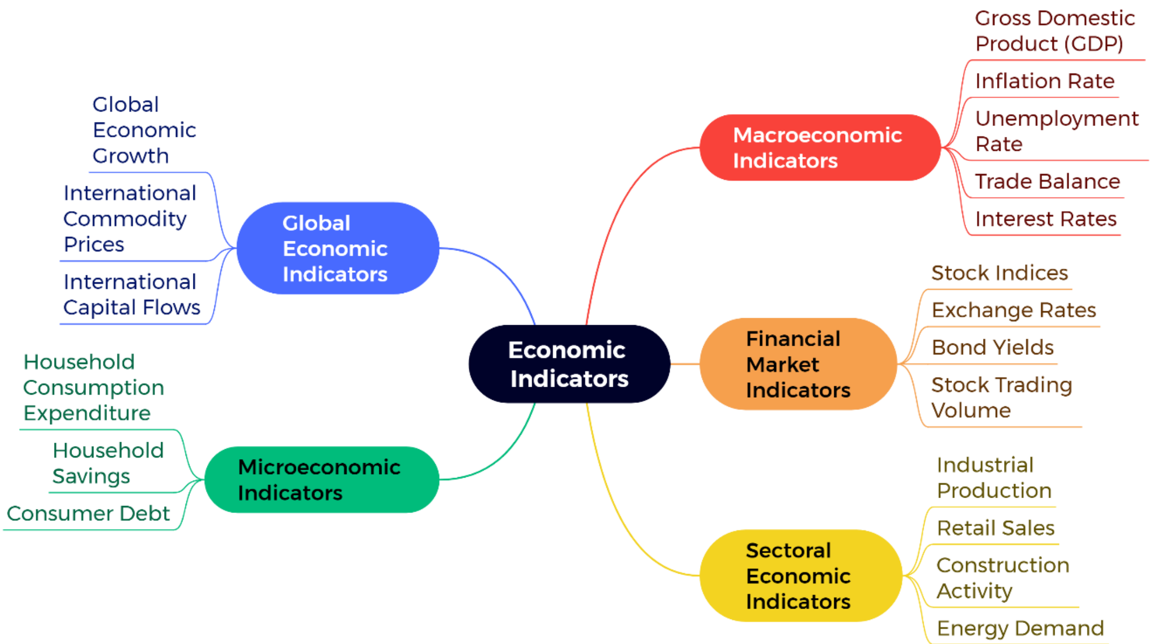

Figure 1. The economic indicators that are commonly predicted by researchers

Figure 1 overview of various key indicators used in economic forecasting and analysis. It categorizes indicators into five main groups: macroeconomic indicators, financial market indicators, sectoral economic indicators, microeconomic indicators, and global economic indicators. Macroeconomic indicators include measures such as Gross Domestic Product (GDP), inflation rate, unemployment rate, trade balance, and interest rates. Financial market indicators encompass stock indices, exchange rates, bond yields, and stock trading volume. Sectoral indicators focus on industrial production, retail sales, construction activity, and energy demand. Microeconomic indicators address household consumption expenditure, savings, and consumer debt, while global indicators cover global economic growth, international commodity prices, and capital flows. Figure 1 aims to provide a comprehensive framework for understanding the diverse range of economic indicators that researchers and analysts use to evaluate economic conditions and make informed predictions.

Next, data selection involves filtering articles based on the established inclusion and exclusion criteria. Data Extraction is performed to gather relevant information from the selected articles, including evaluation metrics and outcomes from various AI models. Analysis and Synthesis are undertaken to assess and integrate findings from the selected studies to identify effective methods and explore the challenges and successes of their implementation. Conclusion is drawn based on the analysis and synthesis results, providing insights into the effectiveness of AI models in predicting economic indicators and offering recommendations for future research and practical applications. The full procedure is described in Figure 2.

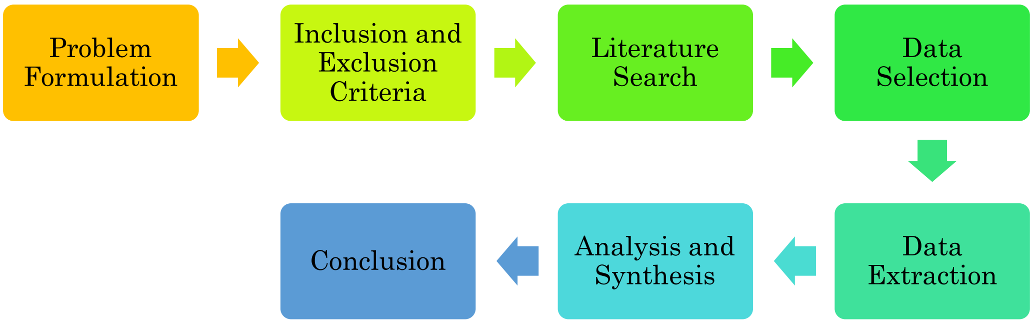

Figure 2. Flow of research implementation

C. RESULTS AND DISCUSSION

We conducted an extensive literature search and identified a total of 2,238 articles from indexing databases. The selection process according to criteria, especially the field of focus, filtered the articles to 374 articles. Further, we shortlisted 127 articles. Several relevant studies offered valuable insights into the effectiveness of AI models in predicting economic indicators. These studies not only support our research focus and objectives, but also provide important information that enhances our understanding of the topic. The data and findings obtained from these various sources enrich our analysis and offer an important additional perspective to evaluate how AI models can be effectively applied in economic forecasting. We have integrated the information from these various studies and developed a more comprehensive and in-depth analysis of the effectiveness of AI models in this context such that we analyzed a total of 30 corresponding articles, as listed in Table 1.

Table 1. Research Variables Discussed in the article

No	Field or Focus	Authors with Similar Focus	Insights or Research Variables
1	General Economic Prediction Using AI	Agu et al. (2022), Jena et al. (2021), Günay (2016)	AI models demonstrate high accuracy in predicting economic indicators such as GDP and electricity demand.
2	Energy Price and Consumption Prediction	Wei et al. (2019), Elmousalami (2021)	Traditional methods outperform in forecasting energy consumption, while XGBoost excels in conceptual cost modeling.
3	Property Price Index Prediction	Abidoye et al. (2019)	- ANNs outperform SVM and ARIMA in predicting the Property Price Index (PPI).
4	Oil Price Prediction	Sehgal & Pandey (2015)	AI models, including neural networks and genetic algorithms, effectively handle the complexity of oil price data.
5	Technical Challenges and Key Factors in AI Effectiveness	Liu et al. (2020), Ahmed et al. (2024), Shepperd et al. (2014), Hazen et al. (2014), Najafabadi et al. (2015), Hutter et al. (2014), Kang & Tian (2018)	The quality and quantity of data are crucial, and appropriate preprocessing techniques and algorithm selection can significantly enhance predictive accuracy.
6	AI Models and Techniques in Economic Prediction	Abdolrasol et al. (2021), Emmert-Streib et al. (2020), Basak et al. (2019)	Neural networks and decision trees are effective in handling complex and nonlinear data.
7	Challenges in Implementing AI Models for Economic Prediction	Nijman et al. (2022), Hammami et al. (2020), Barredo Arrieta et al. (2020), Ying (2019), Bejger & Elster (2020)	Technical challenges such as data quality, overfitting, and interpretability impact the effectiveness of AI models.
8	Trends and Innovations in AI for Economic Prediction	Kumari & Toshniwal (2021), Xu et al. (2022), Hansen & Borch (2022), Langer et al. (2021), Vicari & Gaspari (2021), Zheng et al. (2023), Lu et al. (2015), Minh et al. (2022)	- The use of deep learning, hybrid models, alternative data sources, and explainable AI is increasingly prevalent to enhance predictive accuracy.

Table 1 illustrates the diverse application of artificial intelligence (AI) models across various economic prediction domains, highlighting both the successes and challenges encountered in this field. The table categorizes research into specific areas such as general economic prediction, energy price forecasting, property price index prediction, and oil price prediction. It reveals that AI models, particularly artificial neural networks (ANNs) and XGBoost, have shown superior accuracy in forecasting complex economic indicators like GDP, electricity demand, and property prices. These findings suggest that AI models are highly adaptable and capable of managing the intricacies of economic data, outperforming traditional methods in certain contexts, especially where non-linear relationships and large datasets are involved.

Furthermore, Table 1 underscores the critical factors that influence the effectiveness of AI models in economic prediction. The quality and quantity of data, as well as the selection of appropriate algorithms and preprocessing techniques, are identified as pivotal to achieving high predictive accuracy. The table also highlights ongoing challenges such as overfitting, data quality issues, and the interpretability of AI models, which can hinder their application. Emerging trends and innovations, including the use of deep learning, hybrid models, and explainable AI, are also noted, indicating a continuous evolution in the field aimed at enhancing model accuracy and transparency. These insights suggest that while AI holds significant promise for economic forecasting, careful consideration of data and methodological approaches is essential for optimizing its potential.

1. AI Models Accurate in Predicting Economic Indicators

In the field of macroeconomics, research indicates that artificial intelligence (AI) models generally provide higher prediction accuracy compared to traditional methods. Conventional models, particularly nonlinear regression, have proven superior in forecasting annual energy consumption with the lowest average MAPE of 1.79%, while AI models demonstrate extensive applicability across various domains (Wei et al., 2019). Artificial neural networks (ANNs) have shown superior performance compared to support vector machines (SVMs) and autoregressive integrated moving average (ARIMA) models in predicting property price indices (PPI) in Hong Kong, with key variables such as interest rates and unemployment playing significant roles (Abidoye et al., 2019). AI methods, including neural networks and genetic algorithms, are capable of handling the complexities of oil price data, though there are still challenges regarding feature selection (Sehgal & Pandey, 2015). Furthermore, XGBoost has been identified as the most accurate method in conceptual cost modeling, with a mean absolute percentage error of 9.091% and an adjusted R^2 of 0.929, and excels in managing missing values and outliers (Elmousalami, 2021).

Artificial intelligence (AI) models demonstrate high accuracy in predicting economic indicators. Principal Component Regression (PCR) achieves an accuracy of 89% and a mean squared error of -7.5×10^{21}, outperforming Ridge Regression, Lasso Regression, and Ordinary Least Squares (Agu et al., 2022). A multilayer artificial neural network model predicts GDP for the April–June 2020 quarter with less than 2% error, indicating a sharp decline that necessitates immediate government intervention (Jena et al., 2021). Additionally, a multilayer ANN model forecasting annual electricity demand in Turkey projects an increase to approximately 460 TWh by 2028, demonstrating high accuracy compared to official forecasts (Günay, 2016).

Artificial Intelligence models, particularly Artificial Neural Networks (ANNs), demonstrate superior performance compared to conventional methods in several domains, such as property price prediction and energy demand forecasting. This superiority is attributed to their ability to effectively handle complex and non-linear data. Additionally, models such as XGBoost and Principal Component Regression (PCR) not only provide high accuracy but also exhibit strong capabilities in managing missing data and outliers. However, challenges in feature selection persist, indicating that despite the advantages of AI, the processes of selecting optimal features and parameters require further refinement. Moreover, while AI models are often more accurate, their high complexity can impact interpretability and practical implementation.

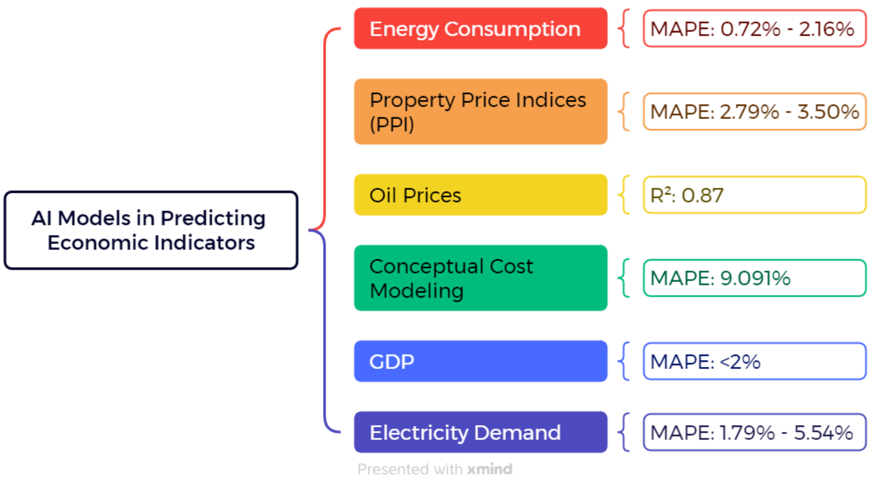

Figure 3. AI Models Accurate in Predicting Economic Indicators

2. Factors Affecting the Effectiveness of AI Models

The quality and quantity of input data play a crucial role in influencing the predictive outcomes of artificial intelligence (AI) models in the economic context (Liu et al., 2020). High-quality data-characterized by accuracy, relevance, and error-free content-enables AI models to better capture underlying patterns and relationships among economic variables, thereby enhancing prediction accuracy (Ahmed et al., 2024). Conversely, flawed or incomplete data can lead to biased or inaccurate model outputs (Shepperd et al., 2014). Additionally, the quantity of data is also significant; larger datasets allow models to learn from a broader range of examples and variability, which improves model generalization and reduces the risk of overfitting (López et al., 2022).

The effectiveness of artificial intelligence (AI) models in economic prediction is influenced by various factors that can either enhance or diminish their performance. A primary factor is the quality of input data; accurate, complete, and relevant data enables the model to generate more precise predictions (Hazen et al., 2014). Additionally, the availability of a substantial volume of data plays a crucial role, as larger datasets help the model identify complex patterns and improve its generalization capabilities (Najafabadi et al., 2015). Moreover, the selection of appropriate algorithms and the fine-tuning of model parameters can significantly enhance predictive accuracy (Hutter et al., 2014). Other contributing factors include data pre-processing techniques, such as normalization and outlier removal, which can improve the quality of the data used (Kang & Tian, 2018). Conversely, the presence of flawed data, a lack of representative data, or errors in model design can reduce the effectiveness of AI models. Excessive model complexity may also lead to overfitting, where the model becomes overly tailored to the training data and performs poorly on new data.

The quality and quantity of data are crucial for the effectiveness of AI models. Accurate and relevant data form the foundation for precise predictions, while large datasets provide more information to understand complex patterns and reduce the risk of overfitting, provided the data is of high quality. The selection of appropriate algorithms and the fine-tuning of parameters are also essential for optimal model performance, while data pre-processing techniques ensure that the data is in the best form for analysis. However, limitations such as overly complex models or flawed data can diminish the effectiveness of AI models. Poor data quality, design errors, and overfitting are challenges that must be addressed to enhance model performance.

3. Performance of Different Types of AI Models

The effectiveness of artificial intelligence (AI) models for predicting specific economic indicators largely depends on the characteristics of the data and the desired analytical objectives. For instance, neural networks are often selected due to their ability to handle highly complex and nonlinear data (Abdolrasol et al., 2021). Neural networks, particularly deep learning models, can learn from large datasets and identify intricate patterns, making them highly useful for long-term predictions or analyses involving diverse data (Emmert-Streib et al., 2020). On the other hand, decision trees and their derivatives, such as random forests and gradient boosting, have also proven effective in economic prediction because they are easy to interpret and can manage data with diverse input variables and outliers (Basak et al., 2019). These models can capture nonlinear interactions between variables and provide robust results even when the available data is not extensive.

There are significant differences in the performance of artificial intelligence (AI) models based on the type of economic indicators being predicted. Each economic indicator possesses unique characteristics and dynamics that influence how AI models process and analyze the data. Predicting inflation or gross domestic product (GDP) often requires the analysis of complex macroeconomic data and temporal variables, making models like neural networks or autoregressive integrated moving average (ARIMA) models with exogenous inputs (ARIMAX) potentially more effective (Sagaert et al., 2015). Conversely, for predicting more specific and volatile financial indicators such as stock prices or exchange rates, models like decision trees or random forests can yield more accurate results due to their ability to handle data with nonlinear patterns and high noise levels (Zhang & Hamori, 2020). Additionally, AI models employing deep learning techniques are often superior in capturing the complex and temporal patterns of economic time-series data (Lai et al., 2018).

Neural networks, particularly deep learning, excel at processing and analyzing large, complex datasets, capturing intricate patterns, and making them valuable for long-term predictions and economic data analysis involving many variables. Decision trees and their derivatives, such as random forests and gradient boosting, are effective for predicting economic indicators with variable data containing outliers, offering ease of interpretation and the ability to handle non-linear interactions. Complex models like neural networks or ARIMAX are suitable for macroeconomic data requiring temporal analysis, while simpler, robust models like decision trees and random forests are better suited for specific, volatile financial data. The main advantages of neural networks are their ability to capture complex patterns and handle large datasets, although they require significant training time and computational resources and can be less interpretable. Decision trees and their derivatives are highly interpretable and handle noisy data well but may struggle with very large or highly complex datasets.

4. Challenges in AI Model Implementation

The application of artificial intelligence (AI) models for predicting economic indicators faces several significant technical challenges. One of the primary challenges is the quality and availability of data. Economic data is often incomplete, contains many missing values, and is inconsistent, which can reduce the predictive accuracy of AI models (Nijman et al., 2022). Additionally, economic data tends to be non-stationary, with patterns and distributions that change over time, requiring AI models to be continuously updated and adjusted to current conditions (Hammami et al., 2020). Another challenge is the selection of relevant features, as identifying the most influential variables is crucial for improving model performance (Barredo Arrieta et al., 2020). Overfitting is also a common issue, particularly when models are overly complex and fit the training data too closely, thereby reducing their ability to generalize to new data (Ying, 2019). Moreover, the interpretability of AI models is a significant concern because stakeholders need a clear understanding of how the models make predictions to ensure that economic decisions can be responsibly justified (Bejger & Elster, 2020). Therefore, the development and implementation of AI models for economic indicator prediction require a careful and ongoing approach to address these technical challenges.

The reviewed studies demonstrate various approaches to addressing the challenges of implementing artificial intelligence (AI) models for predicting economic indicators. One common method is enhancing data quality through imputation techniques to handle missing values and data normalization to reduce inconsistencies

(Aljuaid & Sasi, 2017). Other studies adopt adaptive learning approaches, where AI models are continuously updated and adjusted with the latest data to address the non-stationary nature of economic data (Dixit & Jain, 2022). Additionally, the selection of relevant features is often optimized using advanced feature selection methods, such as genetic algorithms and reinforcement learning techniques (Bouktif et al., 2018). To combat overfitting, several studies implement stricter regularization techniques and cross-validation (Li et al., 2017). Moreover, to enhance model interpretability, many studies utilize explainable AI models, such as decision tree-based models, or post-hoc interpretability tools like SHAP (Shapley Additive Explanations) (Saranya & Subhashini, 2023). While these solutions show promising results, their effectiveness varies depending on the specific context and complexity of the data used, necessitating further evaluation and adjustment to achieve optimal outcomes.

Incomplete and inconsistent data quality and availability can hinder an AI model's ability to learn accurate patterns, necessitating techniques such as data imputation and normalization. Non-stationary economic data require periodic updates and model adjustments to maintain relevance. Proper feature selection is crucial for enhancing prediction accuracy and model efficiency. Overfitting, which can occur when a model is too complex and fits the training data too closely, can be mitigated through regularization and cross-validation. Model interpretability is essential for ensuring stakeholder trust and acceptance. Although data enhancement techniques, regularization, and validation improve model performance and reduce overfitting, challenges persist in poor data quality, adapting to non-stationary data, and the interpretability of complex models.

5. Trends and Innovations in Economic Prediction Using AI

Recent trends in the use of artificial intelligence (AI) for economic prediction, as identified in the reviewed studies, highlight significant and innovative advancements. One major trend is the application of deep learning models, such as long short-term memory (LSTM) networks and convolutional neural networks (CNN), which are adept at capturing temporal and spatial patterns in economic data more effectively (Kumari & Toshniwal, 2021). Additionally, there is an increasing use of hybrid models that combine various AI techniques, such as integrating LSTM with ARIMA models to enhance predictive accuracy (Xu et al., 2022). The use of alternative data sources, such as social media data and Google search trends, is also becoming more prevalent as supplementary to traditional economic data, improving predictions and providing more comprehensive insights (Hansen & Borch, 2022). Furthermore, the adoption of explainable AI (XAI) is growing to enhance the transparency and interpretability of AI models, allowing stakeholders to better understand the basis of predictions (Langer et al., 2021). Advances in natural language processing (NLP) are also being employed to analyze market sentiment and economic news, which can serve as additional indicators in predictive models (Vicari & Gaspari, 2021).

Innovations identified for enhancing the effectiveness and accuracy of artificial intelligence (AI) models in the future include several advanced technological and methodological developments. One major innovation is the development and application of more advanced deep learning models, such as transformers and attention mechanisms, which can improve the model's ability to capture more complex patterns and temporal relationships in economic data (Zheng et al., 2023). Additionally, advancements in transfer learning techniques allow AI models to leverage knowledge gained from one domain to improve performance in a different domain, potentially enhancing prediction accuracy with limited data (Lu et al., 2015). The integration of data from various sources, including sensor data and big data, as well as the use of more sophisticated natural language processing (NLP) techniques for sentiment analysis and market trends, also holds promise for providing deeper and more accurate insights (M. T. Khan et al., 2016). Furthermore, the evolving approach of explainable AI (XAI) can enhance transparency and trust in models by providing clearer explanations of how predictive decisions are made (Minh et al., 2022).

Deep learning models like LSTM and CNN excel at capturing complex patterns in economic data, with LSTM suited for long-term temporal analysis and CNN for spatial data analysis. Hybrid models, such as combining LSTM and ARIMA, enhance prediction accuracy by leveraging the strengths of each technique. Alternative data sources, including social media and search trends, offer additional insights not present in traditional economic data. Explainable AI (XAI) improves transparency and trust in AI models, crucial for stakeholders. Natural Language Processing (NLP) enriches predictive models by analyzing sentiment and news for additional context. Future innovations include advanced deep learning models like transformers, which handle complex data better, and transfer learning, which enhances prediction accuracy with limited data. Integrating diverse data sources allows for deeper analysis and more accurate predictions, while evolving XAI provides clearer model explanations. Despite these advantages, deep learning requires large datasets and intensive computation, hybrid models add implementation complexity, and integrating alternative data sources increases complexity. XAI, although improving transparency, may still struggle to fully explain some models, and NLP can be affected by language ambiguity and context.

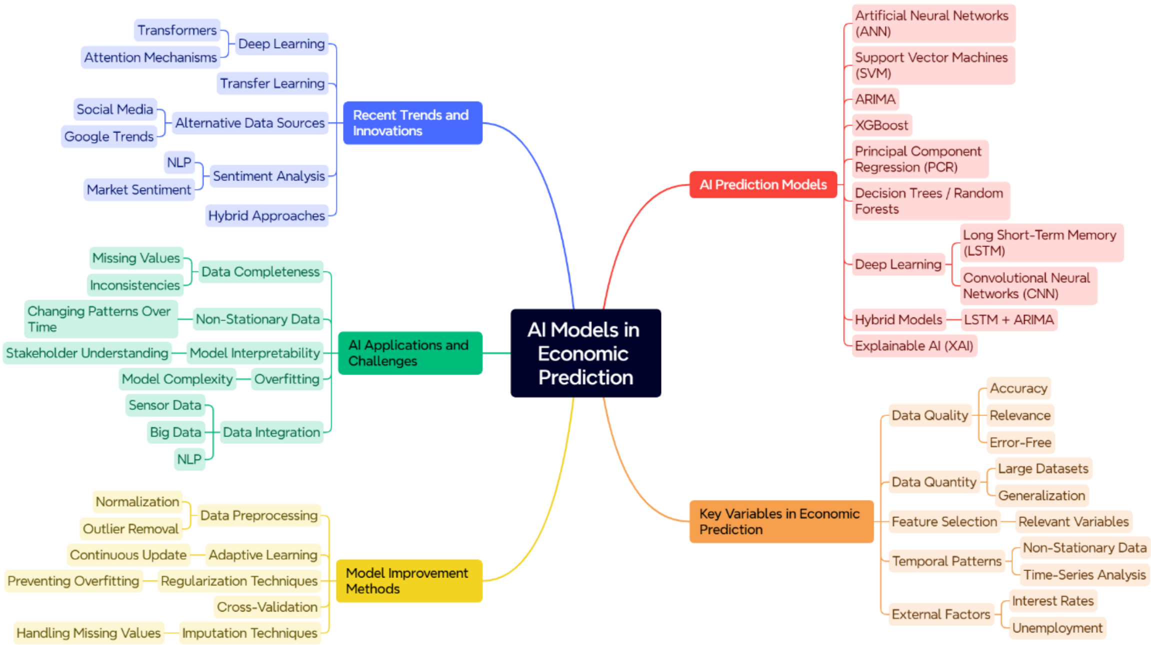

Figure 4. Research variables contained in this study

Figure 4 explains that from 2014 to 2017, research in economic prediction models concentrated on fundamental aspects such as data quality, focusing on imputation, normalization, and correcting data errors. During this period, models and algorithms such as Neural Networks, Decision Trees and their derivatives, and ARIMA/ARIMAX became prevalent. The emphasis was also on handling large datasets and addressing issues related to feature selection and overfitting. Entering 2018-2021, there was a significant shift towards Deep Learning Models, specifically LSTMs and CNNs, along with the development of hybrid models that combine LSTMs with ARIMA. This period also saw the incorporation of alternative data sources, such as social media and Google Search, and advances in Explainable AI (XAI) for better model transparency. In addition, Natural Language Processing (NLP) techniques, including sentiment analysis and interpretation of economic news, rose to prominence. In the latest period, 2022-2024, innovation is characterized by the adoption of Transfer Learning and the integration of diverse data sources. The focus is also on improving model quality and adaptation through more sophisticated deep learning models and the continuous evolution of XAI to increase transparency. Current challenges include advancing automated feature selection techniques, adapting models to non-stationary data, and addressing overfitting through regularization and cross-validation methods.

D. CONCLUSIONS

The evaluation results reveal that AI models, particularly deep learning and hybrid models, offer substantial advantages over conventional methods in predicting economic indicators. Neural networks, such as LSTM and CNN, are adept at capturing complex temporal and spatial patterns, while hybrid models enhance predictive accuracy by combining various AI techniques. The integration of alternative data sources like social media and search trends provides additional insights beyond traditional economic data, enriching predictions. Explainable AI (XAI) further supports the effectiveness of these models by increasing transparency and trust among stakeholders. Additionally, Natural Language Processing (NLP) improves predictive accuracy by analyzing market sentiment and economic news, adding valuable context.

Despite these advancements, challenges such as data quality and availability, non-stationary data, relevant feature selection, overfitting, and model interpretability persist. Incomplete and inconsistent data necessitate advanced imputation and normalization methods, while non-stationary data requires adaptive models that can be continuously updated. Accurate feature selection and managing overfitting through regularization and cross-validation are crucial for model performance. Although XAI has improved transparency, complex models remain challenging to fully explain. Future research should focus on developing more efficient deep learning models, automated feature selection techniques, and adaptive models for non-stationary data, as well as advancing XAI to provide more intuitive explanations of predictions. Addressing these gaps will enhance the utility of AI in predicting economic indicators and support better decision-making in the economic sector.

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