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The Impact of AI on Economic Modelling

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Abstract:

Purpose: *The aim of the article is to examine how artificial intelligence is changing economic modeling, with particular emphasis on its impact on traditional methods, practical applications, and development prospects.*
Design/Methodology/Approach: *The paper analyzes the key benefits of implementing AI in economics, such as improved forecast accuracy, the ability to process large data sets, reduced model creation time, and real-time analysis. It also discusses the challenges and limitations, including issues with model interpretability and dependency on data quality.*
Findings: *The development of AI opens up new possibilities that can complement or replace traditional approaches, introducing greater flexibility and precision in modeling economic phenomena.*
Practical Implications: *Artificial Intelligence (AI) is an interdisciplinary field of research aimed at designing systems capable of learning, analyzing data, and making decisions. Currently, AI is applied in various areas such as medicine, engineering, logistics, and economics, offering modern tools that support analysis and forecasting. Thanks to advanced machine learning and deep learning algorithms, it is possible to process vast data sets and detect patterns that were previously difficult to identify. In traditional economic modeling, econometric techniques such as linear regression or time series models (e.g. ARIMA) play a key role.*
Originality/Value: *Despite their effectiveness in many applications, these methods have limitations due to the need to adopt theoretical assumptions and the difficulty of analyzing complex, nonlinear data.*

Keywords: *Artificial intelligence, modeling, econometrics, machine learning.*

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1. Introduction

Artificial intelligence (AI) is an interdisciplinary field of study that focuses on designing systems capable of learning, analyzing data, and making decisions. Today, AI is widely used in various fields, such as medicine, engineering, logistics and economics, offering modern tools to support analysis and forecasting. With advanced machine learning and deep learning algorithms, AI makes it possible to process vast amounts of data and identify patterns that were previously difficult to detect. In traditional economic modeling, econometric techniques such as linear regression or time series models (e.g., ARIMA) play a key role.

These methods, while effective in many applications, have limitations due to the need to make theoretical assumptions and the difficulty of analyzing complex and nonlinear data sets. The development of artificial intelligence brings new opportunities that can complement or replace traditional approaches, introducing flexibility and greater precision to the modeling of economic phenomena.

The aim of this article is to investigate how artificial intelligence is changing economic modeling, highlighting its impact on traditional methods, practical applications and development prospects. The key benefits and challenges of AI implementation in this field will be analyzed.

The article discusses the following issues, traditional economic models and artificial intelligence, classic econometric techniques, their limitations and the ways in which AI introduces new possibilities of analysis and forecasting are presented.

Artificial intelligence in economic practice, examples of AI applications were presented, such as GDP forecasting, sentiment analysis in financial markets, and prediction of commodity and stock prices (Velinov *et al.*, 2023).

The benefits of using AI in economics, the main advantages are discussed, such as improved forecast accuracy, the ability to process large data sets, reduction of model construction time, and real-time analysis (Tyagi *et al.*, 2023).

Challenges and limitations, key challenges were analysed, including problems with the interpretability of models, dependence on data quality, implementation costs and ethical issues (Thalassinos and Kiriazidis, 2003). The future of AI in economic modeling, forecasts were presented regarding the development of hybrid methods, the use of AI in macroeconomic policy and its role in climate change modeling.

The article concludes by summarizing the key findings and highlighting the importance of interdisciplinarity in economic research, pointing to the need to integrate AI with traditional methods to better solve contemporary economic challenges (Grima *et al.*, 2023; Thalassinos and Thalassinos, 2006).

2. Traditional Economic Models and Artificial Intelligence

Traditional economic models are the foundation of modern economic analysis, enabling the prediction of the directions of changes in the economy, the analysis of interdependencies between macro- and microeconomic variables, and the assessment of the effects of public policies.

In particular, models such as linear regression, ARIMA (AutoRegressive Integrated Moving Average) or VAR (Vector AutoRegression) set the standard framework for econometric modeling. However, the increasing availability of data and advances in computational methods mean that artificial intelligence (AI) is increasingly complementing traditional approaches, providing more flexible and non-linear tools.

2.1 Linear Regression

Linear regression is one of the most basic econometric techniques, used in both macroeconomic (e.g., the impact of interest rates on inflation) and microeconomic (e.g., analysis of demand for consumer goods) studies. The basic form of a linear regression model is as follows:

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_k x_{kt} + \varepsilon_t$$

where:

- y_t– dependent variable (observation in period t),
- x_{it} – i-th explanatory (independent) variable in period t,
- $\beta_0, \beta_1, \dots, \beta_k$ – unknown parameters (model coefficients),
- ε_t– random component (error) in period t.

The assumptions of the linear regression model include, m.in, linearity, lack of autocorrelation, and homoskedasticity (constant variance of errors). If they are violated, it may be necessary to use corrections, e.g., models with autocorrelation correction (HAC) or taking into account heteroscedasticity (e.g., using weights in the least squares method).

2.1.1 Limitations of Linear Regression

Linearity assumption: Many real-world economic relationships are non-linear, so classical linear regression can underestimate or overestimate certain effects.

Sensitivity to least squares outliers is highly susceptible to outliers in the sample.

Difficulties in modeling interactions and nonlinearities, extension with quadratic terms or products of explanatory variables is not always sufficient.

2.2 ARIMA Models

AutoRegressive Integrated Moving Average (ARIMA) models play a key role in time series analysis and forecasting. The abbreviation ARIMA (p,d,q, p,d,q, p,d,q) stands for:

- AR (autoregression, p), the use of lagging values of the dependent variable to predict future values,
- I (differentiation, d), removing trend from data through differentiation (to achieve stationarity),
- MA (smoothing, q), taking into account model errors from previous periods. The ARIMA(p,d,q) model can be generally written as

$$\Phi_p(L)(1-L)^d y_t = \Theta_q(L)\varepsilon_t$$

where L is the delay operator $(Ly_t = y_{t-1})$

$$\Phi_p(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p,$$
$$\Theta_q(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q,$$

and is a process of white noise with mean zero and constant variance ε_t.

Model components:

1. Autoregression (AR)In the AR(p) component, we assume that the current value of a variable is a linear function of its p of past values

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

2. Differentiation (I)To obtain stationarity, the first-order differentiation operator (d=1) is used

$$\Delta y_t = y_t - y_{t-1}$$

   In the case of higher orders (d>1), differentiation is carried out repeatedly.

3. Smoothing (MA)The MA(q) part assumes that the variable is a combination of white noise from previous periods
4. $yt = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_{1q} \varepsilon_{t-q}$

2.2.1 Limitations of ARIMA Models

ARIMA models are linear in parameters by design and therefore do not perform well with nonlinear and complex patterns in time series (e.g., with large transition regimes).

They require stationarity, which can sometimes be difficult to achieve by simple differentiation (especially in the case of financial data or rapidly changing economic processes).

Sometimes it is necessary to expand the model with additional components (e.g., seasonal SARIMA models or models with external variables – ARIMAX).

2.3 Modele VAR (Vector AutoRegression)

Vector AutoRegression (VAR) models are a generalization of the concept of autoregression to multivariate systems. VAR assumes that not only is a single variable explained by its lagged values, but a vector of macroeconomic variables explains itself to each other (through its own lagging values and the lagging values of other variables).

The simplest form of the VAR(p) model can be written in the form

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t$$

where:

y_t to - a vector of endogenous variables (e.g. inflation, GDP, unemployment rate),
c - is a vector of intercepts,
A_i - are matrices of coefficients (parameters) at delayed values,
u_t - is a vector of random components (it is usually assumed that it is white noise with a certain covariance matrix Σ).

2.3.1 Advantages and Limitations of VAR

Advantages:

It can capture the interconnectors between many economic variables.
It enables causality analysis (Granger causality tests).
It provides the basis for deriving the impulse response function (IRF) and the decomposition of the forecast error variance (FEVD).

Constraints:

A large number of parameters to be evaluated (the risk of overparameterization and the problem of overfitting with too short a time series).
The need for some form of stationarity (data or its differences) and determining the order of delays.

2.4 The impact of AI on Traditional Models

Integrating AI methods into economics:
The increasing availability of data (e.g., from social media, administrative databases, transactional systems) is conducive to the use of more advanced analysis methods, such as:

- Neural networks (MLP, RNN, LSTM),
- Machine team methods (Random Forest, Gradient Boosting),
- Deep Learning models.

While traditional models focus mainly on linear structures, AI methods allow for the capture of non-linear relationships and more complex patterns.

Applications in economics and finance:
- Macroeconomic forecasting Neural networks can better capture nonlinearities in economic dynamics (e.g., business sentiment indicators, relationships between unemployment rates and inflation).
- Microeconomic and marketing modelling Machine learning algorithms allow you to predict consumer behavior, segment the market, or personalize offers in real time.
- Financial analysis AI methods [2,8,13] can capture complex patterns in high-frequency data (tick data), making it easier to detect market manipulation or create algotrading strategies, for example.

Benefits and challenges:
Benefits:
- Better quality of forecasts by taking into account non-linear relationships,
- Automation of the process of modeling and selection of variables,
- Ability to process unstructured data (texts, images, sensor data).

Challenges:
- "Black boxes": the complexity of AI methods makes it difficult to interpret the results obtained,
- High demand for computing power and programming skills,
- High risk of overlearning (overfitting) with an excessive number of parameters,
- Ethical and privacy issues in data analysis (especially personal data).

Traditional economic models, such as linear regression, ARIMA or VAR, are still a key element of the analytical workshop of economists and market researchers, mainly due to the interpretability of results, knowledge of well-defined assumptions and estimation procedures, and ease of implementation in standard statistical programs and libraries.

However, with the intensive development of artificial intelligence, there is an opportunity to better capture complex, non-linear relationships and use large, unstructured data sets. In the future, the role of AI methods will certainly continue to grow, but in combination (and not necessarily in replacement) with traditional models, which continue to provide an invaluable interpretative basis and a benchmark for economic inferences.

3. Artificial Intelligence in Economic Practice

Artificial intelligence (Mullainathan and Spiess, 2017; Ng, 2018) (AI) has gained prominence in economic and financial analysis in recent years. The development of efficient machine learning algorithms, the increase in computing power, and access to ever-increasing data sets (big data) enable the use of AI in a range of applications, such as:

- Macroeconomic forecasting (e.g., GDP, inflation),
- Sentiment analysis on financial markets (NLP – Natural Language Processing),
- Prediction of commodity or stock prices.

A common feature of these applications is the non-linear nature of dependencies and the need to integrate multiple data sources (e.g., quantitative, textual or geospatial data). Traditional methods, such as ARIMA or VAR models, are often unable to sufficiently capture such complex relationships.

3.1 Basics of Neural Network Models

One of the most popular AI methods used in economics are Artificial Neural Networks (ANN), whose structure is inspired by biological neural networks. In the most general terms, such a network can be represented as a function of

$$y\hat{} = f(x, w)$$

where:

x - is an input vector (data, e.g., historical values of macroeconomic indicators),
w - is a set of weights (parameters) of the network,
y^ - denotes the projected value (e.g., GDP forecast).

Layers, Weights, and Propagation:
A neural network consists of layers, an input layer, one or more hidden layers, and an output layer. In each layer, a linear transformation of the input is performed, and

then a non-linear activation function is (most often) used, e.g., sigmoid, ReLU, tanh. A simple example of a two-layer neural network (with one hidden layer) can be written by:

$$y^\wedge = \sigma(W^{(2)}\sigma(W^{(1)}x + b^{(1)}) + b^2),$$

where:

$W^{(1)}W^{(2)}$- are weight matrices in the first and second layers,
$b^{(1)}b^{(2)}$- are vectors of intercepts (bias),
σ(·) – is a nonlinear activation function (e.g., ReLU).

Training and updating weights:

Neural networks are usually taught using gradient methods (e.g., gradient descent or Adam). Assuming that we have a training set in which the true output value is known for each input, we minimize some cost function (e.g., mean squared error – MSE) $\{(x^i, y^i)\}_{i=1}^{N}, x^i y^i$

$$L(w) = \frac{1}{N}\sum_{i=1}^{N} \Sigma(y^{\wedge i} - y^i)^2.$$

During training, the parameters in are updated in the opposite direction to the gradient

$$w \leftarrow w - \eta \nabla wL(w)$$

where η is the learning rate. In practice, the backpropagation algorithm is used, which determines partial derivatives effectively for all network weights $\nabla wL(w)$.

3.2 GDP Forecasting Using Neural Networks

Motivation:
Gross Domestic Product (GDP) is a key macroeconomic indicator that reflects the overall economic health of a country. Traditional methods, such as ARIMA or VAR, often have a limited ability to capture complex and non-linear interactions between macroeconomic variables (investment, consumption, fiscal policy, international trade).

RNN and macroeconomic data:
Recurrent neural networks (RNNs) (Chen *et al.*, 2021; Hansen *et al.*, 2018: Zhang *et al.*, 2022) including their variants (LSTM, GRU), are perfect for time series modeling, as they naturally take into account time dependencies. For example, historical observations of GDP, inflation, interest rates, and other macro variables

can be used to create an input vector representing the state of the economy at ttt. The RNN forecasts (e.g., GDP in the next quarter) based on the data so far$x_t y\^{}_{t+1}$

$$y\^{}_{t+1} = f(x_t, h_t; w)$$

where is the hidden state vector of the RNN, "remembering" information about previous observations.h_t

Research results:
Empirical work shows that RNNs can outperform traditional econometric models by 10-20 % in terms of the accuracy of GDP forecasts, especially during periods of economic instability (e.g., recession, financial crisis). One study in the US showed up to 15% higher precision of GDP forecasts using LSTM, compared to classic ARIMA models.

3.3 Financial Market Sentiment Analysis (NLP)

The Critical Importance of Textual Information:
In today's markets, information spreads rapidly through financial media, analytical reports, social media or transcripts of statements from central bank representatives. Natural language processing (NLP) allows you to automatically analyze large text sets and extract information about investor sentiment from them.

NLP models to assess sentiment:
Current NLP models, such as BERT (Bidirectional Encoder Representations from Transformers), are able to identify subtle changes in emotional tone in texts (e.g., mentions of "crisis," "recovery," or "uncertainty"). In sentiment analysis, we get a measure of the positive/negative tone of the publication, which can then be included in models forecasting the behavior of stock prices or stock market indices.

Forecasting Profit:
Empirical research shows that incorporating sentiment analysis results into forecasting models can improve the accuracy of stock price forecasts by 10-20%. This is particularly important in periods of high uncertainty (e.g., political crises, pandemics), when markets react violently to information contained in the media.

3.4 Prediction of Commodity and Stock Prices

The complexity of commodity markets:
The prices of raw materials, such as oil, gold or copper, are shaped by numerous factors: demand and supply, geopolitical events, climate change, economic policies of key producers. Traditional ARIMA models do not always cope with complex, non-linear patterns.

Advanced ML models:

Algorithms such as XGBoost, Random Forest or LSTM networks enable:

- integration of various types of data (time series, text data, macro indicators),
- detection of periodicity and trends in conditions of frequent changes in the market regime,
- learning the correlation between the prices of different raw materials.

Case study: COVID-19 pandemic:
During the COVID-19 pandemic, when financial markets experienced sharp fluctuations, AI models made it possible to detect potential price declines, such as those of crude oil, in advance by correlating textual information about production restrictions, lockdowns, and OPEC statements with current price data.

3.5 Case Study: AI in Price Prediction during the COVID-19 Pandemic

The study conducted by a team of researchers combined textual data (pandemic-related news, government announcements, press releases) with quantitative data (oil price histories, transaction volumes). The LSTM neural network achieved 25% higher accuracy in predicting oil price declines in Q1 2020 compared to standard econometric models. An integral part of the success was the sentiment analysis, which helped to identify the key events (border closures, OPEC decisions) causing the largest price changes.

Conclusions and Perspectives:

1. Improved precision and nonlinearity: Neural networks and other AI algorithms allow you to capture complex, non-linear relationships between variables, resulting in higher prediction accuracy.
2. Integrated data sources: The ability to combine macroeconomic, financial, text (NLP), and geospatial data increases the reach of your analysis.
3. Rapid adaptation: AI is able to "learn" as new information comes in, which is crucial in conditions of rapid market fluctuations (e.g., pandemic, crisis).

Challenges:

1. Interpretability (the so-called "black boxes"),
2. Quality and representativeness of the data,
3. Risk of overfitting with improper regularization.

The development of artificial intelligence opens up new opportunities for economists and market analysts, enabling more accurate forecasting and decision-making based on abundant and diverse data. At the same time, it is necessary to further develop explainable AI and data standardization methods to fully exploit the potential of AI in economics and finance while maintaining the reliability and credibility of conclusions.

4. Benefits of Using AI in Economics

Artificial intelligence (AI) is exerting an increasingly strong influence on modern economic sciences (Agrawal *et al.*, 2019; Domingos, 2015; Varian, 2014), providing tools that allow for a more precise and rapid analysis of complex economic phenomena. Compared to classical approaches such as linear regression models, ARIMA or VAR, AI methods offer:

1. Improving the accuracy of forecasts – thanks to the ability to model non-linear relationships.
2. The ability to process huge data sets (Big Data) – which allows you to include a variety of information sources.
3. Reduction of the time needed to build models – thanks to the automation of the modeling process (AutoML).
4. Real-time analysis – using streaming technology.

The following sections discuss these advantages in detail, referring to empirical examples and research results that confirm the growing importance of AI in economics.

4.1 Improving Forecast Accuracy

One of the key applications of artificial intelligence in economics is to increase the accuracy of forecasting. Traditional econometric models, such as linear regression and the ARIMA time series, have limited flexibility in capturing complex, nonlinear interactions between variables. AI algorithms, such as Artificial Neural Networks (ANNs) and Random Forests, allow for deeper analysis of patterns in data and for taking into account a wide range of macro- and microeconomic factors.

Neural networks and random forests:

Neural networks can model multidimensional phenomena, identify correlations between observations, and take into account nonlinearities, so they can improve the accuracy of forecasts in areas as important as GDP growth, inflation, and the labor market.

Random Forests, by combining multiple decision trees into a single model, reduce the risk of overfitting and are effective in classification and regression problems, which is particularly valuable in predictive analyses with a large number of explanatory variables.

Empirical example:

In a study conducted in the United States, neural networks predicted changes in inflation with an accuracy 20% higher compared to traditional econometric models. The key advantage of AI methods turned out to be the ability to model non-linear effects resulting from unexpected changes in fiscal policy and from global shocks (e.g., commodity crises).

4.2 Ability to Process Huge Data Sets (Big Data)

The era of Big Data has brought economists unprecedented access to large and diverse data sets, including, m.in others, financial data, social media, economic reports, geospatial data, and information on consumer behavior. Traditional statistical methods often fail to cope with such extensive and heterogeneous sets, both in terms of efficiency and interpretation of results.

Machine Learning Algorithms in Big Data Processing:
Artificial intelligence, and in particular machine learning algorithms[5,9,14] such as XGBoost or Gradient Boosting, are adapted to the analysis of large data sets with high dimensionality. Allows:

- We gain the ability to combine data of various nature (e.g., numerical data, texts, images).
- Processing time (after proper parallelization) can be drastically reduced.
- Analyses can be carried out in a distributed mode (e.g., using Hadoop, Apache Spark).

Empirical example:
In the area of financial market analysis, AI models are able to detect unusual patterns in streams of millions of transactions, which makes it possible to identify potential market manipulation or previously unseen signals announcing price fluctuations. In one project, the use of distributed data processing technology allowed more than 10 million transactions to be analyzed in just a few minutes, providing much faster anomaly detection compared to classical methods.

4.3 Reduction of the Time Needed to Build Models

The process of building traditional econometric models (e.g., VAR) can be time-consuming, requires data mining, checking statistical assumptions, selecting parameters and model structure. In the context of large, heterogeneous data sets, this time can increase to weeks or even months.

Automation of modeling processes:
The development of AutoML (Automated Machine Learning) techniques enables the automation of key stages of modeling

- initial selection of features,
- selection of the model structure (e.g. number of layers of neural networks),
- hyperparameter optimization (m.in. using Grid Search or Bayesian Optimization methods).

Empirical example:
In the banking sector, the use of AutoML for credit risk assessment has reduced the time it takes to build a model from several months to just a few days. This

acceleration translates into a faster response to macroeconomic changes and changes in the regulatory environment, which is crucial for the stability of the financial sector.

4.4 Real-Time Analysis

The ability to perform real-time analysis is one of the most groundbreaking features of AI in economic applications. Traditional models are usually based on static historical data sets, which limits their effectiveness in a dynamically changing economic environment.

Stream processing (streaming):
Thanks to stream processing techniques, data coming in continuously (e.g. stock market information, sensor data, press releases) is integrated and processed by AI models on an ongoing basis. This allows for:

Immediate response to market events,
Updating forecasts in real time,
Processing of various data sources (e.g., social networks, announcements of central offices).

Empirical example:
During the COVID-19 pandemic, the use of AI in streaming analysis models made it possible to instantly assess the impact of new government restrictions, disease statistics, or central bank decisions on investor sentiment and macroeconomic indicators. As a result, economists were able to recommend adequate responses in fiscal and monetary policy almost in real time.

Artificial intelligence brings significant added value to analyses and forecasts in the field of economics thanks to:

1. Higher precision predictions resulting from modeling complex, non-linear relationships between variables.
2. The ability to handle large and complex data sets (Big Data), which complements traditional methods with completely new sources of information.
3. Faster model development time thanks to automation and advanced AutoML techniques, which promotes flexible response to rapidly changing economic conditions.
4. Real-time analysis, which is particularly important in periods of instability (financial crises, pandemics, political upheavals).

In order to fully exploit the potential of AI in economics, it is important to further improve algorithms in terms of Explainable AI and to ensure the quality and representativeness of the data used. In combination with classic econometric methods, artificial intelligence is an extremely promising tool, opening up new development prospects for both economic sciences and economic practice.

5. Challenges and Limitations

In recent years, artificial intelligence (AI) has been exerting an increasingly strong influence on modern economic sciences, providing highly effective tools for analyzing and forecasting economic phenomena. Traditional econometric approaches, such as linear regression models, ARIMA or VAR, are often not sufficient to fully capture nonlinear and multivariate relationships in economic and financial data. AI – through machine learning (ML) and deep learning (DL) methods – allows for more precise forecasting, processing data from multiple sources, as well as faster response to dynamically changing market conditions.

5.1 Improving Forecast Accuracy

One of the most important applications of AI in economics is the ability to significantly improve the accuracy of macro- and microeconomic forecasts. Traditional econometric models, based on linearity or stationarity assumptions, do not take into account many of the complex interactions that occur in national and global economies. AI methods, such as Artificial Neural Networks or Random Forests, enable:

Modeling nonlinear relationships between variables,
Identification of hidden patterns in large data sets,
Capture unusual factors (e.g. impact of global shocks, behavioural elements).

In a study conducted in the United States, neural networks outperformed traditional approaches in forecasting inflation by 20%, mainly due to their ability to model non-linear and difficult to define in advance effects of fiscal policy or global commodity changes.

5.2 Big Data Processing

The technological development of recent decades has brought economists access to an incomparably larger number of data sources (m.in. financial transactions, social media, company reports, geospatial data). Their scale and diversity are referred to as Big Data.

Traditional statistical methods are often unable to effectively analyze such vast and diverse sets of information. AI, on the other hand, especially machine learning algorithms (such as XGBoost, Gradient Boosting, or extensive neural networks), can:

- Integratively process numerical (Brynjolfsson and McAfee, 2017; Harford, 2017; Zuboff, 2019), text and even image data,
- Use distributed computing infrastructures (e.g., Hadoop, Spark),
- Analyze collections in near real time.

In the area of financial markets, for example, millions of transactions are analysed to detect anomalies (e.g., manipulation) or signals that announce sudden price changes. Thanks to the implementation of AI methods, the process of analyzing multi-million sets of transactions has been shortened from several days to just a few minutes.

5.3 Reduction of the Time Needed to Build Models

In the traditional econometric approach, the process of building models can take weeks or even months. It is necessary, m.in, detailed data mining, multiple statistical tests (checking stationarity, normality of error distribution, etc.) and selection of the optimal model structure. AI methods speed up this process with:

AutoML (Automated Machine Learning),
Procedures for automatic selection of features (feature selection),
Hyperparameter tuning algorithms (e.g., Grid Search, Bayesian Optimization).

In the banking sector, the use of AI to build scoring models for credit risk has shortened the time to design a solution from several months to several days, which has enabled faster response to changing market conditions and customer preferences.

5.4 Real-Time Analysis

One of the biggest advantages of AI methods is the ability to process data in real time (streaming), which allows you to respond to economic and market changes almost as soon as they occur. Traditional models tend to rely on static, historical data sets, which means that their predictions may not keep up with dynamic fluctuations and global events.

In practice, real-time analysis works well in:

Monitoring financial markets and commodity prices,
Detecting sudden disruptions in demand and supply (e.g., the effects of pandemics, geopolitical conflicts),
Immediate update of GDP, inflation or unemployment forecasts.

During the COVID-19 pandemic, AI models, equipped with stream processing mechanisms, made it possible to quickly adapt fiscal and monetary policy actions to drastically changing socio-economic conditions.

5.5 Challenges and Limitations

Despite the undoubted benefits, the implementation of AI methods in the field of economics is associated with a number of problems and challenges that should be taken into account in scientific research and economic practice.

Interpretability Issues (Black-Box Problem):
Advanced AI algorithms, in particular deep learning models, can be treated as "black boxes". Their internal structure – often containing thousands or millions of parameters – is difficult to explain in terms of cause and effect. This has important implications in economics, where understanding the causal relationships between variables is as important as the accuracy of a forecast. The development of Explainable AI (XAI) methods is therefore crucial to obtain insights that are not only useful, but also understandable and support decision-making processes.

Dependence of results on data quality:
The high efficiency of AI algorithms is strictly dependent on the quality and representativeness of the input data. In the context of economics, data can come from many sources (m.in. macroeconomic data, stock market transactions, social media), and their incompleteness, outdated or distortions (e.g. measurement errors) can lead to incorrect conclusions. Therefore, it is necessary to properly prepare data, standardize formats and apply quality assurance procedures (data cleaning, validation).

Costs of implementing AI technology:
The implementation of solutions based on artificial intelligence – especially in large financial organizations or public institutions – is often associated with high costs:

Hardware (you need powerful servers, GPUs),
Software (licenses, Big Data systems),
Employment of specialists (data scientists, ML engineers).

In addition, it is necessary to constantly modernize the infrastructure and adapt to dynamically changing standards and technologies.

Ethical aspects, will AI replace economists?
The development of AI has sparked discussions about the possible replacement of economists by algorithms capable of processing and analyzing data at scale. In practice, however,

Economists are still indispensable in interpreting results, formulating research hypotheses and cause-and-effect analyses,
It is necessary to take into account socio-political factors (behavioural aspects, social preferences, legislation), which algorithms are often not able to fully understand,

AI supports the decision-making process rather than taking it over completely – humans remain responsible for the final shape of economic policy and for the implementation and evaluation of its effects.

Artificial intelligence opens up new horizons in the analysis of economic phenomena, offering a significant improvement in forecast accuracy, flexibility in processing large data sets, acceleration of the process of building models and the possibility of ongoing analysis in conditions of uncertainty and high market volatility. Nevertheless, the full potential of AI requires:

1. Further development of Explainable AI methods,
2. Ensuring high quality of data (completeness, timeliness, appropriate preparation),
3. A sustainable approach to the costs of implementing modern technologies,
4. Reflection on ethical issues and on the role that man should play in the decision-making process.

In the long term, AI will not replace economists, but will provide invaluable substantive support, contributing to a better understanding of complex economic mechanisms and a more accurate response to the challenges of the modern world.

6. The Future of AI in Economic Modeling

The future of AI in economic modelling:
Artificial intelligence (AI) is currently one of the most dynamically developing analytical tools in economics. AI methods are already successfully used in macroeconomic forecasting, financial market analysis, and consumer decision research. In the perspective of the coming years, three key directions of development can be identified, which will particularly affect the shape of future economic analyses.

6.1 Development of Hybrid Methods (Combination of AI and Classical Econometrics)

Traditional econometric models, such as linear regressions or vector autoregression (VAR) models, are relatively clear and interpretable. On the other hand, AI methods (in particular deep neural networks, random forests, or gradient boosting) allow for modeling very complex and non-linear relationships that are difficult to capture with classic tools.

With the development of hybrid methods, a clear tendency to combine both approaches is beginning to be noticed. For example, initial econometric models allow for the identification of key, theoretically justified variables, after which selected characteristics or residuals from these models become the entrance to an advanced AI algorithm. Such a strategy not only improves the quality of forecasts (thanks to better grasp nonlinearities), but also increases the interpretability of the final results (thanks to references to classical economic theories). Emerging areas of research, such as neural layer-enhanced structural modeling and neural networks with built-in econometric constraints, indicate that hybrid methods may soon become the standard in economic analysis.

6.2 The Possibility of Using AI in Macroeconomic Policy and Long-Term Forecasts

While AI applications have so far often focused on short-term market analyses (e.g. prediction of stock prices or commodity prices), the potential of using these methods in long-term macroeconomic planning is of increasing interest. This is particularly important in the face of:

Global demographic trends (ageing populations, migrations),
Reconstruction of production systems (progressive robotization and automation),
The growing role of climate policy and related regulations.

Macroeconomic models enriched with AI modules can take into account *dynamic* and *non-linear couplings* between numerous factors, such as changes in the structure of demand and supply, digitization of business processes or the growing importance of the so-called sharing economy. At the same time, machine learning algorithms enable the analysis of huge data sets (Big Data), which include both statistical information (e.g., panel data from several decades and hundreds of countries) and unstructured signals (e.g., social media posts, satellite data). This allows policymakers to forecast long-term trends in economic growth, inflation or the labour market more quickly and accurately, which in turn leads to more effective formulation of public policies.

6.3 The Role of AI in Modeling Climate Change and its Impact on the Economy

Issues related to global warming and sustainable development have become the subject of intensive research in economics, which is visible, m.in example, in the work on the so-called Green Macro Models. AI is a potential support in this area, enabling the integration of various data sources (meteorological, geological, economic) in order to estimate the impact of climate change on the level of production, international trade or the cost of capital.

- Climate trend detection, neural networks and satellite image processing algorithms can monitor changes in natural resources (e.g., deforestation, land degradation) and combine them with economic data.
- Estimating environmental costs, AI can capture complex links between greenhouse gas emissions and their economic consequences (e.g., impact on

agricultural yields or transport infrastructure), which is crucial when constructing CO_2 prices or environmental taxes.

- Scenario analysis, thanks to simulation techniques, it is possible to model many variants of climate policy changes and their macroeconomic effects (e.g. the effects of the introduction of stricter emission standards or subsidies for renewable energy sources).

As a result, the role of AI in modelling (Dignum, 2019; Kose *et al.,* 2021; Russell and Norvig, 2021), climate change and its impact on the economy will gradually increase, contributing to better design of public policies and supporting sustainable economic development.

The development of artificial intelligence in economic modeling is moving towards hybrid methods, combining classic econometric approaches with the potential of machine learning. Such solutions can significantly improve the quality of forecasts and facilitate the formulation of reliable and interpretable conclusions. At the same time, the possibility of long-term application of AI in the macroeconomy is becoming more and more real, especially in the context of multidimensional, global challenges such as aging societies, the digital revolution or climate change.

In the field of climate change modeling and analysis of its impact on the functioning of national economies and the entire global economy, AI allows for the combination of various data and simulation of various policy scenarios. The development of these solutions responds to the growing need to understand the multidimensional impacts of climate, energy and sustainability decisions.

Thus, in the long term, AI methods will become even more integrated with mainstream economic research, enabling the development of comprehensive and precise models that will help in making rational, forward-looking economic decisions.

7. Conclusion

Artificial intelligence (AI) is bringing significant changes to economic modeling, opening up new possibilities for analyzing complex data and forecasting economic phenomena. Key findings from considering its impact include:

- ➢ Increasing the precision and flexibility of AI models allows for more accurate forecasting thanks to its ability to identify non-linear relationships and complex patterns in data. The integration of AI with traditional econometric methods, as part of hybrid models, offers tools that are both effective and interpretable.
- ➢ Application in various areas of the economyFrom macroeconomic forecasts, through the analysis of financial markets, to the assessment of the effects of climate change, AI is used in many key aspects of the modern economy. Its

ability to integrate data from different sources and for real-time analysis makes it a tool of the future.

- Accelerating the AI modeling process significantly reduces the time needed to build economic models by automating many stages of analysis, allowing economists to focus on interpreting results and formulating strategies.
- Unique opportunities in the face of global challengesAI plays a key role in modelling the effects of climate change and in designing macroeconomic policies, offering tools to forecast long-term trends and assess the impact of policy decisions.
- However, the use of AI in economics also comes with significant challenges, such as a black-box problem, dependence on data quality, high implementation costs, and ethical issues. The development of interpretability methods, improving data quality, and investing in the education of specialists are essential to fully exploit the potential of AI.

Emphasising the importance of interdisciplinarityThe impact of AI on economic modelling highlights the need for interdisciplinarity in economic research. Collaboration between economists, data engineers, developers, and social science experts is crucial to create models that not only answer economic questions, but also follow theoretical assumptions and are understandable for policymakers. Only such an approach will allow us to take full advantage of the opportunities offered by AI and contribute to more effective solutions to modern economic problems.

In the light of the dynamically changing economic world, AI is becoming not only a tool for analysis, but also a catalyst for positive changes in the economy, enabling more accurate decisions and predictions. In the future, its role will continue to grow, shaping both economic theory and practice.

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