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Promoting Sustainable Development through Innovative Approaches and Regional Management Strategies

The urgent need for sustainable development has become a defining factor in the economic strategies of nations and regions alike. As global challenges intensify, food security and the sustainability of agricultural systems have emerged as critical areas of focus for state leaders and researchers. Furthermore, the integration of digital technologies and the diversification of economic activities play vital roles in fostering resilience and long-term prosperity in the face of ongoing environmental and geopolitical uncertainties.

In the second issue of the journal Sustainable Development and Engineering Economics for 2024, the authors examine various aspects of sustainable development and management models in different sectors.

The first section, 'Economics of Engineering and Innovation Decisions as a Part of Sustainable Development', presents the article entitled 'An Algorithm for Forecasting Future Trends' by Borzov, Sorokin, Mityazov and Shimanova. The authors suggest an algorithm to identify future-relevant topics by collecting data, normalizing it, and applying autoregressive models. The study focuses on implementing autoregressive methods to analyse long-term trends and predict future events, incorporating a new approach to assessing future forecasts.

The section 'Enterprises and Sustainable Development of Regions' presents the article entitled 'Agro-Industrial Complex Sustainability in the Eurasian Economic Union Countries: The Aspect of Food Security' by Ghazaryan and Aleksanyan. The article examines the sustainability of the agro-industrial complex (AIC) in the Eurasian Economic Union countries, focusing on food security amid geopolitical challenges. It analyses data from national and international sources, revealing significant correlations between food security indicators and factors like agricultural production volume, investment, technological development, and government support. Cluster analysis identified three groups of countries based on agricultural development and food security, highlighting the importance of integration, diversification, and innovation investment for AIC sustainability.

An independent analysis of the human development index (HDI) is reflected in the article entitled 'Intellectual Capital in Agribusiness: Integrating Digital Solutions for Sustainable Development' by Aleksanyan and Khachatryan. The authors highlight the integration of digital solutions to enhance sustainable agribusiness development by activating intellectual capital. The study analyses various factors affecting yields and employs models like LSTM, which shows the best prediction accuracy. The findings reveal significant correlations between digital solutions and agricultural productivity while emphasizing the importance of employee education and training on the sustainability of agribusiness.

The third section presents the article entitled 'The Sustainability of China's Economic Growth in an Era of Global Turbulence' by Feng, Dmitriev, Kryzhko and Kuporov. The authors highlight the sustainability of China's economic growth, analysing macroeconomic changes from 1962 to 2022. The analysis concludes that economic diversification and investment in high-tech industries are vital for sustaining growth in China, while also indicating the need for further research on reducing the environmental impact of industrialization and enhancing social policies.

The section 'Management of Knowledge and Innovation for Sustainable Development' includes the article entitled 'A Conceptual Model for the Development of Transmodern Innovations' by Borzov. This study considers a conceptual model for transmodern innovation that examines the dynamics of technological innovation over time, considering the influence of economic, political, technological, and socio-cultural factors. This model serves as a comprehensive tool to analyse changes in innovation activity and external conditions, helping organizations understand and respond to the complexities of the innovation process.

Irina Rudskaya, *Editor-in-Chief of SDEE Journal, Doctor of Economics, Professor*

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An Algorithm for Forecasting Future Trends

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Abstract

The contemporary information landscape is characterised by a huge amount of data available for analysis using a variety of research tools and methods. Considering the limitations of using individual models and methods, it is worth employing an approach that combines functional and logical autoregression methods to conduct a more accurate analysis of trends and topics in the information space. Considering this context, this work aims to develop an algorithm to identify and analyse topics that would be relevant in the future using autoregression methods. The process begins with the quantification and normalisation of data, which significantly affect the quality of analysis. The main focus of this study is to implement the autoregression method to analyse long-term trends and predict future developments in the selected data. The proposed algorithm evaluates the forecast of these future developments and analyses graphical trends, thus conducting a more detailed study and modelling of future data dynamics. The regression coefficient is used as a quality criterion. The algorithm concludes with a polynomial function to help identify topics that will be relevant in the future. Overall, the proposed algorithm can be considered an effective tool for analysing and predicting future trends based on the analysis of historical data, thus contributing to the identification of prospects for technological development.

Keywords: data quantification, time series normalisation, forecasting, autoregression models, data normalization, trends

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Разработка Алгоритма Прогнозирования Будущих Тенденций

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Аннотация

Современная информационная среда содержит огромное количество данных, доступных для анализа с использованием множества инструментов и методов исследования. Применение отдельных моделей и методов может быть ограничено, поэтому стоит использовать комбинированный подход, объединяющий методы функциональной и логической авторегрессии для более точного анализа трендов и тематик в информационной среде. Основная цель работы - разработать алгоритм для выявления и анализа будущих актуальных тематик с использованием методов авторегрессии. В работе был разработан эффективный алгоритм для выявления значимых тем в будущем. Процесс начинается с квантификации и нормализации данных, что существенно влияет на качество анализа. Основное внимание уделяется использованию метода авторегрессии для анализа долгосрочных тенденций и прогнозирования будущего развития данных. Алгоритм оценивает прогноз будущего развития и проводит анализ графических трендов для более детального изучения и моделирования будущей динамики данных. Коэффициент регрессии используется в качестве критерия качества, а завершением алгоритма является нахождение полиномиальной функции, что помогает выявить будущие актуальные темы для исследований. В целом, полученный алгоритм представляет собой эффективный инструмент для анализа и прогнозирования будущих тенденций на основе анализа исторических данных, способствуя выявлению перспектив развития технологий.

Ключевые слова: квантификация данных, нормализация временных рядов, прогнозирование, модели авторегрессии, нормализация данных, тенденции.

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1. Introduction

The rapid growth in the volume and diversity of data has increased the importance of data analysis and interpretation. In this context, forecasting of future trends is gradually becoming a key aspect for various industries, such as the marketing, finance and technology sectors. Notably, this process involves analysing current data and applying various methods to predict future events.

In this paper, we develop an algorithm based on functional and logical autoregression methods that allows for the identification and analysis of topics that are likely to be relevant in the future. One of the main steps involved in this algorithm is the quantification and normalisation of data, which is critical to ensure high accuracy of analysis. Furthermore, the widespread use of autoregressive models in time series analysis serves as the basis for identifying long-term trends and cyclical patterns in data, leading to more stable and reliable forecasts. This work is particularly aimed at analysing graphical trends, thus contributing not only to detailing the dynamics under study but also to optimising the process of making strategic decisions based on available data.

2. Literature Review

The information space is loaded with huge amounts of data available for analysis and interpretation using a variety of tools and methods. Therefore, in recent decades, data analysis has emerged as an object of active study, especially in the context of big data and its features. The main focus in this field includes the collection, processing and interpretation of large amounts of information, which requires researchers to have a deep understanding of the methods and tools that contribute to effective analysis.

An important aspect of forecasting is the use of autoregressive models for time series analysis. These models make it possible to identify time dependencies and predict future values based on available data. One such model is functional autoregression, which calculates the current value of a series in terms of its previous values. Notably, this model accounts for both linear and nonlinear dependencies between successive observations, which makes it a powerful tool for time analysis. The fact that functional autoregression is being used in various fields, such as economics, finance, climatology and medicine, confirms its effectiveness and flexibility in the analysis of complex time dependencies (Puchkov and Belyavsky, 2018; Mestre et al., 2021). In contrast to functional autoregression, logical autoregression helps to analyse dependencies between categorical variables in a data sequence. This method allows for the prediction of the next value of a categorical variable based on historical data, thus modelling the probability of each category based on previous values (Huang et al., 2012).

One of the key stages of data analysis for forecasting is data normalization. This process of standardizing variable values not only improves model performance and simulation quality but also ensures consistent and accurate interpretation of results. As already noted by several researchers (Singh and Singh, 2020; Mahmoud et al., 2023), data normalisation is the basis for improving the quality of predictive models because it facilitates fair comparison between variables, which is especially significant when working with large amounts of data.

Although the application of individual models and methods may yield the desired results depending on the context and objectives of a study, one cannot be entirely certain that the obtained results fully reflect the properties of the aspect being studied. To address this, it is necessary to develop algorithms that combine suitable methods and models to create a synergistic effect that enables the in-depth interpretation of results.

Considering the context of this study, the combined use of functional and logical autoregression methods can help to not only analyse the dependencies between variables over time but also identify the relationships between different topics, thus contributing to the detection of significant trends and patterns in the data flow (Huang et al., 2017; Savzikhanova, 2023). Therefore, the framework of this study adopts the combined use of functional and logical autoregression methods to accurately determine trending topics while also analysing the properties of both methods in the context of long-term forecasting.

3. Materials and Methods

3.1 Data quantification

In the initial stage of the proposed algorithm, the specifics of the data submitted as input, initially in text format, are first taken into consideration. Notably, the choice of data source depends on the context and goals of the study. For instance, the source could be the media, social media, web pages, reports, etc. (Di et al., 2017).

The following are some tools that can be employed to collect text data from various sources:

- Web scraping allows the direct extraction of data from websites from the HTML codes of web pages. For this purpose, Python libraries, such as BeautifulSoup or Scrapy, can be used.

- Many online platforms and services provide application programming interface (API) for accessing their data. The API programming interface allows one to directly receive information from sources such as social networks, news portals, etc.

- RSS feeds, which may be available for some news sites and blogs, make it possible to receive updates automatically in the form of text data.

Figure 1 presents an example of a Python code using the BeautifulSoup library for parsing news from a web page.

```
import request
from bs4 import BeautifulSoup

# URL of  a web page with news for url parsing
url = ' https://www.example.com/news '

# Sending a GET request to this web page
response = request.get(url)

# If  the request is successful, start parsing the content
if  response.status_code == 200:
    soup = BeautifulSoup(response.content, 'html.parser')

    # Find all the news headlines (assume they are in the 'h2' tag)
    news_headlines = soup.find_all('h2')

    # Display the news headlines
    for headline in news_headlines:
        print(headline.text)
else:
    print('Error: The web page could not be accessed')
```

Figure 1. Using the BeautifulSoup library to extract data from a web page.

After the necessary data are obtained, they must be quantified by translating the textual information into structured quantitative indicators (Trewartha et al., 2022; Zhang et al., 2016). For this purpose, text analysis methods can be used. Text analysis allows the extraction of key concepts, themes, emotions and other aspects necessary for research from texts to ultimately present them in the form of digital data (Cover and Thomas, 2005).

In such analyses, texts need to be split so that each word in a single text represents a token. This process is referred to as tokenisation. With regard to the mathematical description of this process (Friedman, 2023; Minogue et al., 2015), assuming that text T has to be tokenised, the text can be represented as a sequence of characters, as follows:

$$T = c_1, c_2, \ldots, c_n \tag{1}$$

Where:

c_i - the i-th item in the text

After the tokenisation process, each word can be represented as a token:

$$T = w_1, w_2, \ldots, w_m \tag{2}$$

Where w_i - the i-th word in the text

Therefore, the tokenisation process can be described in terms of the following function:

$$tokenize(T) = [w_1, w_2, \ldots, w_m] \tag{3}$$

This function converts the input text T into an array of tokens. For example, after tokenization, the sentence “Text tokenization process” will be presented in the form of an array as follows:

$$tokenize(\text{The process of text tokenization}) = [\text{The, process, of, text, tokenization}]$$

In this context, it is worth noting that punctuation marks, numbers, abbreviations and other special characters are also accounted for in the tokenisation process to ensure accurate separation of the text into tokens.

Specialised libraries and tools are often used to divide text into tokens of software code. For example, in Python, the NLTK library can be employed to tokenise text by importing word_tokenize from nltk.tokenize (Zhang et al., 2024; Kadiev and Kadiev, 2016). Figure 2 presents an example demonstrating the use of this library.

```
import nltk
nltk.download('punkt')
from nltk.tokenize import word tokenize

# Input text for tokenization
text = "Example of  the tokenization process in Python."

# Tokenization of  text
tokens = word_tokenize(text, language="russian")

# Tokens output
print(tokens)
```

Figure 2. An example of using the NLTK library.

Therefore, after tokenization, the following list is obtained as output: ‘Example’, ‘process’, ‘tokenisation’, ‘in’, ‘Python’ and ‘.’.

After dividing the text into tokens, the lemmatisation process begins. Lemmatisation involves the transformation of words (tokens) into their basic normalised forms (lemma) using certain rules and algorithms while also accounting for contextual information (Boban et al., 2020; Ozturkmenoglu and

Alpkocak, 2012; Toporkov and Agerri, 2023). Mathematically, the process can be represented as a function applied to each word in the text, as follows:

$$\text{lemma}\left(\text{w}\right) = \text{base\_form} \tag{4}$$

Where:

base_form - the basic form of the word w.

Notably, lemmatisers implement rules and algorithms that account for the morphological characteristics of words. For example, consider the following algorithm comprising a set of conditions and operations for lemmatising verbs into their initial forms:

$\text{lemma}\left(\text{w}\right) =$

$w[:-2]$ if w ends with “-ла”,

$w[:-2]$ if w ends with “-ли”,

$w[:-2]$ if w ends with “-ть”,

otherwise, the word will remain unchanged.

Where:

- w is the root word for lemmatisation,

- $w[:-2]$ indicates removing the last two characters (in this case, the ending) of the word to attain its basic form.

The next step involves clustering the received words based on specific topics. In this context, the main method that can be implemented is TF-IDF. Specifically, this method helps identify keywords or terms that are most characteristic of an individual document in the context of the texts contained in it. The operating principle of TF-IDF (Aizawa, 2003; Dey and Das, 2023; Zhang et al., 2019) involves calculating a measure that evaluates how often a word appears in a document (TF or term frequency). Therefore, the formula for calculating the TF of the word t in document d can be expressed as follows:

$$TF\left(t,d\right)=\frac{n\left(t\right)}{m\left(d\right)} \tag{5}$$

Where:

$n(t)$ − number of times the word t appears in the document,

$m(d)$ − total number of words in document d.

This part of the algorithm allows for the evaluation of the importance of a word in a single document.

Next, the inverse document frequency (IDF), which evaluates the uniqueness of a word within a collection of documents, is calculated (Choi and Lee, 2020; Dagdelen et al., 2024). The formula for calculating the IDF for word t in document collection D can be expressed as follows:

$$IDF\left(t,D\right)=\log\left(\frac{N\left(D\right)}{df\left(t\right)}\right) \tag{6}$$

Where:

$N(D)$ − total number of documents in collection D,

$df(t)$ − number of documents in the collection in which the word t appears.

Notably, the inverse frequency of a document is output in logarithmic form to reduce the influence of common words and to increase the weight of unique words.

Finally, TF-IDF for the word t in document d can be calculated as the product of TF and IDF as follows:

$$TF - IDF(t,d,D) = TF(t,d) * IDF(t,D) \tag{7}$$

Simply put, words with a high TF-IDF value are those that occur frequently within a single document but are rare when considering the entire collection of texts.

Following this, the latent Dirichlet allocation (LDA) model – a probabilistic model used to analyse the thematic structure of documents – is applied. It can be expressed as follows (Gandhi et al., 2008; Jelodar et al., 2019):

$$p(w,z,\theta,\phi|\alpha,\beta) = \Pi(d=1)^{(D)}\, p(\theta_d|\alpha)\left(\Pi(n=1)^{(N)}\, p\left(z_{(d,n)}|\theta_d\right) p\left(w_{(d,n)}|\phi_{\left(z_{(d,n)}\right)}\right)\right) \tag{8}$$

Where:

D - number of documents,

N - number of words in the document,

K - number of topics,

w - a specific word in the document,

α - Dirichlet hyperparameter for the distribution of topics across documents,

β - Dirichlet hyperparameter for the distribution of words by topic,

θ - distribution of topics in the document,

ϕ - distribution of words for a topic,

z - hidden variable indicating the topic of the word w.

The generative process of this model can be described as follows:

- For each document d in the collection:

- Select the distribution of topics θ_d from Dirichlet (α).

- For each word $w_{(d,n)}$ in the document:

- Choose a topic $z_{(d,n)}$ from multinomial (θ_d),

- Choose a word $w_{(d,n)}$ from multinomial ($\phi_{\left(z_{(d,n)}\right)}$).

The main goal of LDA is to find matrices θ and ϕ for the hyperparameters α and β so as to maximise the plausibility of the data. Mathematically, it boils down to finding the posteriori distributions $p(\theta|w,\alpha,\beta)$ and $p(\phi|w,\alpha,\beta)$. In this context, it is also worth noting that a variational method can be employed in the LDA process to maximise the likelihood function, which includes recalculating the parameters and updating the distributions θ and ϕ. Thus, the LDA mathematical model is based on calculating the probability distributions of topics and words, providing an analysis of the thematic structure of documents and highlighting significant topics mentioned in the text data.

After selecting the necessary clusters, the probabilities of each text belonging to a specific topic are generated. Based on the data obtained, one or more classification model are trained (for example, random forest). Subsequently, the trained model was employed to predict the probabilities of each text belonging to the selected clusters. Notably, these probabilities are presented numerically, reflecting the degree of confidence of the model with regard to the text belonging to each cluster selected earlier. In addition, probabilities can be interpreted as the proportion of the presence of a topic in each text.

Thus, the above-mentioned process of quantifying textual data using a probabilistic classification model makes it possible to effectively analyse the text, identify thematic affiliations and make informed decisions based on the results of classification and the probabilities of belonging to clusters.

3.2 Averaging and normalising the received data

In the case of a large dataset, it can be averaged based on a chosen criterion. For example, it can be considered a temporary variable. This is a key action for several reasons:

- Large datasets often contain temporary or random noise, which can make it difficult to identify general trends. Averaging allows for smoothing out these fluctuations, ultimately highlighting more stable and general patterns.

- If the main purpose of a study is to predict a particular trend, averaging can make the data more predictable, as well as improve the predictive ability of models and algorithms.

- Since average values reflect general trends and allow a better understanding of the main characteristics of the data, they help improve the level of interpretation and visualisation.

In this context, the role and relevance of data normalisation, as well as its benefits for analysis and forecasting, must also be emphasised. In the context of previously obtained data being fed into functional and logical autoregression models, the relevance of normalisation becomes even more significant. Considering this aspect, it is worth highlighting the following points:

- When using the operation, more stable and reliable predictive models are created, since the noise and fluctuations in the data are smoothed out, which in turn increases the stability and efficiency of autoregression models.

- Despite changes in the values themselves, normalisation helps preserve the ratios and patterns of the data, which in turn helps identify and retain long-term trends, as well as the cyclicity of autoregressive models.

One of the common methods used for data normalisation is Z-normalisation (standardisation), which modifies the data so that the average value is 0 and the standard deviation is 1. This process can be formulated as follows:

$$z = \left(x - \mu\right) / \left(\sigma\right) \tag{9}$$

Where:

z - the normalised value,

x - initial value of the variable,

μ - average value of the variable,

σ - standard deviation of the variable.

Another such method is min-max normalisation, which scales the data so that it remains within a certain range – often between 0 and 1.

$$x_{norm} = \left(x - x_{min}\right) / \left(x_{max} - x_{min}\right) \tag{10}$$

Where:

x_{norm} - the normalised value,

x - initial value of the variable,

x_{min} - minimum value of the variable,

x_{max} - maximum value of the variable.

The above formula brings the data within the range of 0 to 1, while also accounting for their minimum and maximum values, thus simplifying the comparison and use of features with different ranges of values.

Therefore, it may be concluded that the process of data normalisation brings variables to a common scale, thus standardising their values and preventing distortions in assessing the importance of features. Overall, in the context of data processing, normalisation methods, such as Z-normalisation or min-max normalisation, equip predictive models with the properties of stability, efficiency and greater interpretability of results (Shantal et al., 2023; Peng et al., 2005). By standardising the values of all variables, normalisation offers an opportunity to objectively compare and utilise data in various models and tasks.

4. Results

The application of an autoregression model can be carried out using various methods, such as logistic regression, Markov models or other machine learning methods capable of working with categorical data. In the case of this study, the regression decision tree model was chosen. Notably, in the context of logical autoregression, when the logic is based on a regression decision tree, it indicates that the model is to be used for predicting categorical or qualitative variables based on historical data. The operating principle of a regression decision tree is that the tree is built using nodes, which represent the feature-based data divisions, with the leaves predicting the categorical value. When training this model, the data are first divided into parts, after which the most appropriate categorical value for each division is calculated. The advantages of using a regression decision tree in logical autoregression include ease of interpretation of the rules obtained, the ability to model complex nonlinear dependencies between variables and good generalisation ability.

To predict trends in information flow, the proposed algorithm had to be slightly modified. In particular, the categorical values represent the probabilities of the text belonging to the relevant topic at a specific moment. For example, the trend in the magnitude of the presence of a cluster in texts over a given time period can take the form of a polynomial of the second degree, reflecting the specifics of the dynamics of the selected topic's relevance. In this context, the most relevant example is the history of the development of neural networks. Although the concept of neural networks originated in the 1940s and 1960s, the lack of necessary computing power led to it losing its relevance. However, with the discovery of necessary tools, powerful graphics processors and access to large amounts of data, this niche has regained its relevance. Therefore, on a graph, the dynamics of the urgency of this topic will appear as a polynomial of the second degree. Drawing on this, in the context of researching different niches, it is necessary to look for topics that correspond to the specifics described for the development of neural networks. Furthermore, when using traditional autoregression, it is necessary to predict the values of the selected "trend" topics for the period relevant to the context of the study.

Considering these conditions, the principle for training the model had to be changed – it had to be trained on historical data, after which, based on the values of "relevant topics" obtained using the autoregression method, the probability values of the presence of one or more "potentially relevant" topic should be predicted. After obtaining the predicted values of the share of a particular topic within the average values, a trend can be built, characterising the topic as potentially “relevant” or “irrelevant”.

Although there are several approaches for building a trend, the simplest is to build a linear trend – a straight line reflecting the general trend of the changes in data over time. Linear regression can be conducted to model a linear trend, with time stamps considered as an independent variable and time series values as the dependent variable. Mathematically, the process of obtaining a linear trend model through linear regression can be expressed as follows:

$$Y = a + bt + e \quad (11)$$

Where:

Y - values of the time series;

a - point of intersection with the Y axis, representing the initial value;

b - slope of the linear trend, representing the rate of change;

t - number of intervals, which may have indices of time moments;

e - a random error.

Additionally, to construct a trend line, the logarithmic method can be employed, assuming that the relationship between variables is logarithmic, as follows:

$$ln\left(Y\right) = a + b * ln\left(t\right) + e \quad (12)$$

Another method for establishing a trend is polynomial regression, which utilises a polynomial to represent the trend. Notably, this technique assists in identifying nonlinear relationships in the data. In this context, it is crucial to determine the appropriate degree of polynomial to ensure an accurate fit without underestimating or oversimplifying the model. For example, consider the following formula:

$$Y = a_0 + a_1 x + a_2 x^2 + \ldots + a_n x^n + e \quad (13)$$

Where:

Y - dependent variable (time series value),

x - independent variable (time stamps),

$a_0 + a_0 x + a_0 x_2 + ... + a_n x^n + e$ - coefficients of the polynomial,

n - order of the polynomial,

e - a random error.

To select the optimal coefficients of the model and determine the order of the polynomial, the least squares method may be employed since it minimises the sum of squares of the difference between the actual and predicted values. In this study, we compared the predicted probabilities of a text belonging to a cluster with the actual trend values.

The main quality criterion considered in this study was the regression coefficient obtained after constructing a trend line. Notably, this coefficient can also be used to assess the quality of the models. Although the other quality parameters, such as the average quadratic error, average absolute error, and coefficient of determination, are important $\left(R^2\right)$, they were considered secondary, since the main purpose of the proposed algorithm was to determine the trend of a topic.

In this regard, the specifics of interpreting the regression coefficient must also be discussed. In the case of a positive regression coefficient, the dependent variable increases over time, indicating an upward trend in the data. This property is significant because it allows for a comprehensive understanding of how the dependent variable changes and helps predict future trends. Notably, trends can take various forms – flat sections, oscillations or polynomial curves. By analysing data using a positive regression coefficient, we can identify patterns and make predictions about future changes. Understanding trends not only helps us make informed decisions and develop predictive models but also allows us to anticipate changes and adapt strategies accordingly. Thus, a positive regression coefficient is an essential component of trend analysis and model evaluation. It provides valuable information on the long-term dynamics of the data as well as the direction in which the related variables are moving.

Several models available for analysing time series data, which can be used to detect patterns and trends in the data as well as to visualise them on graphs. However, it is important to consider both the external and internal characteristics of the data when choosing a model. With regard to this study, both logical autoregression and functional autoregression are methods that aim to detect key patterns in the data. However, their analytical approaches differ. Logical autoregression uses operations and rules to identify nonlinear dependencies, while functional autoregression adopts flexible approaches to capture complex functional changes. Effectively, the graphs created using these methods may look similar in terms of shape and direction, but a deeper analysis would reveal significant differences between the two. While logical graphs often show abrupt changes and anomalies, functional graphs are smoother and more natural. Therefore, it is important to choose the right model for the specific dataset being analysed. In particular, logical models may be more suitable for data with nonlinear dependencies, while functional models may be a better choice for analysing data with complex functional changes.

The quality of the models, as determined by the regression coefficient, is another important factor. When analysing the use of cluster methods and forecasting based on flat segments, pulsations and polynomials, it is crucial to consider the intersections of the logical and functional autoregressive trends. These intersections indicate areas of consistency between the methods, thus providing information about the reliability of the results.

Furthermore, to predict future trends, it is often necessary to analyse polynomial curves on graphs. The polynomial function plays a crucial role in predicting future trends and examining the significance of the data. Its shape and extrapolation can provide insights into the development of time series for the future. Therefore, special attention must be paid to polynomial functions for assessing future trends and forecasts based on time series. For instance, a second-degree polynomial function for trend analysis can be expressed as follows:

$$P(x) = a * x^2 + b * x + c \tag{14}$$

Where:

P(x) - value of the function at time x,

a, b, c - coefficients of the polynomial determining the shape of the curve,

x - time or period.

The polynomial function, defined as an equation that includes terms with powers greater than one, allows us to approximate the complex patterns of changes in data over time. Moreover, the analysis of the shape of the polynomial curve on the trend graphs of the logical and functional autoregressions allows for an accurate assessment of the prospects for development of the considered data in the future.

The analysis and evaluation of the resulting polynomial curve on trend charts represent the final step in predicting the relevance of the selected data in the future. The entire algorithm for identifying topics that are likely to be relevant in the future based on the functional and logical autoregression methods is presented in Figures 3 and 4.

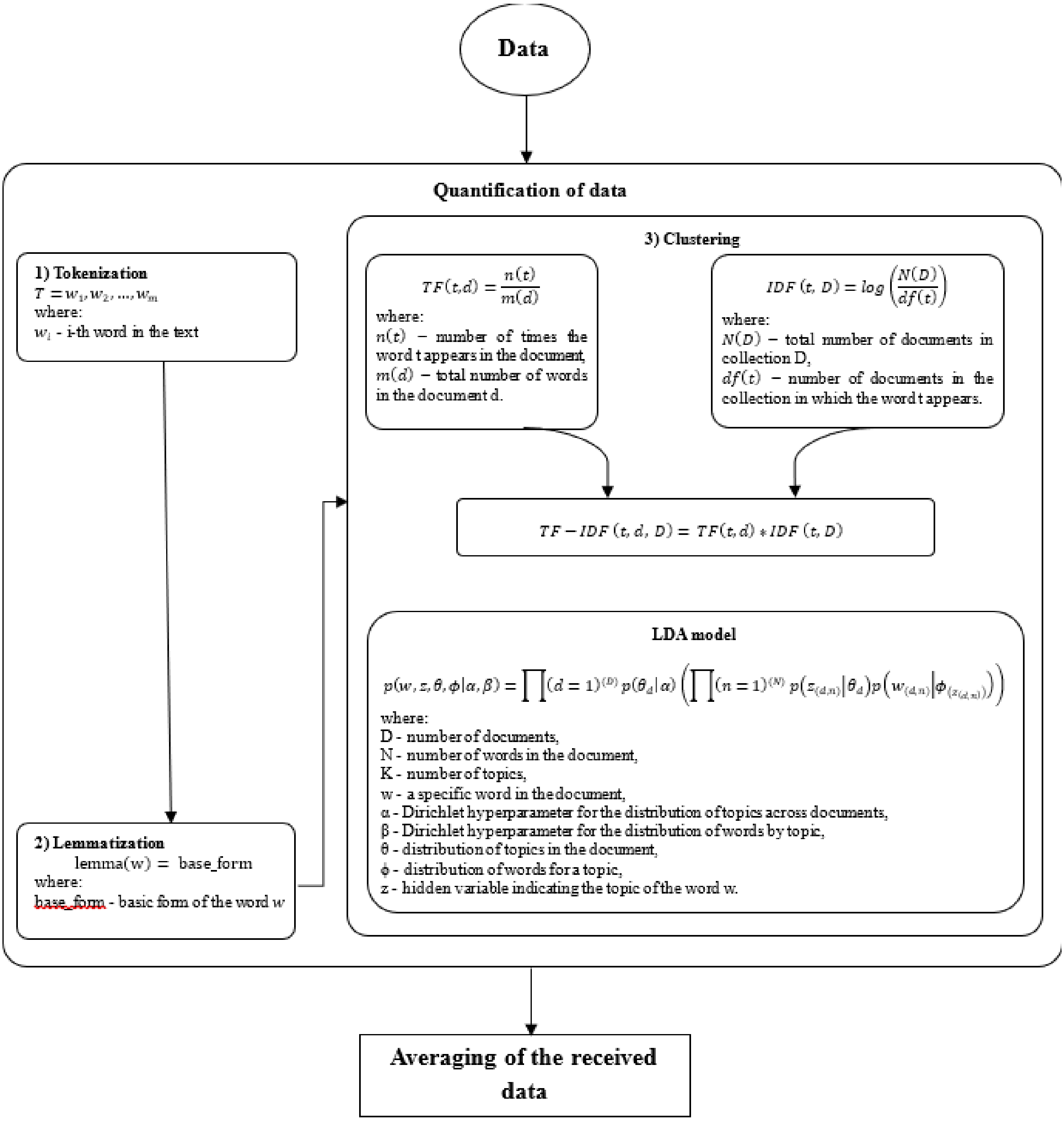

Figure 3. First part of the algorithm for identifying relevant topics for the future

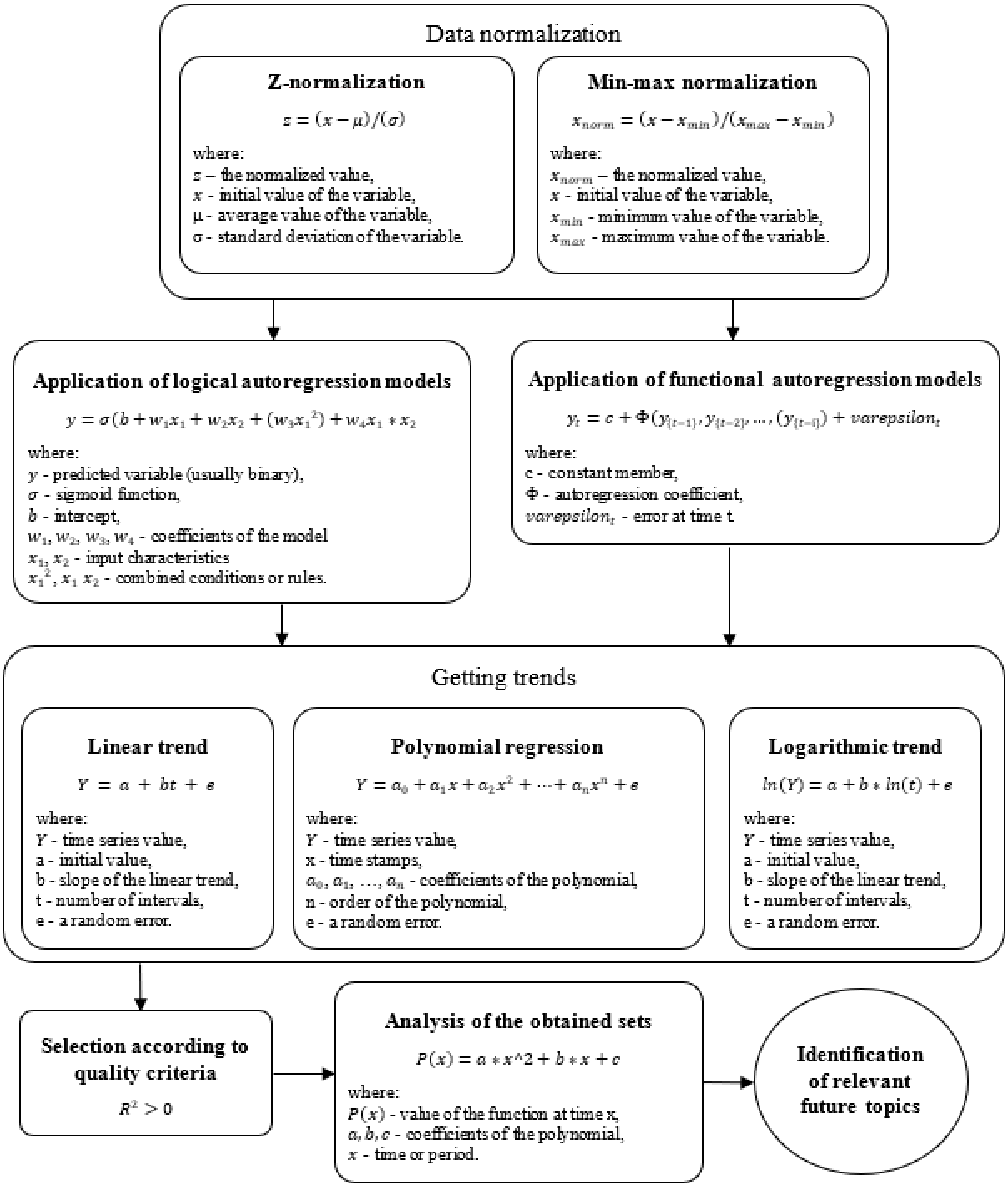

Figure 4. Second part of the algorithm for identifying relevant topics for the future

5. Discussion

As shown in the algorithm diagram in Figures 3 and 4, the process began with data quantification and normalisation. Both of these steps are important to ensure the high quality of the data before analysing them using autoregressive models. Notably, the main focus of this study was to apply autoregression methods to analyse long-term trends and predict future developments in the data through trend analysis. By building a trend using various methods, such as linear, logarithmic and polynomial regression, we were able to model the long-term dynamics of the data and predict its relevance in the future.

Modern information technologies provide researchers with powerful tools for extracting valuable information from large datasets. However, the use of these technologies requires rigorous data preprocessing, with normalisation being a crucial part of this process. Normalisation refers to the process of standardising variable values, which not only enhances the accuracy of forecasts but also leads to a better understanding of trends and patterns within the data.

The algorithm concludes with a polynomial function. By analysing the shape of the polynomial curve on trend graphs, we identified patterns of how the data changed over time, which can help make informed decisions based on forecasts. For instance, in the financial sector, this algorithm can help identify the most promising investment opportunities when prices fluctuate sharply. Furthermore, in the field of marketing and data analysis, studying the variability of topics could help identify current trends in consumer behaviour and user requests.

Thus, the combination of functional and logical autoregression models with polynomial regression trends provides a comprehensive approach for analysing and predicting time dependencies, thereby offering valuable information for strategic decision making and model development.

6. Conclusion

In this work, we developed an algorithm to identify topics that are likely to be relevant in the future. The first step in this process was data collection, followed by the calculation of average values and normalisation. Notably, these steps are crucial to ensure high-quality data for the application of autoregressive models. Data preprocessing significantly improves the accuracy and reliability of the analysis, providing the necessary foundation for subsequent modelling.

The main focus of this study was to implement autoregression methods to analyse long-term trends and predict future developments in the data. The proposed algorithm also incorporated an assessment of future forecasts, which is a novel approach to analysing emerging trends. By analysing graphical trends, we can explore, model and predict future data dynamics in greater precision. Furthermore, the regression coefficient obtained after constructing the trend line was chosen as the quality criterion in this study. This allowed us to analyse all the identified trends, their changes and opportunities for forecasting events and trends in the study area. The algorithm concluded with a polynomial function, which enabled the identification of relevant future topics for further research.

Overall, this algorithm serves as a powerful tool for analysing and forecasting future trends, helping to identify prospects for technological development based on historical data analysis.

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SECTION 2

ENTERPRISES AND THE SUSTAINABLE DEVELOPMENT OF REGIONS

РАЗДЕЛ 2

ПРЕДПРИЯТИЯ И УСТОЙЧИВОЕ РАЗВИТИЕ РЕГИОНОВ

Research article

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Agro-Industrial Complex Sustainability in the Eurasian Economic Union Countries: The Aspect of Food Security

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Abstract

This article analyses the sustainability of the agro-industrial complex (AIC) in the Eurasian Economic Union (EAEU) countries with an emphasis on food security. The study covers challenges and threats to food security in Russia, Belarus, Armenia, Kazakhstan, and Kyrgyzstan, given the difficult geopolitical situation. The article examines data from the national statistical services of the EAEU countries, as well as international sources such as the FAO and the World Bank. Correlation and cluster analysis approaches are applied to assess the impact of socioeconomic indicators on the sustainability of the AIC. Significant correlations between indicators of food security and such factors as the volume of agricultural production, investments in the agricultural sector, the level of technological development, and government support are revealed. On average, for the period from 2015 to 2022, the added value of agriculture amounted to 8.2% of GDP, and the food production index was 104.1. The results of the cluster analysis showed that the EAEU countries can be grouped by levels of agricultural development and food security. Thus, K-means and GMM identified three clusters in which Russia found itself both in a separate cluster and in combination with other countries. Agglomerative and spectral clustering also showed similar results, distinguishing three main groups of countries. The average silhouette coefficient for agglomerative and spectral clustering was 0.41, which indicates a better clustering quality compared to K-means and GMM (0.38). It is confirmed that integration and coordination of efforts within the EAEU, as well as diversification of agricultural production and increased investment in innovation, determine the state of sustainability of the agro-industrial complex.

Keywords: agro-industrial complex sustainability, food security, EAEU, agriculture, cluster analysis, correlation analysis, agricultural sector investments, production diversification

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Устойчивость Агропромышленного Комплекса в Странах Евразийского Экономического Союза: Аспект Продовольственной Безопасности

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Аннотация

Настоящая статья анализирует устойчивость АПК в странах ЕАЭС с акцентом на продовольственную безопасность. Исследование охватывает вызовы и угрозы продовольственной безопасности в России, Беларуси, Армении, Казахстане и Кыргызстане, учитывая непростую геополитическую ситуацию. В статье рассматриваются данные национальных статистических служб стран ЕАЭС, а также международные источники, такие как ФАО и Всемирный банк. Применены методы корреляционного и кластерного анализа для оценки влияния социально-экономических показателей на устойчивость АПК. Выявлены значимые корреляции между показателями продовольственной безопасности и такими факторами, как объем сельскохозяйственного производства, инвестиции в аграрный сектор, уровень технологического развития и государственной поддержки. В среднем за период с 2015 по 2022 годы добавленная стоимость сельского хозяйства составила 8.2% от ВВП, а индекс производства продуктов питания составил 104.1. Результаты кластерного анализа показали, что страны ЕАЭС могут быть сгруппированы по уровням развития АПК и продовольственной безопасности. Так, KMeans и GMM выделили три кластера, в которых Россия оказалась как в отдельном кластере, так и в комбинации с другими странами. Агломеративная и спектральная кластеризация также показали схожие результаты, выделяя три основные группы стран. Средний силуэтный коэффициент для агломеративной и спектральной кластеризации составил 0.41, что указывает на лучшее качество кластеризации по сравнению с KMeans и GMM (0.38). Подтверждено, что интеграция и координация усилий в рамках ЕАЭС, а также диверсификация аграрного производства и увеличение инвестиций в инновации определяют состояние устойчивости АПК.

Ключевые слова: устойчивость агропромышленного комплекса, продовольственная безопасность, ЕАЭС, сельское хозяйство, кластерный анализ, корреляционный анализ, инвестиции в аграрный сектор, диверсификация производства

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1. Introduction

The sustainability of the agro-industrial complex (AIC) in the context of global transformations and geopolitical challenges plays a key role in ensuring food security in the countries of the Eurasian Economic Union (EAEU). Food security directly affects the social and economic well-being of the population. In the current situation, the issues of agribusiness sustainability and food security are becoming increasingly relevant for the EAEU countries. Thus, ensuring the sustainability of the AIC in Russia, Belarus, Armenia, Kazakhstan, and Kyrgyzstan is becoming critical.

The EAEU's growth points lie in the area of integration and joint projects. An analysis of the integration of agricultural and food markets in the context of food security of the EAEU shows that increasing production volumes and strengthening trade ties contribute to increasing the level of self-sufficiency in key food products at the macro level for the EAEU states and at the micro level for the population (Iashina et al., 2023). Developments in breeding, genetics, and agricultural machinery to strengthen food security will help unlock the potential of the Union, orienting countries to achieve full food independence (Gusev, 2023a; Shoba et al., 2023).

The aim of this study is to analyse the sustainability of the AIC in the EAEU countries and assess the factors affecting food security in the region. To achieve this goal, the following steps were taken: 1) challenges and threats to food security in the EAEU countries were analysed, 2) the impact of socioeconomic indicators on the sustainability of the AIC was determined, and 3) methods of correlation and cluster analysis were applied to identify the main trends and patterns.

The object of the study is the AIC of the EAEU countries. The subject of the study is the socioeconomic indicators related to the sustainability of the AIC and food security.

The analysis is based on data from the national statistical services of the EAEU countries, and also includes information from international organizations such as the FAO and the World Bank. To achieve these goals, the following methods were used: 1) correlation analysis to determine the relationships between different socioeconomic indicators and 2) cluster analysis to group countries by similar indicators of food security and agricultural sustainability.

The study contributes to the expansion of theoretical knowledge about the impact of various economic and social factors on the sustainability of the AIC, as well as on the mechanisms of ensuring food security in multinational associations. The results of this work can be used to formulate strategies aimed at strengthening food security and agribusiness sustainability in the EAEU countries, which is especially important for developing measures to respond to challenges associated with geopolitical transformations.

2. Materials and Methods

2.1. Review of Agribusiness Sustainability and Food Security Issues in the EAEU Countries

The study of agricultural sustainability and food security in the EAEU countries relies on a wide range of scientific and analytical sources, including international publications, reports of national statistical services, and data from organizations.

Food security concepts include an analysis of the economic and physical availability of food, as well as the dependence of the domestic market on imports. The current food security criteria are formally met for most food products, but there is still a problem of insufficient economic availability of food in the required volumes and assortment for a significant part of the population. The main part of agricultural raw materials and food imports is supplied from the EAEU partner countries, which reduces the risks of external shocks in the supply of agri-food products and creates prerequisites for softening the targets of the food security concept in the EAEU countries with respect to minimum levels of food self-sufficiency (Polzikov, 2020). At the same time, the development of integration processes and joint projects within the EAEU contributes to strengthening food security and reducing dependence on external supplies. Thus, increasing production volumes and strengthening trade ties within the EAEU contribute to increasing the level of self-sufficiency in key food products. A number of areas can be identified for maintaining the sustainability of the agro-industrial complex in the EAEU countries (Table 1).

Table 1. Directions of agribusiness sustainability in the EAEU countries

Country	Agribusiness sustainability direction
Armenia	• Development of agricultural technologies • Improvement of water supply and irrigation systems • Support to rural farms and territories
Belarus	• Increase in agricultural productivity (return-on effect) • Reduction of waste in production • State support for agricultural producers
Kazakhstan	• Innovations in agriculture • Development of agricultural infrastructure • Reducing dependence on imports (agro-import substitution)
Kyrgyzstan	• Support for small agricultural producers • Improvement systems of the agricultural education system • Development of organic agriculture
Russia	• Technological modernization of the AIC • Development of agro-industrial clusters • Sustainable use of land resources

The desire for economic integration was a central aspect of politics in the post-Soviet space. As a result of several initiatives, a real achievement was the establishment of the Customs Union between Belarus, Kazakhstan, and Russia in 2010, which served as a prerequisite for the launch of the Single Economic Space in 2012. This led to the formation of the EAEU in 2015, which also included Armenia and Kyrgyzstan. The main goal of the EAEU is economic integration, which provides for the liberalization of mutual trade in goods and the development of a common market through the harmonization of internal regulatory requirements and the elimination of other non-tariff barriers. This ambitious project has a significant and fundamental impact on the economy of the participating countries, affecting the production and trade of food products (Götz et al., 2022; Iashina et al., 2023).

The formation of a sustainable food security system is a priority task for the EAEU member states. However, researchers note the need to form mechanisms for ensuring food security at the supranational level with the provision of certain guarantees to the EAEU countries (Kamalyan, 2022; Kusainova et al., 2020). In the context of economic sanctions imposed by the United States and the EU on Russia, the issue of ensuring food security is also relevant for other EAEU countries. The EAEU countries mainly export crop products, while they import livestock products. In this regard, it is necessary to find an effective solution to the problem of ensuring the food security of the EAEU and reducing import dependence, which will require improving the adopted coordinated agricultural policy in a number of areas. In this context, it is proposed to analyse retrospective trends and scenario forecasts of consumption and production of agricultural raw materials and food in the EAEU countries, which will help identify factors that contribute to and prevent the aggravation of contradictions in mutual trade in agricultural products in the future (Glotova, 2014; Ksenofontov et al., 2020).

Maintaining sustainability is closely linked to the use of the resource potential of territories, which can create certain problems in conditions of economic instability. Therefore, it is necessary to analyse available resources and develop strategies aimed at their effective use and adaptation to changes in the external environment (Sorokozherdyev et al., 2023). The development of agriculture in the context of global economic instability requires a flexible approach, including the introduction of innovative technologies and adaptive management methods. In practice, the stability and productivity of the agricultural sector depends on the environment and government policy. To do this, state structures in the EAEU countries should focus investment projects on increasing the return on available resources in order to maximize the return on investment in the AIC, contributing to improving food security (Trofimova et al., 2020; Zhiltsov et al., 2022). Table 2 shows the main guidelines for ensuring food security in the EAEU countries.

Table 2. Directions of food security in the EAEU countries

Country	Food security in the destination country
Armenia	• Ensuring the availability of food for the population • Improving the quality of food
Belarus	• Diversification of agricultural production • Increased exports of food and agricultural products
Kazakhstan	• Provision of strategic food supplies • Support for local production
Kyrgyzstan	• Increasing self-sufficiency in key food products • Fight against food losses in agricultural production
Russia	• Import substitution in agricultural sectors • Improve product safety standards and improve quality control

Conceptual and practical challenges related to the development of sustainable food systems include the development of an ontology of the food system, which implies the systematization and categorization of the main relationships. In this context, there is a need to integrate sustainable and adaptive strategies to improve food security, and the importance of a holistic approach to food security increases (Zhiltsov et al., 2022). Under conditions of uncertainty, many areas are characterized by significant changes. For example, due to the transformation of economic and political factors, the tourism sector is being transformed, which activates the development of specific areas of agribusiness as well as the development of renewable energy sources, contributing to improving energy security in the context of ensuring the stability of the economic systems of territories (Ergunova and Simagina, 2023; Van Wassenaer et al., 2021). It is worth noting that the EAEU countries are activating the innovative development of various economic spheres, which directly affects the state of economic security. A comprehensive assessment of the region's economic security and innovation component involves analysing the region's potential to introduce innovative technologies (Zaytsev et al., 2022).

In order to increase the sustainability of food systems in the EAEU countries, it is necessary to develop and ensure the implementation of multiphase regional programmes aimed at the structural transformation of economic policies to achieve food self-sufficiency and the adoption of 'good' agricultural practices (Adelaja and George, 2021; Haji and Himpel, 2024). The adoption of food security as a component of the EAEU agricultural policy and its political priority affect domestic food production and the interaction of the EAEU with the global agri-food market. The current food policy of the EAEU is focused on reducing dependence on food imports. The EAEU food policy includes three sub-policies, each of which is at the protectionist end of the trade strategy spectrum (Dragneva, 2022):

1. A multi-pronged approach to food security, including reducing dependence on imported food, sustainability of the food system in the traditional sense regarding consumption and nutrition standards, food safety, product tracking, and label reliability.

2. Food self-sufficiency, which refers to efforts to increase agricultural production to meet domestic needs for basic commodities.

3. A policy of import substitution, which involves replacing imported goods with domestic ones (where possible), which can lead to an increase in food prices as imported goods are replaced by domestic ones.

Methodological aspects of developing the concept of collective food security in the EAEU countries are of paramount importance, since the development of such concepts requires taking into account the diversity of socioeconomic conditions and the level of development of the AIC. For these purposes, there is a need to apply advanced analytical and predictive methods (Ksenofontov and Polzikov, 2020). It should be borne in mind that the rent approach to the geo-economic integration of the national economy allows taking into account the specific advantages and resources of each member state of the union, optimizing their use within the common economic space. This approach contributes to a more efficient allocation of resources and increases the competitiveness of the AIC of the EAEU countries (Dmitriev and Zaytsev, 2019, 2020).

Problems of hunger and malnutrition remain acute all over the world, leading to diseases and mental retardation in children. About 1 billion people are malnourished and 1.5 billion are obese. It takes 10 to 30 years of dedicated work to address these challenges, but climate change and population growth may affect these forecasts.1,2 It is important for the EAEU countries to develop international cooperation and trade in safe products, especially to address the problems caused by drought and other climate changes.

Agriculture and agribusiness remain significant sectors of the economy of the EAEU member states and have significant potential for providing food to the domestic market and for the sustainable development of territories. The EAEU AIC demonstrates positive dynamics, and domestic production largely meets the needs of the population. However, it remains dependent on imported fruits and berries, which requires further development of its own production. The main problems include a dependence on imported genetic resources, the development of feed, and the manufacture of plant protection products, and these areas require improvements in the coordinated agricultural policy of the EAEU. Table 3 presents the main challenges for the sustainability of the agro-industrial complex and food security in the EAEU countries.

Table 3. Main challenges for agribusiness sustainability and food security in the EAEU countries

Country	**Main challenges**
Armenia	• Limited water resources • Small size of agricultural land
Belarus	• Dependence on imported agricultural machinery • Lack of population to expand agricultural production
Kazakhstan	• Low soil fertility • Shortage of skilled labour
Kyrgyzstan	• High level of food addiction • Insufficient agro-infrastructure
Russia	• Destruction of agricultural land • Difficult climatic conditions in a large part of the country

For example, agriculture occupies a significant place in the Armenian economy, accounting for an average of 19% of the country’s GDP in the period from 2010 to 2015. The main problems include unfavourable natural and climatic conditions and a dependence on imported genetic resources and agricultural machinery. To solve these problems, state support programmes have been developed aimed at intensifying and industrializing agriculture, including subsidizing loans and introducing anti-hail nets (Kazaryan, 2017). The solution to these problems is associated with the activation of the processes of intensification of innovations and the introduction of innovative technological developments, which is

[1]World Food Programme (WFP) (2022) ‘A global food crisis’. Available at: https://www.wforg/global-hunger-crisis Accessed 15 January 2024.
[2]USDA (2022) ‘USDA Agricultural Projections to 2031’, USDA Long-Term Projections, February. Available at: https://www.usda.gov/ Accessed 15 January 2024.

largely facilitated by interaction between the EAEU countries. Thus, it can be noted that the use of intellectual capital in agribusiness, the active development of scientific research, and the training of highly qualified specialists open up broad prospects for the introduction of innovative technologies and improving production efficiency in the EAEU countries. For this purpose, the EAEU countries are intensifying the improvement of the quality of education and professional training of specialists by introducing modern educational technologies and programmes (Alekseeva and Trofimova, 2017; Ilchenko et al., 2020).

The experience of agricultural industrialization in different countries consists of applying methods and measures that reduce the share of manual labour and increase the level of mechanization and automation. In developed countries, the growth of agricultural production is ensured by the implementation of scientific and technological advances, such as precision farming, genomic selection, and innovative methods of resource management. One of the areas of improving food security in the EAEU countries is the digitalization of the AIC. The introduction of information technologies and automated production process management systems helps optimize resources, reduce costs, and improve product quality (Amirova et al., 2021; Sigarev and Narynbaeva, 2015). Researchers note that in order to increase the sustainability of the AIC and food security in the EAEU countries, it is necessary to actively introduce modern technologies and state support for the industrialization of agriculture (Oganisyan and Kazaryan, 2020).

The use of innovative technologies contributes not only to the development of the AIC but also to improving the efficiency of production in food enterprises. In particular, the EAEU countries' investments in these programmes have led to the introduction of automated quality control and raw material processing systems. The use of innovative technologies in agriculture (precision farming, biotechnologies, and agricultural drones) increases productivity and resistance to adverse climatic conditions, which is especially important for countries such as Armenia. Harmonization of standards and the implementation of joint research and development initiatives within the EAEU contribute to the production of high-quality, competitive agricultural products (Dmitriev, 2020; Dmitriev and Rogozina, 2020; Maslova et al., 2019).

The problems of developing a unified food policy in the field of logistics integration of the EAEU countries are related to taking into account the different levels of consumption and trade opportunities of the population in the participating countries. There is a need to create a balanced food market, given the imbalances in consumption and the development of logistics supply chains, as well as the high volume of unjustified food imports from third countries. For this purpose, the formation of national import substitution programmes is being activated, taking into account the supplies of partners in the EAEU. These areas determine the transformation of sustainability mechanisms and their impact on food security (Stone and Rahimifard, 2018; Zueva et al., 2016). It should be borne in mind that food markets have changed significantly, which complicates the relationship between participants in food chains. Such changes, of course, also affect the markets of the EAEU countries. It is necessary to ensure the identification, assessment, and prevention of factors that negatively affect the competitive environment of food and agricultural product markets in the EAEU countries (Pilipuk et al., 2022).

The UN forecasts unprecedented food shortages along with rising prices and warns that the global food market may face serious pressure due to the growing problem of food insecurity. Establishing sufficient food supply for the EAEU countries, while simultaneously reducing dependence on food imports and reducing the vulnerability of supply, is the basis for improving the level of food security (Arskiy and Khudzhatov, 2021). For these purposes, it is necessary to develop models for making managerial decisions in agriculture that can rationalize economic processes based on multidimensional data analysis. For example, it is necessary to step up the penetration of progressive supply chain management into agribusiness (Lukina et al., 2023; Vakhrusheva et al., 2021). The problem with the logistics system is that transport services take a disproportionately large share in the total volume of logistics services; the logistics sphere of some EAEU countries is limited to transportation, warehousing, and distribution. A comprehensive solution to problems, including training highly qualified specialists and state support for infrastructure projects, can improve the situation (Kazaryan et al., 2022).

2.2. Statistical Analysis of Agribusiness in the EAEU Countries

The EAEU was created with the aim of forming a single market that ensures the freedom of movement of goods, services, capital, and labour within the Union. Initially, the stages of the integration process were planned until 2025, but in December 2023, the EAEU countries approved a declaration on the further development of economic processes with planning until 2030 and for the period up to 2045. Currently, the level of self-sufficiency of the EAEU in food has exceeded 93% (in 2020, this figure was 88%), and over the 10 years of the Union's existence, agricultural production has increased by more than a quarter. For statistical analysis, we used the report of the Eurasian Development Bank (Vinokurov et al., 2023) as well as open access data, in particular data from the national statistical services of the EAEU countries, as well as international sources such as the FAO and the World Bank.

It should be borne in mind that global agri-food chains and the food trade system have become key elements for ensuring global food supply and security. The annual increase in the volume and value of agricultural trade raises questions about the potential threat to food security associated with import dependence and the trade deficit.3 However, in 2023, the production of agricultural products in the EAEU showed a decline. According to the Eurasian Economic Commission (EEC), total agricultural production in the EAEU countries decreased by 1.1%. At the same time, Belarus and Kyrgyzstan experienced growth of 1.1% and 0.6%, respectively, while Kazakhstan and Russia experienced a decrease of 7.7% and 0.3%, respectively.

Food problems primarily affect the population of developing and underdeveloped countries. However, residents of economically developed countries also face increased costs for food and utilities, which leads to a decrease in their standard of living. According to the EAEU data, the total production of agricultural products of all categories increased in 2022 (Borodenko, 2023). According to the EEC, in 2023, in farms of all categories of the EAEU countries, the gross grain harvest after refinement amounted to 169.4 million tons, which is 11.1% less than in the previous year. Potato production increased by 5.4% to 30 million tons, while vegetable production decreased by 0.4% to 22.9 million tons. At the same time, the production of basic livestock products has increased: livestock and poultry for slaughter (in live weight) by 2.2%, milk by 3%, and eggs by 0.8%.

The EAEU has significant resource advantages. The territories of the participating countries contain 10% of all arable land on the planet and 10% of the world's fresh water reserves, more than 13% of the world's wheat reserves, more than 16% of barley, and significant fertilizer reserves—about 10% of nitrogen and phosphate fertilizers and more than 40% of potash fertilizers. Russia and Kazakhstan provide about a third of the world's sunflower oil production. Trends in Russia's economic development demonstrate that the assessment of long-term economic growth rates up to 2035,4 based on alternative scenarios, shows insufficient effectiveness of regular macroeconomic policy measures to stimulate sustainable economic growth (Gusev, 2023b). At the same time, by the end of the decade, Russia plans to increase production in the agricultural sector by a quarter and increase exports by one and a half times, especially cereals, legumes, oilseeds, meat (especially poultry and lamb), fat and oil products, flour, cereals, milk, and confectionery.

The transition to a common agribusiness policy will allow the EAEU countries to jointly increase profits, avoiding unnecessary competition. Self-sufficiency in food products is an important indicator for the EAEU. The level of food self-sufficiency varies among the EAEU countries: Belarus (94%) and Russia (90%) have the highest rates, followed by Kazakhstan (87%), Kyrgyzstan (74%), and Armenia (67%). Russia fully meets domestic demand for grain, pork, poultry meat, and vegetable oils, exporting the surplus both to its EAEU partners and to other countries. However, the production of beef, milk, and certain types of vegetables does not yet cover domestic demand.

[3]Eurasian Economic Commission (2021). Agro-Industrial Complex. Available online at: https://agro.eaeunion.org/Pages/default.aspx Accessed 15 January 2024.
[4]OECD-FAO (2022) 'OECD-FAO Agricultural Outlook 2022–2031'. Available at: https://www.oecd-ilibrary.org/agriculture-and-food/oecd-fao-agricultural-outlook-2022-2031_f1b0b29c-en Accessed 15 January 2024.

A prolonged period of high food prices is projected, driven by population growth, high energy prices, a shortage of skilled labour, increased food consumption in countries, limited opportunities for agricultural land expansion, and climate change. Reduced availability of food increases its value. Food is becoming the new 'black gold': its political significance and export potential will grow. Under the influence of the pandemic, geopolitical tensions, sanctions, the disruption of supply chains, the fuel crisis, and rising production costs, including energy and fertilizers, the cost of food has increased significantly. The Food Price Index (FAO) has increased by 46.5% over the past two years (from 98.1 in 2020 to 143.7 in 2022), remaining above the level of 2021 despite a slight decline in the second half of 2022.

The Eurasian region as a whole ensures its food security. The level of self-sufficiency for most products exceeds 80–95%, which corresponds to food independence. Figure 1 shows the level of self-sufficiency of the EAEU countries in the main areas of agricultural production. The highest level of self-sufficiency is observed for cereals and oilseeds, while the lowest level is observed for fruits.

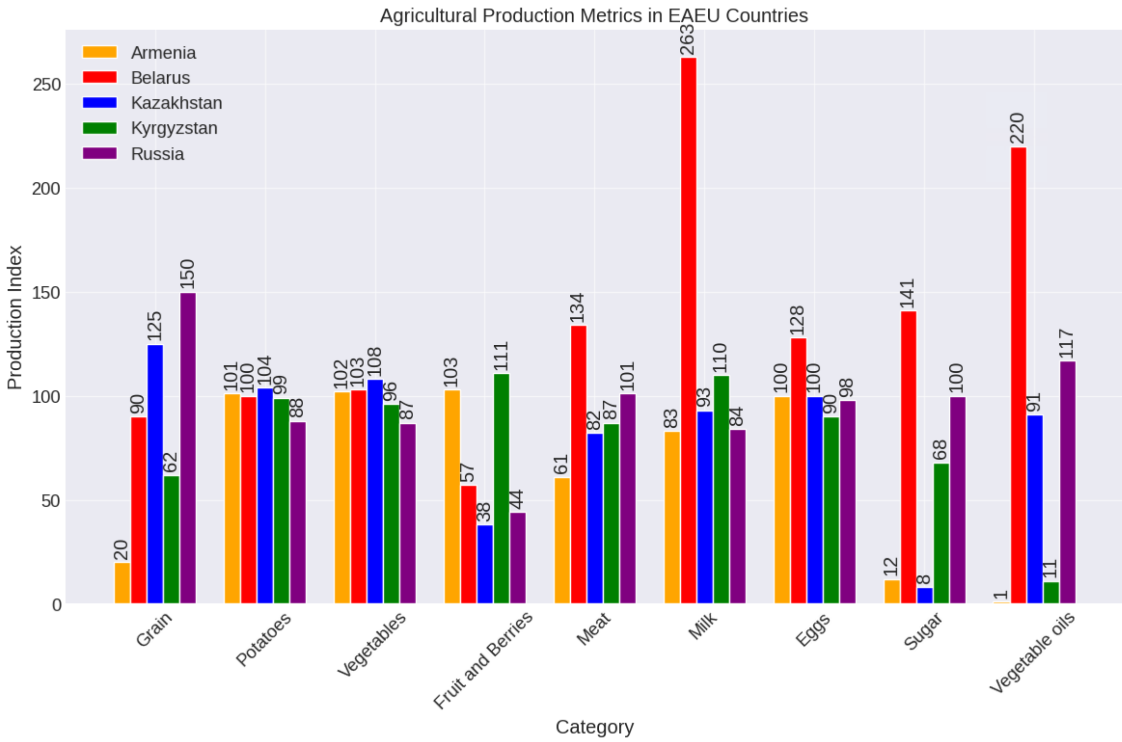

Figure 1. Level of self-sufficiency of the EAEU countries (%)

The realization of the production and resource potential of the AIC can provide the following positive effects for the Eurasian countries by 2035. It is noted that the production multipliers for the agricultural sector (USD per dollar of expenditure per sector) will be: 2.62 for Russia, 2.49 for Kyrgyzstan, 2.44 for Belarus, 1.95 for Kazakhstan, and 1.77 for Armenia. Mutual trade between the countries of the Eurasian region is steadily growing (in 2021 it reached $15.4 billion). The share of mutual exports in the total volume of exports of agricultural products was 33.6%. Over the past 20 years, the volume of mutual export supplies of agricultural products has increased 8.5 times. Since the EAEU started functioning in 2015, mutual trade in agricultural products has grown by a factor of 1.8. The largest increase in exports to the domestic market from 2015 to 2021 was observed in Armenia (3.1 times) and Russia (2.3 times).

The main part of deliveries of agricultural products to the domestic market is accounted for by Russia, Belarus, and Kazakhstan, whose combined share in mutual exports was 90%. These countries are key producers of food products and act as guarantors of food security in the region. In the structure of mutual imports, the main importers are Russia (40.2%) and Kazakhstan (21.9%), with the total share of Russia, Kazakhstan, and Belarus at 72.4% (Figure 2). Outside the EAEU, Uzbekistan is also a significant importer (13.4%).

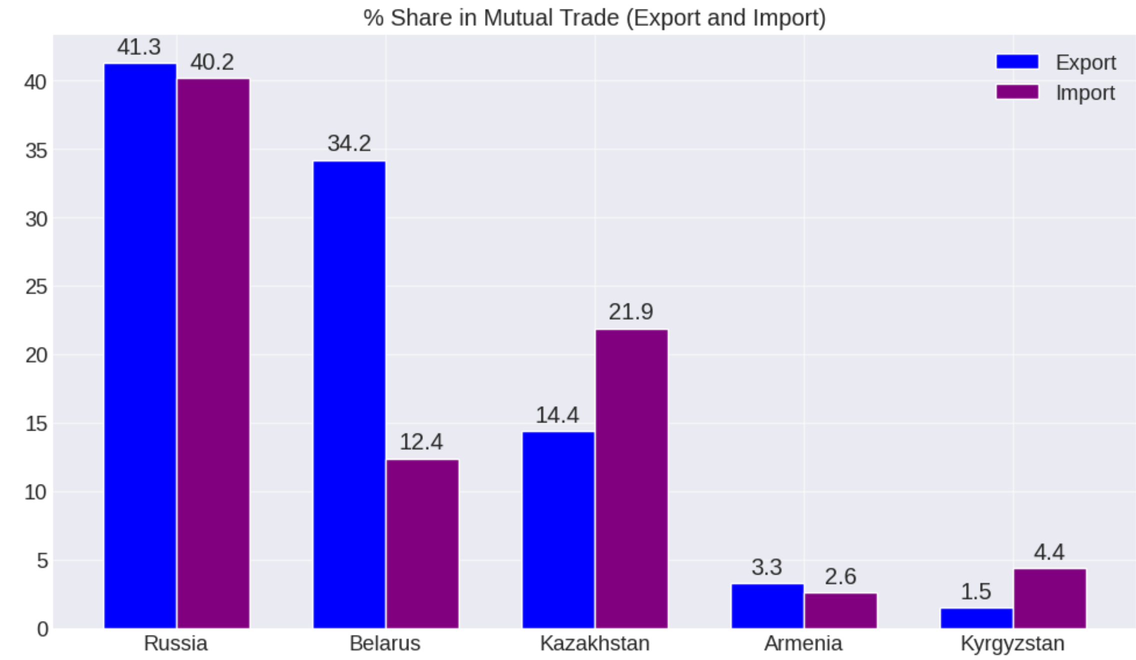

Figure 2. Share of Eurasian countries in mutual trade in agricultural products in 2021 (%)

More than one third of the volume of mutual trade in agricultural products falls into three groups: dairy products, eggs, and honey (17.9%); cereals (9.4%); and fats and oils (9.2%). The main supplier of dairy products is Belarus (85.9% in the structure of mutual exports); of cereals, Kazakhstan (67.7%); and of fats and oils, Russia (70.7%). Exports of such commodity groups as vegetables, fruits, nuts, animal products, fish, and beverages are distributed more evenly between countries.

The Eurasian market is most important for the export of the agricultural products of Belarus (78.8% in 2021) and Kyrgyzstan (69.1%). Regional imports of agricultural products are most important for Kyrgyzstan (76.1%) and Kazakhstan (66.4%). The largest growth rates of imports from Eurasian countries are observed in Belarus (a twofold increase). Kazakhstan accounted for 43.2% and Belarus for 28.4% of Russian exports of agricultural products in 2021. Russia is the main supplier of agricultural products to Belarus (97.6%), Armenia (93.6%), Kazakhstan (81.6%), and Kyrgyzstan (52.4%).

2.3. Review of the Methodological Framework of the Study

Food security diagnostic tools include methods for assessing the availability and quality of food resources, as well as monitoring their distribution and use. To build strategies and practice-oriented models, the state of the territory's resource potential should also be taken into account (Zaytsev et al., 2024). For example, the model of economic and statistical assessment of food security is used to analyse and predict the state of food security at the regional and national levels, which allows us to take into account various socioeconomic factors affecting the availability and quality of food and develop measures to improve food security (Antamoshkina, 2019a, 2019b).

Determinants of food self-sufficiency include the level of domestic production, the efficiency of agricultural technologies, and the volume of imports. Food security is determined by a country's ability to meet the population's needs for basic foodstuffs, ensuring their availability and quality in the long term (Galiev and Ahrens, 2021). Within the framework of this study analysing the sustainability of the AIC and food security in the EAEU countries, the following methodological tools are used:

1. Correlation analysis is used to determine the relationships between socioeconomic indicators. This method allows us to identify which factors (for example, the volume of agricultural production, investment in the agricultural sector, the level of technological development, and state support) affect

food security. The analysis is based on data provided by the national statistical services of the EAEU countries, as well as international organizations such as the FAO and the World Bank.

2. To group the EAEU countries by the level of agribusiness development and food security, cluster analysis methods are used, including K-means, Gaussian mixtures (GMM), and agglomerative and spectral clustering. These methods allow us to identify clusters in which countries are distributed depending on the similarity of their indicators.

3. Results and Discussion

3.1. Data Collection for the Analysis of Agro-Industrial Complex Sustainability in the EAEU Countries

The study collected and analysed data that will help assess the sustainability of the AIC and food security in the EAEU countries. The following is a description of the key indicators and their significance for the study (Table 4).

Table 4. Data for analysis of agricultural sustainability in the EAEU countries

Designation	Indicator	Description
GDP_Nominal	GDP (nominal, USD)	Assessment of the economic state of countries and opportunities to invest in the AIC.
GDP_PPP	GDP (PPP, USD)	Takes into account the purchasing power of the currency.
Agriculture_Value_Added	Agriculture, value added (% of GDP)	The contribution of agriculture to the economy and its significance for GDP.
Agricultural_Land	Agricultural land (% of total land area)	Share of land used for agriculture.
Crop_Production_Index	Crop Production Index (2004–2006 = 100)	Dynamics of agricultural production.
Food_Production_Index	Food Production Index (2004–2006 = 100)	Food production volume and its changes.
Cereal_Yield	Grain yield (kg per hectare)	Efficiency of agricultural land use.
Total_Population	Total population	Indicators per capita and scale of food security.
Mortality_Rate_Under_5	Under-5 mortality rate (per 1000 live births)	Standard of living and health of the population.
CO2_Emissions	CO2 emissions (kilotons)	Environmental impact of the AIC and its impact on the climate.
Renewable_Internal_Freshwater	Domestic renewable freshwater resources (cubic meters per capita)	Availability of water resources for agriculture.
depth_of_Food_Deficiency	Depth of food deficit (kcal per person per day)	The level of malnutrition.
Industry_Value_Added	Industry, value added (% of GDP)	The role of industry in the economy and interaction with agriculture.
Access_to_Safely_Managed_Drinking_Water	Access to safe drinking water (% of population)	Standard of living and food security.
Fertilizer_Consumption	Fertilizer consumption (kg per hectare of arable land)	The level of agricultural intensification.
Agricultural_Land_SqKm	Agricultural land (sq km)	Volume of land for agriculture.

Arable_Land_Per_Person	Arable land (hectares per person)	Availability of arable land per capita.
Arable_Land_Percentage	Arable land (% of land area)	Percentage of land suitable for ploughing.
Methane_Emissions	Methane emissions (cT of CO2 equivalent)	Environmental impact of the AIC.
Livestock_Production_Index	Livestock Production Index (2004–2006 = 100)	Level and dynamics of livestock production.

3.2. Descriptive Statistics for the Analysis Indicators of Agricultural Sustainability in the EAEU Countries

Indicators collected for the period from 2015 to 2022 were used to analyse the sustainability of the AIC in the EAEU countries. Table 5 shows the main results of descriptive statistics.

Table 5. Descriptive statistics of data for the analysis of agribusiness sustainability in the EAEU countries

Indicator	Mean	Standard deviation	Minimum	25th percentile	Median	75th percentile	Maximum
GDP_Nominal	380.96 billion	654.29 billion	6.68 billion	11.54 billion	60.70 billion	187.57 billion	2240.42 billion
GDP_PPP	1063.38 billion	1796.98 billion	25.09 billion	39.03 billion	199.55 billion	586.94 billion	5987.86 billion
Agriculture_Value_Added	8.20	4.12	3.39	4.50	6.85	11.56	17.22
Agricultural_Land	49.53	22.28	13.16	41.06	54.07	58.90	80.11
Crop_Production_Index	100.94	14.91	68.53	92.49	103.71	110.10 Writing	133.67
Food_Production_Index	104.07	10.58	81.27	99.67	104.96	110.76	127.76
Cereal_Yield	2516.57	794.50	1048.80	1903.98	2718.70	3111.18	3690.20
Total_Population	36.27 million	54.94 million	2.78 million	6.17 million	9.43 million	18.82 million	144.50 million
Mortality_Rate_Under_5	10.29	5.62	2.60	5.33	10.25	13.28	22.20
CO2_Emissions	138446.90	236404.50	2319.92	4507.13	17030.29	69929.67	620983.16
Renewable_Internal_Freshwater	9451.83	10556.78	2382.76	3487.09	3612.91	8009.83	29929.24
Depth_of_Food_Deficit	2.99	1.03	2.50	2.50	2.50	2.50	5.80
Industry_Value_Added	29.49	3.44	22.26	26.50	30.76	32.19	35.27
Access_to_Safely_Managed_Drinking_Water	82.42	7.83	66.93	75.99	82.79	89.33	93.10

Fertilizer_Consumption	83.87	91.58	2.92	11.55	22.65	162.78	330.49
Agricultural_Land_SqKm	902492.57	1036836.04	16748.20	83340.00	103708.00	2154940.00	2162597.00
Arable_Land_Per_Person	3.17	4.69	0.04	1.29	5.68	29.66	121.65
Arable_Land_Per-centage	13.75	7.91	6.68	7.43	10.98	15.67	28.21
Methane_Emissions	138446.90	236404.50	2319.92	4507.13	17030.29	69929.67	620983.16
Livestock_Production_Index	107.71	6.57	99.90	102.28	106.24	111.15	124.81

Based on the above data, we can draw the following conclusions:

- The average nominal GDP is 380.96 billion USD with a high variation (standard deviation 654.29 billion USD), which indicates significant differences in the economic state of the EAEU countries.

- The average added value of agriculture is 8.20% of GDP.

- The average yield of grain crops is 2516.57 kg per hectare.

- The average share of agricultural land in the total area is 49.53%.

- CO2 and methane emissions show a significant environmental impact of the AIC.

- The depth of nutrition deficit is on average 2.99 kcal per person per day, which indicates that there are problems with the availability of adequate nutrition.

- On average, 82.42% of the population has access to safe drinking water.

3.3. Economic and Social Determinants of Food Security

Correlation analysis based on socioeconomic indicators allows us to identify the main determinants that affect the sustainability of the AIC and, consequently, food security in the region. In the matrix shown in Figure 3, dark green cells indicate strong positive correlations, and light green cells indicate weak positive or negative correlations (correlations with values from -0.3 to 0.3 are excluded).

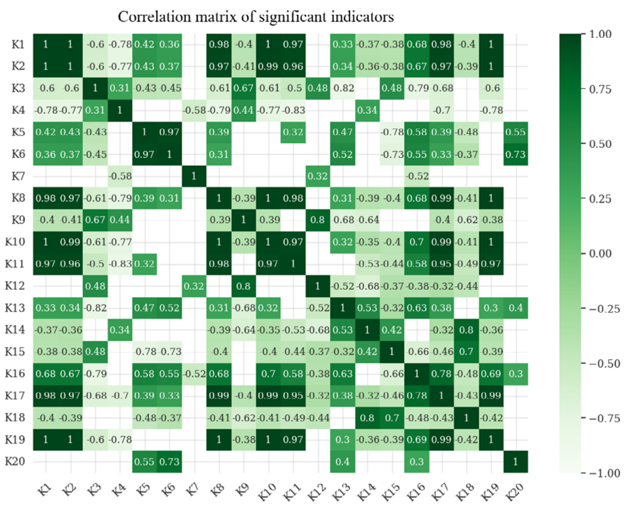

Figure 3. Correlation matrix of significant indicators for the analysis of agribusiness sustainability in the EAEU countries

The legend of indicators: K1 = GDP_Nominal; K2 = GDP_PPP; K3 = Agriculture_Value_Added; K4 = Agricultural_Land; K5 = Crop_Production_Index; K6 = Food_Production_Index; K7 = Cereal_Yield; K8 = Total_Population; K9 = Mortality_Rate_Under_5; K10 = CO2_Emissions; K11 = Renewable_Internal_Freshwater; K12 = Depth_of_Food_Deficit; K13 = Industry_Value_Added; K14 = Access_to_Safely_Managed_Drinking_Water; K15 = Fertilizer_Consumption; K16 = Agricultural_Land_SqKm; K17 = Arable_Land_Per_Person; K18 = Arable_Land_Percentage; K19 = Methane_Emissions; K20 = Livestock_Production_Index.

Economic indicators (K1 and K2):

Nominal GDP (K1) and GDP at purchasing power parity (K2) strongly correlate with total population (K8) (0.98), CO2 emissions (K10) (0.99), domestic renewable freshwater resources (K11) (0.96), and methane emissions (K19) (0.99). The results obtained indicate a significant environmental burden associated with economic growth.

2. Agriculture indicators (K3 and K4):

Agricultural value added (K3) has a negative correlation with nominal GDP (K1) (-0.60) and GDP by PPP (K2) (-0.60). The results obtained indicate that the share of agriculture in the economy decreases with the growth of total GDP.

Agricultural land (K4) is negatively correlated with nominal GDP (K1) (-0.78) and PPP GDP (KK2) (-0.77). The results obtained emphasize the need to improve the efficiency of agricultural land use.

3. Production indicators (K5 and K6):

The crop production index (K5) positively correlates with the food production index (K6) (0.97). The results obtained indicate the synchronous development of these two indicators, which is important for ensuring food security.

Grain yields (K7) have a significant negative correlation with agricultural land (K4) (-0.58). The results obtained indicate the need to optimize the use of land to increase productivity.

Social and environmental indicators (K9 and K10):

The under-5 mortality rate (K9) has a negative correlation with nominal GDP (K1) (-0.40) and PPP GDP (K2) (-0.41). The results obtained indicate that children's health improves as the economy grows.

CO2 (K10) and methane (K19) emissions show high positive correlations with economic indicators, highlighting the environmental impact of agriculture.

Industrial indicators (K13):

Industrial value added (K13) is negatively correlated with agricultural value added (K3) (-0.82). The results obtained indicate their opposite directions of development in the economy.

The correlation matrix emphasizes the importance of an integrated approach to the development of the AIC and ensuring food security in the EAEU countries. Economic development is linked to environmental and social aspects, which requires the integration of new practices and innovative technologies in agriculture. Positive correlations between production indicators (K5 and K6) indicate the importance of synchronous development of agricultural production for achieving stability in food security.

3.4. Results of Cluster Analysis of the EAEU Countries

The analysis was performed using several clustering methods, such as K-means, agglomerative clustering, Gaussian mixture models (GMM), and spectral clustering. Each method used key indicators to identify groups of countries with similar characteristics.

The elbow method was used to determine the optimal number of clusters that can best describe the data. Figure 4 shows that inertia (vertically) decreases sharply as the number of clusters increases from 1 to 3 (horizontally), after which the decrease becomes less noticeable.

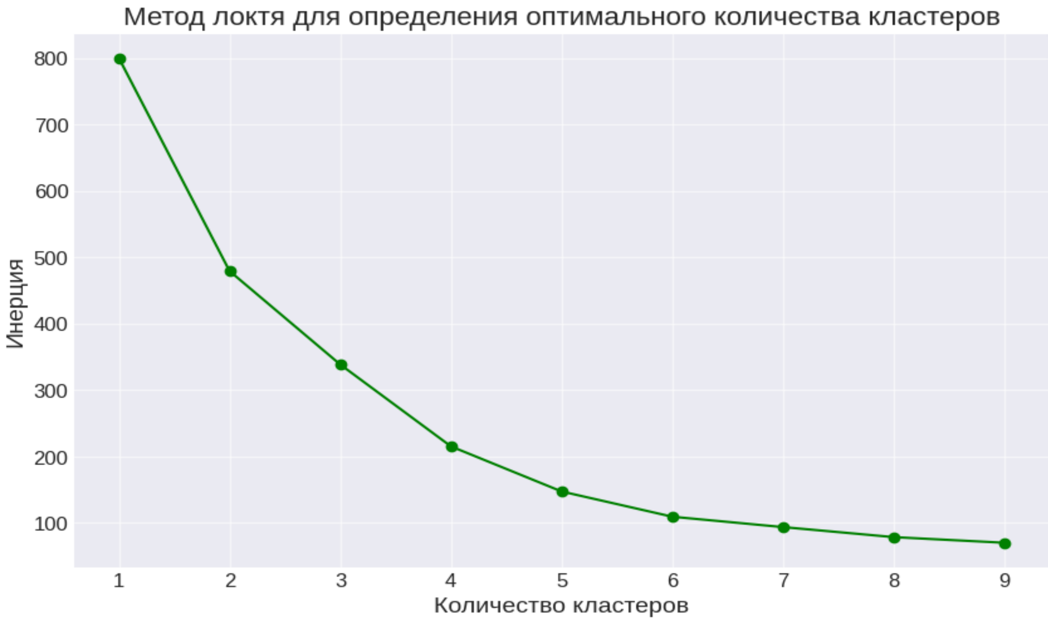

Figure 4. Elbow method for determining the optimal number of clusters

3.4.1. K-means Clustering

Cluster 0 includes Russia; cluster 1 consists of Armenia, Belarus, and Kyrgyzstan; and cluster 2 includes Kazakhstan and Russia. Clustering quality metrics for K-means include the silhouette score (0.38), the Davies–Bouldin score (1.07), and the Calinski–Harabasz score (21.04). The results indicate moderate clustering quality, with Russia being singled out as a separate cluster or combined with Kazakhstan.

3.4.2. Agglomerative Clustering

Cluster 0 includes Belarus and Kazakhstan; cluster 1 includes Russia; and cluster 2 contains Armenia and Kyrgyzstan. The clustering quality metrics for this method were slightly higher: silhouette score = 0.41, Davies-Bouldin score = 1.08, and Calinski–Harabasz score = 26.03. The results obtained indicate that agglomerative clustering can better reflect the data structure, highlighting Russia as a separate cluster.

3.4.3. Gaussian Mixture Models and Spectral Clustering

The clustering method based on Gaussian mixture models (GMM) and spectral clustering showed similar results to K-means. Both methods also identified three clusters: cluster 0 includes Russia; cluster 1 includes Armenia, Belarus, and Kyrgyzstan; and cluster 2 includes Kazakhstan and Russia. The quality metrics for these methods are similar: silhouette score = 0.38 and 0.41, Davies–Bouldin score = 1.07 and 1.08, and Calinski–Harabasz score 21.04 and 26.03, respectively. The results highlight the similarity of the methods and confirm the general trends identified when using K-means.

3.4.4. Generalized results

Cluster analysis methods, such as K-means and Gaussian mixtures (GMM), allowed us to identify three main clusters of the EAEU countries by levels of agribusiness development and food security. Table 3 shows the results of cluster analysis.

Table 3. Results of cluster analysis of the EAEU countries

Method	Silhouette Score	Davies–Bouldin Score	Calinski–Harabasz Score	Clusters
K-means	0.38	1.07	21.04	0: [RU], 1: [AM, BY, KG], 2: [KZ, RU]
Agglomerative	0.41	1.08	26.03	0: [BY, KZ], 1: [RU], 2: [AM, KG]
Gaussian Mixture	0.38	1.07	21.04	0: [RU], 1: [AM, BY, KG], 2: [KZ, RU]
Spectral Clustering	0.41	1.08	26.03	0: [AM, KG], 1: [RU], 2: [BY, KZ]

The results of the cluster analysis confirm that the EAEU countries can be grouped into three main clusters, which highlights significant differences in the level of agribusiness development and food security. This approach allows for a more accurate orientation in the development of strategies and policies to strengthen food security and the sustainability of the AIC in the region.

4. Conclusion

The sustainability of the AIC in the EAEU countries is crucial for ensuring food security and solving socioeconomic problems. The study shows that economic indicators, such as nominal GDP and GDP based on purchasing power parity, are highly correlated with environmental and demographic indicators, which indicates the interrelated nature of economic growth and environmental impact. For example, the high correlation with CO2 and methane emissions highlights the need for sustainable agricultural practices to balance economic development and environmental conservation.

During the cluster analysis, three main clusters of the EAEU countries were identified, depending on the level of their agricultural development and food security. Methods such as K-means, agglomerative clustering, Gaussian mixture models (GMM), and spectral clustering have consistently identified similar groupings, demonstrating that Russia often stands out either separately or in combination with Kazakhstan. Quality indicators such as the silhouette score and the Davis–Bouldin score indicate moderate-to-good clustering performance, highlighting the distinctiveness of these groupings and their importance for policy development.

In conclusion, the analysis emphasizes the importance of an integrated approach to the development of the AIC and ensuring food security in the EAEU. Economic growth must be combined with environmental mitigation strategies, and targeted investments in agricultural technology and infrastructure are also needed. Cooperation and integration within the EAEU can improve food security, reduce dependence on imports, and promote sustainable agricultural practices. The results obtained lay the foundation for strategic planning and policy development aimed at achieving long-term stability and resilience in the agro-industrial sector of the Eurasian region.

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Intellectual Capital in Agribusiness: Integrating Digital Solutions for Sustainable Development

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Abstract

This article explores the integration of digital solutions to enhance the sustainable development of agribusiness through the activation of the introduction of intellectual capital. The analysis is carried out taking into account various factors affecting yields, such as soil type, fertilizer use, market prices, employee education level, product demand, and automation level. The level of automation, the use of geographic information systems, access to big data, and hours of employee training were chosen as factors of intellectualization. Random forest, ARIMA, SARIMA, and LSTM models were used to predict yields. The data were taken from the statistical portals of Armenia and Georgia (137 observations). The results of the study show that the LSTM model demonstrated the best prediction accuracy with an average absolute error of 8.30 and a standard error of 102.47. The random forest model showed an average absolute error of 24.87 and a standard error of 828.23, while the ARIMA and SARIMA models did not show significant results. The study revealed significant correlations between digital solutions characterizing the level of intellectual capital in agricultural enterprises and agricultural land productivity, including the level of automation and access to big data. Analysis was also conducted on the impact of intellectual capital on the sustainability of agribusiness, including the impact of the level of education and training hours of employees. It is concluded that the integration of innovative technologies, such as big data and automation, contributes to improving the efficiency of agricultural production.

Keywords: intellectual capital, agribusiness, sustainable development, digital solutions, yield forecasting, random forest, ARIMA, SARIMA, LSTM, big data, automation, agriculture

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Интеллектуальный Капитал в Агробизнесе: Интеграция Цифровых Решений для Устойчивого Развития

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Аннотация

Данная статья исследует интеграцию цифровых решений для повышения устойчивого развития агробизнеса через активизацию внедрения интеллектуального капитала. Анализ проводится с учетом различных факторов, влияющих на урожайность, таких как тип почвы, использование удобрений, рыночные цены, уровень образования работников, спрос на продукцию и уровень автоматизации. В качестве факторов интеллектуализации выбраны уровень автоматизации, использование геоинформационных систем, доступ к большим данным и часы обучения работников. Применены модели Random Forest, ARIMA, SARIMA и LSTM для прогнозирования урожайности. Данные взяты со статистических порталов Армении и Грузии (137 наблюдений). Результаты исследования показывают, что модель LSTM продемонстрировала наилучшую точность предсказаний со средней абсолютной ошибкой 8.30 и среднеквадратичной ошибкой 102.47. Модель Random Forest показала среднюю абсолютную ошибку 24.87 и среднеквадратичную ошибку 828.23. В то время как модели ARIMA и SARIMA не показали значимые результаты. В процессе исследования были выявлены значимые корреляции между цифровыми решениями, характеризующими уровень интеллектуального капитала на агропредприятиях, и урожайностью сельскохозяйственных угодий, включая уровень автоматизации и доступ к большим данным. Также проводится анализ влияния интеллектуального капитала на устойчивость агробизнеса, включая влияние уровня образования и часов обучения работников. Сделаны выводы о том, что интеграция инновационных технологий, таких как большие данные и автоматизация, способствует повышению эффективности агропроизводства.

Ключевые слова: интеллектуальный капитал, агробизнес, устойчивое развитие, цифровые решения, прогнозирование урожайности, Random Forest, ARIMA, SARIMA, LSTM, большие данные, автоматизация, сельское хозяйство

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1. Introduction

Research on intellectual capital in agribusiness is aimed at analysing the importance of digital technologies and intangible assets in creating efficiency. In terms of economic aspects, we can highlight the importance of knowledge, skills, and innovation in improving efficiency and productivity. The human capital of skilled workers, the structural capital of processes in the organization, and the relational capital obtained from networks and partnerships contribute to the formation of intellectual potential among agricultural producers (Scafarto et al., 2016; Zaytsev et al., 2020).

Automation, big data analysis, geographic information systems (GIS), and other digital solutions help transform traditional farming practices into new forms of management while increasing the efficiency of business operations. Digital technologies make it possible to increase the return on control and management of agribusiness, creating conditions for increasing yields, reducing losses, and increasing the quality of resource use. Integration of digital solutions is necessary to solve problems related to resource reduction and the need to adapt new agricultural practices (Balaji and Mamilla, 2023; Shirokov et al., 2023; Zaytsev et al., 2024).

The purpose of this article is to investigate the integration of digital solutions to increase the sustainable development of agribusiness through the introduction of intellectual capital. This study aims to analyse the impact of various factors on yield, including soil type, fertilizer use, market prices, employee education, product demand, and automation levels. The following methods are used to achieve these goals:

- collection and analysis of statistical data from the statistical portals of Armenia and Georgia
- application of predictive models for yield analysis and forecasting
- correlation analysis to identify significant relationships between digital solutions and productivity
- analysis of the significance of the impact of intellectual capital on the sustainability of agribusiness

The object of this research is the agricultural enterprises of Armenia and Georgia that use digital solutions and intellectual capital in their activities to support strategies aimed at achieving sustainable development. The subject of this study is the factors influencing crop yields, their relationship with intellectual capital, and digital solutions in agribusiness. The research uses predictive models such as random forest, ARIMA, SARIMA, and LSTM.

2. Literature Review

Intellectual capital is the basis for the development of many economic sectors, including agro-industrial production, where the integration of intellectual achievements, primarily digital solutions, is the basis for increasing the sustainability of agribusiness. In the context of agribusiness, intellectual capital includes components that affect the yield and overall development of agricultural enterprises. Table 1 presents the main components of intellectual capital, as well as highlighting aspects that can affect the modelling of intellectual capital in agribusiness (Edvinsson and Malone, 1997; Sveiby, 1997).

Table 1. Components of intellectual capital in agribusiness

Component of intellectual capital	Definition	Example in the context of a business model
Human capital	Knowledge, skills, and experience of employees	Level of education of employees, hours of training
Structural capital	Organizational processes and innovations	Level of automation

Relational capital	Networks and communications, access to information and technology	Access to big data

The efficiency of using intellectual capital and its impact on the sustainable growth of agribusiness can be investigated with a focus on optimizing processes and using human capital to increase productivity. Digital transformation to improve the sustainable value of products and services of agri-food systems can significantly improve the efficiency of supply chains, reducing gaps in access to information and resources, especially for small producers (Balaji and Mamilla, 2023; Silva et al., 2022). The impact of intellectual capital on the profitability of agribusiness companies has shown that structural capital and human capital have the main impacts (Ovechkin et al., 2021).

By analysing the various components of intellectual capital, including human, structural, and relational capital, it is possible to identify their impact on companies' financial performance. In practice, researchers note that the impact of management measures on changing the structure of intellectual capital contributes to the growth of productivity and competitiveness of companies. In this context, it is necessary to ensure the development of new approaches for assessing and managing intellectual capital in various sectors of the national economy, including the agro-industrial sector (Pedro et al., 2018; Xu and Liu, 2020). It is proposed to identify the contribution of intellectual capital to several key indicators of agribusiness (Table 2).

Table 2. Impact of intellectual capital on key agribusiness indicators

Key indicator	**Human capital**	**Structural capital**	**Relational capital**
Productivity	High level of knowledge and skills	Process optimization, use of new technologies	Access to advanced data and information
Financial profitability	Increased productivity	Reduced costs through automation	Improved market positions
Sustainability and environmental friendliness	Efficient use of resources	Introduction of environmentally friendly technologies	Strengthening ties with environmental organizations
Competitiveness	Innovative management methods	Product quality improvement	Expanding market relations

The focus on the components of intellectual capital in the context of their role in ensuring sustainable development makes it possible to form models for managing the processes of intellectualization. A particularly clear manifestation of intellectual capital is positively noted for small and medium-sized enterprises, where investment in human and structural capital contributes to improving the competitiveness of companies. At the same time, depending on the size of the business and the scope of economic relations, it is possible to adapt various methods for evaluating intangible assets and intellectual capital (Gołacka et al., 2020; Osinski et al., 2017). Consequently, it is possible to develop and apply methods for evaluating and managing intellectual assets, including analysing digital solutions that affect the performance of agribusiness entities.

Digital solutions are being actively implemented in the economic management of agribusiness, ensuring the rationalization of management processes at different levels. To achieve these goals, many enterprises attract financing, which makes it possible to activate innovative processes in agro-industrial production. At the state level, the issues of financing innovative processes in the agricultural sector are strategically important (Dumanska, 2018a, 2018b). These aspects define the role of intellectual capital in the strategy of ensuring economic security, emphasizing the formation of potential for managing intellectual resources in the context of achieving sustainable economic development and national security. To a large extent, it is necessary to use methods and tools that can be used to analyse and improve socioeconomic indicators (Rodionov et al., 2020; Zhogova et al., 2020). This study analyses the digital solutions presented in Table 3.

Table 3. Digital solutions in agribusiness

Digital technology	**Description**	**Example in the context of a data model of a mapping model**
Big data	Analysis of large volumes of data for making informed decisions	Access to big data
Automation	Use of automated systems for process management	Automation level
Geographic information systems (GIS)	Spatial data collection, analysis, and visualization	Crop area optimization
Drones	Field condition monitoring and yield assessment	Precise crop control and management
Internet of Things (IoT)	A network of interconnected devices for data collection and exchange	Sensors for monitoring soil conditions and growth
Artificial intelligence (AI)	Using machine learning algorithms for data analysis and forecasting	Yield forecasting and risk management
Robotics	Using robots to perform agricultural tasks	Automated harvesters
Mobile applications	Applications for farmers that provide access to information and tools	Weather forecasting, inventory management, and task planning
E-commerce platforms	Online platforms for selling agricultural products	Direct sales to consumers, supply chain management
Chain	Distributed ledger technology for transparency and traceability	Traceability of product provenance and anti-counterfeiting

The researchers propose methods for improving the innovation management systems in the enterprises of the agro-industrial complex. In order to increase the efficiency of innovation implementation and improve management processes, one should turn not only to financing digital solutions but also to creating conditions for managing digitalization processes (Zinina and Tezina, 2016). The use of digital solutions can significantly improve the efficiency of agro-industrial processes, reduce gaps in access to information and resources, and improve interaction between participants in the agri-food chain. It is proposed to highlight the impact of digital solutions on intellectual capital in agribusiness (Table 4).

Table 4. Impact of digital solutions on intellectual capital in agribusiness

Digital technology	**Human capital**	**Structural capital**	**Relational capital**
Big data	Employee development	Improving data-driven decision-making	Strengthening partnerships through data exchange
Automation	Reducing physical workload	Improving process efficiency	Increasing productivity
Geographic information systems (GIS)	Technology training	Optimizing land use	Access to spatial data
Drones	Operator training	Field monitoring and management	Improving communication with service providers
Internet of Things (IoT) service providers	Improving technical literacy	Monitoring real-time conditions	Exchanging data between devices
Artificial intelligence (AI)	Training in new methods of analysis	Forecasting and optimization	Improving customer interaction
Robotics	Training in working with robotic systems	Automating routine tasks	Improving logistics links

These digital solutions and components of intellectual capital form the basis for improving the efficiency and sustainability of agricultural enterprises. At the beginning of the 21st century, it was noted that digital solutions and other intelligent aspects of farm management should be integrated in agriculture. In practice, this contributes to the development of small food enterprises. It is noted that various aspects of management, including organizational culture and access to technology, directly affect the implementation of innovations in small firms (Avermaete et al., 2003). To analyse the effectiveness of intellectual capital in agribusiness, it is acceptable to use econometric methods that take into account economic and technological factors that affect the productivity and sustainability of agribusiness entities. Based on digital solutions, it becomes possible to form networks of interaction between various participants in the agro-industrial sector to assess their impact on the operational, financial, and social indicators of enterprises (Asatryan et al., 2022; Rey et al., 2023).

3. Materials and Methods

Data from the statistical portals of Armenia and Georgia were used for the study. A total of 137 observations were collected, including a number of variables that affect crop yields (Table 5).

Table 5. Selected indicators for modelling

Variable	Description	Unit of measurement
Months	Observation period	Months
Crop_Yield	Yield	Currency/hectare
Precipitation	Precipitation	Millimetres
Soil_Type	Soil type	1, 2, 3
Fertilizer_Use	Fertilizer usage	Fraction (0–1)
Seed_Fertilizer_Cost	Cost of seeds and fertilizers	Currency
Market_Prices	Market prices for products	Currency
Education_Level	Level of education of employees	1, 2, 3
Demand	Demand for products	Index
Competition	Market competition	Share (0–1)
Farm_Workers	Number of agricultural workers	People
Automation_Level	Automation level	Share (0–1)
GIS_Usage	Usage of geographic information systems	Share (0–1)
Big_Data_Access	Access to big data	Share Data (0–1)
Training_Hours	Employee training hours	Hours

The selected variables allow us to assess the impact of various factors on crop yields and analyse the relationship between digital solutions, intellectual capital, and agribusiness sustainability.

3.1 Modelling

To achieve the goal of the study, predictive models were used that have unique characteristics and methods of data analysis (Table 6).

3.1.1 Random Forest

The random forest model is an ensemble machine learning method that uses multiple decision trees for predictions. Each tree is trained on a random subsample of data, and the final result is obtained by averaging the predictions of all trees.

Advantages:

- Resistance to overfitting

- Ability to work with a large number of attributes

- High accuracy of predictions

3.1.2 ARIMA

The ARIMA model is used for time series analysis and forecasting. It combines autoregression, integration, and moving average, which allows one to model data based on seasonal and time dependencies.

Advantages:

- Designed for time series analysis

- Takes into account seasonal fluctuations

3.1.3 SARIMA

The SARIMA model is an extension of the ARIMA model and includes additional parameters for analysing time series with a particularly pronounced seasonal component.

Advantages:

- Accounts for seasonal changes

- Suitable for data with strong seasonality

3.1.4 LSTM

The LSTM model is a type of recurrent neural network designed to work with sequential data and time series. LSTM is able to store long-term dependencies in data due to its memory cell architecture.

Advantages:

- Accounts for long-term dependencies

- High accuracy of predictions for time series

- Resistance to the problem of vanishing gradients

Table 6. Comparison of predictive models

Model	**Advantages**	**Disadvantages**	**Application examples**
Random Forest	High accuracy, resistance to overfitting	Lots of computing resources, complexity of interpretation	Yield factor analysis
ARIMA	Suitable for time series, seasonality	Limited application with non-linear dependencies	Demand forecasting
SARIMA	Accounting for seasonal changes	Difficulty in setting parameters	Yield forecasting with seasonality
LSTM	Accounting for long-term dependencies, high accuracy	Long learning time, the need for big data	Time series forecasting

The models selected for data analysis allow us to take into account and model complex relationships between variables that affect the yield of agribusiness. Their use allows us to make predictions with increased accuracy, which is the basis for making informed decisions.

4. Results and Discussion

4.1 Results of Predictive Models

4.1.1. Random Forest

The random forest model showed good results:

- Root mean square error (RMSE): 828.23

- Mean absolute error (MAE): 24.87

This model effectively takes into account many factors (Figure 1) that affect yield and can be useful for analysing the relationships between variables. The constructed model takes into account parameters for hyperparametric modelling, which allows initializing the random forest model and searching for the best parameters using GridSearchCV.

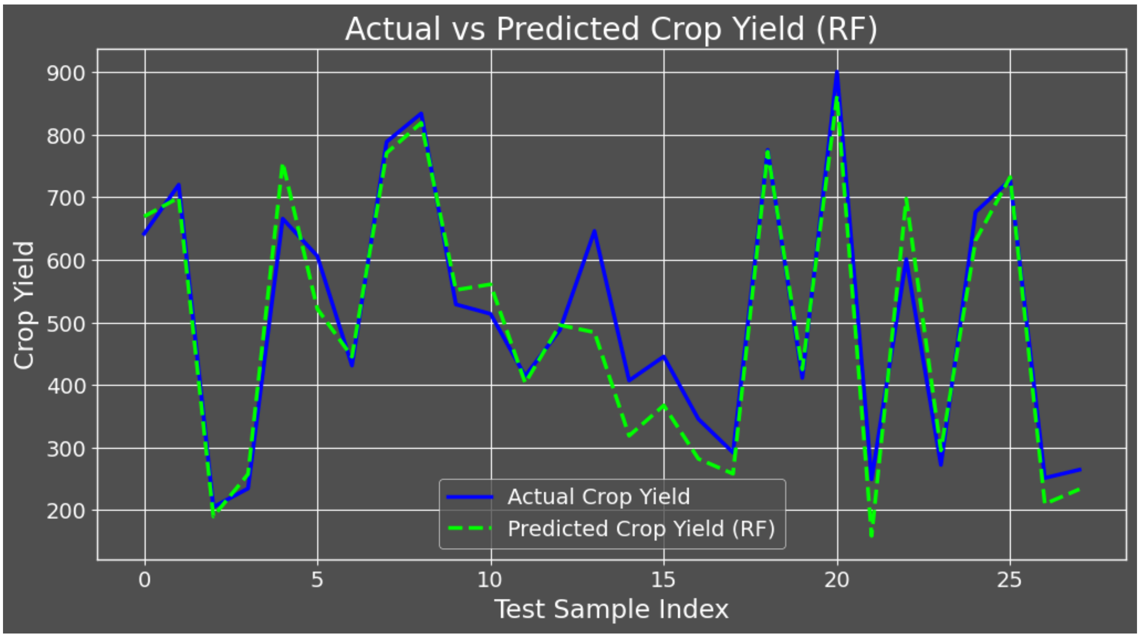

Figure 1. Random forest results

4.1.2. ARIMA

The ARIMA model did not show significant results:

- Root mean square error (MSE): 7810.76

- Mean absolute error (MAE): 80.94

This model did not allow us to identify significant results, which may be due to the high complexity and non-linearity of factors affecting yield (Figure 2).

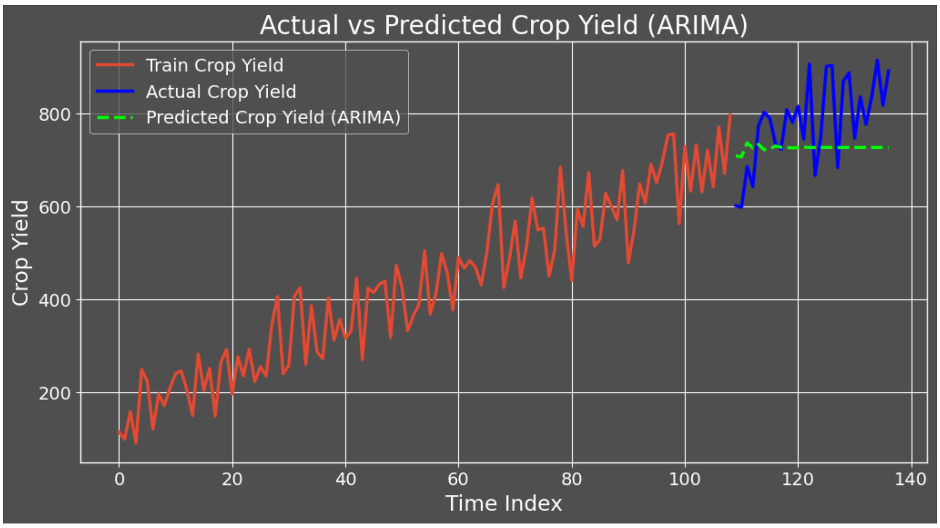

Figure 2. ARIMA results

4.1.3. SARIMA

The SARIMA model also did not show strong results:

- Root mean square error (MSE): 3126.34

- Mean absolute error (MAE): 46.19

This model, despite taking into account seasonal fluctuations, could not take into account all the factors affecting the yield (Figure 3).

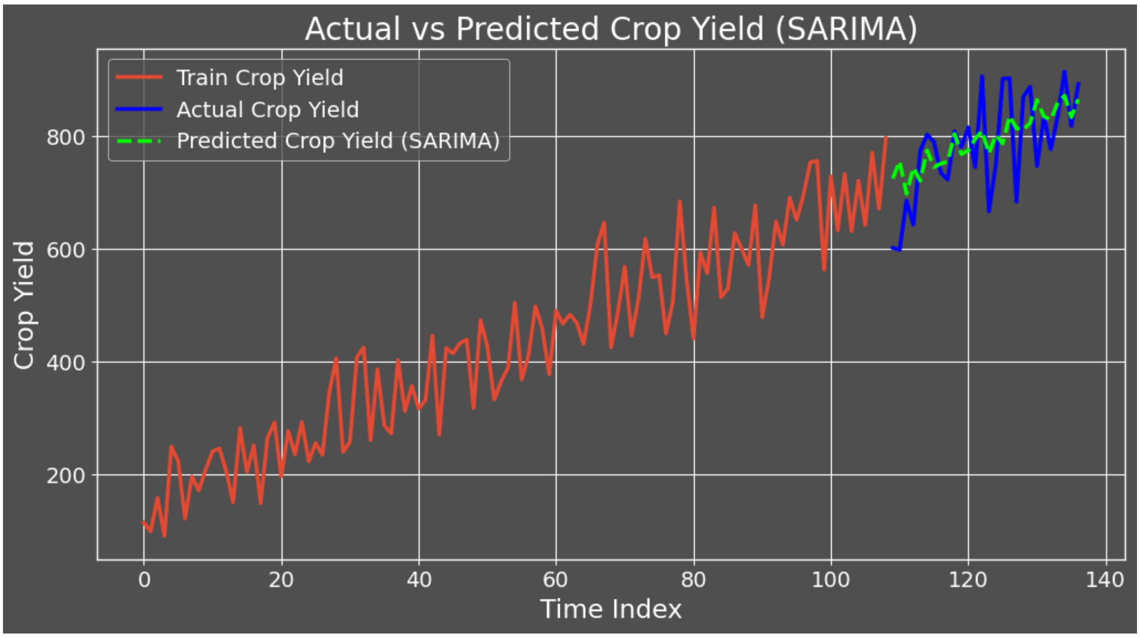

Figure 3. SARIMA results

4.1.4. LSTM

The LSTM model demonstrated high accuracy:

- Root mean square error (MSE): 102.47

- Mean absolute error (MAE): 8.30

This model showed the best results among all the models considered, as it was able to take into account long-term dependencies and nonlinear relationships between variables, taking into account the scaling inversion for the predicted values (Figure 4).

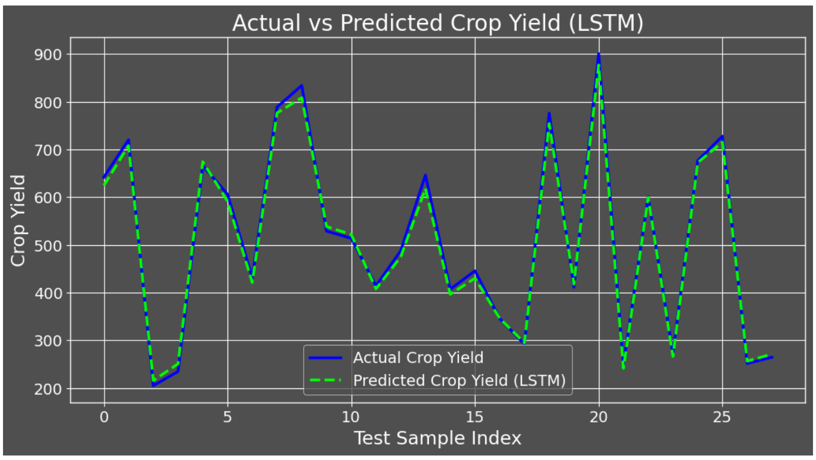

Figure 4. *LSTM results*

5. Discussion

5.1. Model Comparison

The results show that the LSTM model is the most effective for predicting yield revenues of agribusiness enterprises. The ability of the model to process sequential data and take into account complex time dependencies makes it important for conducting research in this area.

Mean absolute error (MAE) and mean square error (MSE) metrics were used to evaluate the predictions of various models. The results showed that the models have different degrees of accuracy in predicting yield (Table 7).

Table 7. Estimation of model accuracy

Model	MAE	MSE
Random forest	24.87	828.23
ARIMA	80.94	7810.76
SARIMA	46.19	3126.34
LSTM	8.30	102.47

The LSTM model showed the best results in comparison with other models, as it has low average absolute error and root mean square error, which indicates the reliability of this model in predicting the yield of agribusiness enterprises—that is, the efficiency of companies' activities. The random forest model showed good results but lost out to LSTM in terms of accuracy. ARIMA and SARIMA were not able to adequately cope with the task of predicting yield in this study.

5.2 Impact of Factors on Yield

Analysis of the significance of various factors affecting yield showed that the following factors have the most significant impact:

- A high level of automation leads to an increase in the efficiency of operations at agribusiness enterprises, which has a positive effect on yields

- Using big data for analysis and decision-making allows us to more accurately predict and optimize processes

- High-quality training of employees contributes to improving their skills, which, in turn, improves the results of their work

Figure 5 shows a graph of Shapley Additive Explanations values that reflects the impact of factors on the yield prediction model. SHAP values show how much each feature affects the model output.

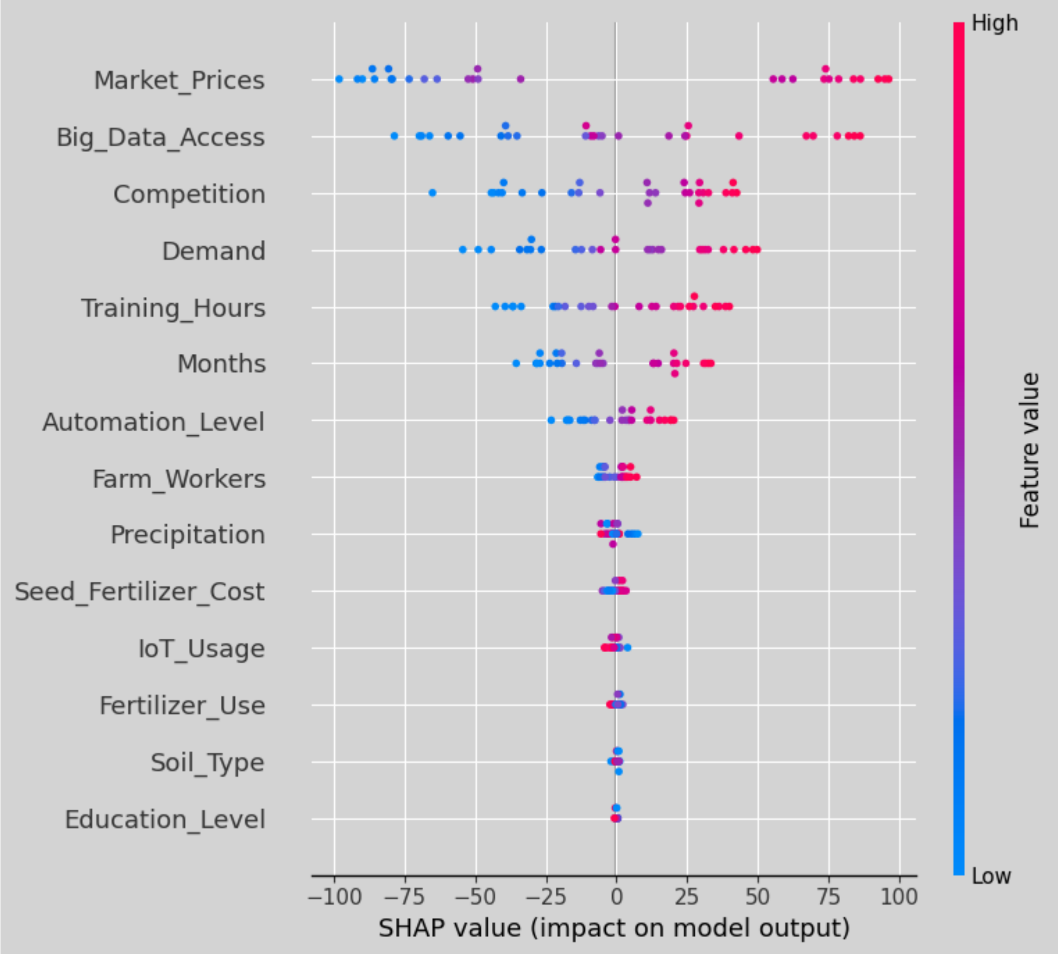

Figure 5. SHapley Additive exPlanations (SHAP) results

Key observations:

- Market_Prices – the impact of market prices on the yield prediction model is very positive, especially for high values of market prices (red dots).

- Big_Data_Access – Access to big data has a positive impact on model prediction, which highlights the importance of information and data in crop management.

- Competition and Demand factors have different effects on the model, which indicates a complex interaction between market conditions and the performance of agricultural enterprises.

- Training_Hours – Employee training hours have a positive impact on model prediction, which confirms the importance of human capital.

- Automation_Level – A high level of automation has a positive effect on the model's predictions, indicating the importance of technological equipment.

- Precipitation – precipitation show mixed effects, which may depend on specific climatic conditions and their impact on the crop.

- Education_Level – This has the least impact on the model's predictions.

- The SHAP value graph allows us to quantify the impact of various factors on the yield prediction model. Figure 6 shows a graph of the significance of traits that reflects the influence of the various factors on crop prediction. The graph shows the relative significance of each factor in the model used for analysis.

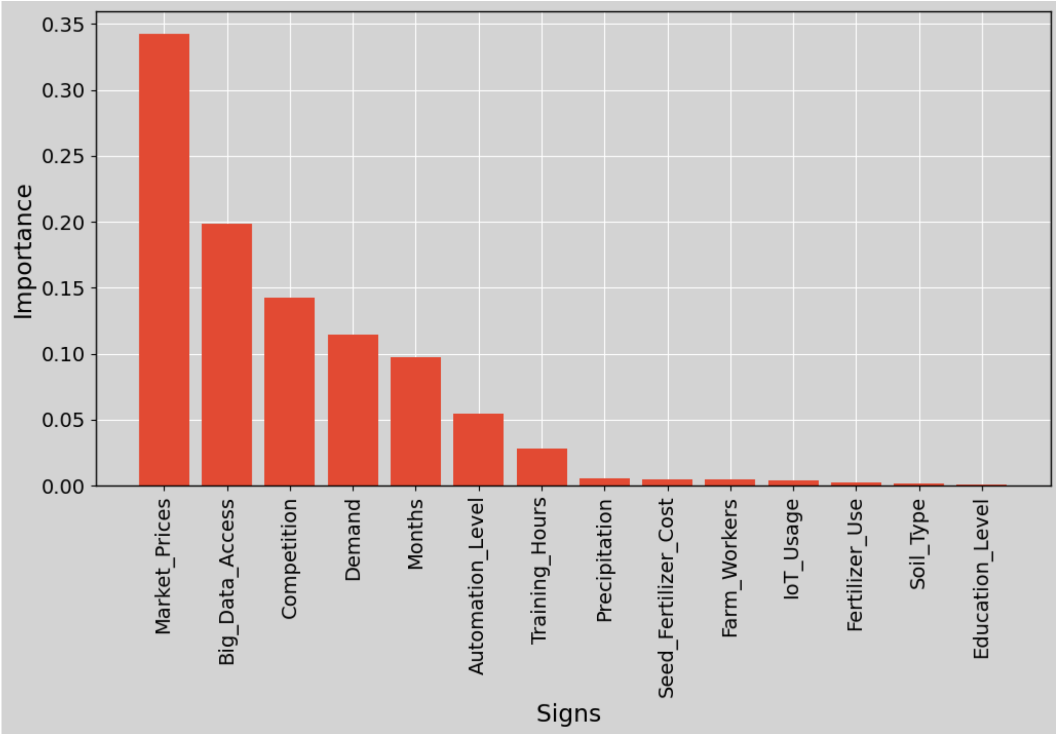

Figure 6. Feature significance graph

Key observations:

- Market_Prices has the highest significance (about 0.35).

- Big_Data_Access is the second most important factor (about 0.2020).

- Competition and Demand factors affect the model with high significance (about 0.15 and 0.12, respectively).

- Months and Automation_Level have a moderate impact, emphasizing the importance of seasonal changes and the level of automation in the production process.

- Training_Hours has a noticeable impact.

- Anticipation has some influence on the prediction of the model.

- The Seed_Fertilizer_Cost, Farm_Workers, IoT_Usage, Fertilizer_Use, Soil_Type, Education_Level factors are less significant than other factors but still contribute to the model.

6. Conclusion

The results of the study highlight the importance of intellectual capital in agribusiness. The level of education of employees and their training have a direct impact on the efficiency of using digital technologies and, consequently, on productivity. The integration of innovative technologies, such as big data and automation, helps to increase crop yields and improve the sustainability of agricultural production. Digital technologies contribute to the sustainable development of agribusiness. The use of big data allows agribusinesses to analyse information for decision-making, which helps optimize processes and reduce costs. Automation allows us to increase the efficiency of agricultural operations, reducing the impact of the human factor and increasing productivity.

The study showed that the use of LSTM models for predicting yield gains is the most appropriate (compared to the random forest, ARIMA, and SARIMA models). Significant correlations were found between digital solutions (level of automation, access to big data) and productivity. Thus, it is possible to develop some recommendations for agribusiness enterprises:

1. Strengthen training and professional development of agricultural workers to improve the efficiency of digital technologies use.

2. Implement and use big data to analyse and make informed decisions in agricultural production.

3. Increase the level of process automation to improve operational efficiency.

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SECTION 3

SUSTAINABLE DEVELOPMENT OF REGIONAL INFRASTRUCTURE

РАЗДЕЛ 3

УСТОЙЧИВОЕ РАЗВИТИЕ РЕГИОНАЛЬНОЙ ИНФРАСТРУКТУРЫ

Research article

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The Sustainability of China's Economic Growth in an Era of Global Turbulence

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Abstract

This article analyses the sustainability of China's economic growth in light of global challenges, focusing on macroeconomic changes in recent decades and their impact on the country's economy. The study covers the period 1962–2022 and uses data from various sources, including the World Bank, International Monetary Fund, Organisation for Economic Cooperation and Development, and national statistical data from the People's Republic of China. Correlation analysis methods are used to assess the impact of socio-economic indicators on economic growth, revealing significant correlations between gross domestic product and various indicators such as external debt, urbanisation, technological development, and the standard of living. The main conclusion of the analysis is that economic diversification and investment in high-tech industries are crucial for maintaining sustainable growth in China. The findings indicate the need for future research assessing the potential for reducing the environmental impact of industrialisation and improving social policies in a changing global economy.

Keywords: economic growth, macroeconomic changes, global challenges, turbulence, sustainability, correlation analysis, industrialisation, diversification, high-tech industries

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Устойчивость Экономического Роста Китая в Эпоху Глобальной Турбулентности

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Аннотация

Настоящая статья анализирует устойчивость экономического роста Китая в контексте глобальных вызовов, акцентируя внимание на макроэкономических изменениях последних десятилетий и их воздействии на экономику страны. Исследование охватывает период с 1962 по 2022 год. В статье анализируются данные Всемирного банка, МВФ, ОЭСР, а также национальных статистических данных КНР. Применены методы корреляционного анализа для оценки влияния социально-экономических показателей на экономический рост. Выявлены значимые корреляции между ВВП и такими показателями, как объем внешнего долга, уровень урбанизации, технологическое развитие и уровень жизни населения, а также с показателями внешней торговли и инвестиций. Подтверждено, что диверсификация экономики и инвестиции в высокотехнологичные отрасли имеют ключевое значение для поддержания устойчивого экономического роста. В заключении исследования подчеркивается необходимость дальнейших исследований для оценки потенциала снижения экологического воздействия индустриализации и улучшение социальной политики в условиях меняющейся глобальной экономической среды.

Ключевые слова: экономический рост, макроэкономические изменения, глобальные вызовы, турбулентность, устойчивость, корреляционный анализ, индустриализация, диверсификация, высокотехнологичные отрасли

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1. Introduction

This study of economic growth and development aims to analyse the stability and sustainability of a country's economic system. This involves examining the quantitative changes in an economy, such as an increase in the production and consumption of goods and services, which are measured by gross domestic product (GDP). Economic growth is based on the dynamics of GDP, as described by Chow and Li (2002) and Jones and Hameiri (2022). In the past half-century, China has shown exceptional economic growth, becoming the world's largest economy in terms of GDP at purchasing power parity (PPP), with more than 33 trillion USD in 2023. Such growth was stimulated by government investments in industry, accounting for about 40% of the country's GDP between 2000 and 2010. This was supported by active export activities and the strategic development of high-tech industries and infrastructure. However, since the 2010s, the global economy has faced new challenges, including financial crises, political upheavals, and pandemics. These have led to questions about the sustainability of China's economic growth (Carmody, Zajontz, and Reboredo, 2022; Repnikova, 2022).

The relevance of this research stems from the rapidly changing economic, social, and technological landscape of the global economy, particularly in light of technological advancements and geopolitical uncertainty. The onset of a period of global turbulence has necessitated adjustments to economic policies and strategies for many countries, including China, which is actively involved in international affairs and is a key player in global affairs. Despite China's significant influence, achieving sustainable economic growth in the country would require reviewing existing economic models and accounting for the trends towards a multipolar world order.

The purpose of this paper is to analyse the sustainability of China's economic growth, considering economic and political challenges, as well as macroeconomic factors modulating these challenges. We aim to understand the impact of global economic turbulence on the Chinese economy, and to identify the main factors that influence China's growth. Our study focuses on the Chinese economic system, including its various components, such as industrial production, agriculture, services, foreign trade, domestic consumption, investment, and public administration. We examine the factors and conditions that contribute to the sustainability of China's economic development.

2. Materials and Methods

2.1. Historical background

Since the establishment of the People's Republic of China in 1949, the country has been moving towards the implementation of socialist principles. This has led to intense socio-economic experimentation and significant fluctuations in its development, with periods of prosperity followed by a decline. During the "Great Leap Forward" period, China set ambitious goals to become a leading economy in a short period of time, but an ill-conceived policy led to an economic crisis. Similarly, the "Great Proletarian Cultural Revolution" caused dysfunction in the party-state apparatus, as described by Tanner (1999) and Heilmann (2008).

The deep economic crisis after the "Cultural Revolution" forced the Chinese government to search for ways to restore economic stability. Consequently, the government implemented effective measures to revive the country's economy. In 1979, a comprehensive economic reform plan was developed with the aim of achieving three main objectives: modernising and accelerating economic growth, expanding international relations, and maintaining political stability. Priority was given to accelerating economic development, focusing on expanding production capacity, strengthening national strength, and improving the living standards of citizens (Wu, 2005; Young, 1995).

The influential British historian Arnold Toynbee expressed the opinion that China could offer the world a "gift" that combined Western dynamism and traditional Chinese stability (Toynbee, 1934). These words proved to be prescient, particularly after Deng Xiaoping, the architect of modern China's economic reforms, formulated the phrase, "It doesn't matter what color a cat is, as long as it catches mice" (Blue, 2000). Regarding Deng's economic policies, it is clear that his desire for a practical and effective approach to economic management led China to succeed in the international arena. This allowed the country to become a leading global producer and exporter (Shirk, 1994).

According to Marxist-Leninist theory, there is a close relationship between the economic base and superstructure, such that changes in the former inevitably lead to alterations in the latter. In this regard, China has developed a unique economic system that has been recognised internationally as "reformed socialism" and domestically as a "middle way". This system integrates certain aspects of capitalist and socialist systems to overcome stagnation and stimulate economic growth (Zweig, 2002; Roland, 2000). During the modernisation process, emphasis has been placed on accelerating economic development while assessing whether activities are in line with socialist ideals based on three key criteria: their ability to promote the development of productive forces, increase national strength, and improve the standard of living for the population (Naughton, 2007; Wu, 2005).

China's reform programme was founded on three core principles: attracting investment, promoting exports, and utilising low-cost labour. Other aspects of the reform efforts included large-scale imports of technology, significant investments in the economy, active government involvement in economic activities, the establishment of special economic zones, and the preservation of a single-party system, which contributed to stability within the country (Ding and Tay, 2016).

The slowdown in China's economic growth may be attributed to the transition from a deficit-focused economy to one with excess production. The country has shifted away from the strategy of extensive and extensive production towards a new model focused on the quality and efficiency of economic development. This transition is accompanied by large-scale economic reform efforts aimed at reducing reliance on exports and investments. Under the "quality" growth model, the primary indicator is not simply an increase in GDP but rather the level of employment among the population (Tian, 2019; Doshi, 2021).

China's current economic transition is a structural transformation, with an industrial-oriented model giving way to a consumer-oriented model based on the growth of the service sector. In this context, a slowdown in GDP growth is not only unavoidable but also beneficial, as it represents a transition to more sustainable and balanced forms of economic growth (Balogh, 2017; Xiao et al., 2022). Table 1 presents a systematic overview of the key historical and economic events that have shaped China's strategic trajectory.

Table 1. Key historical or economic milestones

Year	Event	Economic Policy	Impact on Economy	Global Influence
1949	Establishment of the PRC	Land reform	Redistribution of land, increased agricultural output	Start of shift towards socialism
1958	Great leap forward	Collective farming	Economic downturn due to failed policies	Caused global concern regarding famine
1966	Cultural revolution	Political purge	Disruption of economy, decline in education and industry	Intensified isolation from the West
1978	Economic reforms initiated	Opening up and reform	Rapid industrial growth, improvement in living standards	Increased foreign investment and trade
1990s	World Trade Organization membership preparations	Trade liberalisation	Expansion in manufacturing and exports	Strengthened global economic presence
2001	Entry into the WTO	Market opening policies	Boost in trade, access to international markets	Positioned as a major global trader

2010s	Belt and Road Initiative	Infrastructure investment	Enhanced connectivity and influence in Asia, Africa	Extended China’s geopolitical influence
2020s	Dual circulation strategy	Focus on domestic market	Aims to reduce dependency on foreign markets	Strategic shift in response to global tensions

2.2. Economic growth in the context of worldwide tendencies

China’s economic performance stands out against the backdrop of global trends. Since the initiation of reforms in the 1970s based on the principles of market socialism, China has exhibited one of the most significant growth rates in the world. The degree of integration of the Chinese economy into international processes is unparalleled among most countries. This process was founded on a policy of openness and the attraction of foreign investment. Exports serve as the foundation for attracting the funds necessary for economic growth and modernisation, particularly in industries (Kaplan, 2021).

In 2001, China’s accession to the World Trade Organization (WTO) significantly accelerated integration processes and opened access to new markets. China’s share of global exports of goods increased from 1.9% in 2001 to 13.8% by 2020, consolidating its status as a major global trading power. However, researchers have noted potential challenges associated with this process, such as the volatility of the global economy under the influence of factors, including military conflicts and pandemics, which can lead to economic instability and turbulence. This turbulence can have a direct impact on China’s economic growth, and to counteract these negative externalities, the Chinese government has implemented fiscal and monetary policies to compensate for potential losses. The correlation between public debt and economic cycles has been confirmed in practice (Yang et al., 2022), indicating the importance of these measures in maintaining stability and growth.

The progress of China’s economic growth over the past decade is closely linked to the gradual development of the service sector. This has led to a shift towards the domestic market, stimulated by active consumer and investment demand. According to researchers, the current position of net exports of goods and services is not a significant factor in growth. Further, an analysis of China’s GDP and foreign trade shows the resilience of the Chinese economy in response to fluctuations in trade volumes. It is reasonable to conclude that the export-driven development model has reached its limits. A new innovative development model will differ significantly from the approach of other industrialised countries, as it will be based on the large domestic market and internal growth factors in China. Innovation will replace export-oriented growth and capital accumulation as the primary drivers of economic growth. Current trends are aimed at promoting an intensive form of growth that will replace the extensive model. Factors such as domestic consumer demand, investment, and external exports will continue to contribute significantly to economic expansion (Potapov, 2023).

The increasing instability and turbulence within the context of global economic development and the disruption of previous trends in unipolar globalisation have led to the emergence of a new global economic order. Researchers have concluded that the focus of China’s economic strategy has shifted towards domestic demand and consumption, a trend that intensified following the global economic crisis between 2007 and 2009. The key components of China’s growth model include a low initial level of production, an extensive pool of labour resources in agriculture, foreign direct investment, efficient public administration, and the maintenance of control over key sectors of the economy, particularly the financial sector (Tenyakov and Amirkhanova, 2023).

In response to the environmental challenges posed by rapid urbanisation and industrialisation in China, the country has implemented a sustainable development strategy. This strategy has made technological innovation an essential tool for achieving economic growth. Investments in science and technology by the government have led to the development of new technologies, including those that support sustainable development. The current socio-economic development in China is linked to the goal of maintaining sustainability. Recent studies (Rudskaia et al., 2021; Cao et al., 2014; Qiu et al., 2020) have shown that innovative approaches to technology and sustainable development contribute to economic growth and help address the environmental challenges associated with rapid urbanisation and industrialisation.

Statistical data indicate that companies investing in green technologies enjoy significant economic benefits. For example, they experience a 15% increase in profitability and a 20% improvement in sustainability. This is due to increased demand for environmentally friendly products, reduced energy consumption costs, and compliance with environmental regulations. The active development of energy projects focusing on green energy helps reduce greenhouse gas emissions and creates new jobs, stimulating economic growth. New technologies allow for optimised production processes, increasing labour productivity and contributing to the sustainable growth and competitiveness of companies. As a result, the share of renewable energy in China's energy mix has increased from 20% in 2018 to 30% by 2023. China is transitioning from a high-growth model to a high-quality one, integrating sustainable practices into its economic, social, and environmental policies. This shift is leading to a reorientation of industry towards projects of a new quality, which aim to minimise negative impacts on the environment and society. Examples of such projects include the development of digital platforms for industry and digital infrastructure (Quan, 2018; Jia and Rodionov, 2022). The transition to high-quality growth requires technological innovation, but it also raises concerns about the risks associated with digitalisation and changes in production processes (Zaytsev et al., 2021; Feofilova et al., 2024).

Economic transformations have led to structural changes aimed at boosting domestic consumption and reducing reliance on exports, particularly in the technological sector. Policies to stimulate internal demand, improve working conditions, and increase wages have contributed to a rise in consumer spending. These developments are part of a broader restructuring of China's socio-economic system, driven by a new global economic landscape and the transition towards a model of high-quality growth (Lardy, 2019; Wang et al., 2015; Dmitriev et al., 2023). The new financial strategy has resulted in the adjustment of the economic model to better meet consumer demand. This has been largely driven by the re-examination of institutional aspects of economic security and the integration of sustainable development principles into these frameworks (Breslin, 2021).

Despite a significant amount of research on historical aspects and current trends in economic growth strategies in the context of global instability and the shift towards sustainability and the implementation of new strategies, there is still a need to develop new approaches and perspectives on development. An outdated understanding of economic models often prevents us from developing mechanisms to address threats to economic growth.

This study aims to address the gaps in the analysis of the sustainability of China's economic development. Table 2 presents the key events that have shaped the modern trajectory of the Chinese economy.

Table 2. The evolution of the Chinese economy in the context of global turbulence

Year	Key Events	Economic Reforms	Impact on World Economy	Statistical Indicators
1978	Beginning of Deng Xiaoping's reforms	Introduction of market mechanisms, opening up for foreign investment	Integration of China into the global economy	GDP increased by 10% over the decade, GDP per capita: USD 156
2001	Entry into the WTO	Further trade liberalisation	Strengthening of China's position in the global export market	Share of global goods exports increased from 1.9% in 2001 to 13.8% in 2020, GDP per capita: USD 1,042

2008	Global financial crisis	Stimulation of the domestic market	Stabilisation of global economic fluctuations by China	9% increase in domestic consumption, increase in government spending to stimulate the economy
2013	Announcement of the Belt and Road Initiative	Expansion of international economic influence	Strengthening of trade and infrastructure connections	Overseas infrastructure investments doubled, GDP per capita: USD 9,607
2020	Start of the COVID-19 pandemic	Enhancement of high technology and healthcare support	Acceleration of global digital transformation	GDP growth slowed but remained positive (2.3%), GDP per capita: USD 10,484
2022	Global uncertainty, increased trade tensions	Strengthening of innovative policies, support for the domestic market	Continued growth despite global challenges	GDP growth of 5%, GDP per capita: USD 12,556, increase in the share of domestic consumption in GDP structure

2.3. Methodological underpinnings of the analysis

To examine the sustainability of China's economic development in the face of global economic uncertainty, we conducted a correlational analysis of the association between economic expansion and key macroeconomic variables. Correlational analysis allows for the evaluation of the extent to which various economic, societal, and political transformations influence China's economic expansion. The analysis utilised the following methodologies and instruments:

- Software: Google Colaboratory.

- Programming language: Python.

- Data libraries: Pandas used for data processing, NumPy for numerical operations, and Matplotlib and Seaborn for data visualisation.

- Data sources: World Bank, International Monetary Fund, and OECD. National sources were also used: Chinese government publications, transcripts of speeches, development plans, and programs.

Stages of analysis:

1. Data were collected for the period 1962–2022 by importing them from the indicated sources. Table 3 shows the collected indicators for the key groups.

Table 3. Macroeconomic indicators by groups

Economic indicators	Social indicators	Environmental indicators	Demographic indicators	Financial indicators
Gross domestic product (GDP) (current US$)	Births attended by skilled health staff	CO2 emissions	Net migration	External debt stocks
GDP growth (annual %)	Contraceptive prevalence	Annual freshwater withdrawals	Population density	Net official development assistance
Gross national income (GNI) per capita, Atlas method (current US$)	Fertility rate	Forest area	Population growth	Poverty headcount ratio
GNI per capita, PPP (current international $)	Immunisation, measles	Surface area	Urban population growth	Income share held by lowest 20%

Agriculture, forestry, and fishing, value added	Life expectancy at birth			Personal remittances
Gross capital formation	Mortality rate, under 5			
Electric power consumption	Net migration			
Energy use	Personal remittances			
Exports of goods and services	Population density			
Imports of goods and services	Population growth			
Gross national income	Poverty headcount ratio			
Foreign direct investment	Prevalence of underweight			
High-technology exports	Primary completion rate			
Industry, value added	School enrolment (primary, secondary)			
Revenue, excluding grants	Urban population growth			
Tax revenue	Terrestrial and marine protected areas			
Total debt service (% of exports)	Time required to start a business			
Gross capital formation	Statistical Capacity Score			

2. Correlation analysis. The use of statistical techniques to determine the association between macroeconomic variables and economic growth is referred to as correlation analysis. Specifically, the Pearson correlation coefficient (Equation 1) was employed to assess the strength and direction of the relationship between economic expansion and key macroeconomic factors. Before calculating the correlation coefficient, the data were cleaned and processed to eliminate errors, omissions, and anomalies. This involved applying linear interpolation to fill in missing values (Equation 2). The calculations were performed using Python programming language and the Pandas library.

$$r = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - \left(\sum y\right)^2\right]}}, \tag{1}$$

$$y = y_1 + \frac{\left(x - x_1\right)\left(y_2 - y_1\right)}{\left(x_2 - x_1\right)}, \tag{2}$$

where r is the correlation coefficient, n is the number of observations, x и y are the variables, and x_1, x_2, y_1 and y_2 are the data points for interpolation.

3. Interpretation of the results: Evaluation of the data obtained within the context of recent (2000-2022) and past (1964-2022) economic circumstances in China.

The findings of this study are expected to assist in identifying the correlation between macroeconomic variables and China's economic expansion, as well as in determining which factors have the most significant impact.

3. Results and Discussion

3.1 Correlation of economic indicators: 1962–2022

The correlation analysis was conducted for the period 1962–2022, with an emphasis on such important economic indicators as GDP (current US$), GDP growth (annual %), GNI per capital, Atlas method (current US$), and gross national income (GNI) per capital (PPP) (current international $). The correlation results are presented in Table 4.

Table 4. Correlation coefficients for individual indicators (1962–2022)

Indicator (1962–2022)	GDP (current US$)	GDP growth (annual %)	GNI per capita, Atlas method (current US$)	GNI per capita, PPP (current international $)
Agriculture, forestry, and fishing, value added	-0.730	-0.155	-0.732	-0.841
Annual freshwater withdrawals	0.704	-0.215	0.702	0.768
Births attended by skilled health staff	0.645	-0.562	0.644	0.700
CO2 emissions	0.923	-0.461	0.921	0.951
Contraceptive prevalence	-0.508	0.154	-0.506	-0.521
Electric power consumption	0.939	-0.155	0.938	0.953
Energy use	0.919	-0.115	0.918	0.937
Exports of goods and services	0.493	0.199	0.484	0.114
External debt stocks	0.991	-0.534	0.990	0.973
Fertility rate	-0.466	-0.094	-0.462	-0.430
Foreign direct investment	0.870	-0.296	0.861	0.861
Forest area	0.930	-0.501	0.929	0.961
GNI, Atlas method (current US$)	0.999	-0.178	1.000	0.991
GNI, PPP (current international $)	0.993	-0.589	0.994	1.000
Gross capital formation	0.620	0.307	0.632	0.693
High-technology exports	-0.416	0.362	-0.426	-0.489
Immunisation, measles	0.699	-0.467	0.697	0.789
Imports of goods and services	0.507	0.215	0.499	0.158
Income share held by lowest 20%	-0.099	-0.103	-0.094	-0.203
Industry, value added	-0.108	0.416	-0.135	-0.681
Life expectancy at birth	0.625	0.305	0.691	0.926
Mobile cellular subscriptions	0.985	-0.056	0.985	0.988
Mortality rate, under 5	-0.725	0.146	-0.727	-0.907
Net migration	0.067	-0.191	0.078	0.765
Net official development assistance	-0.742	0.487	-0.742	-0.893
Personal remittances	0.919	-0.502	0.921	0.901
Population density	0.685	0.207	0.691	0.922

Population growth	-0.578	0.285	-0.654	-0.836
Poverty headcount ratio ($2.15/ day)	-0.858	0.422	-0.857	-0.902
Poverty headcount ratio (national poverty line)	-0.928	0.578	-0.927	-0.940
Prevalence of underweight	-0.726	0.345	-0.724	-0.814
Primary completion rate	0.654	-0.643	0.651	0.749
Revenue, excluding grants	0.629	-0.398	0.637	0.609
School enrolment, primary (% gross)	-0.721	0.285	-0.721	-0.906
School enrolment, primary and secondary (% gross)	0.718	-0.139	0.716	0.793
School enrolment, secondary (% gross)	0.842	-0.283	0.840	0.898
Statistical Capacity Score	0.921	-0.821	0.926	0.903
Surface area	-0.752	-0.059	-0.750	-0.689
Tax revenue	-0.625	0.486	-0.637	-0.633
Terrestrial and marine protected areas	-0.485	0.149	-0.439	-0.424
Time required to start a business	-0.888	0.511	-0.888	-0.866
Total debt service (% of exports)	-0.288	-0.201	-0.283	-0.319
Urban population growth	-0.378	0.305	-0.393	-0.982

The purpose of this analysis is to determine the strength and direction of the relationships between economic growth indicators and various socio–economic factors over the entire observation period. It is worth noting that this type of analysis corresponds to most studies that include historical indicators in the analysis without separating modern economic policy from the previous one. To identify the most significant dependencies between the indicators, a selection of links with a correlation above 0.75 or below -0.75 was carried out.

A. GDP (current US$). The dynamics of the indicator are shown in Figure 1.

A1. High correlation (over 75%) with:

• Electric power consumption (kWh per capita) (0.938677)

• Energy use (kg of oil equivalent per capita) (0.918928)

• External debt stocks, total (DOD, current US$) (0.991004)

• Forest area (sq. km) (0.929715)

• Mobile cellular subscriptions (per 100 people) (0.985241)

• Personal remittances, received (current US$) (0.919482)

• Statistical Capacity Score (Overall Average) (scale 0 - 100) (0.921255)

A2. Low correlation (less than 75%) with:

• Poverty headcount ratio at $2.15 a day (2017 PPP) (% of population) (-0.857860)

• Poverty headcount ratio at national poverty lines (% of population) (-0.927616)

• Time required to start a business (days) (-0.888415)

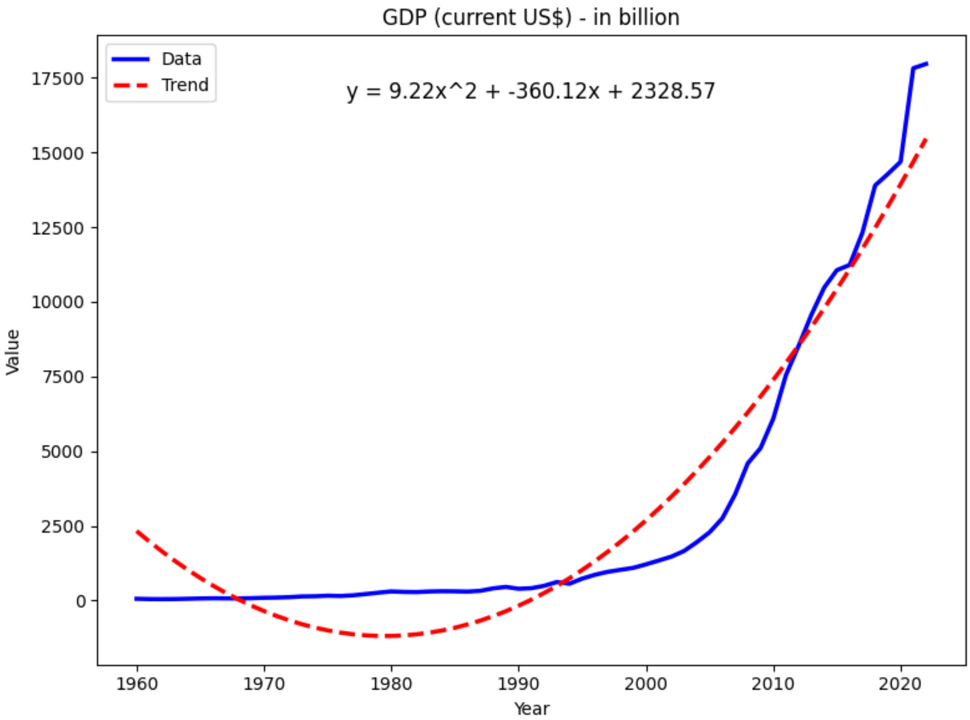

Figure 1. GDP dynamics (current US$) and trend (polynomial)

B. GDP growth (annual %). The dynamics of the indicator are shown in Figure 2.

B1. High correlation (over 75%) with:

• Foreign direct investment, net inflows (0.870089)

B2. Low correlation (less than 75%) with:

• GNI per capita, Atlas method (current US$) (-0.174645)

• GNI per capita, PPP (current international $) (-0.582831)

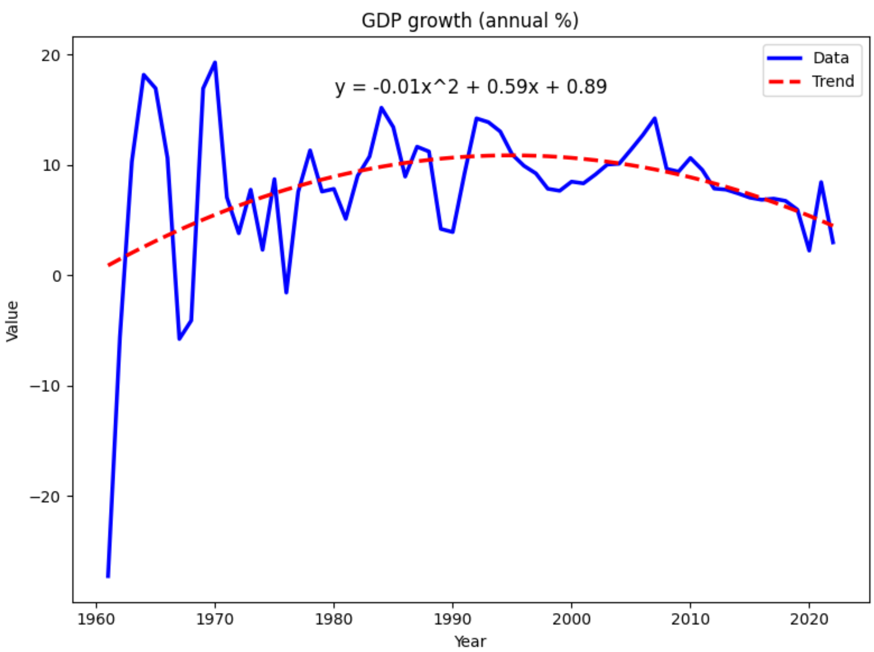

Figure 2. GDP growth (annual %) and trend (polynomial)

C. GNI per capita, Atlas method (current US$). The dynamics of the indicator are shown in Figure 3.

C1. High correlation (over 75%) with:

• GDP (current US$) (0.999424)

• GNI, Atlas method (current US$) (0.999266)

• GNI, PPP (current international $) (0.993947)

• Mobile cellular subscriptions (per 100 people) (0.985235)

• Personal remittances, received (current US$) (0.920836)

• Population (people per sq. km of land area) (0.691338)

• Population, total (0.681870)

• Statistical Capacity Score (Overall Average) (scale 0 - 100) (0.925953)

C2. Low correlation (less than 75%) with:

• Poverty headcount ratio at $2.15 a day (2017 PPP) (% of population) (-0.857482)

• Poverty headcount ratio at national poverty lines (% of population) (-0.927488)

• Urban population growth (annual %) (-0.982482)

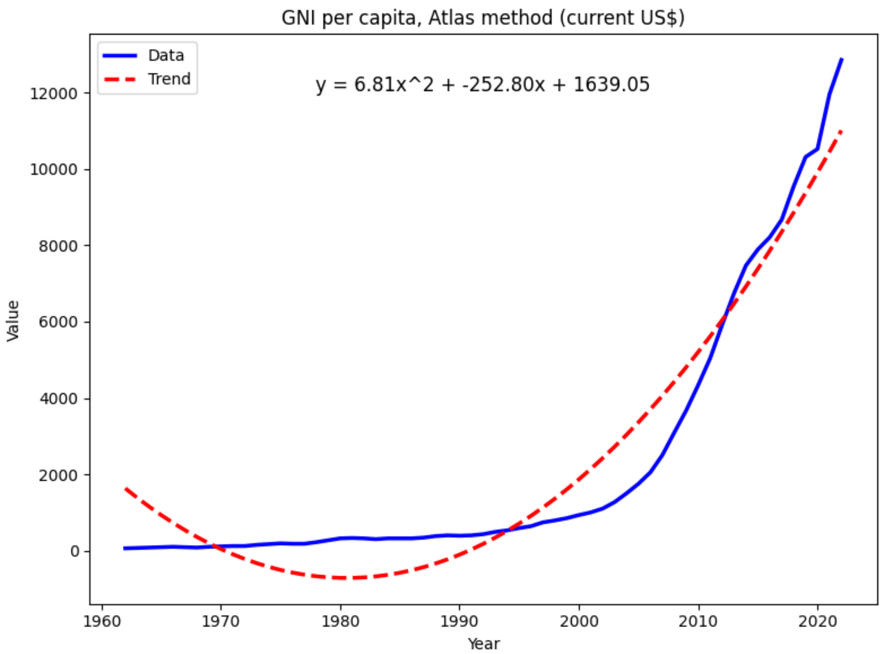

Figure 3. GNI per capita, Atlas method (current US$), and trend (polynomial)

D. GNI per capita, PPP (current international US$). The dynamics of the indicator are shown in Figure 4.

D1. High correlation (over 75%) with:

• GDP (current US$) (0.992190)

• GNI, Atlas method (current US$) (0.990669)

• GNI, PPP (current international $) (0.999777)

• Mobile cellular subscriptions (per 100 people) (0.987961)

• Personal remittances, received (current US$) (0.900863)

• Population density (people per sq. km of land area) (0.922084)

• Population, total (0.922016)

• Statistical Capacity Score (Overall Average) (scale 0 - 100) (0.902675)

D2. Low correlation (less than 75%) with:

• Poverty headcount ratio at $2.15 a day (2017 PPP) (% of population) (-0.902480)

• Poverty headcount ratio at national poverty lines (% of population) (-0.940119)

• Urban population growth (annual %) (-0.982482)

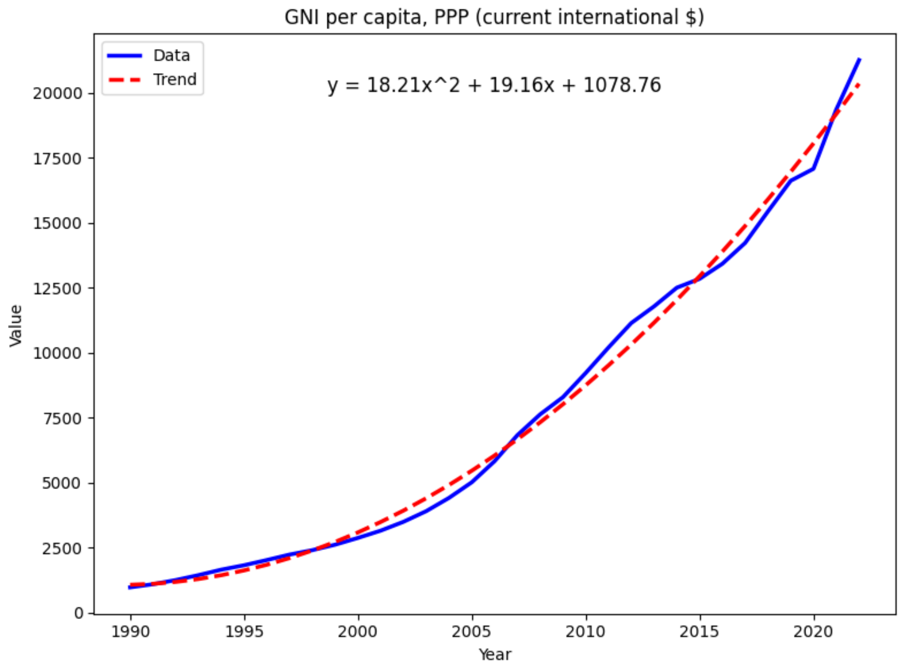

Figure 4. GNI per capita, PPP (current international US$), and trend (polynomial)

Based on the high correlations and their interpretations, several conclusions can be drawn regarding the Chinese economy during the period 1962–2022.

1. Relationship between GDP, energy consumption, and external debt: The strong correlation between GDP and electricity consumption per capita, as well as with external debt, suggests that the energy sector and borrowing play a significant role in China's economic growth. This reflects the country's industrialisation, infrastructure development, and reliance on external financing to support its economy.

2. Importance of mobile communications and personal money transfers: The strong correlation between GDP and mobile phone subscriptions per capita, as well as personal money transfers, highlights the need for continued technological development and international financial integration for China's economic growth. This reflects a high level of digitalisation and involvement in global financial transactions. However, it also makes the country more vulnerable to threats to macroeconomic stability.

3. Strong connection between GNI and GDP: A strong relationship between GNI and GDP indicates that China's economic expansion is accompanied by rising per capita income. This suggests an increase in the prosperity and standard of living of the population.

4. Falling poverty and population growth: The low correlation between poverty and GDP indicates

that China's economic growth has been accompanied by a reduction in poverty. However, population growth has put pressure on the country's social infrastructure and resources.

5. External debt: The high correlation between external debt and GDP highlights the significant dependence of China's economy on external financing sources, emphasising the importance of effectively managing external debt and ensuring sustainable external financial flows for economic growth.

6. Technology and industry: The strong correlation between GDP and technological innovation in exports shows the success of China's technological development and the creation of a strong scientific and industrial foundation, which has contributed to export opportunities and created a competitive advantage in the global marketplace.

7. Stability and risk management: The low correlation between the labour cost index and GDP indicates potential risks in employment and instability in the labour market. This requires attention from the government to ensure the sustainability of the economy and social justice.

8. Environmental sustainability: The high correlation between forest area and GDP emphasises the importance of natural resource management and environmental protection for economic development. This also highlights the significance of environmentally sustainable practices in industry and agriculture.

9. International cooperation and investment: A significant correlation between FDI and GDP highlights the importance of international cooperation in attracting foreign investment. This can stimulate economic growth and help modernise industries.

The findings highlight the diverse aspects of China's economic growth and the need for a comprehensive approach to managing the economy. This approach should take into account various factors, such as technological innovation, social well-being, environmental protection, and international relations. It is also important to note that correlation cannot fully explain economic growth. Therefore, it is necessary to develop more complex models that take into account multiple dependencies.

3.2 Correlation of economic indicators: 2002–2022

We conducted a correlation analysis that used data from 2000 to 2022. The analysis focused on important economic indicators, such as GDP (in current US$), GDP growth (in annual percentage), GNI per capita (Atlas method in current US$), and GNI per capita PPP (in international $). The results of the correlation are presented in Table 5.

Table 5. Correlation coefficients for individual indicators (2000–2022)

Indicator (2000-2022)	GDP (current US$)	GDP growth (annual %)	GNI per capita, Atlas method (current US$)	GNI per capita, PPP (current international $)
Adolescent fertility rate	-0.147	0.260	-0.147	-0.128
Agriculture, forestry, and fishing, value added	-0.904	0.504	-0.902	-0.922
Annual freshwater withdrawals	0.563	-0.291	0.565	0.570
Births attended by skilled health staff	0.827	-0.502	0.823	0.844
CO2 emissions	0.902	-0.538	0.900	0.918
Contraceptive prevalence	-0.628	0.200	-0.625	-0.671
Electric power consumption	0.914	-0.589	0.914	0.919
Energy use	0.874	-0.513	0.873	0.889
Exports of goods and services	-0.624	0.820	-0.630	-0.567
External debt stocks	0.986	-0.739	0.984	0.974

Fertility rate	-0.477	0.444	-0.472	-0.477
Foreign direct investment	0.743	-0.325	0.724	0.747
Forest area	0.975	-0.655	0.975	0.982
Gross capital formation	0.557	-0.222	0.551	0.594
High-technology exports	-0.416	0.362	-0.426	-0.489
Immunisation, measles	0.779	-0.412	0.774	0.807
Imports of goods and services	-0.654	0.803	-0.660	-0.608
Income share held by lowest 20%	0.818	-0.743	0.828	0.794
Industry, value added	-0.860	0.821	-0.870	-0.823
Inflation, GDP deflator	-0.228	0.556	-0.252	-0.192
Life expectancy at birth	0.957	-0.619	0.958	0.968
Merchandise trade	-0.707	0.835	-0.712	-0.656
Military expenditure	-0.797	0.388	-0.784	-0.817
Mobile cellular subscriptions	0.980	-0.694	0.980	0.981
Mortality rate, under 5	-0.911	0.536	-0.910	-0.929
Net migration	0.738	-0.562	0.736	0.735
Net official development assistance	-0.864	0.660	-0.863	-0.841
Personal remittances	0.855	-0.611	0.858	0.841
Population density	0.974	-0.668	0.975	0.977
Population growth	-0.733	0.458	-0.731	-0.769
Poverty headcount ratio ($2.15/day)	-0.914	0.681	-0.915	-0.912
Poverty headcount ratio (national poverty line)	-0.928	0.578	-0.927	-0.940
Prevalence of underweight	-0.827	0.427	-0.827	-0.852
Primary completion rate	0.526	-0.643	0.520	0.511
Revenue, excluding grants	0.629	-0.398	0.637	0.608
School enrolment, primary (% gross)	-0.876	0.568	-0.880	-0.874
School enrolment, primary and secondary (% gross)	0.884	-0.593	0.887	0.892
School enrolment, secondary (% gross)	0.832	-0.481	0.829	0.853
Statistical Capacity Score	0.921	-0.821	0.926	0.903
Surface area	-0.630	0.221	-0.630	-0.670
Tax revenue	-0.625	0.486	-0.637	-0.633
Terrestrial and marine protected areas	-0.485	0.149	-0.439	-0.424
Time required to start a business	-0.888	0.511	-0.888	-0.866
Total debt service (% of exports)	0.179	-0.518	0.187	0.125
Urban population growth	-0.978	0.714	-0.978	-0.984

The purpose of this analysis is to determine the strength and direction of the relationships between economic growth indicators and various socio–economic factors over the current observation period. This view highlights factors that are interrelated with economic growth. To identify the most significant dependencies between the indicators, a selection of links with a correlation above 0.75 or below -0.75 was carried out.

A. GDP (current US$)

A1. High correlation (over 75%) with:

• External debt stocks (0.986)

• Mobile cellular subscriptions (0.980)

• Forest area (0.975)

• Population density (0.974)

• CO2 emissions (0.902)

• Electric power consumption (0.914)

• Life expectancy at birth (0.957)

A2. Low correlation (less than -75%) with:

• Poverty headcount ratio (national poverty line) (-0.928)

• Mortality rate, under 5 (-0.911)

• Agriculture, forestry, and fishing, value added (-0.904)

• Urban population growth (-0.978)

B. GDP growth (annual %)

B1. High correlation (over 75%) with:

• Exports of goods and services (0.820)

• Industry, value added (0.821)

• Merchandise trade (0.835)

B2. Low correlation (less than -75%) with:

• Statistical Capacity Score (-0.821)

• Electric power consumption (-0.589)

C. GNI per capita, Atlas method (current US$).

C. High correlation (over 75%) with:

• GDP (current US$) (0.984)

GNI, PPP (current international $) (0.982)

Forest area (0.975)

Mobile cellular subscriptions (0.980)

C2. Low correlation (less than -75%) with:

• Poverty headcount ratio (national poverty line) (-0.927)

Urban population growth (-0.978)

D. GNI per capita, PPP (current international US$)

D1. High correlation (over 75%) with:

• GDP (current US$) (0.974)

• GNI, Atlas method (current US$) (0.982)

• Population density (0.977)

• Life expectancy at birth (0.968)

D2. Low correlation (less than -75%) with:

• Poverty headcount ratio (national poverty line) (-0.940)

• Mortality rate, under 5 (-0.929)

• Urban population growth (-0.984)

These high correlations and their interpretation suggest several conclusions regarding the Chinese economy, taking into account modern development (since 2000).

1. External and internal factors stimulating the economy: The high correlation of GDP with the volume of external debts, the number of mobile subscriptions, and population density reflect China's integration into global markets and the focus of domestic development on technology and urbanisation.

2. Economic growth stimulated by trade and industry: The significant positive correlation of GDP growth with exports and industry highlights the export-oriented growth model and industrialisation as the main engines of economic expansion.

3. Socio-economic impact. Negative correlations of various economic indicators with poverty and mortality levels indicate that economic growth is associated with an improvement in living standards and health, although inequality problems continue to exist, as shown by negative correlations with urban population growth.

4. Technological and environmental considerations: The strong relationship between GDP and indicators such as CO_2 emissions and electricity consumption highlights the environmental impact of China's industrial growth. However, the correlation between mobile subscriptions and life expectancy demonstrates the positive effects of technological development and improved healthcare.

5. The need for sustainable and inclusive growth: Low correlations between GDP and poverty levels along the national poverty line, as well as high urban growth, indicate difficulties in ensuring a wide distribution of economic benefits among the population, which underlines the need for policies aimed at eliminating inequality and maintaining strategic sustainability.

6. The impact of globalisation: Globalisation plays a key role in shaping economic strategies, as indicated in the relationship between GDP and external debts and exports.

7. The importance of new technologies: The active introduction of mobile technologies and the increase in living space indicate technological progress that stimulates economic activity.

8. Problems of environmental sustainability: High levels of CO_2 emissions and energy consumption require a review in the direction of maintaining environmental sustainability.

9. Growth and inequality: Strong urbanisation and urban population growth in the context of a low correlation with an improvement in the standard of living of the population raise questions about social adaptation and the implementation of policies that promote an even distribution of economic benefits.

4. Conclusion

The study of China's economic sustainability in the context of global economic turbulence demonstrates that the country is successfully addressing the challenges of external instability through the diversification of its economy and strategic investment in high-tech sectors. Despite external pressures and internal contradictions, China retains significant resources and potential for future growth. The correlation analyses identified several factors influencing economic stability, including the role of technology, international trade, foreign direct investment, and public policy. Key macroeconomic indicators, such as GDP, GNI per capita, and external debt, are closely linked to socio-economic factors. However, challenges remain, including managing external debts, reducing poverty, and addressing environmental issues, which require further analysis and tailored policies. To maintain sustainable economic growth, it is essential for China to continue implementing structural reforms and enhancing innovation efforts. Additionally, it is crucial to focus on the development of domestic markets and improving the living standards of the population, as these factors can serve as a foundation for long-term stability and prosperity. In light of the current global uncertainties and shifts in the international economic landscape, further research efforts should be directed towards assessing the effects of economic and political developments on China's economy, as well as identifying internal capacities for adapting to these changes.

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SECTION 4

MANAGEMENT OF KNOWLEDGE AND INNOVATION FOR SUSTAINABLE DEVELOPMENT

РАЗДЕЛ 4

УПРАВЛЕНИЕ ЗНАНИЯМИ И ИННОВАЦИЯМИ В ИНТЕРЕСАХ УСТОЙЧИВОГО РАЗВИТИЯ

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A Conceptual Model for the Development of Transmodern Innovations

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Abstract

Innovation processes are strongly influenced by changes in economic, political, technological and other external factors. For instance, economic instability and political uncertainty can both stimulate and limit innovative activity in organisations. Transmodern innovation is a concept that involves scientific and technological advancements that may remain unutilised until favourable changes occur in technological or economic conditions. The purpose of this study is to develop a conceptual model for transmodern innovation that takes into account the dynamics of innovation, including the intensity, economic prerequisites, external changes and degree of innovation adaptation. This model will help organisations to better understand and respond to the complexities of the innovation process. The resulting model is a comprehensive tool for analysing changes in innovation activity and the external environment over different time phases, including the initial state (t0), the transition to new conditions (t1) and the final state (tx). In this model, the ‘Final stage of tx’ block represents the final stage, which allows us to draw conclusions about the success of adaptation and innovation development. This is the basis for formulating strategic conclusions and recommendations for future development.

Keywords: transmodern innovations, conceptual model, innovative activity, adaptation, time series

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Концептуальная Модель Развития Трансвременных Инноваций

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Аннотация

Инновационные процессы сильно зависят от изменений в экономических условиях, политической сфере, технологических новшествах и других аспектах внешней среды. Экономическая нестабильность, политическая неопределенность, а также технологические и социокультурные изменения могут как стимулировать, так и ограничивать инновационную активность организаций. Трансвременные инновации представляют собой концепцию, включающую научные и технологические достижения, которые могут оставаться неактуальными до тех пор, пока не наступят благоприятные изменения в технологических или экономических условиях. Целью данного исследования является создание концептуальной модели развития трансвременных инноваций с учетом различных аспектов динамики инновационных технологий, таких как интенсивность инноваций, экономические предпосылки, изменения внешней среды и степень адаптации инноваций. Полученная модель представляет собой комплексный инструмент для анализа изменений в инновационной активности и внешней среде на различных временных фазах, включая начальное состояние (t0), переход к новым условиям (t1) и конечное состояние (tx). В полученной модели блок «Конечное состояние tx» представляет собой завершающую фазу, которая позволяет сделать выводы об успешности адаптации и развитии инноваций, что является основой для формулирования стратегических выводов и рекомендаций для будущего развития.

Ключевые слова: трансвременные инновации, концептуальная модель, инновационная активность, адаптация, временные ряды

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1. Introduction

Adaptation to changing environmental conditions, particularly during economic crises or legislative changes, is essential for the survival and long-term success of organisations. In a rapidly changing environment, where innovation is key to maintaining competitiveness and promoting sustainable growth, understanding the factors that influence adaptation and innovation has become increasingly important. This process involves a thorough examination of the external factors that may impact the integration and implementation of innovative solutions across various sectors.

The purpose of this study is to develop a conceptual model that will allow us to evaluate and predict the dynamics of transmodern innovation through the analysis of interactions between economic, political, technological and socio-cultural factors. We aim to understand how innovations can adapt and evolve over time, considering both current and future economic, political and socio-cultural circumstances.

The focus of the research is on assessing innovative systems' ability to respond to external challenges through a time-series analysis. Developing a transmodern model would allow us not only to evaluate the current state and effectiveness of innovation activities but also to provide strategic recommendations for companies striving to enhance their competitiveness and market presence.

2. Literature Review

Trans-temporal innovation (TTI) is a category of innovative solutions, of various forms, formed in the period t_0, which remain in the stage of delayed relevance until the period t_x, characterised by the anamorphosis of environmental factors that form the economic prerequisites for their development (Urbinati, 2022).

TTI properties:

Deferred Relevance (τ) – the period of time between the formation of an innovative solution I_i and its actualisation in the period t_x:

$$\tau\left(I_i\right) = t_x - t_0, \leq t_x \tag{1}$$

Environmental Readiness (A_t) – the ability of the external environment for a period of time tx to create the economic conditions for the implementation of an innovative solution I_i:

$$A_t\left(I_i, t\right) > A_t\left(I_i, t_0\right),\ t \geq t_x \tag{2}$$

The Power of Diffusion (Θ) – a measure of the speed and degree to which an innovative solution I_i is distributed in the relevant research and applied field:

$$\Theta\left(I_i, t\right) > \Theta\left(I_i, t_0\right),\ t \geq t_x \tag{3}$$

Market Awakening (M_a) – the growth of market demand and the level of potential economic feasibility of an innovative solution I_i:

$$M_a\left(I_i, t\right) \propto V\left(I_i, t\right),\ t \geq t_x \tag{4}$$

Environmental Provocateur (P_t) – an event or sequence of events that stimulate the actualisation of TTI:

$$P_t \rightarrow \left(A_t\left(I_i,\ t\right) \wedge \Theta\left(I_i,\ t\right) \wedge M_a\left(I_i,\ t\right)\right),\ \ t \approx t_x \tag{5}$$

So, we can conclude that transmodern innovations are formed within the framework of scientific research and innovative experiments, but their value and benefits are not realised until the onset of the tx period, when changes in technological processes, accompanying scientific discoveries or the evolution of market and economic conditions allow these innovative solutions to achieve the economic feasibility of potential applications (Palfreyman, 2022; Marion, 2021; Koloskova, 2020).

A clear illustration of the transmodern nature of innovation is the neural network. Neural networks were developed in the last century but were limited by insufficient computer performance and insufficient amounts of data for their training. With the development of computing power, increased availability of large amounts of data and improved algorithms, neural networks have found wide application in areas such as machine learning, natural language processing and computer vision. In the modern technological order, neural networks are a powerful tool for solving complex problems and are one of the key technologies in the field of artificial intelligence and machine learning (MacMahon, 2019; Milling, 2002; Meissner, 2015).

Electric vehicles can also be considered as a good example of this. The initial prototypes and ideas were proposed by Thomas Davenport and Robert Davidson about 200 years ago. However, a lot of time passed before their mass production and popularisation, as the development faced technological limitations, such as capacity, battery performance and weak infrastructure of charging stations. At the moment, the electric vehicle market is growing and developing rapidly, especially in countries with high fuel prices (Žižlavský, 2013; Siguaw, 2006; Schoen, 2005).

Another example of a transmodern innovation is genomic sequencing. Initial genomic sequencing technologies were developed with the long-term goal of understanding the genetic information of organisms, but limitations in performance, cost and speed of analysis limited their use. With the development of technologies in bioinformatics, biochemistry, computing and DNA analysis methods, genomic sequencing has become faster, more accurate, affordable and scalable. This has allowed scientists and physicians to expand the scope of this innovation in practice, using it for the diagnoses of diseases, the study of genetic mechanisms, plant and animal breeding and other applied tasks (Elzinga, 2023; Giannopoulou, 2011).

The purpose of this study is to develop a conceptual model for the development of transmodern innovation, which will be used to analyse various aspects of the dynamics of the development of innovative technologies.

3. Materials and Methods

The methodology relies on general scientific methods, including analysis and synthesis, induction and deduction and the abstraction and systematisation of information. The study examines the process of the development of transmodern innovations through two time periods: the initial period t0, in which innovations are formed, and the future period tx, in which they find their relevance and development due to changes in the external environment.

The process of innovation transformation can be represented in the form of successive steps, each of which is described by a system of nonlinear equations that reflect the relationship between innovations and the conditions of their development.

As parameters for modelling the transformation process of transmodern innovations, one can distinguish the *intensity of innovation*, which is an It parameter that can be interpreted as a measure of the activity and effectiveness of innovation implementation at a certain point in time t. Many researchers have described this characteristic of the innovation process. Peter Drucker's works, in particular, emphasise the importance of a systematic search for innovative development opportunities and the generation of new solutions within the framework of enterprise competitiveness management, which largely correlates with an understanding of the intensity of innovation (Mohr, 2009). Everett Rogers's research includes tools for analysing the speed and mechanisms with which innovative solutions are integrated into public practice, which is mainly applicable to the concept of innovation intensity (Dibra, 2015). Thus, the intensity of innovation can be viewed from several points of view, such as the speed of creation and implementation of innovations, their impact on the economic and social environment as well as the willingness and ability of the system to accept and adapt to these changes.

The state of economic prerequisites Et in the context of modelling the process of transmodern innovation refers to a set of conditions of the economic environment that affect the possibility and effectiveness of the development and implementation of innovations at a certain point in time t. This parameter can include a variety of factors, such as the level of economic development, the availability of financial resources, tax policy, inflation, interest rates, public investment in research and development as well as the general state and dynamics of the market. Robert Solow, in his model of economic growth, postulated the thesis that productivity gains and economic growth are more driven by technological innovations than by an increase in the number of production factors, which emphasises the importance of economic conditions that intensify the economic process and the contribution of innovative results to economic development. Paul Romer, in turn, argued that economic growth can be supported by investments in human capital and innovations aimed at increasing production efficiency and opening up new opportunities for growth. Thus, economic prerequisites play a significant role in the innovation process, since they not only determine the readiness and ability of the economy to generate and implement innovations, but also create conditions for their further development and commercialisation. In the context of transmodern innovation, changing these conditions over time provides information about the optimal time intervals for launching and promoting innovative solutions, and makes it possible to model potential difficulties or growth points associated with this process (Travassos, 2024).

The changing environmental conditions of St reflect the dynamics and intensity of changes in how environmental specifics evolve and influence the development and implementation of innovations. This parameter has been indirectly investigated in the works of many scientists. Michael Porter analysed the economic structure of the industry through the prism of the ‘five forces’, which can be considered the key elements of environmental change in the context of economic and strategic perspectives (Porter, 1995). John Cotter, within the framework of the ‘eight steps’ model of change management, defined the key role of the external environment in initiating and maintaining change processes in organisations. Ulrich Beck, in his concept of ‘risk societies’, argued the thesis that modern societies are characterised by increasing uncertainty and that the associated risks, as part of a changing external environment, require societies and organisations to develop innovative approaches and strategies for their reification (Prieger, 2007). Thus, changes in the external environment have deep significance within the framework of the transformation process of transmodern innovations, since they can both stimulate and restrain innovative activity, influencing the time frame and conditions under which innovations are actualised in science and practice (Dahlander, 2021).

The degree of adaptation of an innovation At reflects the ability and readiness of an innovative process or product to change or modify to meet fundamentally new or changing environmental conditions during time t. This parameter is important for understanding the labour intensity involved in adapting an innovative solution to new market requirements, technological standards, socio-cultural norms or environmental constraints. Everett Rogers, within the framework of the theory of diffusion of innovations, studied the processes by which innovations spread between participants in the social system, addressing the issue of adaptation as one of the factors influencing the success of innovation (Globe, 1973). Rogers also discussed how social, cultural and individual characteristics influence the acceptance and adaptation of innovations by society. Michael Tushman and Philip Anderson, within the framework of the concept of ‘technological shifts’, investigated how companies adapt to radical technological changes, focusing on the need to adapt management practices and organisational structures for the effective integration of new technologies (Sivarajah, 2024; Hekkert, 2007). Clyden Christensen, within the framework of the theory of ‘disruptive innovation’, described how new technologies that are initially created in niche markets can eventually radically change industries, displacing established companies (Damanpour, 2012). In Christensen’s concept, adaptation to new conditions is a key element of the survival and sustainable development of companies (Chursin, 2016). Understanding and analysing the degree of adaptation of innovation is critical to assessing the viability and potential for the long-term development of innovations.

In the context of modelling transmodern innovations, At emphasises the need for a flexible approach to the development and implementation of innovative ideas (Seebode, 2012).

4. Results

The relationship of the proposed parameters can be described by the following system of equations:

$$\frac{dI}{dt} = f_1\left(E(t), A(t)\right) \tag{6}$$

$$\frac{dE}{dt} = g\left(S(t)\right) \tag{7}$$

$$\frac{dS}{dt} = h\left(t, S(t)\right) \tag{8}$$

$$\frac{dA}{dt} = k\left(I(t), S(t)\right) \tag{9}$$

Function f1 describes how changing economic prerequisites and the degree of adaptation of innovation affect its development. The deterioration of economic conditions may imply a number of scenarios – from macroeconomic instability to local financial crises – that can have a significant impact on the operation of enterprises, the investment climate, consumer sentiment and overall economic activity. These changes in the economic and political landscape can be caused by a variety of reasons. These include, for example, economic downturns, which lead to a decrease in total output and the number of jobs. Inflation also plays a role, increasing the price level and thereby reducing consumer opportunities. An increase in interest rates can complicate the process of obtaining loans for both individual consumers and corporations, which makes investment activity more difficult. Instability in the political arena can increase business risks and reduce investor confidence. Finally, global financial crises involving multiple countries can lead to consistent economic disruptions in different regions. The deterioration of economic conditions has a direct impact on innovation processes. In times of economic uncertainty, both companies and investors may show restraint in investing in new projects and developments, which leads to a reduction in investment in innovation activities. This fact changes consumer preferences, leading consumers to favour products and services that either satisfy basic needs or offer a relatively high value per unit cost. In response, companies are forced to adjust the supply structure, optimise operating costs and rethink innovative strategies to maintain competitiveness and, as a result, profitability. However, these uncertain conditions can also stimulate the innovation process, as enterprises are forced to look for alternative ways to survive and develop. In some cases, the crisis may additionally motivate companies to develop new products or optimise processes in order to achieve long-term development and increase sustainability.

The g-function mathematises how the dynamics of changes in the external environment interact with economic fundamentals, emphasising the complex impact of various factors on the economic state, which, in turn, directs the development of innovations. These factors cover global economic trends, including the growth or decline in gross domestic product (GDP) of the world’s leading economies, which can expand or narrow international markets; political stability and changes in legislation that ensure the predictive ability of business; rapid changes in technologies that redefine industry standards; and socio-cultural changes affecting consumer preferences and behaviour. Environmental changes are also critically important, forcing companies to rethink production processes and market approaches. The logical and meaningful nature of the g-function allows us to form a deep understanding of how these changes shape the economic atmosphere by indirectly stimulating or constraining innovation activity. These variables can play a role in expanding new markets, accelerating investment activity, stimulating entrepreneurship and technological development, as well as in shaping new industrial dynamics.

The h-function provides a critical analysis of how variations in the external environment, including economic fluctuations, political instability and technological innovations, affect different systems over time. This function is characterised by potential nonlinearity, emphasising that even minor changes in bifurcation conditions can lead to significant and not always predictively significant effects within the system. The inclusion of time dynamics in the analysis allows one to track how changes affect the system over time, providing an understanding of both short-term and long-term consequences. Modelling these changes is critically important for organisations focused on strategic planning and risk management, as it allows them to prepare more effectively for future scenarios and optimally respond to emerging challenges, minimising the potential negative consequences of external destabilisation factors.

The k-function mathematically approximates the relationship between the intensity of innovation activity, including the development of new technologies, product improvement and innovative business practices, and changes in the external environment. These changes can range from economic fluctuations to socio-cultural trends, technological innovations as well as changes in policy and legislation. The interaction of these two elements impacts how effectively innovations can adapt to new external conditions. For example, a favourable external environment equipped with supportive legislation and technological advances can facilitate the application and dissemination of innovations. However, in the context of legislative barriers or an economic recession, even active innovation can face obstacles, which require innovators and companies to adapt more deeply and develop innovative strategies to overcome these obstacles.

Figure 1 shows a conceptual model for the development of transmodern innovation.

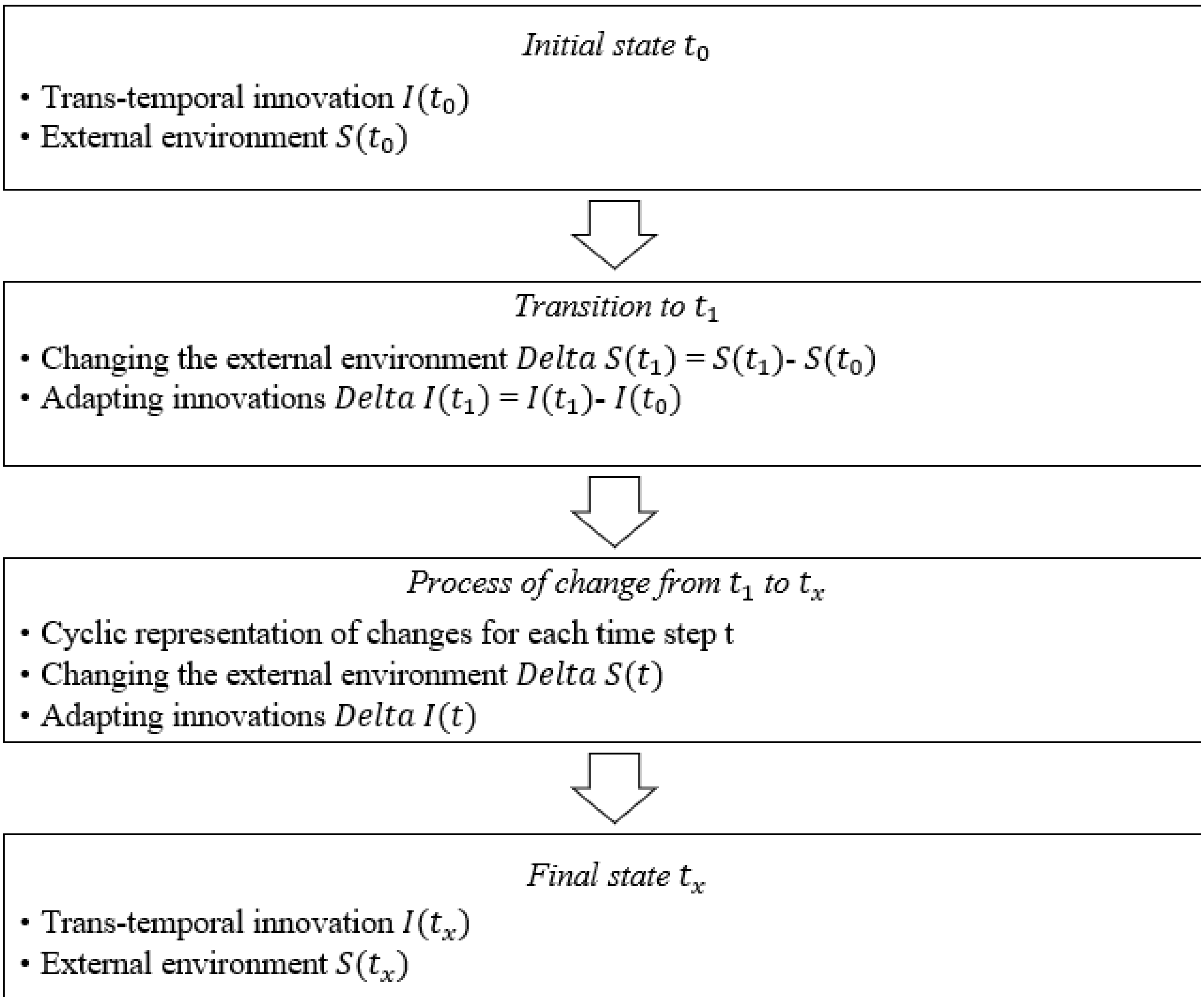

Figure 1. Conceptual model of the development of transmodern innovation.

The 'Initial state t0' block is the basis of the entire flowchart, which sets the initial parameters for the subsequent modelling of the properties of transmodern innovation and changes in the external environment. Within this block, the basic levels of innovation activity are established, which reflect the beginning of innovative processes, products or technologies. Also, the characteristics of the external environment at time t0 are determined, and the data are supplemented by taking into account political, economic and technological factors that approximate the context that can influence the further development and adaptation of innovative results. These initial parameters play a critical role in modelling the initial state and provide reference points for monitoring the dynamics of changes throughout the time period under consideration.

In the flowchart, the 'Transition to t1' block represents the initial stage of changes, within which there is an active interaction between innovations that have the property of duration in time and the changing external environment. This section focuses on two main aspects: the first comprises changes directly in the external environment, covering all the key economic, political, technological and social shifts that occurred earlier; the second is the adaptation of innovations, which may include processes such as the introduction of new technologies, the recycling of existing products or a change in strategic direction in response to new conditions and challenges of the time. This section illustrates how innovations begin to adapt to new external conditions, marking the initial stages of this transition process. In fact, this block is a significant analytical point for assessing how effectively the innovation system is able to respond to external challenges and adapt at the initial stage of this interaction.

The block 'Process of change from to to tx' plays a key role in the structure of the flowchart, covering the constant process of adaptation and transformation of transmodern innovations and environmental changes during the analysed time period. In this block, each time point is considered individually, which makes it possible to monitor recurring changes in the external environment and adaptation processes within the framework of innovation activities. Changes in the environment and how innovations respond to them are documented in each individual time interval. These adaptation processes may include the introduction of relevant technologies, strategic business reorientation or other forms of innovative activity aimed at increasing competitiveness and realising new opportunities. Each time period also includes an analysis of the impact of key political, economic and technological factors of development, which contributes to a deep understanding of how they form the context in which major changes occur. Thus, the block describes in detail the complex interaction between changing conditions and innovation activities, demonstrating the evolution and adaptation of business processes and approaches in a rapidly changing world and forming a pool of effective long-term development strategies.

The 'Final state of tx' block in the flowchart visualises the final phase of modelling, within which a summary of all transformations and adaptations that took place during the analysed time is presented. This block displays the final state of transmodern innovation and the external environment, allowing one to assess the impact of events that have occurred. It reflects the current state and nature of innovation activity, which demonstrates how successful the adaptation and development of the innovations have been. The analysis of the current state of the external environment is also carried out, which includes economic, political, socio-cultural and technological changes. Understanding the impact of significant events in the fields of politics, economics and technology allows us to determine their significance in the formed results of innovation activity and environmental conditions. This block is critically important for synthesising the results of the entire process, highlighting achievements and shortcomings in innovation management and allowing one to formulate strategic conclusions and recommendations for future development.

5. Discussion

The importance of the resulting model lies in its ability to provide insight into the nature of innovations over time and their potential application in various industries.

The conceptual model examines the evolution of innovation, paying attention to the interaction of innovation processes with economic, political, technological and other changes in the environment. Changes in economic stability, the political environment, technological progress and socio-cultural aspects can both stimulate and inhibit the innovative activity of an organisation. This means that even active innovation can face obstacles, such as legislative barriers or economic downturns. Overcoming these obstacles requires deeper adaptation and innovative strategies.

In the context of studying the development of transmodern innovations, this model can be applied to track the progress of technological advances in different time periods, allowing researchers and practitioners to identify key points of innovation, technological shifts and their consequences. Moreover, it can become the basis for forecasting future technological trends and achievements, thereby supporting strategic decision-making in various industries.

Thus, the transmodern innovation development model is an important tool for evaluating and predicting the dynamics of innovative technologies to formulate strategic conclusions and recommendations for future development.

6. Conclusion

In this study, a conceptual model of the development of transmodern innovation was obtained, which can be applied to track the dynamics of technological innovations at different points in time, in particular, from t_0 to t_x. It can serve as a basis for understanding how innovations evolve and transform from t_0 to t_x, potentially shedding light on patterns, breakthroughs and disruptions in technological development. The mathematical functions f_1, g, h and k represent a complex interaction of economic, political, technological and socio-cultural factors and allow us to analyse how changes in economic prerequisites, the external environment as well as political and technological innovations affect innovation processes at various time stages.

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