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The Decision Tree Neural Network as Part of a Cognitive Model for Forecasting the Sustainability of the Russian Economy

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Abstract

This study addresses the problem of sustainable economic growth, a subject that is highly relevant in the current conditions of market uncertainty. Given the importance of having an accurate forecast of GDP in uncertain market conditions, this study proposes a digital cognitive model that includes an artificial intelligence (AI) system decision tree for forecasting GDP values. This study aims to test whether using a cognitive model with the application of the AI system decision tree can afford a more accurate forecast of GDP than known forecasting methods. To achieve this goal, this study: 1) investigated the theoretical fundamentals of sustainable economic growth; 2) identified the development trends of AI systems in economics and finance to create the model's dataset; and 3) calculated the forecast value of GDP using the digital cognitive model that included the AI system decision tree. The methodology involves the formation and use of a cognitive model that uses a decision tree neural network based on the Python language in the Google Collab cloud environment. Further, monographic, analytical, and computational-constructive methods were used. The results showed that the developed digital cognitive model, which included an AI system decision tree, was capable of forming GDP forecast values under changing external parameters.

Keywords*:* digital cognitive model, AI system, decision tree, GDP forecast

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Нейросеть «дерево решений» в составе когнитивной модели для прогнозирования устойчивости экономики РФ

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Аннотация

Предметом исследования является проблема устойчивого роста экономики. Актуальность в том, что в условиях рыночной неопределенности важно иметь точный прогноз ВВП, который может быть получен на основе применения Digital когнитивной модели, составной частью которой используется AI-система «дерево решений», что обуславливает практическую значимость полученных результатов. Целью исследования является доказать или опровергнуть гипотезу о том, что, используя когнитивную модель, с применением AI-системы «дерево решений», можно получить прогноз величины ВВП. Для достижения поставленной цели были решены следующие задачи: 1) исследовать теоретические основы устойчивого роста экономики; 2) изучить тренды развития систем искусственного интеллекта в сфере экономики и финансов, сформировать датасет модели; 3) рассчитать прогнозное значение ВВП с использованием Digital когнитивной модели, составной частью которой выступала AI-система «дерево решений». Методология, положенная в основу исследования, предусматривает формирование и использование когнитивной модели, которая использует нейросеть «дерево решений», при этом используется язык Python в облачной среде Collab. Кроме того, в ходе проведения научного исследования использовались монографический, аналитический, расчетно-конструктивный методы. Результатами исследования являются: прогнозное значение ВВП, полученное на основе Digital когнитивной модели, составной частью которой использовалось AI-система «дерево решений», способная формировать прогнозные значения при изменяющихся внешних параметрах.

Ключевые слова: цифровая когнитивная модель, AI-система, дерево решений, прогноз ВВП

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1. Introduction

The objects of this study are the economic sphere and the financial sector. One of the important problems with their development is ensuring financial sustainability, which is impossible without an accurate GDP forecast for the next year. To fill the gap, we offer a novel approach to a cognitive model to formulate accurate GDP forecasts to achieve sustainable development of the domestic economy. This is relevant because in conditions of market uncertainty, it is important to have an accurate numerical forecast of GDP, which can be obtained through the use of the digital cognitive model, an integral part of which is the AI system decision tree. The study tested the hypothesis that a cognitive model with the application of the AI system decision tree can offer an accurate forecast of GDP value. To achieve this goal, this study:

- Investigated the theoretical fundamentals of sustainable economic growth.

- Identified the development trends of artificial intelligence (AI) systems in economics and finance to create the model's dataset.

- Calculated the forecast value of GDP using the digital cognitive model, part of which was the AI system decision tree.

- Analysed the obtained results, both from a methodological perspective (what are the limitations, the problems of applying this method, how to eliminate them), and from a mathematical perspective (how big the forecast error is, how it changes).

The application scope of the results is the economic system, the credit and financial sector, the real economy, the business community, investors, and higher education. The use of the results will be of interest to anyone interested in accurate forecasting of the country's GDP for the annual forecast horizon, particularly decision makers who make strategic decisions. Economic and financial systems can become consumers of information generated by the digital cognitive model, an element of which is the AI system decision tree. The formation of forecasts of the GDP value when the input parameters of the model vary in the changing global economic landscape under conditions of market uncertainty is of great importance.

2. Literature review

The Russian economy faces the problem of sustainable development in the environment of increasing market uncertainty and a number of factors caused by the effects of the COVID-19 pandemic, increased economic sanctions by the United States, escalating global military and political confrontation, the appearance of the new technological paradigm "Industry 4.0", and others. Studies show that economic sustainability is a complex and multifaceted concept. Many works of Russian and foreign scientists have been devoted to researching the problems of economic system stability. These problems are reflected in the works of economists such as Gurvich, Prilepsky, Bobylev, M.A. Konishchev, and others (Abdrakhmanova et al., 2019). Improving the mechanism of fiscal policy is certainly an important aspect of the proper work of a financial and economic system. Thus, Nizhegorodtsev et al. (2018) attempted to identify the logic of the system paradigm in the economy, considering Kleiner and Rybachuk's position in *Systemic Balance of the Economy*. Kleiner and Rybachuk proposed a normative model of the distribution of role functions in subsystems by stages of the economic crisis cycle.

The problem of developing a cognitive model of the national financial market with the peculiarities of its structure and the possibility of using it to assess the security of its functioning was studied by Loktionova (2022). The author developed a "target loop with negative feedback" that includes a mechanism of foreign capital inflow to the national financial market, which in its essence demonstrates the interaction between the financial market and the real sector of the economy. Badvan et al. (2018) studied issues of financial market sustainability on the basis of cognitive modelling. The cognitive modelling of factors for financial market sustainability and the construction of cognitive maps were considered by

Emelianenko and Kolesnik (2019).

As research has shown, the use of AI systems is important in solving problems of economic sustainability. Mohammed et al. (2020) found that many industries are in the midst of a digital transformation that emerged as a result of advances in information and data technologies, increased use of computers, and automation through intelligent and autonomous systems based on data and machine learning. This revolution has become widespread in the industry through the use of digital technology, sensor systems, intelligent machines, and intelligent materials in their processes (Mohammed et al., 2020).

In modern conditions, it has become relevant to study the use of AI to ensure the sustainable development of the economy, reducing financial risks in the context of increasing market uncertainty. Abdalmuttaleb and Al-Sartawi (2021) reviewed recent research in the field of the application of AI for stable financing and sustainable technologies. Burova et al. (2021) proposed a cost management mechanism for an industrial enterprise that (1) takes into consideration the high level of environmental volatility inherent in the digital economy and the impact of risks on cost management; (2) can be used to control the level of target costs and make timely adjustments to costs in accordance with changing external and internal conditions to ensure target profitability; and (3) is based on the use of modern and highly accurate tools and methods to assess risks and their impact on the costs and profitability of an IS.

The developed neural network model presented by Lomakin et al. (2019) allows forecasting of the profit of real sector enterprises. The analysis showed that the risk of financial income of enterprises increased in chronological sequence, unstably from the level of 0.4 in the second quarter of 2015 to the maximum of 3.1, with subsequent consolidation to 2.8 billion rubles, with its average value of 2.09 billion rubles. Nadezhina (2021) assessed the risks of integration processes in the EU. Two indicators were used for the quantitative assessment of convergence: 1) convergence and 2) divergence. This is very important in today's environment.

Some aspects of the use of neural networks in the financial sphere intersect with the issues of economic analysis in the financial management system, as noted by Morozova et al. (2017). In the context of the development of the modern economy, for effective operation of an enterprise in conditions of constantly increasing competition, it is necessary to respond to various changes of all factors affecting the enterprise in a timely manner (Morozova et al., 2017). The reliability of the banking sector is an important factor in the financial stability of the economy, and prevention of overdue debt increases is one of the most urgent issues in ensuring reliability. To prevent the development of overdue debts in the credit sector, it is important to assess the creditworthiness and financial stability of an enterprise. Rybyantseva et al. (2017) considered some approaches to assessing the financial stability of an enterprise. The deep risk model proposed by Hengxu et al. (2021) offers a solution for deep learning and the analysis of hidden risk factors while improving the variation matrix estimation. Experiments were conducted on stock market data and demonstrated the effectiveness of the proposed solution. This method allows for obtaining 1.9% more revealed variance and reducing the portfolio risk of the global minimum variance (Hengxu et al., 2021).

An important aspect of financial sustainability, such as the formation of an investment portfolio, remains of interest. Zhan et al.'s (2021) analyses on the development of graphical models of financial time series and portfolio selection are of practical utility. The authors investigated various graphical models for creating optimal portfolios. Graphical models, such as PCA-KMeans, automatic encoders, dynamic clustering, and structural learning, can capture time-varying patterns in the covariance matrix and allow for an optimal and reliable portfolio. By comparing portfolios derived from different models with the methods of the strategy of plotting graphs underlying them, the authors showed steadily increasing returns at a low risk that outperformed the S&P 500 index using the models. This work suggests that diagram plotting models could effectively examine time dependencies in time-series data (Zhan et al., 2021).

Financial risk assessment using the VaR model provides high performance to support managerial

decision making in the financial sector. Nakagawa et al. (2020) proposed an approach based on the RM-CVaR model. Variance is known to be the most fundamental measure of risk that investors seek to minimise, but it has a number of drawbacks. Conditional value at risk (CVaR) is a relatively new measure of risk that overcomes some of the shortcomings of well-known measures of variance risk and has gained popularity because of its computational efficiency (Nakagawa et al., 2020).

3. Materials and methods

In the present work, we used research methods such as monographic, analytical, statistical, and cognitive models, including the AI system decision tree, as well as the Graphviz program, which is a package of utilities developed by AT&T Labs for the automatic visualisation of graphs. The main research method applied was the cognitive model. Modelling financial and economic sustainability based on the cognitive model allowed the author to model the problem of supporting managerial decision making in conditions of financial and economic sustainability of the financial system of Russia, the most important prognostic parameter of which is the GDP value.

The study proposes the hypothesis that under conditions of uncertainty and the increase of all types of risk, application of the digital cognitive model that includes an AI system decision tree can accurately forecast the GDP value to support managerial decision making to ensure sustainable economic development. The practical significance of the study lies in the fact that it formed the prerequisites for solving an important national economic problem: forecasting the value of GDP and ensuring sustainable development of the country's economy. Managerial decision making requires the assessment of global risks and the identification of many disparate factors, which can be successfully achieved using the capabilities of the AI system decision tree as an element of cognitive modelling. To achieve this goal, the following tasks were set and accomplished: 1) Theoretical foundations of the financial sustainability of the country's economy and the formation of GDP were studied. 2) The factors determining the stability of economic development were identified. 3) Forecast values of the GDP were calculated using the digital cognitive model, an integral part of which was the AI system decision tree.

As is known, the economic development of countries depends to a large extent on exports. Exports of goods and services provide an impetus for national production, income, and employment, contributing to the economy and GDP growth. The coronavirus pandemic led to an 8% decline in trade in goods and a 21% year-on-year decline in trade in commercial services in 2020. Thus, global exports of manufactured goods declined by 5.2% in 2020, and total exports of goods declined by 7.7% in total. Russia's goods turnover for 2021 was $784.4 billion (of which exports = $491.2 billion, imports = $293.1 billion), which increased by +38.1% compared to the same period of the previous year. Exports from Russia in 2021 amounted to $491.2 billion, which increased by +46% compared to the previous year period.

Studies have shown that the sustainability of the Russian economy is largely influenced by partner countries. The economies of different countries have shown different levels of economic sustainability. Exports of goods from Russia remained below the two-year ago level (-8%), whereas China's exports rose sharply (+31%). The standard deviation calculated from the results of fluctuations in quarterly parameters of the countries' gross domestic product for 2020 reflects the value of financial risk, which can be used to assess the sustainability of a country.

The cognitive model acts as a kind of trigger, which in turn triggers methods as independent modular programmes, in particular the decision tree, which allows for obtaining a forecast value of GDP. The dataset of the decision tree model is shown in Table 1.

Table 1. The set of data for the formation of the dataset of the decision tree neural network (fragment)

Year	Key rate	Increase in bank assets, %	Share of overdue loans, %	GDP, billion rubles	RTS Index	USD exchange rate
2021	8.5	16	23.5	131015	1608	73.7
2020	4.25	16.8	17.8	1073015	1376	73.8
2019	7.25	10.4	5.9	109241	1549	61.9
2018	7.75	6.4	7.5	103861	1157	69.8
2017	8.25	-3.5	9.3	91843	1154	57.6

Table 1 (continued)

Year	Investment in assets to GDP, %	Share of robots in the exchange, %	Capital outflow, billion rubles	Risk (VaR) of the banking system, billion rubles	Banking assets, trillion rubles	GDP forecast, billion rubles
2021	21.2	58	72	-108.5	120	131015.0
2020	16.5	55	53	-72.7	103.7	107315.5
2019	20.6	55	25,2	-77.5	92.6	109241.5
2018	20.6	51	60	-77.1	92.1	103861.7
2017	21.4	51	33,3	-58.8	85.2	91843.2

The data presented in the table were collected manually, but the process can also be automated using a data parsing program. The neural network was generated in the cloud of Google Collab using Python programming language.

4. Results

4.1. Digital cognitive model

To visualise the digital cognitive model, it is reasonable to use the Graphviz program, which is a package of utilities developed by AT&T Labs, for the automatic visualisation of graphs presented in the form of text descriptions. The package is distributed with open-source files and works on all operating systems, including Windows, Linux/Unix, and Mac OS. The code script in the Dot language is shown in Figure 2.

```
digraph G {
Algorithm_for_GDP_AI_forecast ->
Data_collection -> Dataset_for_AI_desicion_tree ->
Decision_tree_architecture->GDP_neuroforecast;
Dataset_for_AI_desicion_tree -> Data_collection;
Decision_tree_architecture-> Dataset_for_AI_desicion_tree;
Error_level -> Dataset_for_AI_desicion_tree;
GDP_neuroforecast->Error_level;
Error_level->Forecast_use }
```

Figure 2. Code script of the digital cognitive model in the Dot language

The visualisation of the digital cognitive model is shown in Figure 3.

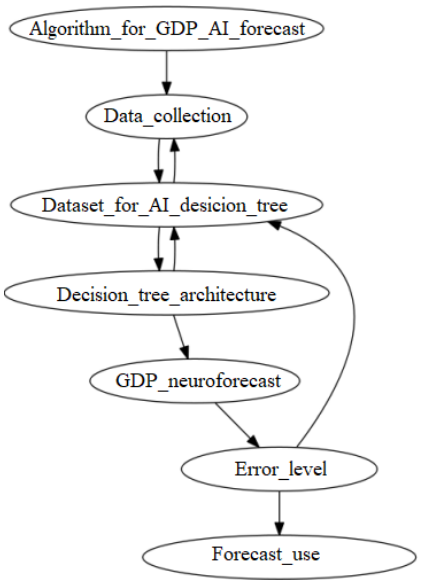

Figure 3. Digital cognitive model

A component of the digital cognitive model is the AI system decision tree, which forms the neuroforecast of the GDP.

4.2. AI system decision tree

Decision trees are based on a non-parametric, teacher-assisted learning method that is used for classification and regression. The goal of this method is to create a model that predicts the value of the target variable on the basis of learning simple decision-making rules derived from the characteristics of the data. The tree can be viewed as a piecewise constant approximation. The deeper the tree, the more complex the decision-making rules and the more accurate the model will be. Decision trees are used for both classification and regression problems. Understanding the importance of variables in random forests has been presented in many works, including that of Louppe et al. (2020).

A binary classification tree (according to regression) (Breiman et al., 1984) is an input-output model represented by tree structure T from random input vector ($X_1 \ldots X_p$), taking its values in ($X_1 * \ldots * X_p$)=X to random output variable Y ϵ *Y*. The tree is constructed from a training sample of size *N* taken from $P(X_1 \ldots X_p, Y)$, using a recursive procedure that identifies the partition $s_t = s^*$ at each node *t*, for which partitioning the samples of node N_t into t_L and t_R maximises the reduction of some impurity measure *i*(t) (e.g. the Gini index, Shannon entropy, or the variance of Y),

$$\Delta_i(s,t) = i(t) - p_L i(t_L) - p_R i(t_R) \quad (1)$$

where $p_L = Nt_L/N_t$ and $p_R = N_{tR}/N_t$. The construction of the tree stops, for example, when the nodes become pure by *Y* or when all the variables X_i are locally constant.

The AI system decision tree included indicators reflecting the dynamics of the domestic economy: banking assets, in trillion rubles, and the GDP forecast, in billion rubles. Using the code presented below, the initial data were input into the model (Figure 4).

```
import numpy as np
import pandas as pd
# Creating a 2 dimensional numpy array
data = np.array(
[['2021', 120, 131015],
['2020', 104, 107315],
['2019', 93, 109242],
['2018', 92, 103862],
['2017', 85, 91843],
['2016', 73, 85616],
['2015', 77, 83087],
['2014', 49, 79030],
['2013', 50, 72986],
['2012', 47, 68103],
['2011', 42, 60114],
['2010', 25, 44491],
['2009', 29, 38807],
['2008', 28, 41276]
])
print(data)
```

Figure 4. Input of initial data into the AI system decision tree

Using the command "from sklearn.tree import DecisionTreeRegressor", the library "DecisionTreeRegressor" was used, which was imported into Google Collab. The decision tree neural network was successfully generated. Visualisation of the results is shown in Figure 5.

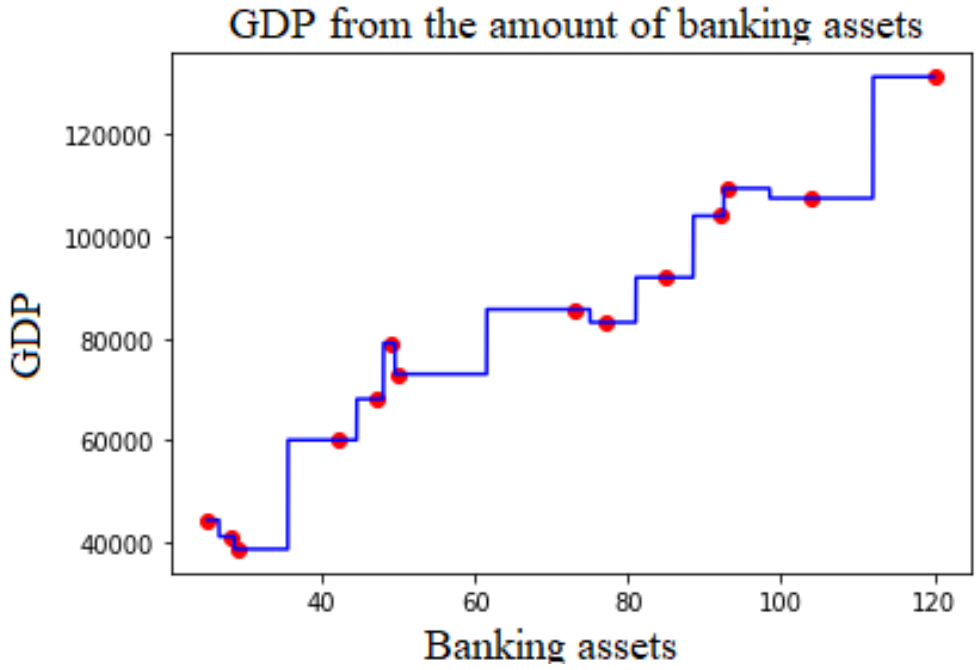

Figure 5. Visualisation of the results of the decision tree neural network

The tree is finally exported and displayed in the tree structure below, visualised using WebGraphviz[1] by copying data from the tree. Below is the first level of the decision tree (Figure 6).

[1] WebGraphviz. Available at: http://www.webgraphviz.com

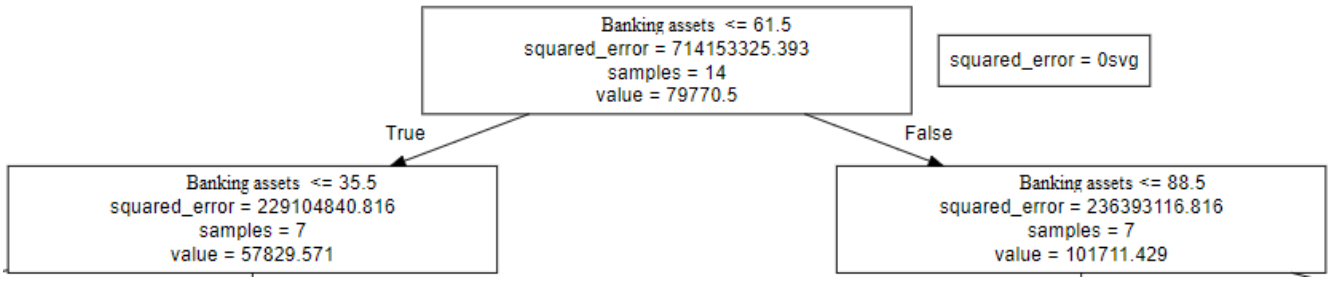

Figure 6. The first level of the decision tree

In full format, the generated decision tree neural network has five levels. To obtain the forecast value of the Russian GDP for the next year, we should use the following code, substituting the recent value of the "banking assets" input parameter. Since, according to experts' forecasts, banking assets may lose 7 trillion rubles, the value of 113 trillion rubles was used as the input parameter (Figure 7).

```
# predicting a new value

# test the output by changing values, like 3750
y_pred = regressor.predict([[113]])

# print the predicted price
print("Predicted price: % d\n"% y_pred)
```

```
Predicted price:  131015
```

Figure 7. Script for calculating the forecast value of GDP with the AI system decision tree

The forecast value of Russia's GDP, calculated by the AI system decision tree in 2023, may be 131015 billion rubles, which coincides with the actual value in the previous year. The neural network forecasts a stable level of GDP. In this case, we can assume that the neural network has "learned" all values, and even if the input parameter changes, it "outputs" the value corresponding to the closest value of the GDP on the given leaf of the tree. The overlearning of the model can be explained by some limitations of the dataset, including its small number of values (14 years) in the learning sample. When analysing the obtained results from the methodological point of view, it should be noted that in contrast to well-known classical methods, such as extrapolation and correlation-regression modelling, the use of the forecasting algorithm with decision tree regression has certain advantages. This is because the decision tree is a tree, the leaves of which are the values of the target function, and in the other nodes, the transition conditions (for example, "sex is male"), which determine which of the edges to follow. If, during classification, the resulting classes are in the leaves, then during regression, some value of the target function is in the leaves.

Decision tree models are based on the use of machine learning, which goes beyond the competitions in comparison with classical ones. Machine learning is typically applied to problems such as forecasting, classification, regression, clustering, and association, and various algorithms are used in this analysis, such as logistic regression, simple linear regression, support vector machine, and the naive Bayes algorithm. A prime example is the model based on decision tree regression, which makes a forecast of housing prices in Boston (Sanyal, 2023).

The root mean square error was used to evaluate the quality of the forecasts. This parameter measures the standard deviation of prediction errors (residuals). Notably, the level of the standard deviation of prediction errors varies in different models. For example, the simple linear regression model showed a value of 4.329, the polynomial regression model (degree = 2) showed 4.279, and the ridge regression had an error of 2.888.

5. Discussion

The results obtained in the present study are certainly related to other studies presented in the international scientific arena. By correlating the obtained results with the issues presented in the introduction, we can recommend other advanced neural network models for further research. The convolutional neural network (CNN) is a deep learning algorithm that can take input parameters and assign importance (convenient weights and offsets) to different areas/objects depending on the research goal. The development of the computational power of modern cloud clusters makes it possible to use advanced CNN-based neural algorithms, using parallel computations of the open-source frameworks Hadoop and Spark, to generate complex forecasts in the economic and financial fields.

The concept of the sustainability of the financial and economic system is receiving increasing attention from domestic and international scientists. This is due to the fact that, in the past, the market systems of various countries did not have the degree of volatility and connectivity experienced in the current market, which together lead to the threat of their overall destabilisation and significantly complicate carrying out effective financial and macroeconomic policies. This category is quite complex, so economic science has not yet developed a clear and unambiguous definition of it. Problems related to financial sustainability have been the subject of research by many Western scientists. Among them are John Chant, Andrew Crockett, Wim Duisenberg, Roger Ferguson, Michael Foot, Sir Andrew Large, Frederick Mishkin, Garry Schinasi, and others. For example, Michael Foot identified four criteria of financial sustainability, stating that it occurs when "(a) the monetary system is functioning stably; (b) the level of employment is close to full employment; (c) there is confidence in the stability of key financial institutions and markets; and (d) there are no relative price fluctuations in property and financial resources within the economy which undermines (a) or (b)". The Financial Conduct Authority is the financial regulator in the United Kingdom but operates independently of the UK government and is funded by fees from representatives of the financial services industry (Foot, 2022).

The application of the AI system decision tree and the random forest model is impossible without AI. The use of AI is increasingly evident in the use of robo-advisors, and the financial sector is no exception. Catherine D'Hondt, Rudy De Winne, Eric Ghysels, and Steve Raymond conducted a study on the use of the AI system "Alter Ego" in the robotic investment industry. The authors introduced the concept of AI Alter Egos, which are shadow robot investors. Using a unique dataset covering the brokerage accounts of a large number of investors in the sample from January 2003 to March 2012, including the 2008 financial crisis, the benefits of robo-investing were evaluated (D'Hondt, 2019). One promising area is the use of deep neural networks in banking. For example, Krzysztof et al. (2022) proposed a neural risk assessment in networks of unreliable resources.

In the opinion of the authors, it is reasonable to use an algorithm based on GNN, which is trained only on random graphs generated using the Barabasi–Albert model. Clarkson et al. (2022) proposed the neural network DAMNETS, which is a deep generative model for Markov chain time series. Time series chains are found in many fields, such as trading and payment networks in economics. The use of generative models is helpful for Monte Carlo estimation and for improving the dataset, which is of interest for both data privacy and model fitting. Bingyan (2022) studied the distribution-resistant estimation of expected function values on temporal data. He approximated test functions using neural networks and proved the sampling complexity using Rademacher complexity. Neufeld (2022) proposed the use of reliable statistical arbitrage strategies based on data using deep neural networks. A promising area of research is the risk reduction of a bank's loan portfolio. It is of interest to develop approaches to the study of model risk in loan portfolio models. Meyer (2022) studied model risk in loan portfolio models. His approach suggests a way to deal with uncertainty in all parameters of the model in a comprehensive but easy-implementing way.

The use of the proposed cognitive model provides ample opportunities to use the whole variety of AI systems for supporting managerial decision making to improve economic and financial sustainability. In prospect, the random forest model should be used. A random forest is a learning algorithm with a

teacher. It can be used for both classification and regression. It is also the most flexible and easy-to-use algorithm. A forest consists of trees. The more trees are in a forest, the stronger it is. A random forest creates decision trees for randomly chosen data samples, gets a forecast from each tree, and chooses the best solution by voting. Random forest, according to Tongtian Zhu, is a flexible algorithm with a wide range of applications that works well with a large number of datasets (Tongtian, 2020). In addition, random forest is immune to statistical assumptions as well as pre-processing load and can handle large datasets with high dimensionality and missing values.

6. Conclusion

Several conclusions can be drawn from the findings of this study. First, at least in Russia, AI technologies, machine learning decision trees, data management, and others are just beginning to enter the phase of interest and demand. In particular, this trend is confirmed by the growing demand for DataOps engineers and the state trend towards digitalisation. Second, the use of the digital cognitive model, an integral part of which is the AI system decision tree, is important for achieving sustainable economic growth based on the forecast of GDP of the country because it contributes to improving the mechanism of fiscal policy and competitiveness of the domestic economy as a whole, providing a high accuracy of the forecast. Third, the use of the results of the digital cognitive model, an integral part of which is the AI system decision tree, offers a wide range of applications of the whole variety of AI systems to provide managerial decision support to improve the sustainability of the economy and the financial sector. Lastly, the results obtained are of practical importance; the developed algorithm can be used for GDP forecasting. The areas of the result application are the economic system, the credit and financial sector, the real sector of the economy, the business community, investors, and higher education. Researchers investigating the problems of obtaining accurate forecasts of the domestic GDP value for the annual forecasting horizon, particularly stakeholders of strategic decisions, will be interested in the use of the results from this study.

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