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Big Data and Artificial Intelligence for Decision-Making in the Smart Economy

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Introduction—Big Data and Artificial Intelligence: A Systemic View on Decision-Making in the Smart Economy Under Industry 4.0

Big data and artificial intelligence (AI) form the technological core of the smart economy in the current era of Industry 4.0. They are utilized as independent technical solutions and in combination with other advanced technologies. The value of big data and AI lies in their collective ability to systemically automate monitoring and analytical activities.

This automation transforms decision-making into a high-tech process that serves as the foundation for other economic processes in a smart economy. By automating decision-making, cyber-physical systems gain autonomy, propelling the progress of the Fourth Industrial Revolution. However, the challenge lies in the fact that the various aspects of decision-making automation in the smart economy, driven by big data and AI, are studied separately in the existing literature.

The first aspect is organizational and managerial. Even with ready-to-implement big data and AI, their practical application in decision-making requires appropriate scientific and methodological developments that consider the peculiarities of managerial processes, industries, and the national context of the smart economy in which they are used. Although existing literature offers some methodological recommendations, the overall methodological foundation for decision-making automation in the smart economy based on big data and AI remains weak.

There is a wide variety of ways to combine these technologies in decision-making, sequences for their application, and distribution of functional loads among automation tools. Economic entities in the smart economy need clear instructions on applying big data and AI to their decision-making practices. Therefore, it is necessary to specify the organizational and managerial measures in the smart economy and their expected benefits for management, including increased decision-making efficiency, rationalization, and reduced risk of decision errors.

The second aspect is economic. The smart economy represents a phenomenon of decision-making automation across various fields of economic activity, displacing humans from managerial operations and creating an effect of intellectualizing cyber-physical systems. While the general conceptual understanding of the smart economy is formed and widely accepted, there remain fundamental gaps regarding which specific areas of economic activity and processes can and should be automated.

Although certain solutions exist in many economic operations, not all of these operations are subject to complete automation. In some cases, automation can only be partial with the current capabilities of big data and AI. Additionally, it is necessary to financially justify the return on investment in decision-making automation for each applied development and economic operation. Thus, it is essential to generalize accumulated experience and consider future forecasts for the development of the smart economy.

The third aspect is ethical, encompassing social-legal and environmental considerations. The ethics of big data and AI involves contentious consequences of decision-making automation in the smart economy, eliciting support and criticism. The psychological perception of the emergence of a data-driven society and economy is highly differentiated among representatives of various social categories.

The transition from personal to anonymized aggregated data can improve the technological perception of big data and AI. Additionally, social adaptation measures are necessary to modernize the economy from a social perspective. These measures range widely, from developing telecommunications infrastructure and filling gaps in digital skills to reducing the digital divide by addressing income inequality.

The automation of decision-making in the smart economy based on big data and AI also requires a robust institutional and legal framework. The top priorities in the legal agenda of the smart economy include the issue of registering and protecting intellectual property rights for AI and big data and the creative outputs generated by AI. The question of liability for decisions made by AI, which may be incorrect due to insufficient, distorted, or misinterpreted big data, also warrants attention.

Furthermore, the environmental consequences of decision-making automation in the smart economy based on big data and AI require scientific study and mitigation. It is crucial to ensure high energy efficiency in collecting big data and operating AI. It is also necessary to leverage big data and AI to make environmental decisions, transition to clean energy, and support green growth and decarbonization.

The fourth aspect is technological. Although a general understanding of applying big data and AI in key decision-making practices has been established, some technical details remain unclear. Particularly, the issues of human-machine communication in big data collection and decision-making support require in-depth study and more thorough development. These include questions of linguistics, visual image recognition, and the creation of user-friendly interfaces for big data and AI, as well as machine learning issues.

This book aims to bridge the gap between these aspects and provide a comprehensive understanding of decision-making automation. This book aims to form a systemic vision of decision-making in the smart economy in the context of Industry 4.0 using big data and AI. The book's contribution to the development of scientific literature on big data and AI lies in uncovering the “black box” of decision-making automation in the smart economy using these technologies.

The theoretical significance of the research results presented in the book is explained by their clarification of the role and importance of big data and AI in decision-making in the smart economy. The book's practical significance is expressed in its extensive coverage of international experiences in decision-making automation

in the smart economy, using examples from Armenia, Kyrgyzstan, and other Central Asian countries, as well as from countries in various economic categories, classified by income levels.

The managerial significance of the scientific and practical developments included in this book lies in their potential to optimize decision-making practices in the smart economy through the more flexible and efficient application of big data and AI. The book is unique because it contains exclusive case reviews from Central Asia, applied algorithms, and innovative mechanisms for utilizing big data and AI to automate decision-making in the smart economy.

The book's content is divided into four parts. The first part presents advanced organizational and economic models for decision-making based on big data and AI. The second part explores the latest trends in the development of the smart economy utilizing big data and AI. The third part explains the socio-environmental and legal aspects of the ethics of using big data and AI technologies. The fourth part provides forward-looking applied solutions for decision-making in the smart economy based on big data and AI.

The book is primarily intended for scholars studying big data and AI. Representatives of this target audience will find a comprehensive overview of the possibilities and limitations of automating decision-making in the smart economy, along with thorough scientific justification for using big data and AI in this process.

Additionally, the book may be of interest to practitioners in the smart economy. Decision-makers in the smart economy will gain a holistic understanding of the benefits and organizational-economic frameworks for automating decision-making using big data and AI, along with practical recommendations for leveraging these advantages and implementing the proposed schemes.

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Advanced Organizational and Economic Models for Decision-Making Based on Big Data and Artificial Intelligence

Intelligent Support for Personnel Decision-Making and Socially Responsible HRM Using Big Data and AI



Aziza B. Karbekova , Saltanat A. Tashbolotova, Ainura B. Mamatova , and Ashirkan Uraimhalilova

Abstract The research aims to define the contribution of big data and AI technologies to socially responsible HRM and develop recommendations for improving the practice of intelligent support in personnel decision-making using these technologies. The authors examine WIPO statistics for Central Asian countries in 2023. The authors developed regression models to reveal the causal relationships of using these technologies in enterprise personnel decision-making in Central Asia in 2023. The theoretical significance of these models lies in their ability to enhance the predictability of HR management automation in Central Asia. The authors conclude that big data and AI technologies increase the effectiveness of socially responsible HRM by creating knowledge-intensive jobs and promoting gender neutrality in labor. A forecast for the development of socially responsible HRM through the expanded use of ICT is made using the Kyrgyz Republic as an example. Its practical significance is that it can serve as a roadmap for the socially-oriented development of the labor market in the Kyrgyz Republic. A mechanism for intelligent support in personnel decision-making in socially responsible HRM using big data and AI has been developed. The managerial significance of this mechanism is that it will enable the rationalization of HR management practices.

Keywords Intelligent decision support · Personnel decision-making · Socially responsible HRM · Big data · Artificial intelligence

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1 Introduction

The global trend towards socially-oriented development of economic systems suggests the implementation of socially responsible human resource management (HRM). However, despite the widespread recognition of its necessity and the high and growing level of engagement in adopting and implementing socially responsible HRM practices, these practices remain underdeveloped. They are cautiously implemented and demonstrate low effectiveness. The main reasons for this problem include the following.

One reason is that the desire to enhance the company's reputation as an employer can lead to retaining employees who no longer contribute to the company's success. Employee loyalty is intended to boost productivity and product quality. However, with low competition for jobs, employees lose motivation and show decreased productivity. Therefore, in each HR management case, a balance must be found between social responsibility and effective personnel decisions.

Another reason is that the ongoing high-intensity automation of workplaces reduces the human labor required in economic processes. By artificially maintaining a large workforce, enterprises face a heavy wage burden. At the same time, the release of staff is usually perceived as a manifestation of a lack of social responsibility in HRM.

A further reason is the complexity of making personnel decisions in large companies. In most cases, an HR manager cannot comprehensively monitor and control the performance of every employee. This results in incomplete informational support for personnel decisions, delaying their implementation and hindering their rationalization.

Another reason is the high degree of subjectivity in HR managers' decision-making. Personnel decisions are influenced by the HR manager's psychological state, interpersonal communications with employees, and the company's bureaucratic structure. Subjectivity in personnel decisions reduces workforce inclusiveness and raises barriers to new hires, fair distribution of incentives, and career advancement for the best employees.

To address the identified problem, this research proposes rationalizing personnel decisions through intelligent support using big data and artificial intelligence (AI). The research aims to define the contribution of big data and AI technologies to socially responsible HRM and develop recommendations for improving the practice of intelligent support in personnel decision-making using these technologies.

2 Literature Review

This research addresses the theory of personnel decision-making [1, 3, 8]. Despite a considerable number of publications, there is still no consensus. The scientific debate continues about the implications of integrating big data and AI into HRM

practices. Accordingly, this research poses the following research question (RQ): “What contribution do big data and AI technologies make to socially responsible HRM?”.

The scientific literature related to this theory [12, 16] indicates limitations in the potential use of big data and AI in socially responsible HRM practices. One limitation is that big data and AI can only monitor the labor process in a limited way, while machine vision systems cannot capture a significant portion of social and labor communications [2].

Another limitation is the complexity of recognizing information obtained through machine vision and the relatively high probability of errors in AI's interpretation of social and labor phenomena [10]. Additionally, big data and AI cannot account for the socio-psychological aspects of labor relations [11], making the criteria for socially responsible HRM strictly limited [15].

Fenwick et al. [4] and Jia and Hou [5] provide evidence of the advantages of using big data and AI in the intelligent support of personnel decision-making, such as accelerating decision-making processes and enhancing their objectivity. The cited advantages are as follows:

- Creating knowledge-intensive jobs for employees involved in the use of big data and AI in their professional activities [7, 9];
- Ensuring gender neutrality in social and labor relations and processes, including research activities in the workplace [6, 13].

Based on this, the following hypothesis (H) is proposed: “Big data and AI technologies enhance the effectiveness of socially responsible HRM by creating knowledge-intensive jobs and promoting gender neutrality in labor.”

3 Materials and Methods

This research focuses on Central Asia (as classified by UNESCO) as a unique region with dynamically developing digital economies and a progressive culture of socially responsible HRM. To determine the contribution of big data and AI technologies to socially responsible HRM, the authors conducted regression modeling to analyze the causal relationships in using these technologies in HR decision-making by enterprises in Central Asia in 2023.

WIPO materials [14] serve as the source of statistical data for this research. In the regression analysis, the outcome variables are “knowledge-intensive employment” (KIE) as an indicator of knowledge-intensive jobs and “females employed with advanced degrees” (FME) as an indicator of gender neutrality in labor. The factor variable is “ICT use” (U_{ICT}), which represents the intensity of advanced information and communication technology (ICT) use, including big data and AI (Table 1).

The authors presented the positive values of the regression coefficients as evidence for the proposed hypothesis. Based on the results of the regression analysis, the authors made a forecast for the development of socially responsible HRM through

Table 1 Indicators of socially responsible HRM and ICT use in Central Asian countries in 2023

Economy	Knowledge-intensive employment, %	Females employed with advanced degrees, %	ICT use, score 0–100
	KIE	FME	U _{ICT}
China	0.00	0.00	87.75
India	12.96	2.60	49.16
Iran (Islamic Republic)	19.93	7.57	75.34
Kazakhstan	36.92	20.72	80.92
Kyrgyzstan	18.06	11.73	69.24
Mongolia	26.77	23.93	76.01
Pakistan	11.44	2.00	35.06
Russian Federation	45.48	26.14	86.34
Tajikistan	0.00	0.00	12.72
Uzbekistan	0.00	8.05	74.48

Source Developed by the authors based on WIPO materials [14]

the expanded use of ICT (using the Kyrgyz Republic as an example). Additionally, the authors developed recommendations to improve the practice of intelligent support in personnel decision-making using big data and AI technologies, supporting the implementation of the author's forecast in practice.

4 Results

To establish the contribution that big data and AI technologies make to socially responsible HRM in Central Asian countries in 2023, the authors performed a regression analysis of the data from Table 1. The obtained results are shown in Table 2.

Table 2 Regression analysis of the dependence of knowledge-intensive jobs and gender neutrality of labor on ICT use in Central Asian countries in 2023

Model	Variable	Coefficients	Standard error	t-statistic	P-value	Multiple R	F	Significance F
KIE	Y-intercept	- 2.3311	13.7219	- 0.1699	0.8693	0.4708	2.2787	0.1696
	U _{ICT}	0.3012	0.1995	1.5095	0.1696			
FME	Y-intercept	- 5.0073	8.0521	- 0.6219	0.5513	0.5807	4.0695	0.0784
	U _{ICT}	0.2362	0.1171	2.0173	0.0784			

Source Calculated and compiled by the authors

The results from Table 2 indicate that the creation of knowledge-intensive jobs in Central Asia in 2023 is by 47.08% determined by ICT usage activity. The regression equation is as follows:

$$KIE = -2.3311 + 0.3012 * U_{ICT} \quad (1)$$

Guided by Eq. (1), we can conclude that with an increase in ICT usage activity in Central Asian countries in 2023 by 1 point, the share of knowledge-intensive jobs in these countries increased by 0.3012%. The equation corresponds to a significance level of 0.20, passing the Fisher's F-test (observed $F = 2.2787$, significance $F = 0.1696$) and the Student's t-test for the factor variable (t -statistic = 1.5095), confirming its reliability and validity.

Similarly, the results indicate that gender neutrality in labor in Central Asia in 2023 is by 58.07% determined by ICT usage activity. The regression equation takes the following form:

$$FME = -5.0073 + 0.2362 * *U_{ICT} \quad (2)$$

Based on Eq. (2), we can conclude that with an increase in ICT usage activity in Central Asian countries in 2023 by 1 point, the proportion of female researchers in these countries increased by 0.2362%. The equation corresponds to a significance level of 0.10, passing the Fisher's F-test (observed $F = 4.0695$, significance $F = 0.0784$) and the Student's t-test for the factor variable (t -statistic = 1.20173), confirming its reliability and validity.

The results of the regression analysis confirmed hypothesis H. Based on regression modeling, revealing the causal relationships in the use of the considered technologies in personnel decision-making by enterprises in Central Asia in 2023, a forecast for the development of socially responsible HRM through the expanded use of ICT (using the example of the Kyrgyz Republic) has been compiled. The author's forecast revealed that an increase in ICT activity by 44.43% (to 100.00 points compared to 69.24 points in 2023) in the Kyrgyz Republic would provide the following benefits for socially responsible HRM:

- Increase in the share of knowledge-intensive employment by 50.47% (to 21.17% compared to 18.06% in 2023);
- Growth in the proportion of female researchers by 66.08% (to 19.49% compared to 11.73% in 2023).

To provide scientific-methodological support for implementing the author's forecast in practice, the authors developed a mechanism for intelligent support in personnel decision-making in socially responsible HRM using big data and AI (Fig. 1).

To elaborate on the mechanism from Fig. 1 to improve the practice of intelligent support in personnel decision-making using big data and AI to support the implementation of the author's forecast in practice, the following recommendations have been developed:

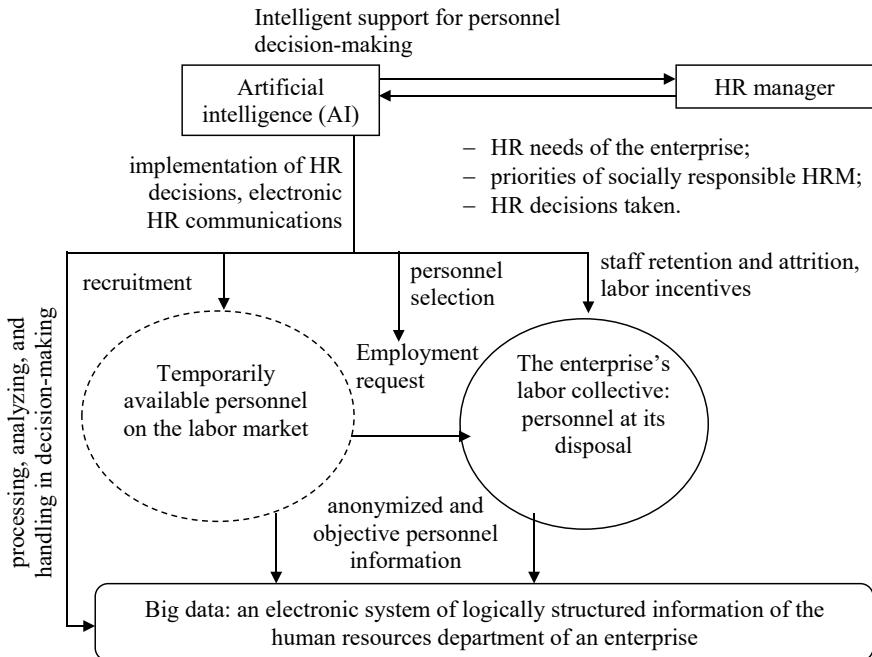


Fig. 1 Intelligent HR decision support mechanism in socially responsible HRM using big data and AI. *Source* Developed by the authors

- Aggregating depersonalized and objective information about all personnel from the labor market and within the enterprise's workforce into big data as an electronic system of logically structured information of the enterprise's HR department;
- Processing, analyzing, and accessing big data with AI when making personnel decisions;
- Providing AI with information about the enterprise's staffing needs, its socially responsible HRM priorities, and the personnel decisions made by HR managers;
- Providing intelligent support for personnel decision-making, implementing the decisions made, and conducting electronic HR communications with AI when recruiting from the labor market, selecting candidates seeking employment at the enterprise, and in retention, talent screening, and work incentivization at the enterprise.

The advantages of the developed mechanism and associated practical recommendations for improving the practice of intelligent support in personnel decision-making using big data and AI are as follows:

- Simplifying interaction and alleviating social-psychological pressure on HR managers and employees through the intermediation of their communications by AI;

- Ensuring the objectivity of information about personnel used in HR management decision-making;
- Enabling flexible adjustment of socially responsible HRM considering changing social and enterprise priorities, as well as the transformation of the labor market.

5 Discussion

The research builds upon the scholarly works of Abdurakhmanov et al. [1], del Val Núñez et al. [3], and Odilova [8], which pertain to the theory of personnel decision-making, specifying the contribution of big data and AI to socially responsible HRM. In contrast to Prikshat et al. [12], Prikshat et al. [11], and Zhou et al. [16], based on the findings (examining the countries of Central Asia in 2023), this research argues that the potential of utilizing big data and AI in the practice of socially responsible HRM is quite extensive. Moreover, it contends that the use of these technologies does not hinder but rather supports the rationalization of personnel decisions in entrepreneurship.

Supporting and extending the series of studies by Fenwick et al. [4] and Jia and Hou [5], the research established that the utilization of advanced ICT, including big data and AI, creates knowledge-intensive jobs [7, 9] and ensures gender neutrality in social and labor relations and processes, including research activities in workplaces [6, 13].

6 Conclusion

The main result of the conducted research is the confirmation of the hypothesis and the author's conclusion that big data and AI technologies enhance the effectiveness of socially responsible HRM through the creation of knowledge-intensive jobs and the promotion of gender neutrality in labor. Specifically, the following scientific results were obtained, contributing to the advancement of knowledge in the theory of personnel decision-making:

- Regression models were obtained, revealing the causal relationships of the use of the examined technologies in the personnel decision-making of enterprises in Central Asia in 2023. The theoretical significance of these models lies in their enhancement of the predictability of HR management automation in Central Asia;
- A forecast for the development of socially responsible HRM through the expansion of ICT usage was compiled using the example of the Kyrgyz Republic. The practical significance of the forecast is associated with its potential application as a roadmap for the socially oriented development of the labor market in the Kyrgyz Republic;

- A mechanism for the intellectual support of personnel decision-making in socially responsible HRM using big data and AI was developed. The managerial significance of the mechanism is expressed in its ability to rationalize HR management practices.

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Algorithm for Managerial Decision-Making Using Big Data and AI



Anton S. Smetanin , Aktam U. Burkhanov , Abdula M. Chililov ,
Yluana V. Ashmarina , and Elvira A. Kamalova

Abstract The research focuses on developing an algorithm for managerial decision-making using big data and artificial intelligence (AI). It relies on such scientific research methods as structural-functional, critical, and comparative analysis and schematic visualization of organizational-economic processes as a sub-method of qualitative modeling of dynamic economic systems. The scientific novelty of the proposed algorithm lies in its two levels of decision-making (AI and manager), unlike the existing algorithm. Management is limited to the manager, with all stages seamlessly transitioning from one to another and being intrinsically linked. The theoretical significance of the developed algorithm is that it addresses the shortcomings of the existing algorithm and adapts the decision-making process to contemporary challenges. The practical significance of the author's algorithm is that automating decision-making using big data and AI offers the following advantages for management: faster decision-making by eliminating intermediaries in the form of lower-level managers, comprehensive identification of relevant business opportunities and problems, reduced managerial workload and a smaller managerial apparatus, and

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the possibility of remote employment for managers. This collectively supports the humanization of managerial labor. Automated big data collection (through managerial communications, problem identification, alternative selection, optimal decision-making, and implementation) ensures improved corporate monitoring and control.

Keywords Decision-making algorithm · Managerial decisions · Management automation · Big data · Artificial intelligence (AI) · Business management

JEL Codes C44 · D81 · M21 · O32

1 Introduction

Managerial decisions are crucial for maintaining the effective functioning of a business and realizing its development potential, even in a relatively stable and favorable market environment. In today's context, the market environment is subject to significant fluctuations and crises, making it unfavorable for business operations. The following contemporary challenges contribute to this situation in the global economic system, affecting global, national, and local markets.

One reason is the shift in the vector of globalization. The transition from universal globalization to a fragmented one (i.e., limited to participants in specific integration associations) has initiated a process of market boundary revisions, changes in market presence conditions, and restructuring of cross-border supply and distribution chains. This prevents business structures from relying on past experiences and requires the establishment of new economic relationships and the development of new organizational schemes for production–distribution processes.

Another reason is the need to harmonize socio-ecological and economic-technological priorities of sustainable development in business activities and systematically support sustainable development goals. This results in multi-criteria managerial decisions, significantly increasing the complexity and responsibility of decision-making. Additionally, the peak of the Fourth Industrial Revolution and the overlapping Fifth Industrial Revolution require digital modernization of production–distribution processes, necessitating a similar pace and technological support for business management automation.

These reasons increased the importance of the managerial decision-making process for business preservation and growth potential realization. The problem is that the existing decision-making algorithm does not meet the latest business management demands due to three key shortcomings. The first shortcoming is that the existing algorithm is burdened with numerous stages, resulting in insufficiently rapid managerial decision-making.

The second shortcoming is the suboptimal sequence of stages, leading to the separation of management information collection and analysis. In the existing algorithm, data collection and processing are independent processes, separated in timing (data

is usually collected in advance, failing to address data shortages in critical decision-making situations) and responsibility (low-level managers are responsible for data collection, while top managers are responsible for decision-making).

The third shortcoming is the insufficient use of advanced management automation capabilities. Attempts at automation are limited to individual stages of the managerial decision-making process. This results in the fragmentation of the decision-making algorithm stages, further slowing down the decision-making process.

These points highlight the relevance of improving the decision-making algorithm to overcome the listed shortcomings and adapt it to contemporary challenges. Therefore, this research aims to develop a managerial decision-making algorithm using big data and artificial intelligence (AI).

2 Literature Review

The fundamental basis of this research is the theory of managerial decision-making [2, 8, 12, 18]. The following key characteristics of the existing decision-making algorithm are systematized based on this theory:

- One level of decision-making: decisions are made solely by the top manager as the head of the management of a business structure [6], which results in a high workload and responsibility for the top manager;
- The decision-making technology involves the top manager relying on their own knowledge, experience, and intuition [14], introducing a significant degree of subjectivity in processing corporate data and making decisions;
- The organizational structure of the business's management is hierarchical and bureaucratic [5], reducing the flexibility of the decision-making process;
- The stages of decision-making are noticeably separated in time [3], which lengthens the decision-making process;
- Each stage is isolated [7], which causes fragmentation in the decision-making algorithm and leads to disruptions.

A literature review revealed that various aspects of management automation are widely covered in numerous publications by authors such as Bogoviz [1], Kusakina et al. [10], Sommer [16], and Sultanova et al. [17]. In the automation of managerial decision-making, technologies such as big data and AI play a leading role, with practical applications studied in the works of Franke and Hiebl [4], Justino et al. [9], Lindebaum et al. [11], Patrucco et al. [13], Ragazou et al. [15], and Zhao et al. [19].

While the advantages of these technologies are widely recognized, a specific decision-making algorithm using big data and AI is not presented in the existing literature, representing a gap. This research fills this gap by developing a prospective decision-making algorithm based on big data and AI.

3 Materials and Methods

The research relies on several scientific research methods, including structural-functional, critical, and comparative analysis and schematic visualization of organizational-economic processes as a sub-method of qualitative modeling of dynamic economic systems. The starting point of this research is the author's representation of the existing managerial decision-making algorithm used by businesses formed based on a literature review (Fig. 1).

According to Fig. 1, the existing managerial decision-making algorithm employed by businesses involves a clear delineation of two organizational and managerial processes. The first process involves collecting data from various sources of business management information and integrating it into a corporate information system. This preparatory process is carried out by all participants of the enterprise's management.

Low-level managers engage directly with the market environment in which the business operates. The production low-level manager communicates with counterparties (suppliers, investors, etc.) regarding resource supply issues. The low-level marketing and sales manager interacts with consumers regarding the sale of finished products. Low-level managers also contact the business's competitors and transfer all gathered information to the corporate information system.

Government business regulators provide the top manager with national, local, and industry priorities, standards, norms, requirements, regulations, business support, and other informational exchanges. The top manager duplicates the information exchange with market entities and transfers the collected information to the corporate information system.

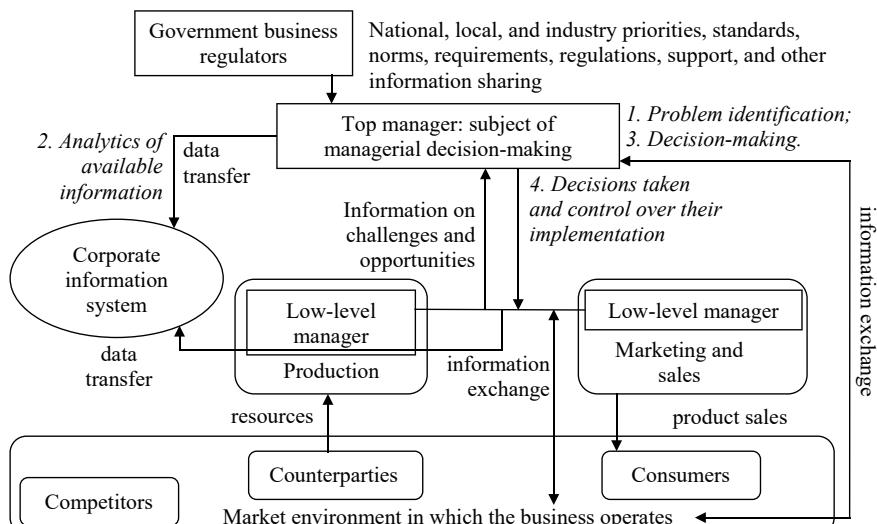


Fig. 1 Algorithm of managerial decision-making used by businesses. *Source* Developed by the authors

The second process involves processing the available data and making decisions. The top manager carries out this primary process as the decision-making entity in the business. In the first stage of the algorithm, the top manager identifies a relevant business problem that needs resolving. In the second stage, they analyze the available information by referring to the corporate information system materials. In the third stage, the top manager makes a managerial decision. In the fourth stage, the top manager communicates the decisions to low-level managers for implementation and monitors their execution.

Critical analysis has shown that the considered algorithm makes it possible to automate only certain stages of the managerial decision-making process using standard digital technologies. For instance, the corporate information system may be in electronic form and computerized; communications with market entities may occur via the Internet. To integrate advanced technologies such as big data and AI into management, a fundamental revision of the decision-making algorithm is required.

4 Results

To address the issue of management automation using advanced technologies such as big data and AI, the authors developed a new managerial decision-making algorithm (Fig. 2).

As shown in Fig. 2, the two previously separate managerial processes involved in decision-making are now integrated and interconnected in the new algorithm. This integration is achieved by combining big data and AI into a unified automated business management system. To illustrate the specifics of the new algorithm, it is necessary to examine these processes individually, similar to the existing algorithm.

The process of collecting data from available sources of business management information and integrating it into the corporate information system is carried out using big data technology. Information from all market environment entities flows directly into big data, bypassing intermediaries like managers, as in the previous algorithm. Government business regulators can access the corporate big data system to monitor business activities.

The process of processing available data and making decisions is executed using AI technology. In the first stage, AI identifies a problem relevant to the business. In the second stage, AI performs an automated analysis of the big data. In the third stage, AI provides intelligent support for managerial decision-making. In the fourth stage, the top manager, still the decision-making entity, makes the optimal decision.

In the fifth stage, the top manager communicates the decision to AI. In the sixth stage, AI automatically implements the decisions and autonomously monitors their execution in production, marketing, and sales. These stages are conditionally separated, whereas, in practice, they occur in real time. Consequently, transitioning from problem identification to resolution in business practice can take minutes or hours rather than days, as in the previous algorithm.

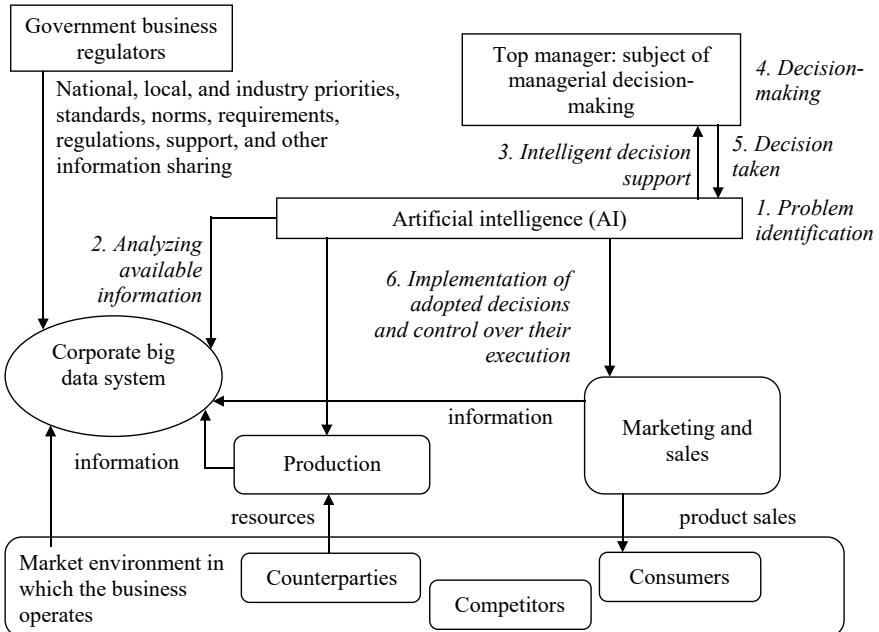


Fig. 2 A new management decision-making algorithm involving big data and AI. *Source* Developed by the authors

5 Discussion

The contribution of the new scientific results obtained in this research to the literature [2, 8, 12, 18] lies in advancing the theoretical framework of managerial decision-making through the specification of a decision-making algorithm using big data and AI. A comparative analysis of alternative decision-making algorithms in business activities, highlighting the advantages of the author's scientific and practical development, is presented in Table 1.

As shown in Table 1, unlike Guchhait and Sarka [6], the new algorithm involves two levels of managerial decision-making: the first (lower) level is AI, providing intellectual support, and the second (higher) level is the top manager, who makes the decisions directly.

In contrast to Quick and Sayar [14], in the new algorithm, decision-making is not carried out entirely independently by the manager but is supported by such management automation technologies as big data and AI. Unlike Georgiev and Georgiev [5], in the new algorithm, the managerial apparatus is not hierarchical and bureaucratic but is limited to the manager, ensuring flexibility in decision-making.

In contrast to Cleophas and Schütze [3], the new algorithm overcomes the time-separation of the stages of the decision-making process—all stages transition seamlessly from one to another. Unlike Hinrichs et al. [7], in the new algorithm, the stages

Table 1 Comparative characterization of alternative algorithms for making managerial decisions in the activities of businesses

Areas of comparison of algorithms	Existing algorithm applied by the business	New algorithm recommended to businesses
Levels of decision-making	One level: decisions are made solely by the top manager [6]	Two levels: decisions are made by the top manager with intellectual support
Decision-making technology	Decisions are made by the manager based on knowledge, experience, and intuition [14]	Automated decision-making using big data and AI
Organizational structure of management	Hierarchical management apparatus with a bureaucratic structure [5]	Management is limited to the manager, ensuring decision-making flexibility
Stages of decision-making	Stages are noticeably separated in time [3]	Stages seamlessly transition from one to another
Integrity of the decision-making algorithm	Each stage is isolated, causing disruptions in the algorithm [7]	All stages are interconnected, eliminating disruptions in the algorithm

Source Developed by the authors

of the decision-making process are not isolated but are interconnected, eliminating disruptions in the algorithm.

This research contributes to the scientific discussion by Bogoviz [1], Kusakina et al. [10], Sommer [16], and Sultanova et al. [17] on the automation of managerial decision-making, clarifying the role of big data and AI in this process, and continuing the work on the use of these technologies in management by scholars such as Franke and Hiebl [4], Justino et al. [9], Lindebaum et al. [11], Patrucco et al. [13], Ragazou et al. [15], and Zhao et al. [19].

6 Conclusion

The result of the conducted research was the development of a managerial decision-making algorithm using big data and AI, which ensured the achievement of the set goal. The scientific novelty of the proposed algorithm lies in its two levels of decision-making (AI and manager), unlike the existing algorithm. Management is limited to the manager, with all stages seamlessly transitioning from one to another and being intrinsically linked.

The theoretical significance of the developed enhanced algorithm is that it overcomes the shortcomings of the existing algorithm and adapts the decision-making process to contemporary challenges. The practical significance of the author's algorithm is that, by automating decision-making with the help of big data and AI, this algorithm provides the following advantages for management:

- Faster decision-making due to the elimination of intermediaries such as low-level managers;
- More comprehensive identification of relevant business opportunities and problems;
- Reduced managerial workload and a smaller managerial apparatus and the possibility of remote work for the manager, collectively supporting the humanization of managerial labor;
- Automated collection of big data (through managerial communications, problem identification, alternative selection, optimal decision-making, and implementation), ensuring improved corporate monitoring and control.

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Big Data and AI as Human–Machine Interaction Technologies in Managerial Decision-Making Within Digital Business



Elena G. Popkova 

Abstract The research defines a promising organizational model for using big data and AI in human–machine interaction during managerial decision-making within digital business. It examines the advanced international experience of the top 20 countries in the world, which have gained the most significant advantages from management automation in 2023. The authors developed a regression model to analyze the impact of social and technical factors on the outcomes of management automation. As a result, the authors proved that optimizing the influence of technical factors on management automation in digital business is more important than social factors. This research highlights that optimizing human–machine interaction in managerial decision-making based on big data and AI in Russia will make it possible to realize management automation potential in Russian digital business more fully. The authors developed a set of original recommendations to best organize human–machine interaction in managerial decision-making using big data and AI technologies. This will minimize the time managers spend complying with state requirements and increase gender neutrality in employment within digital business management.

Keywords Big data · Artificial intelligence · Human–machine interaction · Decision-making · Managerial decisions · Digital business

JEL Codes C44 · D81 · G34 · O32

1 Introduction

Although the digital modernization of business represents a unified contemporary trend, approaches to organizing automated business processes vary significantly depending on the technologies employed. The approach that has been most fully developed involves total automation through the creation of smart industries based

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on technologies such as robots, machine vision, and the Internet of Things (IoT). In this approach, the optimal organization of business processes is determined by the reliability and efficiency of machine communications.

In contrast, there is a much less developed approach that assumes a fundamentally different organization, where automation is limited and relies on technologies like big data and artificial intelligence (AI). In this case, the optimal organization depends on the stability and flexibility of human–machine communications. The increased complexity (compared to predominantly machine interaction) of organizing human–machine interaction in managerial decision-making in digital business can be explained by several reasons.

One reason is related to the necessity of labor division (i.e., the functions performed by humans and machines). For each specific business process, it is necessary to determine the extent to which its automation is preferable and the appropriate proportion of human and machine labor required for its execution. For example, in making investment decisions, their intelligent support might be fundamental. In making environmental decisions, intelligent support might involve verification and rethinking by a green manager. In making HR decisions, intelligent support might not be applied. The entire responsibility could belong to the HR manager.

Another reason lies in the necessity of establishing multi-level communications. Human communications occur at the social level. These can involve workers within a labor collective, managers within a management team, and interactions between workers and managers. Closed machine communications take place at the technical level. For example, big data can be collected through ubiquitous computing, the IoT, and machine vision. AI can analyze this big data using pre-set computer programs without manager involvement.

Human–machine communications occur at the intersection of the social and technical levels. An example of this is the manual input of information into the big data system to supplement data that cannot be collected automatically or is not yet automated in the operations of a given digital business entity. Similarly, human–machine communications occur during the intelligent support of managerial decision-making. Organizing the entire spectrum of these communications and ensuring their seamlessness and informativeness requires complex configurations.

Another reason is the preservation of social and labor risks during automation if it involves human–machine interaction. These include the risk of psychological adaptation of workers to machine control and management and the adaptation of managers to human–machine interaction. Additionally, there is the risk of workforce reduction during the next wave of business process automation, which is a concern for workers and the management of digital businesses.

Due to these reasons, there remains uncertainty in existing scientific literature and economic practice regarding how human–machine interaction in managerial decision-making in digital business should be organized. The need to fill this gap in the literature is explained by the fact that the approach to organizing limited automated business processes based on big data and AI remains rudimentary. Its insufficient detail hinders and reduces the effectiveness of its practical implementation. This research aims to define a promising organizational model for using big data and

AI as technologies for human–machine interaction in managerial decision-making within digital business.

2 Literature Review

The fundamental basis for the research is the scientific concept of business management automation. The published scientific literature related to this theory has thoroughly examined issues associated with the following:

1. The use of big data and AI as technological support for business management automation [7];
2. The intelligent support of managerial decision-making [3];
3. Managerial decision-making in digital business [10].

However, the issues of human–machine interaction in managerial decision-making in digital business using big data and AI technologies have only been partially studied and remain largely unclear. The uncertainty about how to best organize human–machine interaction in managerial decision-making in digital business using big data and AI technologies represents a gap in the literature that this research aims to fill.

As a result of a review and content analysis of the published scientific literature on the considered concept, this research identifies two key advantages that digital business seeks to achieve through the initiation of management automation processes:

- Ensuring gender neutrality within management and creating greater opportunities for women to engage in management practices [1];
- Reducing the time and labor intensity of managerial processes necessary to comply with state requirements for digital business [11].

Simultaneously, the academic community has not reached a consensus regarding the nature of the factors that determine the effectiveness of organizing human–machine interaction in managerial decision-making in digital business using big data and AI. Some scholars believe that the following social factors play a leading role:

- The level of digital skills development among managers [2];
- The overall competence of management personnel [12].

The economic significance of the influence of social factors on human–machine interaction in digital management lies in the fact that the readiness and involvement of managers in this interaction determine whether AI suggestions will be heard and correctly interpreted and whether intelligent support will make sense—leading to the rationalization of managerial decisions. Other researchers believe that the following technical factors are most important:

- The technical (software) refinement of big data and AI [8];

- Cybersecurity [9].

The economic significance of the influence of technical factors on human-machine interaction in digital management is that the performance and technical perfection of big data and AI determine how accurately they will provide intelligent support, how comprehensible this support will be for professional managers, and how effectively it will rationalize managerial decisions when made based on AI recommendations.

The research question is which nature of factors—social (the level of digital skills development among managers and the overall competence of management personnel) or technical (the technical refinement of big data, AI, and cybersecurity)—more significantly determines the outcomes of intelligent support for managerial decision-making (the involvement of women in management practices and the acceleration of compliance with state requirements) in the activities of digital business.

3 Materials and Methods

This research is based on the advanced experience of a specially formed sample, which includes the top 20 countries in the world that have gained the most significant advantages from management automation in 2023. The criteria for adding countries to the sample were as follows:

1. The highest values of female participation in management practices (FM) [13];
2. The lowest values of time spent on complying with state requirements (RQ) [14] in digital business activities in 2023 (based on 2022 results).

The research is conducted using the regression analysis method, which establishes the dependence of FM and RQ on social factors (the level of digital skills development among managers ($Humn_1$) [4] and the overall competence of management personnel ($Humn_2$) [5]) and technical factors (the technical refinement of big data and AI ($Mash_1$) [5]) and cybersecurity ($Mash_2$) [6]). The empirical data referred to in this research are compiled in Table 1.

The results of regression analysis are used to determine the prospects for optimizing human-machine interaction in making managerial decisions in digital business based on big data and AI (using Russia as an example). The authors determined such a combination of factors of a social and technical nature, at which RQ is minimized. The change in FM that occurs in this case is assessed.

Table 1 Management automation and influencing factors of a social and technical nature in 2023

	Firms with female top managers, % of firms	Time spent dealing with the requirements of government regulations, % of senior management time	Digital/technological skills, score 0–10	Competent senior managers are readily available, score 0–10	Use of big data and analytics to support decision-making, score 0–10	Global cyber security index, score 0–100
	FM	RQ	Humn ₁	Humn ₂	Mash ₁	Mash ₂
Austria	18.8	10.7	6.00	4.78	4.89	93.89
Bulgaria	28.8	10.5	6.31	4.00	4.37	67.38
Croatia	27.0	15.0	7.00	3.73	4.39	92.55
France	19.9	20.7	6.94	5.57	4.63	97.60
Germany	14.2	9.2	5.54	5.61	4.60	97.41
Hungary	22.1	10.4	5.5	3.11	4.3	91.28
Indonesia	22.1	0.9	6.89	6.70	6.17	94.88
Kazakhstan	26.0	4.3	5.78	5.86	6.42	93.15
Latvia	32.6	26.8	6.04	4.77	4.63	97.28
Lithuania	30.7	6.2	8.69	5.86	5.98	97.93
Malaysia	33.2	5.2	7.12	6.29	5.43	98.06
Mongolia	38.9	18.5	6.00	3.07	3.82	26.20
Philippines	29.9	5.4	6.21	5.89	5.16	77.00
Poland	27.8	7.7	6.35	5.54	5.63	93.86
Russia	24.3	5.6	6.13	5.84	5.17	98.06
Slovak Republic	22.9	16.5	7.18	3.85	5.54	92.36
South Africa	38.5	9.7	5.59	4.51	5.38	78.46
Spain	17.6	13.4	6.73	5.35	4.32	98.52
Thailand	64.8	4.8	6.74	6.24	5.73	86.50
Venezuela	31.1	27.6	4.35	3.65	4.25	27.06

Source Developed by the authors based on IMD [4, 5], ITU [6], and World Bank [13, 14]

4 Results

To establish how factors of different natures affect the results of management automation, the authors performed a regression analysis of the statistics from Table 1. The identified results are reflected in Table 2.

Table 2 Results of regression statistics

Type of analysis	Statistical indicator	FM	RQ
Correlation analysis	Multiple R	0.5237	0.7062
	Observation	20	20
Variance analysis	Significance F	0.2763	0.0267
	Significance level	0.3	0.05
	Tabular F	1.3424	3.0556
	Observed F	1.4168	3.7298
Regression coefficients	Y-intercept	10.8952	45.6379
	Humn ₁	2.4277	-0.0669
	Humn ₂	1.1308	-1.8036
	Mash ₁	4.6459	-4.4390
	Mash ₂	-0.3158	-0.0276

Source Developed by the authors

Based on the materials from Table 2, the following conclusions can be drawn. The studied factors collectively determine 52.37% of women's involvement in management practices and 70.62% of the speed of compliance with state requirements.

The validity and reliability of the established relationship between the considered factors and FM are confirmed at a significance level of 0.3 (tabular F = 1.3424; observed F = 1.4168, Fisher's F-test is passed), and for RQ at a significance level of 0.05 (tabular F = 3.0556; observed F = 3.7298; Fisher's F-test is passed). The regression model is as follows:

$$\begin{cases} \text{FM} = 10.8952 + 2.4277 * \text{Humn}_1 + 1.1308 * \text{Humn}_2 \\ \quad + 4.6459 * \text{Mash}_1 - 0.3158 * \text{Mash}_2, \\ \text{RQ} = 45.6379 - 0.0670 * \text{Humn}_1 - 1.8036 * \text{Humn}_2 \\ \quad - 4.4390 * \text{Mash}_1 - 0.0276 * \text{Mash}_2. \end{cases} \quad (1)$$

Model (1) showed that a one-point increase in the level of digital skills development among managers results in a 2.4277% increase in the proportion of women in top management and a 0.0670% decrease in the proportion of time managers spend complying with state requirements. A one-point increase in the overall competence of management personnel leads to a 1.1308% increase in the proportion of women in top management and a 1.8036% reduction in the proportion of time managers spend on compliance with state requirements.

An improvement in the technical refinement of big data and AI by one point results in a 4.6459% increase in the proportion of women in top management and a 4.4390% decrease in the proportion of time managers spend on compliance with state requirements. An increase in cybersecurity by one point leads to a 0.3158% decrease in the proportion of women in top management and a 0.0276% reduction in the proportion of time managers spend on compliance with state requirements.

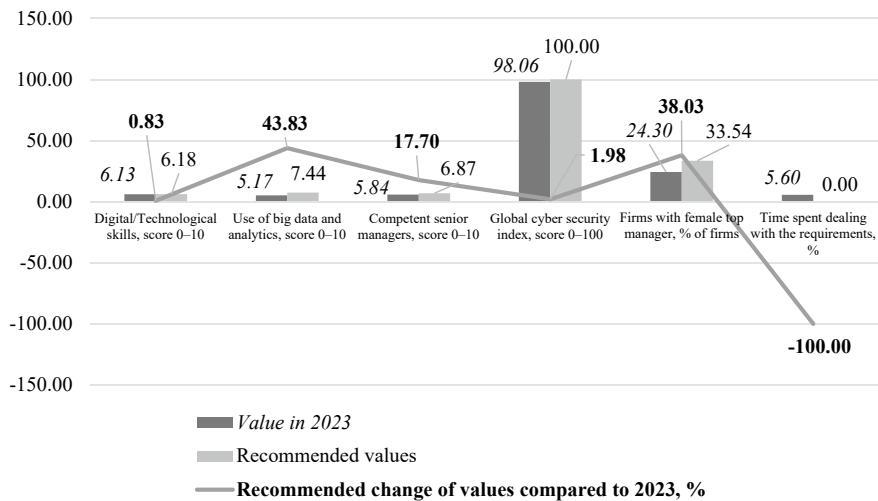


Fig. 1 The prospect of optimizing human–machine interaction in managerial decision-making based on big data and AI in Russia. *Source* Developed by the authors

Model (1) served as a basis for determining the prospects for optimizing human–machine interaction in managerial decision-making in digital business, relying on big data and AI (using Russia as an example). Based on Model (1), the authors identified a combination of social and technical factors that minimizes RQ and assessed the corresponding change in FM (Fig. 1).

Figure 1 showed that optimizing human–machine interaction in managerial decision-making based on big data and AI in digital business activities in Russia will, in the long run, reduce the time managers spend complying with state requirements to 0. Additionally, the proportion of women in top management could increase by 38.03% (from 24.30% in 2023 to 33.54%).

To optimize human–machine interaction in managerial decision-making based on big data and AI in the activities of digital business in Russia, the authors proposed the following scientific and practical recommendations:

- Increase the level of digital skills development among managers by 0.83% (from 6.13 points in 2023 to 6.18 points);
- Increase the overall competence of management personnel by 43.93% (from 5.17 points in 2023 to 7.44 points);
- Improve the technical refinement of big data and AI by 17.703% (from 5.84 points in 2023 to 6.87 points);
- Enhance cybersecurity by 1.98% (from 98.06 points in 2023 to 100.00 points).

5 Discussion

The research contributes to the literature [3, 7, 10] by advancing the scientific concept of business management automation by explaining how to best organize human-machine interaction in managerial decision-making in digital business using big data and AI technologies. The research question has been answered, revealing the nature of the influence of social and technical factors on the outcomes of intelligent support for managerial decision-making (Fig. 2).

According to Fig. 2, technical factors significantly enhance the outcomes of intelligent support in managerial decision-making. The sum of the regression coefficients for technical factors is 8.80, compared to 5.43 for social factors. The most significant factor is the technical refinement of big data and AI (9.08) (confirming Kurbonov et al. [8]).

The second most significant factor is the level of digital skills development among managers (2.93) (in confirmation of Abdurakhmanova, Khachaturov, Isaeva, and Kostyuchenko [2]). The third most significant factor is the overall competence of management personnel (2.49) (in confirmation of Veselovsky, Izmailova, Bogoviz, Lobova, and Alekseev [12]). The least significant factor is cybersecurity (−0.29), which supports the reduction of time spent on complying with state-mandated requirements but, unlike Litvinova et al. [9], does not contribute to increasing gender neutrality within the management of the digital business.

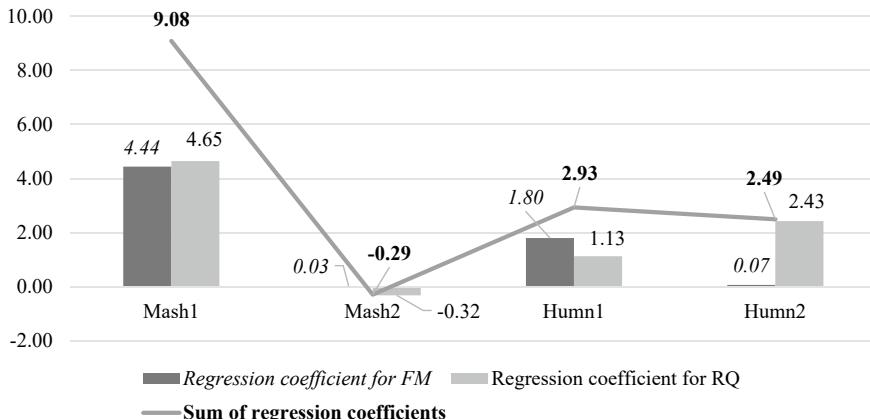


Fig. 2 Influence of factors of social and technical nature on the results of intelligent support of managerial decision-making. *Source* Developed by the authors

6 Conclusion

The primary outcome of this research is developing a set of original recommendations to best organize human–machine interaction in managerial decision-making in digital business using big data and AI technologies. The theoretical significance of the results lies in proving the greater importance of optimizing the impact of technical factors on the automation of management in digital business compared to social factors.

The practical significance is expressed in the perspective of optimizing human–machine interaction in managerial decision-making based on big data and AI in Russia. This will make it possible to realize the potential of management automation in Russian digital business. The managerial significance of the authors' conclusions and recommendations is associated with their potential to focus digital management efforts on the most significant factors (technical in nature), thereby increasing the efficiency of organizing human–machine interaction in managerial decision-making using big data and AI.

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The Mechanism of Automatization of Smart Business Through Decision-Making and Management of Production Based on Big Data and AI



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Abstract The research develops a mechanism for automating smart business through decision-making and production management based on big data and AI. Relying on the latest statistical data from Bloom Consulting and WIPO for 2023, the authors developed an econometric model for automating smart business in Central Asia. The developed model holds theoretical significance because it unveils the relatively unexplored experience of automating smart business in Central Asia and clarifies the impact of management factors on the outcomes of this automation in the region. Based on this model, the authors forecasted the automation of smart business in Kyrgyzstan, Russia, and Uzbekistan. The practical benefit of this forecast lies in its ability to facilitate more precise planning of smart business automation in these Central Asian countries. To support the practical implementation of the forecast, the authors developed a mechanism for automating smart business through decision-making and production management based on big data and AI. The new features of the mechanism include unified AI management of smart production as a special object of automation in smart business operations, storing production information in a separate big data cell to accelerate its processing, and recognizing production as the central and priority object of smart business management, with its automation progressing

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at its own pace. This mechanism will enhance production management efficiency and more fully realize the potential of smart production automation, underscoring its managerial significance.

Keywords Automation mechanism · Smart business · Decision-making · Production management · Big data · Artificial intelligence (AI) · Smart production

JEL Codes D24 · E27 · G31 · L23

1 Introduction

The emergence of the digital economy has led to the rise and popularization of a new form of entrepreneurship—smart business. It is characterized by a high level and growing scale of automation in economic operations. However, its potential is not fully realized despite the priority given to comprehensive automation. This problem arises from the lack of a proper automation mechanism for smart business, complicated by the complex nature of digital modernization, which has a contradictory interpretation.

On the one hand, comprehensive automation is justified in terms of ensuring the technological unity of the business structure as a micro-level socio-economic system. Balanced automation facilitates the unification of business operations within the structure, supporting the development and adherence to corporate standards. On the other hand, economic operations vary in their susceptibility to automation. Production is the most automatable, while other business processes can be automated only partially.

This is demonstrated by numerous examples from international practice. For instance, there is experience in creating autonomous productions within multinational corporations that are separate from other divisions. The operations of these smart productions are fully automated. Nevertheless, they are not self-sufficient for conducting business, requiring other associated economic processes. For example, the think tanks of multinational corporations are usually located in different countries, far from the smart productions. The activities of these think tanks are much less automated due to the high labor intensity of economic processes and their connection with social communications—with consumers, counterparties, and government services.

In striving to maintain a uniform pace of digital modernization of economic processes, smart business focuses on non-production operations, which are the least automatable, thereby slowing down the digital modernization of production operations. This shortcoming indicates the imperfection of the current automation mechanism used by contemporary smart businesses and highlights the need to develop a new mechanism that will more fully realize the potential of digital modernization of production operations.

The empirical experience of recent years shows that the technological foundation of smart productions consists of robots, which are much less demanded by other business processes. As an alternative, this research proposes using big data and artificial intelligence (AI). The advantage of the recommended technologies is that they can be applied with relatively equal effectiveness across all economic processes of today's business in production and non-production areas.

Due to this advantage, big data and AI are promising technological tools for automating smart business. As a connecting link between production and non-production processes for their systemic automation, it is proposed that managerial decision-making be used. This recommendation is based on the fact that all economic processes require management; decision-making is a common characteristic of these processes.

While general issues of decision-making automation based on big data and AI are widely covered in published business management literature, specific issues of applying big data and AI technologies in automating smart productions are insufficiently addressed. This research aims to clarify these issues and develop a mechanism for automating smart business through decision-making and production management based on big data and AI.

2 Literature Review

The theoretical foundation of this research is the scientific concept of production management. According to this concept, production is automated separately from other economic processes in smart business. Published works highlight the following as the main factors for deriving positive effects from the automation of management based on big data and AI:

- Automation of export activities in smart business [6].
- Automation of investment decision-making in smart business [7].
- Ensuring the automation of decision-making by digital management personnel [5].

The most significant manifestations of the results of smart production automation are as follows:

- The volume of high-tech production [2];
- High-tech exports [10];
- High-tech imports [13].

However, the existing literature does not explain how these factors influence the identified results, which is a shortcoming of the available publications. The current mechanism for automating smart business assumes the following:

- The separation of decision-making related to production management (tactical decisions made by the production manager) and overall corporate decision-making (strategic decisions made by top management) [8];
- The routine nature of production management as a sub-process in the management system, necessitating the integration of production information with general corporate data [1];
- The equal status of management objects in the smart business management system, leading to insufficient attention paid to decision-making for production management as a complex management object by the enterprise's management apparatus [12].

The application of big data and AI in production has been studied in several published works by Dewangan and Kumar [4], Li et al. [9], Rashid et al. [11], and Yildiz et al. [15]. However, the issues of managerial decision-making related to production using big data and AI are underexplored, creating a gap in the literature that this research aims to fill by developing a mechanism for automating smart business through decision-making and production management based on big data and AI.

3 Materials and Methods

The methodology of this research involves factor analysis of the automation of smart business. The analysis is performed using regression analysis to model the influence of factors (AM) on the results (RS) of automation. The research focuses on Central Asia as a region with a rapid pace and unique traditions of smart business automation. The research covers the period of 2023 (Table 1).

Based on the regression modeling results, the authors made a forecast for the automation of smart business in Kyrgyzstan, Russia, and Uzbekistan, assuming these countries reach the maximum values of the factor variables within the sample.

4 Results

To determine the real impact of smart business automation factors on its results in Central Asian countries in 2023, the authors conducted a regression analysis using the data from Table 1. The results are presented in Table 2, which also includes a reliability test for these results.

According to Table 2, the combined influence of the examined factors of smart business automation determines the volume of high-tech production in Central Asia in 2023 by 77.08%, high-tech exports by 97.92%, and high-tech imports by 68.40%.

Table 1 Factors and results of smart business automation in Central Asian countries in 2023

Economy name	Factors of smart business automation			Results of smart business automation		
	Exports (%)	Investment (%)	Talent (%)	High-tech manufacturing (%)	High-tech exports, % total trade	High-tech imports, % total trade
	AM ₁	AM ₂	AM ₃	RS ₁	RS ₂	RS ₃
Afghanistan	1	5	8	0.00	0.00	0.00
China	13	13	9	48.52	28.04	22.61
India	1	10	5	34.23	4.04	10.00
Iran (Islamic Republic of)	1	8	4	28.62	0.17	5.07
Kazakhstan	1	7	10	15.32	5.13	9.92
Kyrgyzstan	2	4	6	1.85	1.89	8.34
Mongolia	1	7	8	3.84	0.29	5.87
Pakistan	1	6	5	21.10	0.69	16.18
Russian Federation	2	8	11	29.03	2.27	8.61
Tajikistan	1	3	7	2.58	0.02	8.49
Turkmenistan	1	6	5	0.00	0.00	0.00
Uzbekistan	0	3	5	24.76	0.09	10.86

Source Developed by the authors based on Bloom Consulting [3] and WIPO [14]

Table 2 Regression analysis and reliability test of its results

Statistical indicators	Values in regression equations		
	RS ₁	RS ₂	RS ₃
Multiple R	0.7708	0.9792	0.6840
Significance F	0.0548	0.000007	0.1491
Significance level	0.10	0.01	0.15
F-observed	3.9043	62.0275	2.3450
F-tabular	2.9238	7.5910	2.3366
F-test	Passed	Passed	Passed
Regression coefficients	Y-intercept	- 1.3587	- 3.6432
	AM ₁	0.7555	1.9824
	AM ₂	3.7594	0.3555
	AM ₃	- 1.1263	0.1006
- 0.2065			

Source Developed by the authors

$$\begin{cases} RS_1 = -1.3587 + 0.7555 * AM_1 + 3.7594 * AM_2 - 1.1263 * AM_3, \\ RS_2 = -3.6432 + 1.9824 * AM_1 + 0.3555 * AM_2 + 0.1006 * AM_3, \\ RS_3 = 7.5392 + 1.2625 * AM_1 + 0.0132 * AM_2 - 0.2065 * AM_3. \end{cases} \quad (1)$$

According to model (1), with a 1% increase in the level of automation of export management in smart business in Central Asian countries, the share of high-tech production increases by 0.7555%, the share of high-tech exports rises by 3.7594%, and the share of high-tech imports decreases by 1.1263% (the reliability of the regression relationships is confirmed by the F-test, passed at a significance level of 0.01).

With an increase in the level of automation of investment decision-making in smart business in Central Asian countries, the share of high-tech production increases by 1.9824%, the share of high-tech exports rises by 0.3555%, and the share of high-tech imports increases by 0.1006% (the reliability of the regression relationships is confirmed by the F-test, passed at a significance level of 0.15).

With an increase in the provision of decision-making automation by digital management personnel in Central Asian countries, the share of high-tech production increases by 1.2625%, the share of high-tech exports rises by 0.0132%, and the share of high-tech imports decreases by 0.2065% (the reliability of the regression relationships is confirmed by the F-test, passed at a significance level of 0.10).

Based on model (1), the authors made a forecast for the automation of smart business in Kyrgyzstan, Russia, and Uzbekistan, assuming these countries reach the maximum values of the factor variables ($AM_1 = 13$, $AM_2 = 13$, and $AM_3 = 11$) within the sample (Fig. 1).

The forecast from Fig. 1 suggests that in Kyrgyzstan, the level of automation of export management in smart business will increase by 550.00%, the level of automation of investment decision-making will rise by 225.00%, and the provision of decision-making automation by digital management personnel will grow by 83.33%. As a result, the following is projected:

- An increase in the share of high-tech production by 805.84% (from 1.89% in 2023 to 17.12%);
- An increase in the share of high-tech exports by 152.61% (from 8.34% in 2023 to 21.07%);
- An increase in the share of high-tech imports by 334.8% (from 1.85% in 2023 to 8.04%).

The forecast for Russia indicates that the level of automation of export management in smart business will grow by 550.00% and the level of automation of investment decision-making by 62.50%. Consequently, the following is projected:

- An increase in the share of high-tech production by 681.11% (from 2.27% in 2023 to 17.73%);
- An increase in the share of high-tech exports by 164.47% (from 8.61% in 2023 to 22.77%);

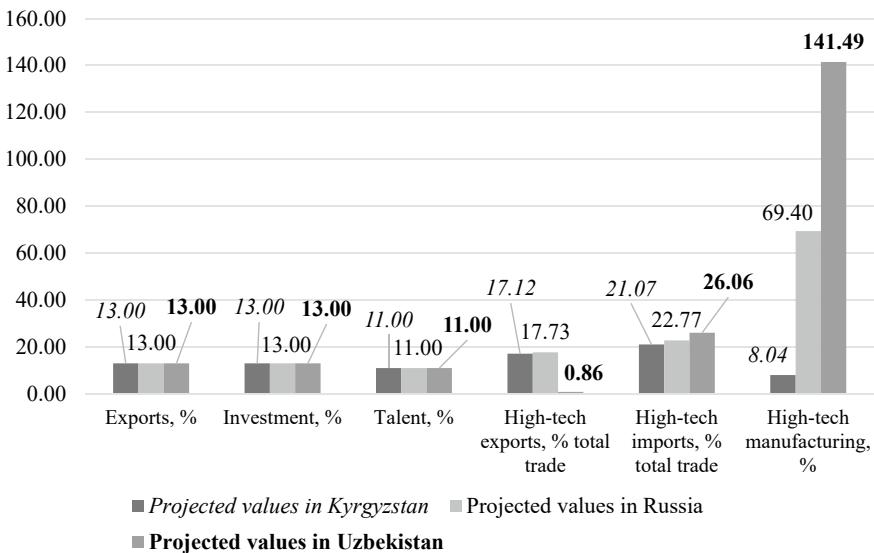


Fig. 1 Forecast of smart business automation in Kyrgyzstan, Russia, and Uzbekistan. *Source* Developed by the authors

- An increase in the share of high-tech imports by 139.08% (from 29.03% in 2023 to 69.40%).

The forecast for Uzbekistan shows that the level of automation of investment decision-making will grow by 33.33%. The provision of decision-making automation by digital management personnel will increase by 120.00%. As a result, the following is projected:

- An increase in the share of high-tech production by 855.07% (from 0.09% in 2023 to 0.86%);
- An increase in the share of high-tech exports by 140.01% (from 10.86% in 2023 to 26.06%);
- An increase in the share of high-tech imports by 471.43% (from 24.76% in 2023 to 141.47%).

To achieve these forecasted values in practice, the authors developed a mechanism for automating smart business through decision-making and production management based on big data and AI (Fig. 2).

The mechanism presented in Fig. 2 suggests that smart production is the central object of automated management within the business structure. Information about production is stored separately in the big data system and processed by AI as a priority. Based on big data, AI makes decisions and carries out automated production management. The manager monitors and adjusts the AI's work as needed.

Simultaneously, AI provides intelligent support for managerial decision-making in other areas of management: human resource management (HRM), finance,

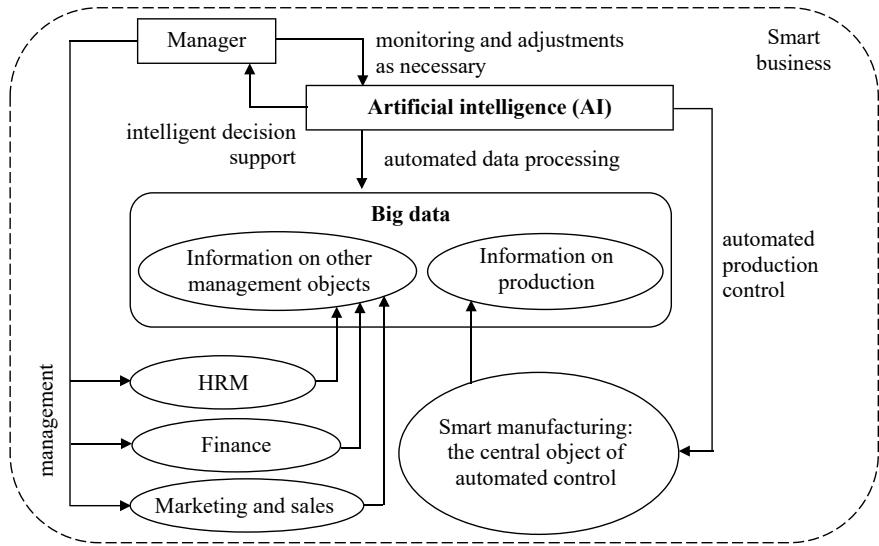


Fig. 2 Mechanism for automating smart business through decision-making and production management based on big data and AI. *Source* Developed by the authors

marketing, and sales, among others. Information about these management objects also enters the corporate big data system, stored separately from production information. With the intelligent support provided by AI, the manager makes decisions and manages these areas of smart business activities.

5 Discussion

The contribution of this research to the literature lies in the development of the scientific concept of production management [2, 5–7, 10, 13] by revealing previously unknown cause-and-effect relationships in the automation of smart business, which involves decision-making and production management based on big data and AI. The developed mechanism for automating smart business significantly differs from the existing one because it emphasizes decision-making and production management based on big data and AI.

In contrast to Kirillova et al. [8], in the new mechanism, tactical and strategic decisions related to production are not separated but unified through the integrated management of smart production as a unique object of automation in smart business activities. All decisions related to smart production are made by AI.

Unlike Agarwal et al. [1], in the developed mechanism, production information is stored in a separate big data cell, accelerating the processing of production information and improving informational support for production decision-making in smart business.

Unlike Tuffnell et al. [12], in the proposed mechanism, production is the central and priority object of management in smart business. Its automation proceeds at its own pace to fully unlock the potential for growth in production capacity, productivity, and quality in smart production.

6 Conclusion

Thus, the conducted research yielded the following key results. First, the authors developed an econometric model for automating smart business. The model's theoretical significance lies in its revelation of the relatively unexplored experience of smart business automation in Central Asia and the clarification of the impact of managerial factors on the outcomes of this automation in the region.

Second, the authors created a forecast for automating smart business in Kyrgyzstan, Russia, and Uzbekistan. The practical significance of this forecast is that it aids in more precise planning of smart business automation in these Central Asian countries.

Third, the authors developed a mechanism for automating smart business through decision-making and production management based on big data and AI. The managerial significance of this mechanism is that it will enhance production management efficiency and more fully realize the potential of smart production automation.

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Methodological Approach to Analyzing the Effectiveness of Intelligent Decision Support Using Big Data and AI



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Abstract The research identifies the shortcomings and develops a new methodological approach to analyzing the effectiveness of intelligent decision support using big data and AI. The method (hierarchical procedure) by T. L. Saaty serves as the foundation of this new approach. Using statistics from the top 20 countries most actively employing big data and AI in 2023, the authors tested their approach using Russia as an example. The authors evaluated the effectiveness of intelligent decision support using big data and AI in Russia in 2023 using alternative approaches. The evaluation results were compared to identify differences between the approaches. As a result, the authors identified the advantages of the new approach. These advantages include better adaptation to the context of the Decade of Action, ranking the results of implementing intelligent decision support practices by their contribution to achieving the SDGs, and more accurate (technological instead of financial) cost measurement, enabling its application by mature digital economy organizations. The new approach advances the theory and methodology of analyzing the effectiveness of intelligent decision support, which constitutes its fundamental value. The use of the new approach by digital economy organizations will allow them to apply big data and AI as intelligent decision support technologies more reasonably and flexibly and increase the effectiveness of their application in management, which is the practical significance of the author's approach.

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JEL Codes C31 · C44 · O32

1 Introduction

Intelligent decision support through AI is widely practiced in developed and rapidly developing countries with progressive digital economies. The problem is that resorting to intelligent decision support is not always justified. Moreover, it can pose a risk of worsening an organization's market position instead of improving it as expected.

In some cases, trying to keep up with competitors in the pace of automation, organizations adopt intelligent decision-support practices without considering the real need for them. This poses a significant threat to the market position of small and medium enterprises with limited financial resources. Without clear advantages from management automation, this practice becomes irrational because it involves significant costs that do not pay off.

In other cases, intelligent decision support can lead to a decline in management productivity and a decrease in the quality of management operations. While automation aims to rationalize decision-making, it does not provide any guarantees. At this stage of the Fourth Industrial Revolution, decision support relies on big data and AI.

However, these technologies have certain limitations. For example, big data systems accept only formalized electronic information. A significant portion of corporate information does not meet the criteria required for integration into big data. Accounting for incomplete information distorts the organization's situation when making management decisions. Consequently, automation can lead to less optimal decisions compared to those made by a manager. Considering subjective and informal information and relying on intuition can sometimes be more beneficial and preferable than automated decision-making.

Additionally, AI can make semantic errors when analyzing information due to incomplete consideration of the causal relationships between changes in corporate accounting indicators. For instance, intelligent monitoring via the Internet of Things can detect a breakdown in production equipment. Nevertheless, AI might not be able to determine the cause, which could be related to either physical wear or improper use by employees in their production activities.

In this case, the management decision would be incomplete—limited to repairing the equipment, which might fail again without addressing the breakdown's root cause. Unlike AI, a manager can identify the real cause and address it through organizational management. Similarly, when analyzing corporate big data, AI might detect a decline in labor productivity. The standard AI solution would be to increase material incentives for the staff to boost productivity.

In reality, the existing incentives might be sufficient; the drop in productivity could be due to frequent equipment breakdowns or a decline in team morale. A manager is better equipped to identify and address these issues, whereas AI's functional scope is significantly limited. This underscores the relevance of research into the methodological questions of assessing the feasibility of decision support using big data and AI, with the most informative indicator being effectiveness.

2 Literature Review

In the concept of decision support through AI, the effectiveness of this management practice is defined as the positive managerial outcomes achieved in relation to the costs incurred for decision support [2, 6, 11]. The most significant results of decision support mentioned in the available research literature include the following:

- Innovative activity of organizations and the share of innovative products they produce: Intelligent decision support aims to enhance this aspect through improved risk management of innovative activities [5];
- Production of technologically complex ICT products: High-tech organizations that automate production–distribution and management operations specialize in this aspect [4];
- Export of ICT products: Decision support is intended to improve this aspect by strengthening the global digital competitiveness of organizations [12].

The existing methodological approach to analyzing the effectiveness of decision support involves the following:

- Considering organizational crisis resilience as the basic premise and criterion for the effectiveness of decision support [10];
- Equivalence of the above indicators of intelligent decision support outcomes [3];
- Accounting for the costs of organizational innovation activities as a reflection of managerial expenses on decision support [7].

A review of the scientific literature has revealed significant shortcomings in the current methodological approach to analyzing the effectiveness of decision support. This approach is not fully adapted to the context of the Decade of Action because it does not consider the Sustainable Development Goals (SDGs) when evaluating the outcomes of intelligent decision support implemented in the sustainable development of organizations in the digital economy.

In practice, the results of intelligent decision support are not always equivalent. For some enterprises, increasing innovative activity is more important. For others, boosting ICT product exports is more important. Financial cost measurement is not entirely accurate because an organization may already have big data and AI technologies that can be integrated into management processes without additional expenses.

Based on the results of the literature review and drawing on the works of Kliestik et al. [8], Lăzăroiu et al. [9], and Samieva et al. [13], which highlight the key role of big data and AI in intelligent decision support practices, this research develops a new methodological approach to analyzing the effectiveness of this practice to overcome the identified deficiencies in the existing approach.

3 Materials and Methods

This research develops a new methodological approach to analyzing the effectiveness of intelligent decision support using big data and AI. The authors rely on the method (hierarchical procedure) developed by T. L. Saaty. The evaluation of the effectiveness of intelligent decision support proceeds according to the following algorithm.

1. In the first stage, the values of each indicator in the studied country are compared to the maximum value in the sample;
2. In the second stage, the weighting coefficients for all evaluated indicators are determined. This involves calculating the correlation coefficients of these indicators with sustainable development as the new criterion for the effectiveness of decision support. The sum of the correlation coefficients is calculated. The ratio of each correlation coefficient to the total sum is found, which constitutes the weighting coefficients;
3. In the third stage, weighted values are calculated as the products of the adjusted indicators and their weighting coefficients;
4. In the fourth stage, hierarchical synthesis is calculated as the sum of the weighted values of the indicators;
5. In the fifth stage, the effectiveness of decision support is determined as the ratio of the hierarchical synthesis to the weighted value of each technology used in this process.

To test the developed approach, the authors formed a sample of the top 20 countries most actively using big data and AI in 2023. The statistical data for the countries in the sample are compiled in Table 1.

The validation is carried out using Russia as an example. Based on the data from Table 1, the authors evaluated the effectiveness of decision support using big data and AI in Russia in 2023, employing alternative approaches. The evaluation results are compared to identify differences between the approaches.

Table 1 Intelligent decision support performance in the top 20 countries in terms of big data and AI use in 2023

Country	Level of innovation activity in the organization (%)	Share of innovative goods, works, and services in the total volume of shipped goods, performed works, and rendered services (%)	Share of the ICT sector in GDP (%)	Export of ICT-related services (\$ million)	Share of expenses on innovation activities in the total volume of shipped goods, performed works, and rendered services (%)	Proportion of organizations analyzing big data (%)	Proportion of organizations using AI (%)	Sustainable development index, points 1–100
Russia	13.9	10.8	3.0	5831.0	4.5	11.0	8.0	73.8
Austria	82.5	33.5	4.4	10,076.0	6.2	9.0	9.0	82.3
Belgium	89.9	35.9	4.3	18,421.0	9.0	23.0	10.0	79.5
Bulgaria	61.8	19.1	7.4	3018.0	3.9	6.0	3.0	74.6
Hungary	56.1	9.3	6.3	3109.0	3.0	7.0	3.0	79.4
Germany	91.3	20.9	5.4	41,258.0	9.8	18.0	11.0	83.4
Denmark	83.7	23.2	4.4	7427.0	6.1	27.0	24.0	85.7
Spain	57.4	33.3	3.4	16,015.0	4.5	9.0	8.0	80.4
Italy	75.2	15.6	3.7	9620.0	5.2	9.0	6.0	78.8
Latvia	51.3	0.0	6.1	1301.0	2.1	9.0	4.0	80.7
Lithuania	75.0	26.2	4.3	1842.0	3.2	11.0	5.0	76.8
Norway	85.5	9.4	4.2	3519.0	6.8	19.0	11.0	82.0
Poland	58.8	21.2	4.3	13,419.0	6.2	9.0	3.0	81.8
Portugal	76.9	31.6	4.0	3934.0	3.8	11.0	17.0	80.0
Slovakia	56.8	13.4	5.2	1946.0	2.5	6.0	5.0	79.1
France	76.9	14.7	5.0	24,372.0	4.1	22.0	7.0	82.0
Croatia	83.3	26.0	5.5	1531.0	0.0	14.0	9.0	81.5

(continued)

Table 1 (continued)

Country	Level of innovation activity in the organization (%)	Share of innovative goods, works, and services in the total volume of shipped goods, performed works, and rendered services (%)	Share of the ICT sector in GDP (%)	Export of ICT-related services (\$ million)	Share of expenses on innovation activities in the total volume of shipped goods, performed works, and rendered services (%)	Proportion of organizations analyzing big data (%)	Proportion of organizations using AI (%)	Sustainable development index, points 1–100
Czech Republic	78.2	23.7	7.0	6883.0	5.4	9.0	5.0	81.9
Sweden	78.8	30.0	6.9	20,646.0	10.6	19.0	10.0	86.0
Estonia	74.9	24.9	8.4	2449.0	0.0	10.0	3.0	81.7

Source Developed by the authors based on the materials of Abashkin et al. [1] and the United Nations [14]

4 Results

To validate the developed methodological approach for analyzing the effectiveness of intelligent decision support using big data and AI and identify its differences from the existing approach, the authors assessed this effectiveness in Russia in 2023 using both approaches. The obtained results are reflected in Table 2.

Let us consider the assessment provided in Table 2 step by step according to the algorithm for evaluating the effectiveness of intelligent decision support using big data and AI, corresponding to the new approach. In the first stage, we found the ratio of the values of each indicator in the studied country to the maximum value in the sample. For example, the maximum level of organizational innovation activity among the top 20 countries in the sample most actively using big data and AI in 2023 is 91.30%. In Russia, this indicator corresponds to 13.9% of organizations. The calculated value of this indicator in Russia is $13.9/91.30 = 0.15$.

In the second stage, the weighting coefficients for all evaluated indicators were determined. For example, the correlation coefficient of organizational innovation activity with sustainable development was 0.63. The sum of all calculated correlation coefficients was as follows: $0.63 + 0.24 + 0.19 + 0.41 + 0.55 + 0.46 = 2.47$. The ratio of each correlation coefficient of organizational innovation activity with sustainable development to the total sum was as follows: $0.63/2.47 = 0.25$. This is the weighting coefficient of the considered indicator.

In the third stage, we calculated weighted values. For example, for organizational innovation activity, the weighted value was calculated as follows: $0.15 * 0.25 = 0.04$. In the fourth stage, hierarchical synthesis was calculated as follows: $0.04 + 0.03 + 0.03 + 0.02 = 0.12$. In the fifth stage, the effectiveness of decision support using big data was calculated as $0.12/0.09 = 1.33$. The effectiveness of using AI was calculated as $0.12/0.06 = 1.95$. For comparison, the result of the assessment using the existing approach was as follows: $(0.15 + 0.30 + 0.36 + 0.14)/0.42 = 0.95/0.42 = 2.26$.

5 Discussion

This research contributes to the literature on the concept of intelligent decision support by advancing the methodology for evaluating the effectiveness of this managerial practice. The newly developed approach to analyzing the effectiveness of intelligent decision-making support using big data and AI has the following features, which overcome the shortcomings of the existing approach.

Unlike [10], the new approach considers the support of sustainable development through the prism of sustainable development goals (SDGs) rather than crisis resilience as the basic premise and criterion for the effectiveness of decision-making support. Thanks to this, the new approach is better adapted to the specific context of the Decade of Action.

Table 2 Results of evaluating the effectiveness of intelligent decision support using big data and AI in Russia in 2023

Country	Level of innovation activity of organizations (%)	Share of innovative goods, works, and services in the total volume of shipped goods, performed works, and rendered services (%)	Specific weight of ICT sector in GVA (%)	Export of ICT-related services (\$ million)	Share of organizations analyzing big data (%)	Share of organizations using AI (%)	Share of expenditures on innovation activities in the total volume of shipped goods, performed works, and rendered services (%)
Maximum	91.30	35.90	8.40	41,258.00	27.00	24.00	10.60
Ratio of values in Russia to the maximum	0.15	0.30	0.36	0.14	0.41	0.33	0.42
Correlation with sustainable development	0.63	0.24	0.19	0.41	0.55	0.46	—
Total correlation:	$0.63 + 0.24 + 0.19 + 0.41 + 0.55 + 0.46 = 2.47$						—
Weighting coefficients	0.25	0.10	0.08	0.16	0.22	0.18	—
Weighted values	0.04	0.03	0.03	0.02	0.09	0.06	—
Hierarchical synthesis	$0.04 + 0.03 + 0.03 + 0.02 = 0.12$						—
Efficiency of intelligent decision support	—	—	—	—	$0.12/0.09 = 1.33$	$0.12/0.06 = 1.95$	$(0.15 + 0.30 + 0.36 + 0.14)/0.42 = 0.95/0.42 = 2.26$

Source Developed by the authors

In contrast to [3], the indicators of decision-making support outcomes are not considered equivalent but are ranked according to assigned weighting coefficients. This aligns the practice of intelligent decision-making support with SDGs and the sustainable development of contemporary organizations.

In contrast to [7] the reflection of managerial expenses on intelligent decision-making support is based not on the expenditures on innovation activities but on the activity of using technologies (e.g., big data and AI). The shift from financial to technological expenditures, made in the new approach, makes it possible to more precisely evaluate the resource intensity of decision-making support by organizations in the digital economy employing big data and AI in production and distribution operations.

6 Conclusion

Thus, the developed methodological approach to analyzing the effectiveness of intelligent decision support using big data and AI overcomes the shortcomings of the existing approach and possesses several advantages. First, the author's approach is adapted to the context of the Decade of Action by introducing a new criterion for the effectiveness of decision support: sustainable development support through the implementation of SDGs.

Second, the ranking of the results of implementing the practice of intelligent decision support in the new approach by their contribution to the implementation of SDGs ensures the focus of this practice on the sustainable development of organizations in the digital economy.

Third, thanks to the non-financial measurement of costs, the evaluation results have become more accurate because it is challenging to calculate specific expenses for intelligent decision support in practice. The technological measurement of costs used in the new approach makes their assessment more precise and allows mature organizations in the digital economy to apply the approach, unlike the previous one, which was suitable only for newly established organizations in the digital economy.

The theoretical significance of the developed approach lies in its advancement of theory (through a new set of evaluation indicators and a new criterion for effectiveness) and methodology (through a new evaluation algorithm and new evaluation formulas) for analyzing the effectiveness of intelligent decision support. The practical significance of the author's approach is expressed in its application in the empirical activities of organizations in the digital economy, allowing them to more substantively and flexibly apply big data and AI as technologies for intelligent decision support and increase the efficiency of their application in management.

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Decision-Making on Economic Crisis Management of Business Based on Big Data and AI



Adambek B. Turkbaev Saltanat A. Melisova Baktygul B. Esenalieva , and Svetlana E. Karpushova

Abstract The research introduces an economic-mathematical model created using regression analysis. The developed model shows the noteworthy and predominantly positive impact of big data and AI on economic crisis management. The model delineates the key facets of counter-cyclical business management, particularly concerning big data and AI, thus underscoring the theoretical importance of this research. The novelty of this research lies in its revelation of Russia's pioneering role as a progressive economy, highlighting its impressive strides in mitigating the global sanction crisis. Based on the developed model, the authors illustrate the potential of increasing the efficiency of counter-cyclical management by automating decision-making in economic crisis management using big data and AI in Russia. The managerial significance of this identified perspective lies in its ability to refine decision-making practices in economic crisis management through more efficient utilization of big data and AI. The practical significance of the proposed recommendations, aimed at implementing this identified perspective, lies in their potential to contribute to a more comprehensive realization of Russia's economic growth prospects during the Decade of Science and Technology (until 2031).

Keywords Decision-making · Economic crisis management · Counter-cyclical business management · Big data · Artificial intelligence (AI)

JEL Codes C44 · E32 · G01 · H12 · O32

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1 Introduction

Economic crises pose one of the most serious threats to business development. While crises still exhibit clear economic manifestations, their causes increasingly stem from non-economic factors (e.g., environmental, political, or social issues). This significantly reduces the accuracy of predicting the cyclical nature of contemporary economic systems, leading to the unpredictable emergence of economic crises.

Given the uncertainty of when the next economic crisis will strike, businesses find themselves in a bind: they must either maintain a perpetual state of readiness for a potential sudden downturn, constraining their operational scope, or risk losing market footholds if a crisis catches them unprepared. These prevalent strategies in economic crisis management impede the pursuit of growth and development opportunities.

This underscores the importance of devising a new approach to economic crisis management for businesses. This approach must enable agile responses to signals of economic recession, swiftly and efficiently adjusting business processes to mitigate or entirely evade the adverse effects of crises. Such a strategy is crucial to empower businesses to capitalize on market opportunities during periods of economic stability and safeguard market positions amidst economic downturns.

An obstacle to embracing the aforementioned practical approach is the lack of flexibility among decision-makers overseeing contemporary business structures. For example, small and medium-sized enterprises face a shortage of managerial resources, while large corporations are burdened by overly complex bureaucratic management hierarchies. In both scenarios, organizational shortcomings within the business management framework impede responsiveness to market shifts and hinder timely adaptation during economic crises.

This research proposes a promising way to overcome this barrier—the modernization of the business management system based on advanced decision-making automation tools: big data and artificial intelligence (AI). Although existing literature provides ample scientific evidence that big data and AI generate benefits for management by enhancing its efficiency, the application of these technologies in the practice of decision-making in economic crisis management for businesses is insufficiently explored. The research aims to implement the impact of utilizing big data and AI on the resilience of businesses to crises.

2 Literature Review

According to the concept of making anti-crisis decisions [3, 6], the key indicator by which the effectiveness of decision-making in counter-cyclical business management is assessed is the maintenance of stability—preserving economic growth in unfavorable, crisis-ridden conditions of the market environment [9, 10]. In this regard, it is worth considering Russia's advanced experience as a progressive economy, demonstrating outstanding success in confronting the global sanction crisis.

Based on the works by Abdelhalim [1] and Kokshagina et al. [7], which provide compelling arguments in favor of using big data and AI to enhance decision-making efficiency, this research poses a hypothesis that automating economic crisis management based on these technologies provides increased resilience of businesses to cyclical fluctuations in the economy. Moreover, despite the general uncertainty about which of these conditions are most significant, the existing literature lists the following conditions potentially determining the effectiveness of using big data and AI in business management:

- Digital personnel with competencies in using big data and AI [2];
- Digital economy infrastructure providing practical opportunities for the application of big data and AI [14];
- Legal environment defining the regulatory framework for the application of big data and AI [4];
- Academic leadership in the study of big data and AI technologies [15];
- Availability of applied big data and AI technologies [11];
- Digital economy institutions ensuring the implementation of the national strategy for disseminating big data and AI [8];
- Investment support for implementing big data and AI in the digital economy [13].

To delineate the circle of key factors in counter-cyclical business management, this research models the dependence of decision-making effectiveness in economic crisis management on the listed conditions related to big data and AI.

3 Materials and Methods

To comprehensively capture the experience of the global economic system, the authors developed a sample that includes ten leading economies from developed and developing countries, representing various geographic regions of the world. The sample consists of countries with the highest values in the Global AI Index [12]. The research involves regression modeling to assess the impact of the use of big data and AI on business resilience to crises based on data from 2023.

According to the International Monetary Fund (IMF), the performance indicator for decision-making in economic crisis management is “GDP growth (annual %)” (EcCr) [5]. Tortoise Media indicators are used to characterize the influence of potential factors related to Big Data and AI [12]. Empirical data on these indicators are summarized in Table 1.

The positive regression coefficients indicate the beneficial influence of the factors on the outcomes of decision-making in business economic crisis management. For further scientific and methodological support in strengthening Russia’s resilience to sanctions, an additional in-depth study is conducted. This study aims to identify the potential for enhancing the effectiveness of counter-cyclical management through the automation of decision-making in economic crisis management for businesses.

Table 1 Factors and outcomes of decision-making in business economic crisis management based on big data and AI in 2023

Country	Talent	Infrastructure	Operating environment	Research	Development	Government strategy	Commercial	GDP growth (annual %)
	AI ₁	AI ₂	AI ₃	AI ₄	AI ₅	AI ₆	AI ₇	EeCr
USA	100.0	100.0	82.8	100.0	100.0	90.3	100.0	2.531
Singapore	56.9	82.8	85.7	48.8	24.4	81.8	26.4	1.075
UK	53.8	61.8	79.5	38.1	19.8	89.2	20.0	0.145
Canada	46.0	62.1	93.1	34.0	18.9	93.4	18.9	1.066
South Korea	35.1	74.4	91.4	24.3	60.9	91.9	8.3	1.357
Germany	57.0	68.2	90.7	29.3	19.5	93.9	10.3	-0.305
Switzerland	44.5	68.0	81.9	41.3	24.9	9.0	13.3	0.764
Finland	34.5	73.0	97.7	27.4	13.1	82.7	9.5	-0.957
Netherlands	45.2	65.7	90.3	27.1	15.7	71.8	7.9	0.093
Japan	38.0	80.8	92.4	18.6	22.2	80.3	6.8	1.923
China	30.0	92.1	lePara>	99.7	54.7	80.6	93.5	43.1
India	86.2	34.7	91.1	12.0	7.6	56.0	8.9	7.827
UAE	16.9	80.8	77.8	9.4	1.7	72.8	5.3	3.404
Russia	25.1	64.1	80.7	7.9	6.7	91.3	1.7	3.585
Saudi Arabia	14.3	63.3	88.1	8.2	1.3	100.0	6.0	-0.755
Brazil	29.3	55.8	75.7	8.5	1.9	71.4	3.3	2.908
Turkey	25.0	45.5	93.6	6.9	0.3	72.5	2.0	4.517
Chile	15.0	67.5	71.6	3.8	0.6	76.3	5.2	0.219
Qatar	3.5	61.0	73.1	19.9	0.5	39.2	1.5	1.558
Malaysia	19.4	65.3	72.2	6.8	0.7	48.1	2.4	3.680

Source Compiled by the authors based on IMF [5] and Tortoise Media [12]

4 Results

The authors conducted a regression analysis to examine the relationship between the effectiveness of decision-making in business economic crisis management and factors related to big data and AI. The correlation coefficient reached a high value, indicating that in 2023, 74.83% of decision-making effectiveness in business economic crisis management was determined by factors related to big data and AI.

The results of the regression analysis were statistically significant. The Fisher's F-test is passed at a significance level of 0.15 (observed F = 2.1811, significance F = 0.1125). Moreover, several regression coefficients took positive values, supporting the hypothesis. The economic-mathematical model describing the dependence of decision-making effectiveness in business economic crisis management on factors related to big data and AI is represented by the following equation:

$$\begin{aligned} \text{EcCr} = & 3.9458 + 0.0188 * \text{AI}_1 - 0.0355 * \text{AI}_2 + 0.0631 * \text{AI}_3 - 0.1973 * \text{AI}_4 \\ & + 0.0524 * \text{AI}_5 - 0.0511 * \text{AI}_6 + 0.1525 * \text{AI}_7 \end{aligned} \quad (1)$$

In Eq. (1), values of the selected factors that positively influence the outcome are substituted, increased by 25%. The obtained perspective is projected for the Decade of Science and Technology in Russia (until 2031) and is illustrated in Fig. 1.

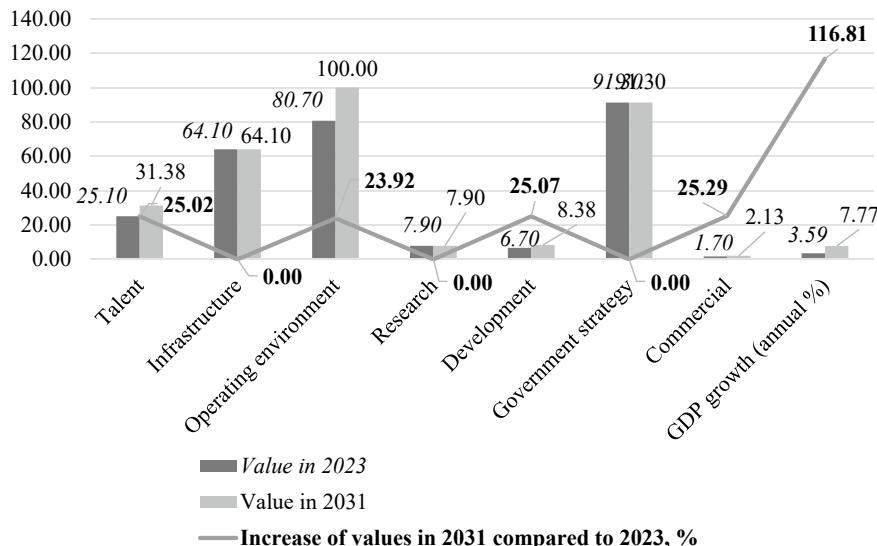


Fig. 1 The prospect of enhancing the effectiveness of counter-cyclical management through the automation of decision-making in business economic crisis management based on big data and AI in Russia. *Source* Developed by the authors

According to Fig. 1, the effectiveness of counter-cyclical management in Russia could increase by 116.81% through the automation of decision-making in business economic crisis management based on big data and AI. In the Decade of Science and Technology in Russia (until 2031), the annual rate of economic growth in Russia could reach 7.77% (compared to 3.59% in 2023). To achieve this growth, the following recommendations are proposed to unleash the potential of automating decision-making in business economic crisis management based on big data and AI:

- Increase the availability of digital personnel to 31.38 points;
- Fully exploit the potential for optimizing the legal environment of business automation;
- Accelerate the diffusion of advanced technologies in the business environment to 8.38 points;
- Strengthen investment support for business automation to 2.13 points.

5 Discussion

The contribution of this research to the literature in the field of decision-making in business economic crisis management, including the works by Dragomir et al. [3] and Kalogiannidis et al. [6], lies in specifying the conditions that determine the effectiveness of using big data and AI in business management. Supporting the findings of Abdurakhmanova et al. [2], this research substantiated that digital personnel with competencies in using big data and AI enhance decision-making effectiveness in business economic crisis management.

Contrary to van der Vlist et al. [14], the research yielded scientific evidence showing that business resilience to crises is not in a clear direct relationship with automation infrastructure. Confirming Dumouchel [4], it is proven that optimizing the legal environment creates the prerequisites for business automation.

Unlike Ziarek [15], the research found that theoretical elaboration of business automation does not ensure its practical implementation. Supporting Sozinova et al. [11], the research provided evidence that accelerating the diffusion of advanced technologies in the business environment generates a pronounced positive effect related to enhancing business resilience to crises.

Contrary to Li et al. [8], for the first time, scientific evidence was obtained showing that the institutional environment does not significantly contribute to improving business resilience achieved through automation. Confirming Tursunov [13], the research proved that investment support for implementing big data and AI in the digital economy enhances the effectiveness of decision-making in business economic crisis management.

6 Conclusion

Thus, the conducted research substantiates the significant contribution of big data and AI to the economic crisis management of contemporary businesses, quantitatively measured using an economic-mathematical model. The theoretical significance of this model lies in its ability to outline the key factors of counter-cyclical business management related to big data and AI.

The demonstrated potential for increasing the effectiveness of counter-cyclical management through the automation of decision-making in economic crisis management based on big data and AI in Russia holds practical significance. This potential will enhance the practice of decision-making in business economic crisis management through the highly effective application of big data and AI. Implementing the proposed recommendations to realize this identified potential will make it possible to fully realize Russia's economic growth potential in the Decade of Science and Technology (until 2031).

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Optimization of Decision-Making in Business Integration and Cooperation Using Big Data and AI



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Abstract The research defines the prospects for optimizing decision-making in managing contemporary enterprises through business integration and cooperation using big data and AI. Based on the unique experience of Central Asia in 2023, the authors developed a regression model. The developed model explained the impact of automation in management on the implementation of business cooperation and integration processes in entrepreneurship. The fundamental significance of the obtained results lies in their contribution to the theory of using integration-cooperation mechanisms in crisis management by explaining previously unknown organizational aspects and causal relationships in applying these technologies in decision-making for business integration and cooperation. The author's forecast for the development of business integration and cooperation processes through the expanded use of big data and AI in management in the Kyrgyz Republic is of practical importance because it can be implemented in the planning practices of these processes in the Kyrgyz Republic. The developed organizational approach to applying big data and AI in decision-making practices for business integration and cooperation is of managerial significance because it will optimize these decisions in entrepreneurship.

Keywords Optimization of decisions · Decision-making · Business integration · Cooperation · Management automation · Big data · Artificial intelligence (AI) · Central Asia

JEL Codes G34 · O33 · P13

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1 Introduction

Business integration and cooperation represent a promising mechanism for managing competitiveness and the efficiency of entrepreneurial activities. This integration-cooperation mechanism is especially sought after in today's business environment, marked by successive global crises, as it makes it possible to prevent business activity from declining and revitalize enterprises after the recession.

Despite growing necessity, enterprises do not actively utilize the integration-cooperation mechanism of crisis management in their economic activities. This issue stems from the need for rapid collection and comprehensive analysis of large volumes of information to make decisions on business integration and cooperation. Incomplete data analysis and processing errors distort the manager's understanding of the market situation and the enterprise's integration opportunities.

Managers often fail to timely gather all necessary information, which leads to missed short-term opportunities for participating in market integration processes. For example, beneficial projects in regional industry-specific and pilot innovation clusters initiated by local public authorities are often missed. The lack of awareness about participation opportunities in these projects hinders potentially interested enterprises.

In other cases, internal needs for business integration and cooperation are unmet due to insufficient informational and analytical support from management. For instance, through the analysis of corporate information, managers may identify several problems, addressing which involves activating the integration-cooperation mechanism of crisis management. However, due to the unavailability of necessary information for decision-making, managerial decisions are postponed until the problems are either resolved by other means or the enterprise is caught in a crisis. Thus, the opportunity for business integration and cooperation closes.

Additionally, past unsuccessful experiences make enterprises wary of the integration-cooperation mechanism, limiting the possibilities of corporate crisis management. For example, due to inadequate informational support, managers might make erroneous decisions regarding business integration and cooperation. As a result, the economic position of the enterprise and its market stance may deteriorate. Consequently, the enterprise will be cautious about the integration-cooperation mechanism of crisis management and avoid using it even when it is preferable in the future.

Therefore, there is a need for scientific exploration of issues related to realizing the full potential of the integration-cooperation mechanism of crisis management in business. To address this problem, this research proposes using advanced management automation technologies, such as big data and artificial intelligence (AI), in making managerial decisions for utilizing the integration-cooperation mechanism of crisis management. Thus, the research aims to define the prospects for optimizing decision-making in managing contemporary enterprises through business integration and cooperation using big data and AI.

2 Literature Review

The theoretical aspects of using the integration-cooperation mechanism in crisis management within entrepreneurship have been thoroughly studied in published scientific literature by Cai et al. [4], Mkrtchyan et al. [8], and Zhong [17]. The content analysis of the cited literature allowed the authors to identify the following fundamental characteristics of the existing approach to decision-making for business integration and cooperation:

- Reliance on internal corporate accounting data for managerial decision-making regarding business integration and cooperation, leading to a closed management information system, which causes limitations and incompleteness [10];
- Delayed transmission of information from the production–distribution environment of the enterprise to its management apparatus, resulting in lagging identification of the enterprise's need for business integration and cooperation, and only an approximate, rather than precise, assessment of this need [5].
- The use of brainstorming and market analysis technology to select alternative solutions for business integration and cooperation, leading to a framework nature (insufficient detail) of these alternatives [9];
- High transaction costs associated with discussing potential and ongoing business integration and cooperation projects, reducing the efficiency of managing these projects [16];
- High complexity in obtaining approval (e.g., from the antimonopoly service) and legal formalization of business integration and cooperation deals during their registration with government authorities [7].

The most common and promising forms of business integration and cooperation in modern entrepreneurship include the following:

- Cooperation between enterprises and universities based on innovation networks and technology parks [6];
- Strategic alliances of enterprises [13];
- Cluster associations of enterprises [1].

Various aspects of using big data and AI in management are covered in several published works by Akour et al. [2], Alotaibi [3], Srinivasan et al. [11], and Wu et al. [15]. However, existing scientific literature does not explain the organizational aspects and causal relationships of applying these technologies in decision-making for business integration and cooperation in entrepreneurship. This gap in the literature is what this research seeks to address.

3 Materials and Methods

The research examines the unique experiences of Central Asian countries, drawing on the latest data from 2023. To determine the contribution of using big data and AI to an enterprise's activity in business integration and cooperation, the authors applied the regression analysis method. Regression modeling is conducted to assess the impact of the management automation factor (ATM) (based on statistics [12]) on the activity of implementing business cooperation and integration processes in entrepreneurship (IC) (based on statistics [14]). The empirical basis of this research is presented in Table 1.

Based on the results of the regression modeling, the authors made a forecast to reveal the potential of business integration and cooperation through the expanded application of big data and AI in management in the Kyrgyz Republic. Next, the authors developed an organizational approach to decision-making for business integration and cooperation using big data and AI.

Table 1 Statistics of business integration, cooperation, and management automation in Central Asian countries in 2023

Countries	University-industry R&D collaboration, score 0–100	Joint venture/strategic alliance deals/bn PPP\$ GDP, score 0–100	State of cluster development, score 0–100	Digital quality of life index, share of 1
	IC ₁	IC ₂	IC ₃	ATM
China	86.75	6.00	91.37	0.56
India	44.42	17.43	28.34	0.52
Iran (Islamic Republic of)	12.21	0.00	33.14	0.34
Kazakhstan	20.32	2.87	16.60	0.53
Kyrgyzstan	6.03	3.17	21.33	0.44
Mongolia	21.71	5.46	17.51	0.36
Pakistan	59.21	9.88	55.16	0.35
Russian Federation	45.66	3.50	43.09	0.51
Tajikistan	30.98	5.49	16.32	0.23

Source Developed by the authors based on Surfshark [12] and WIPO[14]

4 Results

To quantitatively measure the contribution of using big data and AI to enterprise activity in the field of business integration and cooperation, the authors conducted a regression analysis of the data from Table 1. This analysis made it possible to develop the following regression model, mathematically describing the impact of the management automation factor on the activity of implementing business cooperation and integration processes in entrepreneurship in Central Asia in 2023:

$$\begin{cases} IC_1 = 0.13 + 84.92 * ATM, R^2 = 0.3733; \\ IC_2 = 2.35 + 8.49 * ATM, R^2 = 0.1878; \\ IC_3 = -196 + 88.68 * ATM, R^2 = 0.4034. \end{cases} \quad (1)$$

Model (1) indicates that management automation by 37.33% determines the activity in cooperation between enterprises and universities based on innovation networks and technology parks, by 18.78% determines the activity in forming strategic alliances, and by 40.34% determines the activity in enterprise clustering. An increase in the level of management automation (ATM) by 1 unit results in an increase of 84.92 points in the activity of cooperation between enterprises and universities based on innovation networks and technology parks, an 8.49-point increase in the activity of forming strategic alliances, and an 88.68-point increase in the activity of enterprise clustering.

Model (1) make it possible to identify the expected consequences of widespread management automation practices in Central Asian countries on the integration and cooperation processes in their entrepreneurship. This can be useful for corporate and governmental management of these processes. Guided by model (1), the authors developed a forecast to reveal the potential of business integration and cooperation through the expanded application of big data and AI in management in the Kyrgyz Republic (Fig. 1).

The forecast presented in Fig. 1 showed that with full management automation ($ATM = 1$, which is 2.27 times higher than the 2023 level of 0.44) in the Kyrgyz Republic, the activity of cooperation between enterprises and universities based on innovation networks and technology parks will increase by 2.27 times (reaching 13.68 points compared to 6.03 points in 2023), the activity of forming strategic alliances will increase by 1.77 times (reaching 5.62 points compared to 3.17 points in 2023), and the activity of enterprise clustering will increase by 2.34 times (reaching 49.96 points compared to 21.33 points in 2023).

To fully realize the potential of business integration and cooperation processes identified by the forecast, the authors developed an organizational approach to decision-making in these processes using big data and AI technologies (Fig. 2). This is an improved approach that integrates these technologies to optimize decision-making.

As shown in Fig. 2, the developed organizational approach suggests that decision-making in management relies on big data, representing an open system that includes

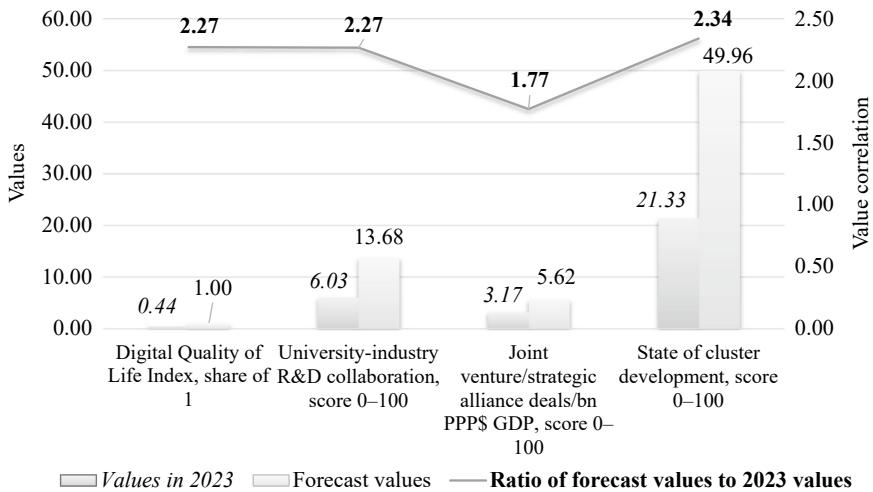


Fig. 1 Forecast of business integration and cooperation through expanding the application of big data and AI in management in the Kyrgyz Republic. *Source* Calculated and compiled by the authors

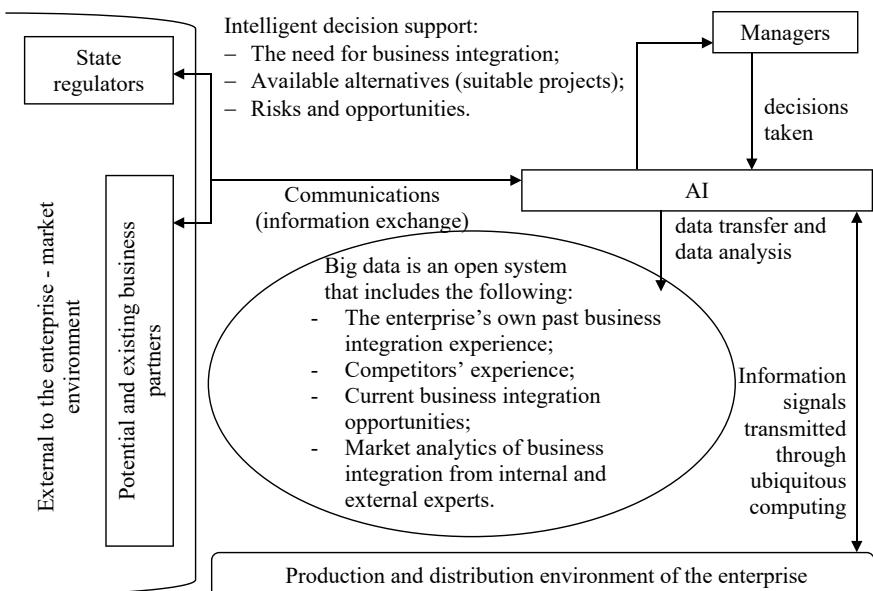


Fig. 2 An organizational approach to business integration and collaboration decision-making with big data and AI. *Source* Calculated and developed by the authors

the enterprise's past experience in business integration, the experience of competitors, current opportunities for business integration, and market analytics on business integration from internal and external experts.

AI receives information signals transmitted through pervasive computing from the enterprise's production–distribution environment and transfers them to big data. AI also receives information from potential and existing business partners from the market environment, which is also provided to big data. AI analyzes big data and provides comprehensive intelligent decision-making support to the manager, including justifying the need for business integration, available alternatives (suitable business integration and cooperation projects), and their risks and opportunities.

The manager makes managerial decisions on business integration and cooperation and transmits them to AI. In turn, AI disseminates the corresponding information signals to the enterprise's production–distribution environment. AI also communicates with business partners and registers completed business integration and cooperation deals with government regulators.

5 Discussion

The scientific results obtained in this research advance the theory of applying the integration-cooperation mechanism of crisis management in entrepreneurship [4, 8, 17] by explaining previously unknown organizational aspects and causal relationships of these technologies in decision-making for business integration and cooperation.

The author's conclusions reinforced the evidence base that management automation using big data and AI stimulates the most common and promising forms of business integration and cooperation in modern entrepreneurship: cooperation between enterprises and universities based on innovation networks and technology parks (in support of [6]), strategic alliances of enterprises (in support of [13]), and cluster associations of enterprises (in support of [1]).

6 Conclusion

Thus, the set goal has been achieved, revealing a significant potential for optimizing decision-making in managing contemporary enterprises regarding business integration and cooperation using big data and AI. The theoretical significance lies in the developed model, which explained the impact of the management automation factor on the activity of implementing business cooperation and integration processes in entrepreneurship in Central Asia in 2023.

The practical significance is endowed in the author's forecast for the development of business integration and cooperation processes through the expanded application of big data and AI in management in the Kyrgyz Republic. This forecast can be

implemented in the practice of planning these processes in the Kyrgyz Republic. The managerial significance is found in the developed organizational approach, which proposes a preferred sequence for applying big data and AI in the decision-making practice for business integration and cooperation to optimize these decisions in entrepreneurship.

The developed approach to decision-making for business integration and cooperation, through the use of big data and AI technologies, has the following advantages compared to the existing alternative approach:

- Openness of the information system and, consequently, comprehensive informational support for management;
- Timely and accurate assessment of the enterprise's needs in engaging the business cooperation and integration mechanism for crisis management purposes;
- Detailed parameters of the decisions made;
- Reduced transaction costs;
- Simplified legal formalization of business integration and cooperation deals.

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Decision-Making in Foreign Economic Activities of a Business Using Big Data and AI



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Abstract The research justifies the advantages and develops recommendations for making the most optimal decisions in foreign economic activities of business using big data and AI. Thus, the authors consider the advanced practices of the top 20 countries most active in using big data and AI in 2023. The research establishes correlations between management professionalism, protectionism, and automation based on big data and AI with the outcomes of businesses' foreign economic activities. The optimality of the corresponding managerial decisions is highlighted. As a result, the authors substantiated the preference for using big data and AI to improve decision-making practices in foreign economic activities. The authors identified the advantages of these technologies, including the increased global presence of national brands and the accelerated growth of goods exports. The authors propose a new technocratic model and a set of original recommendations for making optimal decisions in foreign economic activities of a business using big data and AI. The implementation of these recommendations will provide various benefits, including reduced uncertainty in the foreign economic situation, increased flexibility, and rationalization of managerial decisions. This approach will ensure the most optimal decisions in the foreign economic activities of a business through the use of big data and AI.

Keywords Managerial decisions · Decision-making · Foreign economic activities · Business management · Artificial intelligence (AI) · Big data

JEL Codes C44 · D81 · O32

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1 Introduction

In the globalized world economic system, conducting active and highly effective foreign economic activities is essential for maintaining competitiveness and market presence for most business structures. The challenge lies in the fact that the shift to a new globalization paradigm has significantly increased the complexity of decision-making related to business foreign economic activities for several reasons.

One reason is the need to consider the diverse international migration flows. Previously, migration was predominantly from developing to developed countries. Currently, there is a strong reverse flow. Rapidly growing economies in developing countries are creating more jobs, including knowledge-intensive ones. In many developed countries, automation reduces the number of jobs and limits opportunities for human potential. This situation created threats to the staffing of international businesses.

Another reason is the reorientation of international investment flows. Similar to migration, investment is now flowing into the economies of developing countries, which are seen as progressive and innovative. Another contributing factor is the sharp increase in uncertainty in the global financial system. Sanction restrictions on certain currencies and payment systems make international transactions less transparent and require businesses to be more flexible in their execution.

One more complexity is the heightened barriers to enter global markets in the face of stricter international economic sanctions. These barriers disrupt and reorganize global value chains. Reorganizing branch networks, reconsidering international transport corridors, and adjusting production and distribution operations require significantly faster decision-making. Managerial decisions must also account for the increased role of country integration associations because the conditions of international trade and the composition of customs unions are constantly changing.

Due to the aforementioned reasons, the risks of making suboptimal decisions in foreign economic activities saw a significant increase. This casts doubt on the applicability of the previous decision-making model in the current conditions of globalization. The established decision-making model was formed in an environment of barrier-free, stable, and predictable globalization. This environment allowed managers to rely on past experience when making current decisions.

The existing model relies on the knowledge, managerial skills, and intuition of managers. However, this may no longer be sufficient for making optimal decisions under increased uncertainty and risk. This underscores the importance of scientific research in improving decision-making practices in foreign economic activities of businesses, including revising the approach to the technical and economic organization of this practice.

Special attention should be given to exploring the potential of advanced automation tools such as big data and Artificial Intelligence (AI) in this managerial practice. These technologies are widely used and successfully employed in other areas of business management. However, insufficient scientific and methodological support hinders their application in decision-making for foreign economic activities. This

research aims to justify the advantages and develop recommendations for making the most optimal decisions in foreign economic activities of businesses using big data and AI.

2 Literature Review

This research delves into the scientific concept of managerial decision-making related to business operations in foreign economic activities [1–3]. According to this concept, the established scientific and practical decision-making model in foreign economic activities can be termed anthropocentric. When making decisions in the specific management area, the established model depends on the human resources within the management of the business entity [12, 16].

The basic premise of the established model is the assumption that the higher the professionalism of management, the more effective the decision-making in foreign economic activities [11, 15]. Moreover, Galoyan and Matevosyan [4] emphasize that protectionism is an important condition for optimizing managerial decisions in foreign economic activities. It largely determines the market context and international trade opportunities.

Specific issues regarding the use of big data and AI in making managerial decisions are addressed by Karbekova et al. [8], Konina [10], and Vechkinzova et al. [14]. However, these publications do not cover specific cases or explain the specifics of applying big data and AI in decision-making for business's foreign economic activities. This constitutes a gap in the literature. To address the identified gap in the literature, the authors pose the following research question (RQ): “How does the use of big data and AI technologies affect the optimality of decision-making in foreign economic activities of a business?”.

Drawing on the works of Galoyan et al. [5], Kholmuminov et al. [9], and Savelyeva et al. [13], which highlight the advantages of employing advanced technologies such as big data and AI in management, this research hypothesizes that the use of big data and AI enhances the optimality of decision-making in foreign economic activities of a business. The hypothesis is tested by modeling the relationship between all three factors highlighted in this literature review (management professionalism, protectionism, and automation based on big data and AI technologies) and the effectiveness of foreign economic activities of a business as a reflection of the optimality of corresponding managerial decisions.

3 Materials and Methods

In the first stage of this research, the authors justify the preference for making decisions in foreign economic activities of a business using big data and AI. This task is accomplished using correlation analysis to establish correlation relationships

between management professionalism [7], protectionism [6], and automation based on big data and AI [6] with the outcomes of foreign economic activities of a business. These outcomes include the growth rate of goods exports [6] and the presence of national brands in global markets [6], reflecting the optimality of making corresponding managerial decisions.

For this research, the authors formed a sample from the top 20 countries in the world most actively using big data and AI, according to the IMD 2023 ranking [7]. Statistical data for these countries is presented in Table 1.

Positive correlation coefficients indicate positive relationships between the indicators. The hypothesis is considered proven if both results of foreign economic

Table 1 Foreign economic activities of businesses and the decision-making factors associated with them in the top 20 countries that most actively used big data and AI in 2023

Country	Exports of goods—growth, % change, USD values	Image abroad or branding, score 0–10	Use of big data and analytics, score 0–10	Protectionism (government protectionism does not impair the conduct of business), score 0–10	Competent senior managers are readily available, score 0–10
Belgium	15.30	7.67	6.87	7.43	7.33
Qatar	48.86	8.29	6.79	7.26	6.82
USA	17.70	7.08	6.74	6.17	6.75
Israel	22.32	6.50	6.72	5.26	6.64
Denmark	4.05	8.36	6.62	8.30	7.20
Saudi Arabia	48.62	7.53	6.57	7.31	6.88
Jordan	31.32	6.56	6.48	6.17	5.76
Sweden	4.37	7.46	6.48	7.33	6.73
Kazakhstan	39.65	6.80	6.42	5.35	5.86
Singapore	12.78	7.86	6.41	6.03	6.88
Norway	56.02	6.84	6.39	6.35	6.67
Netherlands	14.94	8.20	6.33	7.80	7.04
Iceland	23.43	8.12	6.21	6.24	6.21
Indonesia	26.12	7.30	6.17	5.63	6.70
China	7.01	6.81	6.15	5.53	6.20
Canada	17.70	7.35	6.14	6.35	6.46
Finland	4.41	7.89	6.11	8.44	6.53
Czech Republic	6.47	7.15	6.09	8.00	6.64
India	14.68	7.31	5.98	5.45	6.41
Lithuania	13.84	6.44	5.98	6.04	5.86

Source Developed by the authors based on IMD materials [6, 7]

activities of a business show positive correlation coefficients with automation based on big data and AI.

The task of the second stage is to develop recommendations for making optimal decisions in foreign economic activities of a business using big data and AI. The authors developed a conceptual model for decision-making in foreign economic activities of a business using big data and AI. For this purpose, the authors used descriptive and graphical methods of scientific research are used.

4 Results

Within the framework of the first stage of this research, the authors conducted a correlation analysis of the data from Table 1 to justify the preference for making decisions in foreign economic activities of a business using big data and AI. As a result, drawing on the advanced practices of the top 20 countries that most actively used big data and AI in 2023, the authors established the following:

- The growth rate of goods exports is closely and positively correlated with automation based on big data and AI (the correlation coefficient reached 31.98%) but weakly associated and decreases as protectionism activities intensify (the correlation coefficient reached – 25.05%) and the reliance on management professionalism increases (the correlation coefficient reached – 11.74%);
- The presence of national brands in global markets is strongly and positively correlated with protectionism activities (the correlation coefficient reached 63.77%), management professionalism (the correlation coefficient reached 63.17%), and automation based on big data and AI (the correlation coefficient reached 18.65%).

Correlation coefficients between the outcomes of foreign economic activities of a business and automation based on big data and AI yielded positive values. This confirms the proposed hypothesis. Drawing on the scientific argumentation obtained, the authors developed a new model for making such decisions (Fig. 1).

In accordance with the author's model, the following recommendations were developed for making the most optimal decisions in foreign economic activities of a business using big data and AI:

- Consolidation of previously disparate and fragmentarily considered information from various sources (i.e., industry reviews and analytical notes, information from corporate accounting materials, requirements and forecasts of government regulators, foreign forecasts, and measures regulating international trade) into big data for its structuring and establishment of logical relationships;
- Continuous implementation of smart analytics of big data characterizing foreign economic activities of a business with AI for systemic consideration of all relevant and up-to-date information related to this activity: accounting for multivariate international migration flows, accounting for the reorientation of international investment flows, accounting for the possibilities and limitations of the global

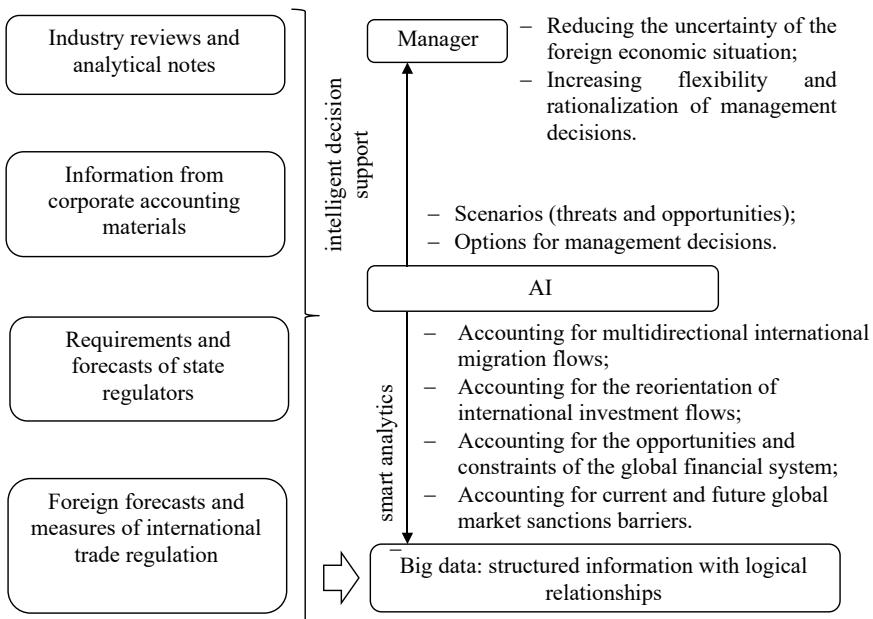


Fig. 1 Decision-making model for foreign economic activities of a business using big data and AI.
Source Developed by the authors

financial system, and accounting for current and potential future sanction barriers in global markets;

- Intellectual support for decision-making by business managers in foreign economic activities, including scenarios (threats, risks, opportunities, and probabilities), and options for managerial decisions.

The implementation of the author's model and the application of the compiled recommendations will provide the following advantages:

- Reducing uncertainty in the foreign economic situation;
- Increasing flexibility and rationalization of managerial decisions;
- Guaranteeing the adoption of the most optimal decisions in foreign economic activities of a business using big data and AI.

5 Discussion

The obtained results contribute to the literature [1–3] and clarify the positions of the scientific concept of managerial decision-making related to conducting business in foreign economic activities. This is done through specifying the cause-and-effect relationships of decision-making in foreign economic activities.

In contrast to Lee et al. [11] and Yan et al. [15], this research justified that management professionalism has a limited impact on the effectiveness of decision-making in foreign economic activities, increasing the scale of representation of national brands in global markets but slowing down the growth rate of goods exports.

In contrast to Galoyan and Matevosyan [4], the authors established that protectionism has a contradictory effect on the optimality of managerial decisions in foreign economic activities, increasing the scale of representation of national brands in global markets but slowing down the growth rate of goods exports.

Moreover, the research explains the specifics of using big data and AI in decision-making in foreign economic activities of a business. In confirmation of Galoyan et al. [5], Kholmuminov et al. [9], and Savelyeva et al. [13], the research proved that the use of big data and AI enhances the optimality of decision-making in foreign economic activities of a business, increasing the representation of national brands in global markets and accelerating the growth rate of goods exports.

The scientific novelty of this research lies in developing an innovative decision-making model for foreign economic activities of a business characterized by reliance on big data and AI, making this model technocentric.

6 Conclusion

Based on the reference to the advanced practices of the top 20 countries that were most active in utilizing big data and AI in 2023, the authors achieved the following results:

1. The authors substantiated the preference for employing big data and AI to enhance decision-making practices in foreign economic activities of a business. Additionally, the authors identified the benefits of using these technologies, associated with increasing the scale of representation of national brands in global markets and accelerating the pace of goods export growth;
2. The authors proposed a new technocratic model and a set of recommendations for making optimal decisions in foreign economic activities of a business using big data and AI. The model's specificity lies in aggregating previously disparate and fragmentary information from various sources into big data, continuous and systemic smart analytics of big data, characterizing foreign economic activities of a business, and artificial intelligence (AI), and intellectual support for managerial decision-making in foreign economic activities of a business.

The theoretical significance lies in revealing previously unknown possibilities and advantages of utilizing big data and AI in decision-making in foreign economic activities of a business. The practical significance is associated with the fact that the developed model and authorial recommendations will make it possible to enhance contemporary decision-making practices in foreign economic activities of a business through the highly effective application of big data and AI.

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The Internet of Things (IoT) as a Big Data Collection Technology for Interactive Decision-Making



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Abstract The research substantiates the advantages and develops scientific and practical recommendations for using the Internet of Things (IoT) as a technology for collecting big data for interactive managerial decision-making by today's enterprises. Using the top 30 countries in management automation in 2023 as an example, the authors employed a regression analysis method to model the impact of IoT and big data utilization on the target outcomes of interactive managerial decision-making in contemporary business management. As a result, the model revealing the influence of IoT and big data usage on the target outcomes of interactive managerial decision-making uncovered previously unknown causal relationships in the automation of contemporary business management. The model identified advantages such as increased export activity of enterprises, optimized logistics, enhanced innovation activity, and accelerated and simplified corporate reporting to government regulators. The demonstrated perspective of maximizing the benefits of interactive managerial decision-making in Russia holds practical significance because it will enhance the accuracy and reliability of planning, forecasting, and state and corporate management of the automation processes in Russian business management. The authors developed a technology for collecting big data using IoT. The managerial significance of the developed technology is confirmed by the following advantages for interactive decision-making: acceleration of big data collection and improvement of its objectivity, greater systematization of big data and more precise causal relationships among its elements, and increased completeness and reliability of big data due to a broader spectrum of its sources.

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Keywords Internet of things (IoT) · Big data · Interactive decision-making · Management decision-making · Management automation

JEL Codes F14 · F23 · G34 · O33

1 Introduction

In recent years, big data has become a widely applied technology for managing corporate information systems. The high interest in this technology is due to the wide advantages it offers for corporate management. Compared to paper-based information carriers, big data is more convenient to use because all corporate information is consolidated into a unified system. This consolidation simplifies and accelerates the search for necessary information.

Compared to electronic information, big data represents a much more complex information system because it accounts for and continually updates the connections between information units. Electronic information repositories are typically isolated from each other, whereas big data is always systemic, preventing data gaps. For instance, instead of separate forms of electronic corporate reporting divided by years, big data presents this reporting in a time series system, ensuring the integrity and continuity of corporate accounting data.

The transition to big data has been a significant challenge for enterprise management, requiring extensive efforts to consolidate the vast amount of corporate information available to management into big data. The problem lies in the complexity of regular information collection, which has prevented the transition to big data from fully meeting the expectations of organizations' management, generating only a fraction of the anticipated benefits.

When planning the automation of corporate management, managers expected that a one-time initial formation of big data followed by the automation of corporate information management would suffice. This assumption was based on an analogy with the financing of the transition to big data, which involved significant initial capital expenditures followed by economic operation. However, this analogy proved incorrect. Big data requires regular and large-scale informational support.

The most critical drawback of the current big data collection technology is, first and foremost, the slow speed of information gathering. The main idea behind using big data in management is to obtain all necessary information more promptly for earlier enterprise diagnostics, quicker identification of problems, and rapid selection of potential solutions. Delays in information collection hinder the practical implementation of this concept.

Second, subjectivity distorts the purpose of automation, which is intended to overcome it. Big data is integrated into the decision-making process to rationalize these decisions. However, if the data is entered manually, it remains subjective, reducing management effectiveness. Third, the logical connections between information units in big data do not arise spontaneously—they must be externally defined. Manual

establishment of these connections can reflect only a small portion and is highly labor-intensive.

Fourth, although big data is conceived as a comprehensive information system, this has not yet been achieved in practice. Nowadays, enterprises have managed to integrate only internal corporate information into big data, while information from external sources remains outside the big data corporate information system. This results in gaps in big data, reducing its effectiveness in the decision-making process.

The aforementioned issues complicate interactive managerial decision-making and highlight the need for more advanced big data collection technology. This research proposes the Internet of Things (IoT) as a promising new technology. The purpose of this research is to substantiate the advantages and develop scientific and practical recommendations for the use of IoT as a big data collection technology for interactive managerial decision-making by contemporary enterprises.

2 Literature Review

This research is based on the scientific concept of interactive managerial decision-making [8]. According to this concept, interactivity means making managerial decisions in real time with immediate responses from automation tools to the manager's requests and commands [4].

The economic essence of interactive managerial decision-making lies in the manager's ability to flexibly adjust decision support tools to optimize them according to the changing needs of the enterprise's management apparatus. The existing big data collection technology has the following main characteristics:

- Manual data entry into big data by the manager [10];
- Fragmentation of logical connections between information units, set manually by the manager [1];
- Limitation of big data to corporate information from the enterprise's internal data sources [2].

Some aspects of using IoT for big data collection are discussed in the works by Vanchukhina et al. [11] and Wu [18]. However, the published literature does not explain how big data collection through IoT contributes to interactive managerial decision-making. This represents a gap in the literature and raises the research question of the consequences of using IoT as a big data collection technology for interactive managerial decision-making. The existing literature lists the following expected benefits of interactive managerial decision-making:

- Increased export activity of the enterprise [5];
- Ensuring gender neutrality in management [6];
- Optimization of enterprise logistics [9];
- Growth in the innovative activity of the enterprise [7];

- Acceleration and simplification of corporate reporting to government regulators [3].

To answer the research question, this research examines the relationship between the use of IoT and big data with the actual realization of these listed benefits in the interactive managerial decision-making process in contemporary business management.

3 Materials and Methods

For this research, the authors created a sample from the top 30 countries in the world in terms of management automation in 2023. These countries are leaders in the National Research University Higher School of Economics [12] ranking for their activity in the application of big data and IoT (Table 2).

In the experimental part of this research, the authors used a regression analysis method to model the impact of IoT and big data on the target outcomes of interactive managerial decision-making in contemporary business management (MnM). Based on the results, the authors identified the potential for maximizing the benefits of interactive managerial decision-making (using Russia as an example).

4 Results

To establish causal relationships in management automation based on the statistics in Table 1, the authors conducted a regression modeling of the impact of IoT and big data on the target outcomes of interactive managerial decision-making in contemporary business management. As a result, the following system of multiple linear regression equations was formulated:

$$\begin{cases} \text{MNM}_1 = 94.72 + 0.95 * \text{IoT} - 1.85 * \text{BgD}, \quad r^2 = 30.89\%; \\ \text{MNM}_2 = 24.27 - 0.05 * \text{IoT} - 0.46 * \text{BgD}, \quad r^2 = 39.41\%; \\ \text{MNM}_3 = 2.78 + 0.01 * \text{IoT} + 0.04 * \text{BgD}, \quad r^2 = 77.64\%; \\ \text{MNM}_4 = -9.26 + 0.65 * \text{IoT} + 1.03 * \text{BgD}, \quad r^2 = 66.99\%; \\ \text{MNM}_5 = 12.27 - 0.01 * \text{IoT} - 0.18 * \text{BgD}, \quad r^2 = 20.84\%. \end{cases} \quad (1)$$

Model (1) indicates that an increase in the activity of using IoT results in a 0.95% GDP growth in exports, a 0.01-point improvement in logistics efficiency, a 0.65% increase in the share of innovation-active enterprises, and a 0.01% reduction in the time required for corporate reporting to government regulators by top management.

Table 1 Statistics on managerial decision-making in the top 30 countries for management automation in 2023

Country	Target results			Factors				
	Merchandise trade (% of GDP)	Firms with female top manager (% of firms)	Logistics performance index: overall (1 = low to 5 = high)	Firms that spend on R&D (% of firms)	Time spent dealing with the requirements of government regulations (% of senior management time)	MNM ₅	16T	Share of organizations analyzing big data (%)
Austria	94.14	18.80	4.00	39.20	10.70		51.0	9.0
Brazil	32.62	19.40	3.20	0.00	14.20		14.0	6.0
Bulgaria	119.86	28.80	3.20	14.00	10.50		0.0	6.0
Croatia	97.22	27.00	3.30	6.00	15.00		23.0	14.0
Cyprus	55.92	8.20	3.20	15.00	5.50		33.0	6.0
Denmark	64.14	8.30	4.10	42.70	5.80		20.0	27.0
Estonia	127.64	22.50	3.60	27.30	3.90		17.0	10.0
Finland	64.85	12.90	4.20	71.00	7.10		41.0	22.0
France	51.68	19.90	3.90	21.10	20.70		22.0	22.0
Germany	79.08	14.20	4.10	37.40	9.20		36.0	18.0
Greece	71.28	17.20	3.70	12.60	6.10		23.0	13.0
Hungary	178.10	22.10	3.20	14.50	10.40		22.0	7.0
Ireland	67.47	15.10	3.60	24.00	13.90		34.0	23.0
Italy	65.68	15.30	3.70	8.80	8.90		32.0	9.0
Korea, Rep	84.53	0.00	3.80	0.00	0.00		18.0	14.0
Latvia	130.99	32.60	3.50	19.90	26.80		28.0	9.0
Lithuania	142.70	30.70	3.40	6.00	6.20		28.0	11.0

(continued)

Table 1 (continued)

Country	Target results				Factors		
	Merchandise trade (% of GDP)	Firms with female top manager (% of firms)	Logistics performance index: overall (1 = low to 5 = high)	Firms that spend on R&D (% of firms)	Time spent dealing with the requirements of government regulations (% of senior management time)	MNM ₅	IoT
MNM ₁	MNM ₂	MNM ₃	MNM ₄	MNM ₅			BgD
Luxembourg	53.65	7.40	3.60	34.80	9.60	22.0	19.0
Netherlands	184.77	13.70	4.10	43.00	6.30	21.0	27.0
Norway	59.89	0.00	3.70	0.00	0.00	24.0	19.0
Poland	107.79	27.80	3.60	5.60	7.70	19.0	9.0
Portugal	77.24	14.00	3.40	6.80	9.90	23.0	11.0
Romania	76.22	17.20	3.20	9.20	20.10	11.0	5.0
Russian Federation	38.77	24.30	2.60	15.70	5.60	11.0	11.0
Serbia	110.45	18.20	2.80	18.70	10.00	20.0	2.0
Slovak Republic	190.75	22.90	3.30	13.70	16.50	27.0	6.0
Slovenia	232.15	18.80	3.30	39.40	7.50	50.0	7.0
Spain	64.31	17.60	3.90	19.60	13.40	28.0	9.0
Sweden	67.60	14.00	4.00	31.40	4.40	40.0	19.0
Turkiye	68.12	3.90	3.40	11.20	5.90	21.0	9.0

Source Compiled by the authors based on the materials from the National Research University Higher School of Economics [12] and World Bank [13–17]

Table 2 Comparative analysis of alternative big data collection technologies

Areas of comparison for technologies	Existing technology	New technology
Data entry into big data	Manual data entry by the manager [10]	Automatic data collection via IoT
Method of establishing logical connections between data units in big data	Logical connections are manually set by the manager, making them fragmented and conditional [1]	Logical connections are automatically established, making them systemic and accurate
Sources from which data is collected into big data	Internal sources, primarily corporate reporting [2]	Internal (electronic equipment and machine vision) and external (consumer applications, partners, and business government administration) sources

Source Developed and compiled by the authors

Similarly, an increase in the activity of using big data results in a 0.04-point improvement in logistics efficiency, a 1.03% increase in the share of innovation-active enterprises, and a 0.18% reduction in the time required for corporate reporting to government regulators by top management.

Combined, the application of big data and IoT leads to a 30.89% increase in export activity, a 77.64% optimization in enterprise logistics, a 66.99% increase in innovation activity, and a 20.84% acceleration and simplification of corporate reporting to government regulators. However, using IoT and big data does not enhance gender neutrality in management. Based on Model (1), the authors identified the potential for maximizing the benefits of interactive managerial decision-making in Russia (Fig. 1).

According to Fig. 1, with the application of big data and IoT by all enterprises in Russia, the following benefits of interactive managerial decision-making will be realized:

- A 5.08% increase in exports (from 38.77 to 40.74% of GDP);
- A 92.31% improvement in logistics efficiency (from 2.60 to 5.00 points);
- A 536.94% increase in the share of innovation-active enterprises (from 15.70 to 100%);
- A 100% reduction in the time required for corporate reporting to government regulators (from 5.60 to 0% of top management's time).

To fully and reliably realize these identified benefits, the following technology for big data collection for interactive managerial decision-making using IoT has been developed (Fig. 2).

The new technology presented in Fig. 2 suggests that a manager, acting as the decision-making authority within the enterprise, conducts AI analytics and requests additional data when consulting big data as a means of interactive decision-making. In

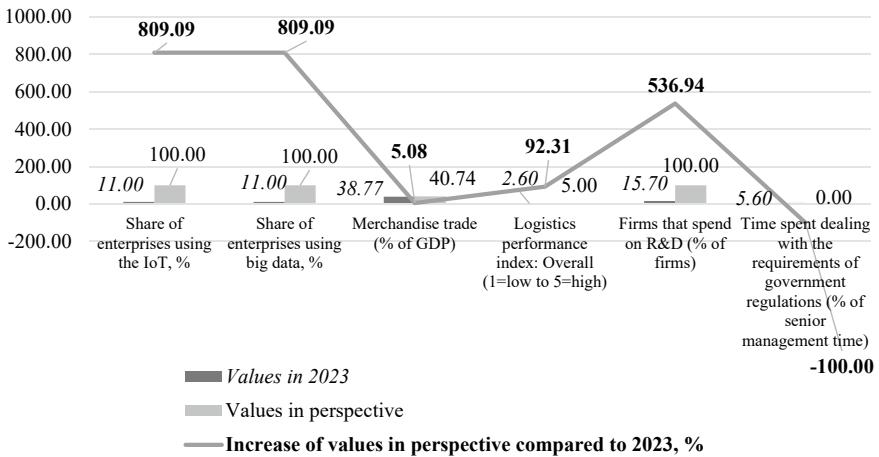


Fig. 1 Perspective on maximizing the benefits of interactive management decision-making in Russia. *Source* Calculated and developed by the authors

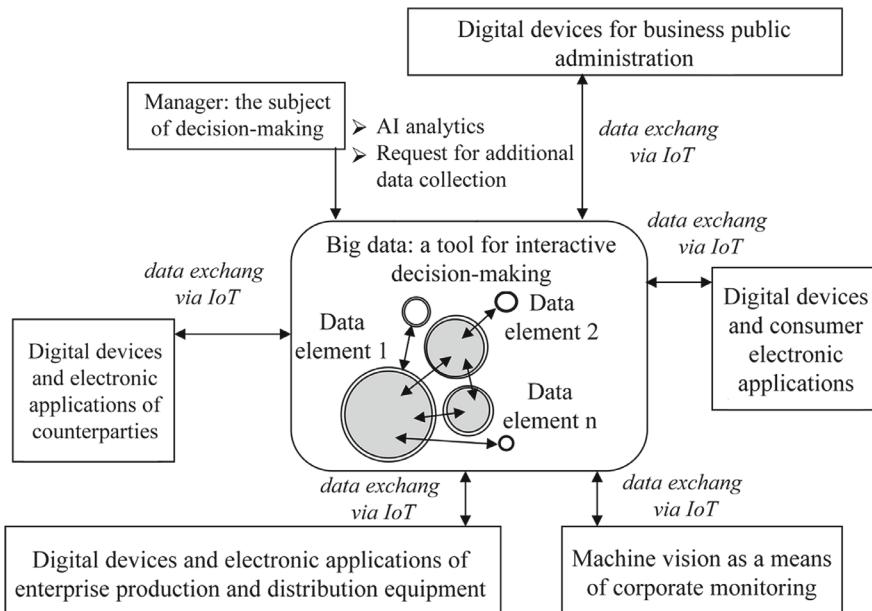


Fig. 2 Big data collection technology for interactive management decision-making using IoT. *Source* Developed by the authors

big data, all data elements are grouped; the connections between them are established automatically.

First, internal corporate information flows into big data through IoT automatically from digital devices and electronic applications of the enterprise's production–distribution equipment and from machine vision used for corporate monitoring. Second, external information comes from digital devices and electronic applications of consumers, partners, and business government administration.

5 Discussion

This article contributes to the literature, including the works of Arundel et al. [4] and Nisar et al. [8], related to the concept of interactive managerial decision-making by developing a technology for big data collection using IoT, the features of which are detailed in Table 2.

As seen in Table 2, unlike Shafique et al. [10], the developed technology involves automatic big data collection via IoT. Unlike Abdelhalim [1], in the new technology, logical connections are established automatically, making them systemic and accurate. In contrast to Albqowr et al. [2], in the author's technology, sources of information for big data include internal (electronic equipment and machine vision) and external (consumer applications, partners, and business government administration) sources.

Second, it clarifies the consequences of using IoT for big data collection in interactive managerial decision-making. Unlike Corallo et al. [5], this research found that the synergy effect of the comprehensive use of big data and IoT in management does not lead to increased export activity of the enterprise.

In contrast to Karaboga et al. [6], the authors established that using big data and AI does not enhance gender neutrality in management. In support of Riggs et al. [9], it is proven that the systemic use of big data and IoT in management optimizes enterprise logistics.

In support of Kokshagina et al. [7], it is justified that using big data and AI in management promotes the growth of the enterprise's innovation activity. In support of Andronie et al. [3], it is proven that the use of big data and AI accelerates and simplifies corporate reporting to government regulators.

6 Conclusion

Thus, the main result of the conducted research is the justification of the advantages of using IoT as a technology for big data collection in interactive managerial decision-making by contemporary enterprises. These advantages include increased export activity, optimized logistics, enhanced innovation activity, and accelerated and simplified corporate reporting to government regulators.

The theoretical significance lies in the fact that the developed model of the impact of IoT and big data usage on the target outcomes of interactive managerial decision-making revealed previously unknown causal relationships in the automation of contemporary business management.

The practical significance of this research is associated with the potential to maximize the benefits of interactive managerial decision-making in Russia, which will improve the accuracy and reliability of planning and forecasting, as well as the state and corporate management of the automation processes in Russian business management.

The managerial significance lies in the fact that the developed big data collection technology using IoT offers the following advantages for interactive decision-making:

- Accelerated Big Data collection and increased objectivity;
- Greater consistency of big data and more precise causal relationships among its elements;
- Greater completeness and reliability of big data due to a broader range of sources.

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Machine Learning Based on Big Data as a Technology for Enhancing Intelligent Decision-Making Support



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and Olga A. Pecherskaya^{ID}

Abstract The research develops scientific and practical recommendations for improving intelligent decision-making support through a new technology: machine learning based on big data. The authors conducted a comparative analysis of the existing technology and proposed new technology to support intelligent decision-making. The authors also carried out a SWOT analysis of the transition to machine learning based on big data as a new technology for intelligent decision-making support. The authors developed a framework for organizing machine learning based on big data as a technology for enhancing intelligent decision-making support. The conclusion is that machine learning based on big data will enhance intelligent decision-making support by improving information support (enabled by the Internet of Things and big data), expanding the functional capabilities of smart analytical tools (artificial intelligence), and transitioning from template-based to creative solutions (enabled by machine learning). The practical significance of the developed framework for organizing machine learning based on big data as a technology for enhancing intelligent decision-making support lies in its potential to increase the efficiency of today's organizational management.

Keywords Machine learning · Big data · Decision making technology · Intelligent decision support · Management decisions

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1 Introduction

Nowadays, management is characterized by a high degree of automation, which is indispensable for management structures in large enterprises and in many small and medium-sized businesses. The need for automation of management procedures arises from the requirement for contemporary enterprises to have flexible and instantaneous management responses to even the slightest changes in market dynamics. Simultaneously, the criteria for optimal management decisions are complex and contradictory. The consequences of management decisions can be critical for the business.

While the practice of intelligent decision-making support is an objective necessity for contemporary businesses, this support is often insufficiently robust. In other words, there is a problem with the imperfection of technology for intelligent decision-making support. This problem has two main manifestations. The first manifestation is the limited functionality of artificial intelligence. Although intelligent support tools are intended to alleviate the analytical burden on managers in contemporary organizations, in many cases, managers are forced to double-check the data processing results provided by artificial intelligence and critically reassess and adjust the proposed solutions.

Second, there are gaps in management information. In traditional management, information came from numerous sources and took various forms: from verbal information to official documentation. Management information must meet strict criteria so that AI can process it. This is often not the case for all the information available to an organization and is crucial for making accurate decisions. Therefore, either the manager must standardize the management information to make it accessible for AI processing, or they must adjust the AI-proposed solutions by considering additional information.

Given that the implementation of intelligent decision-making support technologies involves significant financial burdens on contemporary organizations and necessitates complex restructuring of the management organizational structure and operational model, the inefficiency of these technologies hinders the return on investment. This highlights the importance of addressing this issue, for which this research proposes improving intelligent decision-making support through a new technology—machine learning based on big data. This research aims to develop recommendations for making these improvements.

2 Literature Review

The topic of intelligent decision-making support is thoroughly studied and detailed in the existing literature by Khapre et al. [3], Mahdi et al. [5], Mochinski et al. [7], Omari et al. [9], and Turginbayeva et al. [14].

Available publications [4, 11, 15] acknowledge and describe the advantages and disadvantages of the technology used by organizations for intelligent decision-making support. This technology is based on artificial intelligence that automatically processes management information available in electronic form.

Specific technological aspects of using machine learning and big data in management are discussed in several published works, including those by Amellal et al. [1], Hammann [2], Mahdi et al. [6], Nazir et al. [8], Phong et al. [10], Tatar et al. [12], Teruel et al. [13], and Zhang et al. [16].

However, the organizational aspects of applying machine learning and big data in intelligent decision-making support are insufficiently explored. This lack of research hinders the implementation of these technologies. To address this gap, this research develops practical organizational and technical solutions for implementing intelligent decision-making support through machine learning based on big data.

3 Materials and Methods

This research presents an empirical study aimed at addressing three applied tasks. The first task is to justify the feasibility of applying machine learning technology based on big data in intelligent decision-making support. To achieve this, the authors used a comparative analysis method, allowing for a multi-criteria comparison of the existing and proposed new technology for intelligent decision-making support.

The second task is to assess the ability of contemporary organizations to transition to the new technology. For this purpose, the authors employed SWOT analysis to determine the readiness of contemporary organizations to adopt machine learning based on big data as a new technology for intelligent decision-making support.

The third task is to offer practical recommendations for organizing the application of the proposed new technology. To this end, a framework for organizing machine learning based on big data as a technology to enhance decision-making support is developed. This framework is visualized using the graphical representation of scientific information.

4 Results

To address the first task, which involves justifying the feasibility of applying machine learning technology based on big data in the practice of intelligent decision-making support, the authors conducted a comparative analysis of the existing and new technology for intelligent decision-making support (Table 1).

The comparative analysis conducted in Table 1 revealed certain advantages of machine learning technology based on big data in the practice of intelligent decision-making support, justifying the feasibility of applying this technology. Instead of outdated templates created once, machine learning makes it possible to create updated and creative (non-template) solutions.

In this new technology, AI serves as the source of solutions rather than the manager or outsourcing specialist (the quality and correctness of templates depend on their competence), offering new solutions through machine learning. Unlike the existing technology of AI, which relies on limited, initially obtained, and non-updated data, machine learning based on big data utilizes more comprehensive and continuously updated data. While the existing technology handles disparate and unsystematic data

Table 1 Comparative analysis of the existing and proposed new technology for intelligent decision-making support

Comparison criterion	Existing technology: artificial intelligence	New technology: machine learning based on big data
Type of decisions	Outdated templates created once	Updated, creative (non-template) solutions
Source of decisions	Created by the manager or outsourcing specialist (the quality and correctness of templates depend on their competence)	Artificial intelligence as a source for creating new solutions through machine learning
Experience incorporated into decisions	Based only on past experience	Past and current cutting-edge experience
Completeness of data considered	Limited, initially obtained, and non-updated data	Comprehensive and continuously updated data
Integrity of the data considered	Disparate and unsystematic data (electronic database)	Consideration of systemic, logical connections in data (big data)
Method of data transfer to artificial intelligence	Data manually entered by the manager (time-consuming, labor-intensive, limited data)	Automated collection of big data via the Internet of Things
Ability to adjust decisions	Decisions made are static and unchangeable after implementation	Decisions can be adjusted even after being made—during implementation
Decision-making algorithm	Linear (each decision is independent)	Cyclical (all decisions are interconnected)

Source Developed by the authors

(electronic database), the new technology considers systemic and logical connections in data (big data).

In the existing technology, data is manually entered by the manager (time-consuming, labor-intensive, and limited data). The new technology collects data automatically through the Internet of Things. Unlike the established technology, where decisions are static and unchangeable after implementation, in the new technology, decisions can be adjusted even after being made—during implementation. The decision-making algorithm in the new technology is not linear (each decision is independent) but cyclical (all decisions are interconnected).

To address the second task, which involves assessing the possibility of organizations transitioning to the new technology, the authors conducted a SWOT analysis of transitioning to machine learning based on big data as a new technology for intelligent decision-making support (Table 2).

As reflected in Table 2, the strengths (S) of transitioning to machine learning based on big data include comprehensive staffing (availability of digital management personnel) and favorable business culture (high digital competition).

The weaknesses (W) of transitioning to machine learning based on big data include financial barriers (high cost of the considered technology) and a deficit of management technologies (machine learning and big data are not prepared for use in decision-making).

The opportunities (O) of transitioning to machine learning based on big data are associated with the expansion of government support for implementing these technologies in management practice and the adaptation of technologies to management.

The threat (T) of transitioning to machine learning is a further reduction in funding (governmental and private) and the theorization of created technologies (their development by universities without technology diffusion in the business environment).

To address the third task, which involves proposing practical recommendations for organizing the process of applying the proposed new technology, the authors developed a framework for organizing machine learning based on big data as a technology for enhancing intelligent decision-making support (Fig. 1).

The process of organizing the use of machine learning based on big data in management, illustrated in Fig. 1, involves the continuous transmission of market

Table 2 SWOT analysis of the transition to machine learning based on big data as a new technology for intelligent support of managerial decision-making

S: Strengths	W: Weaknesses
<ul style="list-style-type: none"> • Comprehensive staffing; • Favorable business culture 	<ul style="list-style-type: none"> • Financial barriers; • Shortage of management technology
O: Opportunities	T: Threats
<ul style="list-style-type: none"> • Government support for implementation; • Adaptation of technologies to management 	<ul style="list-style-type: none"> • Further reduction in funding; • Theorization of the created technologies

Source Developed and compiled by the authors

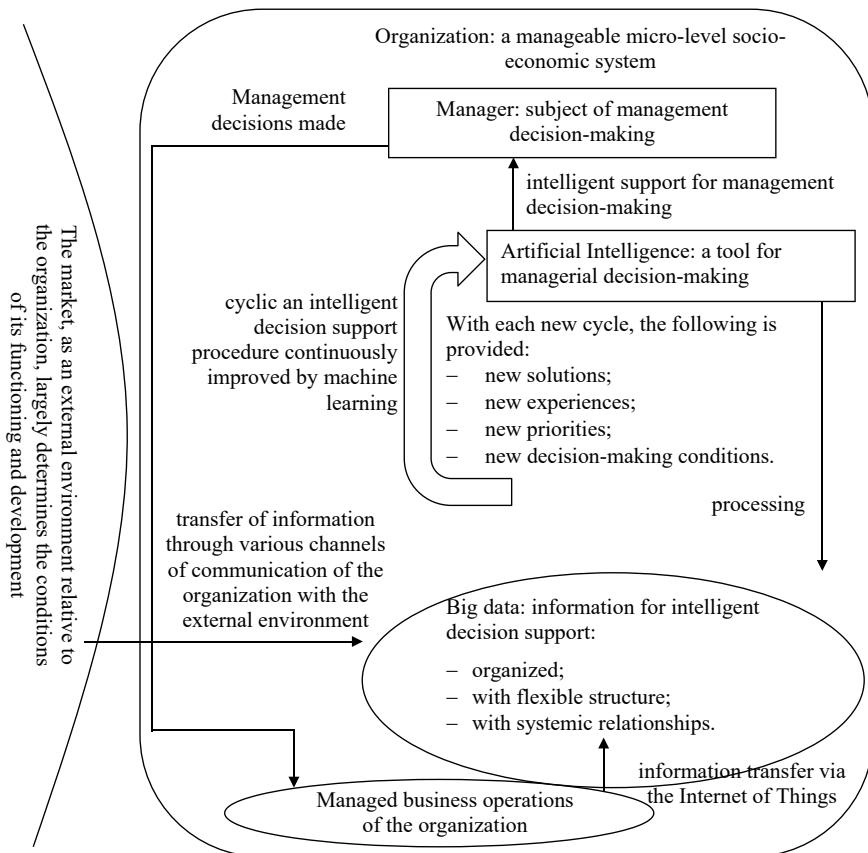


Fig. 1 The order of organization of machine learning based on big data as a technology for improving intellectual support of decision-making. *Source* Developed by the authors

information through various communication channels between the organization and the external environment, as well as internal information about the organization's managed business operations through the Internet of Things. This information is consolidated into big data, where it is organized, given a flexible (changing as needed) structure, and endowed with systemic interconnections. Big data serves as informational support for intelligent decision-making.

Artificial intelligence is a tool for making management decisions. It carries out a cyclical procedure of intelligent decision-making support, continuously improving through machine learning. With each new cycle, new solutions, experiences, priorities, and decision-making conditions (conditions that determine which decision is preferred) are provided. The organization's manager acts as the decision-maker. The decisions made by the manager are then implemented in the organization's managed business operations.

5 Discussion

The results obtained in this research contribute to the literature, including the works of Khapre et al. [3], Mahdi et al. [5], Mochinski et al. [7], Omari et al. [9], and Turginbayeva et al. [14], advancing the theory of intelligent decision-making support through the development of systemic applied organizational and technical solutions for implementing intelligent decision-making support using machine learning based on big data.

In contrast to Lobova et al. [4], Przhedetsky et al. [11], and Veselovsky et al. [15], this research identified the limitations and shortcomings of artificial intelligence as the existing technology for intelligent decision-making support. The identified limitations include incomplete information support, limited decision-making functionality, and template-based solutions.

Continuing the series of studies by Amellal et al. [1], Hammann [2], Mahdi et al. [6], Nazir et al. [8], Phong et al. [10], Tatar et al. [12], Teruel et al. [13], and Zhang et al. [16], this research revealed the advantages of machine learning based on big data as a new technology for intelligent decision-making support: enhanced information support, flexibility in the decision-making process, and innovative solutions.

6 Conclusion

The final conclusion based on the results obtained in the research is that machine learning based on big data will enhance intelligent decision-making support by improving information support (provided by the Internet of Things and big data), expanding the functional capabilities of smart analytics tools (artificial intelligence), and transitioning from template-based to creative solutions (made possible by machine learning).

The practical significance of the developed framework for organizing machine learning based on big data as a technology for enhancing intelligent decision-making support lies in its potential to increase the management efficiency of contemporary organizations. The managerial significance of the proposed technology is explained by the following advantages:

- Optimization of the flow of management information within the organization;
- Strengthening competitive advantages through the creativity of management decisions, which are often unexpected for competitors;
- Increasing management flexibility (through machine learning) instead of the traditional decrease (due to bureaucratization) as the organization grows and develops.

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The Role of Artificial Intelligence and Digitalization in Enhancing the Quality of Management Culture in Large Russian Companies



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Abstract The research problem lies in assessing the necessity of implementing digitalization and artificial intelligence (AI) at strategic and technical-management levels. The research aims to present the agents of influence of AI and digitalization on the quality of management culture in large Russian companies. Through comparative analysis methods, the authors identify the specific impacts of AI and digitalization at strategic and technical-management levels within large companies. AI and digitalization enhance the quality of management strategies at all management levels, align the interests of the corporate community in corporate communication, and indicate trends for further improvement in management strategy development. The evaluation of such quality is based on the nature of intra-systemic component connections between AI and digitalization, their depth, and quantitative prevalence, allowing various management developments to achieve multi-industry efficiency and improve the quality of their methodological and theoretical-practical foundations. AI and digitalization create a precedent for synchronizing the process of developing management strategies across different levels of corporate governance while maintaining a company's competitive advantages by balancing market interests with those of the internal corporate community.

Keywords Digitalization · Management culture · Artificial intelligence · Social enterprise · Social innovation · Human capital

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JEL Classification E600 · E660 · E650 · L230 · L25 · L260 · O210 · O320 · O350

1 Introduction

Artificial intelligence (AI) and digitalization can be seen as key informational trends in society. They are gradually entering all areas of human activity and sometimes transform them beyond recognition.

Corporate and management culture is no exception—related corporate and management communications require regulation from direct participants and from supervisory corporate structures, including corporate management levels. The research aims to identify the specific impacts of AI and digitalization on strategic and technical-management levels. Accordingly, the research objectives are as follows:

- To examine the influence of AI and digitalization on the strategic management level within the framework of managerial integration and diversification;
- To study the impact of AI and digitalization on the technical-management level;
- To reflect the influence of AI and digitalization on the civilizational management level, maintaining human morality in large companies over the long term.

2 Materials and Method

The management culture of a large company is characterized by a multitude of corporate standards, which can be challenging to regulate due to their inherent diversity and potential contextual contradictions. Addressing this complexity can be optimized by implementing advanced algorithmic-analytical methods, such as artificial intelligence and digitalization, applicable at various management levels (strategic and technical and technological levels). Digitalization serves as a conceptual foundation for enhancing task-solving efficiency, rooted in the information society and advancements in information technology [1]. AI acts as an additional layer built upon this foundation, playing a crucial role by using algorithms to ensure the completion of embedded tasks [2].

In examining the digital maturity of Russian manufacturing companies, the following trends emerge. Digitalization of relationships with suppliers (56% of respondents) and consumers (51%) is the most prevalent. The third area in terms of digital technology use intensity is core production activities (49% on average), driven mainly by sectors such as automotive (65%), mechanical engineering and metalworking (57%), and the chemical and pharmaceutical industries (53%). Next, there are administrative activities (39%) and marketing (38%) [3].

Applying AI and digitalization tools in large companies can provide a more universal economic assessment. The trend observed is that industry affiliation does

not affect profitability for larger companies. In turn, this parameter remains significant (at the 5% level) for smaller companies, showing a weak positive correlation [4].

3 Results

3.1 *Artificial Intelligence and Digitalization at the Strategic Management Level*

3.1.1 Management Integration

The strategic management level is a collective typology of managerial activities where strategy results from synthesizing multi-level managerial decisions within the initial corporate agent. Consequently, the quality of this synthesis directly depends on the thoroughness of these decisions [5]. In a large company, this “multi-levelness” is extremely high. Furthermore, assessing the quality of synthesis is challenging due to this multi-levelness. Therefore, strictly manual regulation of strategy is impractical and likely to result in numerous errors, some of which could be fatal to continuing the corporate agent’s economic activities. AI and digitalization can become indispensable tools in such managerial integration, aiding in developing the required strategic decisions. They can optimize the statistical collection of information on implemented multi-level managerial decisions, analyze their relevance to the subject and object of active use, and assess the effectiveness of previously used strategies based on the similarity or dissimilarity of multi-level managerial decisions. These factors can become vectors of information-management optimization and automation provided by these tools. For example, in the oil and gas industry, a unified digital platform that ensures high-speed processing of informational and analytical data in real time can enhance the economic efficiency of companies’ production activities through multiplicative effects [6].

3.1.2 Management Diversification

Although the informational and methodological synthesis is a crucial part of an effective management decision, assessing any strategy’s practical orientation stems from its applicability to the maximum number of structural objects. In a large company, these objects include departments, divisions, and subsidiary groups. The practice of strategy within the “department-division” system determines the list of informational additions that should be timely integrated into the strategy locally for complete adaptation, aiming to achieve the highest efficiency from its local implementation. Thus, when a strategy initially “transitions” into the informational field of a company’s

division, it remains somewhat abstract, considering corporate standards of the organization's higher management levels along with the basic standards of the dependent "department-division" systems. However, due to the corporate variability of these systems, which may not be promptly tracked by the management center, these systems can implement their local strategic standards, provided they do not contradict the corporate standards of the management center [7].

This scenario presents the problem of strategic synchronization between the management center and its dependent "department-division" systems. The capabilities of AI and digitalization make it possible to effectively address these issues by optimizing the transmission of management strategies between the center and divisions based on criteria of completeness and timely availability in a hardware-interface format. Working on any given strategy in real-time becomes possible through software-command development tools, which can learn from the strategic standards input and subsequently offer local contextual recommendations for enhancing strategy effectiveness based on criteria such as informational completeness and industry relevance.

In turn, departments can offer their recommendations for the strategies planned for implementation by the management center. Combined with digitalization, AI can also learn from these recommendations and, subsequently, propose programmatic recommendations to the management center for strategy optimization at a software level. Alternatively, they can suggest contextual modifications to the recommendations for the "department-division" systems to enhance temporal and labor efficiency.

3.2 Artificial Intelligence and Digitalization at the Technical and Technological Level of Management

3.2.1 Management Integration

Developing a new technological solution can be just as labor-intensive as crafting a new strategy because it requires prior analysis of a series of similar technological solutions to assess their suitability for the current production task [8]. For a large company, a technological solution may be a direct factor in innovative activity, linked to its direct development, and as a means of "monetary-material inheritance," involving the complete or partial buyout of technology or a technological solution. Thus, a preliminary assessment of the feasibility of this action remains relevant. It is essential to have a clear understanding of the subject of the technological inquiry and pre-analyze available technologies in the market that best correspond to the stated subject. With the advancement of internet technologies, the complexity of analysis significantly increases. Sometimes, it is necessary to analyze numerous cross-industry solutions, varying in their degree of meeting the technical-production needs of a large company. Consequently, various evaluation criteria for these solutions arise, often challenging to determine solely through manual labor or significantly

contextually limited computer programs. Coupled with digitalization, AI makes it possible to create a robust preliminary analytics framework, including multi-criteria decision support. The importance of AI notably increases in the contextual generation of technological solutions, where technology can be developed by several computer programs on a pre-trained array of technical-management data—either within an industry or solely from a subject-corporate origin.

3.2.2 Management Diversification

The development of technology requires a significant amount of material and informational resources for each separately designated stage of development. The complexity of technological development often lies in the need for one employee to fulfill various functional obligations, where these obligations may closely intertwine among different employees. Therefore, there is a need to introduce a necessary employee with separately designated functions at the required stage of development [9]. In the context of the flow production of technological innovations, the process of monitoring the timely introduction of required employees, combined with tracking the completeness of implementing functional obligations, is significantly complicated. It can lead to disruptions in technological development chains and, which is particularly dangerous, in production development chains. Therefore, introducing effective external control tools is required in elaborating technological solutions. Artificial intelligence and digitalization help create external control tools for such flow production, assessing technological hypotheses, stages of their development, and phases of implementation into various production processes. Thus, the processes of technological and production development of a product are more closely linked. Technological control through AI can be implemented at the software and hardware levels. In the former case, the ultimate goal is to develop a specific management software product. In the latter case, the goal is to develop hardware with certain software functionality. In both cases, the software functionality is coupled with the capabilities of AI: automated analysis of technological development chains in conjunction with contextual generation of recommendations to enhance the efficiency of analysis in the given chain.

3.3 Artificial Intelligence at the Civilizational Level of Management: Preserving Human Morality in Large Companies in the Long-Term Retrospective

Although relatively new phenomena, AI and digitalization pose a key question of how they will influence society and technology in the long term, despite the potential variability in their activity levels. For humans, a crucial part of various social processes is maintaining the social core in complex phenomena of socio-personal evolution.

This core helps shape an individual's basic understanding of the world, which can later be altered through more independent human manipulations of this process. Therefore, despite the novelty of AI and digitalization, these systems will have to inherit the fundamental tasks of all active social systems in preserving the moral and ethical qualities of individuals and society as a whole, regardless of their typological affiliation. Reducing the role of such typological attachments is also crucial for social management within large corporations, where corporate morality must be transmitted to all active labor participants in the production process. In collaboration with digitalization, AI will help formulate the fundamental principles of corporate moral flexibility concerning its anticipated subjective-collective utilization within specific divisions and departments.

Market efficiency and social satisfaction from work can be viewed as eternal opposing entities in constant conflict. This conflict's intensity is particularly evident in large organizations, where the community comprises individuals with diverse views and varying production and social experiences. However, market efficiency cannot be absolutized within a company's value orientation, which operates on long-term strategies, as any large organization does. Serving as a social mechanism, market efficiency reflects the moral and ethical values embodied in corporate culture. While the market may and should yield to social values, social values yield to the market only in a few cases.

Tracking the interaction between the market and the social values of employees in a large organization is extremely challenging, particularly exerting structurally-strategic influence on them. This influence should primarily stem from preliminary local recommendations for adjusting the vector of social communications and transmitting corporate culture among all members of the large company's society. AI and digitalization can be seen as additional tools in addressing this task, primarily through their utilization in corporate messengers. Digitalization provides a platform for broad employee engagement in all possible forms of digital communication (text, voice, and video formats), while AI accesses data from corporate messengers, analyzes ongoing chat communication, and formulates personalized recommendations for each employee to enhance communication efficiency, primarily at a local level. This process is also feasible at the level of corporate strategy.

The interaction between the market and the social values of employees in a large organization begins during the recruitment stage into the company—in the HR field. One of the main advantages of implementing AI in HR is a 75% reduction in recruitment costs [10]. However, in this case, AI can have significant value importance similar to its use in corporate messengers, where the communication object is initial employment. AI tools help identify differences between employees and office solutions, conducting employee training programs [11]. Thus, the hiring process can become more accessible and transparent.

One of the main issues in using AI solutions for all management levels remains the availability of standard solutions. Standard AI solutions on the market are not always available at a reasonable price and do not truly address staffing shortages or solve other business challenges [12]. In this case, it is worth noting that if the business

factors behind the implementation of AI are not developed and demonstrated, AI will undoubtedly go through another stage of immaturity [13].

4 Conclusion

AI based on digital communications enables the optimization of managerial processes in large companies at the strategic and technical and technological levels. It facilitates the synchronization of strategy and technology development processes across various managerial levels, offering recommendations to enhance the quality of corporate digital communication in line with corporate standards. Furthermore, it assists in establishing a balance between the market and social interests of the company as a long-term socio-economic entity.

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The Use of Artificial Intelligence for Optimizing Project Management in IT Companies



Artem V. Kaledin, Alexander G. Rasnyuk, and Tatiana V. Novikova

Abstract This paper examines the planning process for project teams in IT companies that use agile management methods and the challenges that arise. The research aims to determine a method for calculating labor productivity for specialists in the IT sector and propose a way to integrate AI into workflows to improve the estimation of task completion times and optimize their distribution among employees. While evaluating task completion time, the authors studied articles from the ArXiv and CyberLeninka systems. Additionally, the authors analyzed open datasets from the GitHub system and statistics from internal workspaces. The research defines the essence of calculating labor productivity for IT company specialists, aimed at maximizing utility. A flexible scheme for evaluating and distributing tasks for the team is proposed. The proposed scheme considers the characteristics of the project and specialists. The paper highlights potential issues that may arise when using this tool. The research suggests ranking tasks by priorities and performers, creating a general universal model that optimizes numerous tasks for the team as a whole rather than for individual performers.

Keywords Machine learning · Artificial intelligence · Automation · Project management · Sprint planning

JEL Classification M15 · O32

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1 Introduction

External challenges, first the COVID-19 pandemic and then economic sanctions, forced businesses to constantly optimize their processes [1]. Many companies transitioned these processes into projects, which is particularly relevant for IT organizations [2]. Thus, it has become crucial for enterprises to learn how to manage projects effectively.

Although effective project management methodologies have been developed (e.g., agile methodologies) [3], there is potential to enhance them further. This can be achieved by integrating artificial intelligence (AI) methods into workflows, automating a range of routine tasks, and eliminating employee biases in risk and deadline assessments (e.g., excessive optimism) [4].

Existing studies emphasize the issues identified in products developed by IT companies. These issues are usually described in specialized software called issue tracking systems, with Jira by Atlassian being frequently mentioned in research [5]. In addition to tracking issues, Jira (and similar systems) makes it possible to describe arbitrary tasks and assign responsible individuals, thereby enabling IT companies to fully organize all workflows through this system.

Generally, labor productivity in enterprises is measured by the amount of product produced by an employee per unit of time [6]. This definition loses relevance for IT companies because their employees do not create tangible products. Instead, many researchers suggest measuring the number of lines of code written by a programmer per hour [7]. However, this approach has its drawbacks. Implementing the same algorithm requires a different number of lines depending on the programming language [8]. Moreover, some IT specialties do not involve programming (e.g., business analysts or technical writers). Therefore, as an alternative, one could measure the number of tasks resolved by a specialist in Jira per unit of time (e.g., per month).

Agile project management methods typically organize processes within teams by breaking the entire development cycle into sprints (iterations of fixed duration). During sprint planning, decisions are made about which tasks will be performed by whom in the current iteration [9]. Given the significant rise in the popularity of agile methodologies over the past decade [3], it is reasonable to assume that the studied team operates in sprints.

A usual sprint planning scenario consists of the following two phases [10]:

1. The leader (decision-maker) ranks the existing tasks by priority;
2. Team specialists estimate the time required to complete each task, after which the executors are assigned.

These forecasts are often intuitive, based on the employees' previous experience [11]. Consequently, such estimates are inaccurate due to human biases [4].

Previous efforts to optimize project management have long been based on unrealistic assumptions: the tasks were assumed to be uniform. The abilities of employees were considered almost equivalent. This is clearly seen in the study by Basu and Banerjee [12], where a bot was created to automatically distribute tasks among developers without considering their abilities and current workload.

A significant step forward is the work of Volodina and Starikova [13], who proposed an adaptive algorithm for estimating the duration of project tasks, dynamically considering the skills of specialists and the projects' specifics. The strengths of this work include categorizing tasks by type, as they have varying degrees of complexity, and their decomposition into subtasks to improve the accuracy of estimates. However, the algorithm requires expert assessment of task durations, which contradicts the previously mentioned issue of human bias [4]. A drawback of this study is the lack of selection for each task of the executor who can complete it the fastest.

The work of Bonnedahl [14] continues the previous research and highlights the importance of task evaluation, allowing for an average task closure acceleration of 55.1%. The study involves statistical modeling and machine learning methods, emphasizing the potential of using AI to solve such tasks. However, the author does not propose a unified methodology, focusing on the technical complexities of implementation.

There are other works containing interesting ideas. However, these ideas are difficult to implement in today's enterprises. For example, the work by Sudakov and Titov [15] evaluates the time required to complete a task by a group of several programmers, but Jira does not structurally allow assigning more than one executor per task [16].

Without diminishing the significance of the aforementioned works, it is necessary to note the following:

- First, the studies do not address the issue of ranking tasks based on the priorities of the IT company;
- Second, they tackle specialized problems, meaning that they do not build a general model that optimizes the work of the team as a whole rather than its members.

Based on the above, the authors pose the following research questions:

1. What should be included in the concept of labor productivity to better align with the goals of an IT company?
2. How can AI optimize work planning in an IT company?
3. What challenges arise in this process?

2 Methodology

The authors analyzed existing research available on ArXiv using the keywords project management, artificial intelligence, story points, and productivity. They also used similar keywords in Russian when analyzing existing research in the electronic library CyberLeninka. Additionally, the authors studied datasets related to the articles found on GitHub. Finally, to support the proposed hypotheses, the authors exported statistics for each task from the authors' Jira workspace system in CSV format. The resulting methodology was reduced to an integer programming problem.

3 Results

The following subsections of this section address the research questions posed in the introduction.

Assessing labor productivity in an IT company based on the number of tasks completed is not viable. First, tasks vary in their complexity. The authors analyzed task estimates in story points (a relative measure that assigns weights to tasks) using data from open repositories on various projects [17]. As shown in Fig. 1 (see “Data Availability,” p.1), task estimates vary depending on the project.

Notably, the data reveal outliers for certain tasks. This indicates that teams may decompose tasks differently and categorize them by epics (i.e., large tasks requiring significant time) and the specifics of certain tasks. Figure 2 (see “Data Availability,” p. 2) shows the diversity and frequency of tasks based on the number of story points. Even within a single project (datamanagement), short tasks (1–2 story points) predominate. The distribution of medium and large tasks (6, 8, and 10 story points) is uniform after removing outliers.

Second, tasks have different levels of importance. For instance, critical errors prevent clients from using the product or service. Often, the company is contractually obligated (as per the SLA) to compensate customers for the issues experienced [18].

In this research, the metric of labor productivity will be reformulated in terms of the utility of its outcomes. To achieve this, the following assumption is made: “There exists a function $U = U(t)$, which assigns a quantitative utility value to the completion of an arbitrary task t ”. This function can be naturally called a utility function.

It is important to note that utility refers to the measure of a product’s enhanced ability to meet customer needs. The fact that different tasks have varying utility has already been demonstrated with the example of critical issues. In some studies, the term task priority may be used in a similar context [10].

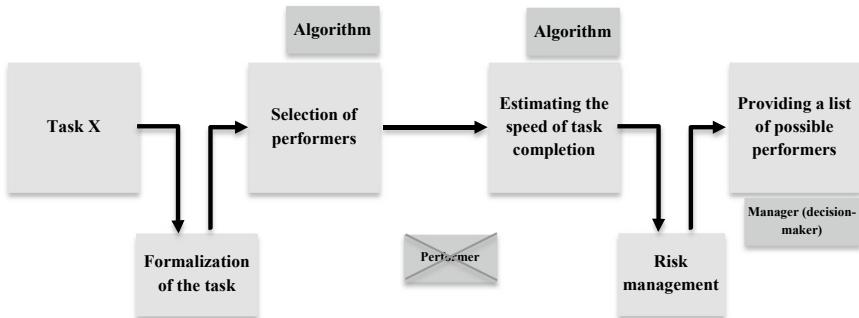
The labor productivity of a team consisting of multiple employees $E = \{e\}$ for a sprint s is defined as the ratio of the total utility of all fully completed tasks $T = \{t\}$ during the sprint to its duration $D(s)$:

$$P(E, T) \equiv \frac{\sum_{t \in T} U(t)}{D(s)}$$

The durations of individual tasks are intentionally not summed in the denominator since employees can work simultaneously.

Thus, increasing a team’s labor productivity in an IT company reduces to maximizing the above ratio for each iteration.

In the previously described sprint planning process, tasks are usually evaluated on special digital boards (scrum boards), which contain this information and, crucially for this work, provide actual results for the completion time of specific tasks. Machine learning models, which are part of the AI methods family, can be trained based on this



Scheme 1 Evaluating the task without the performer's participation. *Source* Compiled by the authors

information. The authors propose the following scheme (Scheme 1) for predicting task completion time using AI algorithms.

When discussing the scope of tasks, executors do not possess the full context and can only provide more accurate estimates after deeper immersion. In this aspect, the formalization of the task (block “Task Formalization”) is crucial. The description is often a formality or filled out at the last minute. Agreements formed through correspondence or calls generate requirements. Generative AI models can be used at this stage (i.e., a type of machine learning algorithm designed to create new data similar to the training data) [19]. Specifically, these models can analyze incoming call records, texts, and diagrams, producing particular research steps, key points or descriptions of the required skills, connections to other epic implementation stages, and highlighting blockers.

Based on the time markings of task execution for a specific team, an algorithm can be trained to predict the completion time of new tasks with a certain level of confidence. Thus, depending on the data quality, we obtain a confidence interval for the task completion time and can interpret the result as follows: the task will be completed in τ days with probability P by executor A or in $\tau + \Delta\tau$ days with probability $P + \Delta p$.

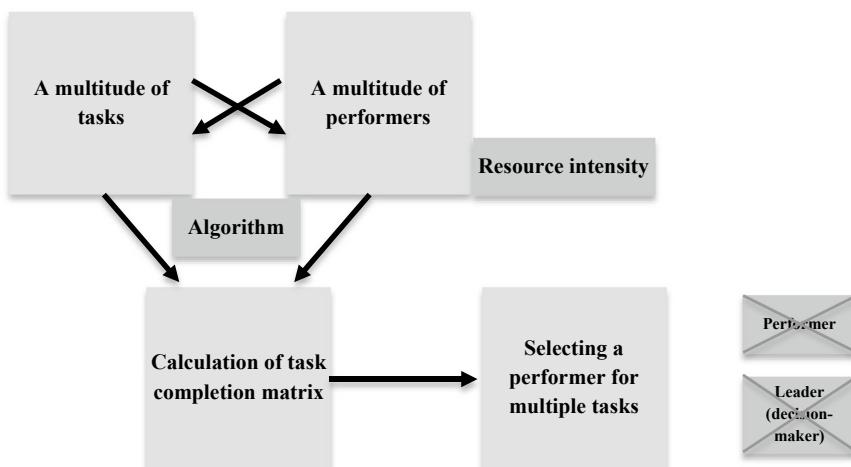
The authors constructed an example distribution of time markings for their workspace for 2022 (see “Data Availability,” p. 3). The graph clearly shows two peaks of a normal distribution—most tasks are closed in 1–2 days or in 5 days, indicating task typification: executors fulfill assigned requests in different time frames. If we cannot decompose a task into shorter stages, segmentation and typification can provide a more accurate estimate of the completion time for specific types of tasks. Without typification, the model may make more significant errors, adhering to the “garbage in–garbage out” (GIGO) principle. Despite advanced technologies, the user must also make efforts to categorize tasks.

Another issue arises after formalizing and classifying the task: different specialists may complete it at different times. For example, Basu and Banerjee [12] showed that the speed of problem resolution can vary significantly within a single team.

Therefore, in the next step (blocks “Executor Selection” and “Task Completion Speed Estimation” from Scheme 1), the algorithm estimates the task completion time for each executor without considering risks and blockers. Hence, the algorithm needs explicit information on how long the task was blocked (block “Risk Accounting” from Scheme 1), which raises the need for accurate time tracking (bringing the team back to the GIGO concept).

Thus, at the output of the “Issuing List of Potential Executors” block, a ranked list of executors will be obtained as follows: executor A will complete the task in τ_1 , executor B in τ_2 , where $\tau_1 < \tau_2$. The decision-maker (DM) can then overlay risk assessments and employee availability on these estimates to optimally select the executor. If the sprint duration is $D(s)$ days, there may be a situation where the minimum task completion time is $\tau_{\min} > D(s)$, indicating that the task cannot be completed within the sprint by the given executors. This could be due to improper task decomposition, which might be one of the reasons for project delays.

The proposed Scheme 1 can be expanded by removing the decision-maker and transferring the optimization problem of “task-executor” pairs to AI algorithms. To achieve this, several parameters need to be added to the algorithms. Planning is carried out at the beginning of the sprint. Thus, the team already knows their outstanding tasks from the previous sprint, leaves, and blockers for specific tasks. Hence, the available time for each executor is calculated as $D(s) - \tau_{out} - \tau_{leave}$. The system enables for flexible planning: when new blockers or risks arise during the resolution of current tasks, it is possible to switch to backlog tasks by simply recalculating the available time for the executors. Thus, the planning scheme is transformed into the form presented in Scheme 2.



Scheme 2 Sprint planning without the involvement of the performer and the DM. *Source* Developed by the authors

In Scheme 2, a calculation similar to Scheme 1 is performed for each task. However, the output of this stage is now a matrix structure (“Task Execution Matrix” block), where pairwise calculation of execution times is carried out for each executor and the entire set of planned and described tasks. In the next stage (“Executor Selection for Task Set” block), considering the available time for each employee, possible options for workload distribution among them are explored using linear programming. The algorithm minimizes employee downtime and attempts to fit more tasks into the sprint.

Assuming there are m tasks and n employees, the optimization question of distribution boils down to maximizing the functional:

$$u_1(x_{11} + \dots + x_{1n}) + u_m(x_{m1} + \dots + x_{mn}),$$

where u_i denotes the usefulness of the i th task relative to $m \times n$ integer target variables x_{ij} , which equals 1, if the i th task should be assigned to the j th employee, and 0 otherwise, considering the following constraints:

$$\begin{aligned} x_{11}\tau_{11} + \dots + x_{m1}\tau_{m1} &\leq a_1, \\ &\dots \\ x_{1n}\tau_{1n} + \dots + x_{mn}\tau_{mn} &\leq a_n, \end{aligned}$$

where τ_{ij} —is the AI-estimated time for the i th task by the j th specialist and a_j is the resource consumption index of the j th employee, which should be measured in the same units as τ_{ij} (hours, days, or story points). This integer programming problem can be solved using free software such as GLPK [20].

Nowhere above was it specified how to numerically determine the usefulness of specific tasks. Unfortunately, it cannot be reconstructed based on historical data, optimizing the same functional with respect to u_i variables due to its symmetry. This once again shows that the problem of increasing labor productivity cannot be solved solely by AI and that managers still need to perform prioritization manually, guided by some prior knowledge, experience, and intuition. Nevertheless, this process can be simplified using specialized algorithms. For example, Montgomery et al. [21] described a machine learning model that predicts which issues may become blockers for other tasks in the future with 88% accuracy.

4 Discussion

The presented methodology for task assessment and planning has the advantage over existing solutions in that it allows, first, the integration of the solution to several problems previously considered separately and, second, the consideration of factors that were previously ignored. However, at the current moment, the application of AI

in the context of project management optimization faces several challenges, which prevent the complete exclusion of human decision-making processes:

1. Lack of culture in using Jira or similar systems, including irregular time tracking and the absence of tracking blockers;
2. Absence of task types, leading to the algorithm incorrectly estimating the expected time for their execution based on historical data;
3. Lack of task decomposition, preventing the algorithm from fitting them within one sprint;
4. The inability to automatically assess the usefulness of solving a particular task without expert assistance.

5 A Data Availability

Data on the time distribution of the tasks on which the study relies are available at <https://figshare.com/> with the following identifiers:

1. https://figshare.com/articles/figure/iris1_eng/25928284
2. https://figshare.com/articles/figure/iris2_eng/25928212
3. https://figshare.com/articles/figure/iris3_eng/25928248

6 Conclusion

Scheme 1 and Scheme 2 propose a new method for assessing and distributing tasks within a team based on AI during iterations. The primary practical significance of the proposed methodology lies in saving team resources on planning and in automating this process at all stages by excluding performers and managers. For practitioners, including teams implementing this scheme, the most important question is assistance to artificial intelligence: correct filling of the digital board in Jira, project decomposition, logging work hours, and adequate assessment of task significance.

In theoretical terms, developing this methodology is important in considering the specificity of the product team and the quality of training data. The following issues deserve separate consideration:

- How to evaluate new employees (the so-called cold start problem)?
- What volume of data is needed to build a model?
- Interpretability of predictions—it is necessary to develop a system that will have explanatory power.
- Model error handling—depending on the quality of the data, the model's predictions may differ from the actual values, and these risks need to be incorporated into planning.

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Latest Trends in the Development of the Smart Economy Using Big Data and Artificial Intelligence

Smart Economy as a Market Environment for Digital Business Based on Big Data and AI



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Abstract The research determines the impact of the smart economy market environment on the application of big data and AI in digital business. Moreover, the research identifies prospects for optimizing this influence. Based on the advanced international experience of the top 20 countries in terms of the prevalence of big data and AI technologies in the business environment in 2023, the authors created a regression model to analyze the impact of smart economy market conditions on applying these technologies in digital business. The fundamental significance of the developed model lies in its scientific explanation and justification of how various smart economy market conditions influence the use of big data and AI. The theoretical importance is found in the author's classification and ranking system of smart economy market conditions based on their impact on the use of big data and AI. The authors monitored the favorability of the smart economy market environment for disseminating big data and AI. The research reveals prospects and provides the author's recommendations for spreading big data and AI in a more favorable smart economy market environment. Their practical significance is that they will help improve the practice of public management of digital business.

Keywords Smart economy · Market environment · Digital business · Big data · Artificial intelligence (AI) · Government market regulation

JEL Classification G38 · K23 · O38

1 Introduction

Digital businesses are experiencing strong incentives for digital modernization, one of the most promising directions of which is the automation of business processes based on big data and artificial intelligence (AI). The advantage of these technologies

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is that they can be used in various business operations: managerial (for intelligent decision support), production (for production control and personnel management), and distribution (for optimizing marketing, logistics, and sales).

Incentives for digital business modernization come from all market agents, including the following:

- Consumers demanding digital products;
- Suppliers building digital supply and distribution chains;
- Competitors strengthening digital competitive advantages;
- Digital professionals seeking knowledge-intensive and high-productivity jobs;
- Investors prioritizing the financing of digital innovations;
- Government regulators supporting digitalization, implementing standards for energy efficiency and product quality.

The problem is that the market environment generates incentives and determines the opportunities for digital business modernization, which are insufficiently addressed in existing scientific literature and are uncertain. There are three basic market conditions that shape the opportunities for the digital modernization of businesses. The first condition is the resource provision for digital modernization. If resources, such as digital professionals or venture investments, are insufficient or of low quality, digital businesses cannot increase the level and pace of their automation activities.

The second condition is the infrastructural support for digital modernization. Telecommunications infrastructure is required by digital businesses to implement advanced innovations, develop high-tech production, and move to a higher level of automation. Technological infrastructure is also required. Its importance for conducting digital business is explained by the fact that, in the absence of technology, its insufficient novelty or inadequate development of applied aspects, and weak engineering support, the business either will not be able to carry out technological modernization or it will not contribute to strengthening the digital competitive advantages of the business.

The third condition is the institutional support for digital modernization. Regulatory practices that favor the technological modernization of digital business can significantly accelerate this process. The development of the e-government system increases the accessibility of public services for digital businesses, allowing them to automate their business processes in interactions with public administration and management bodies. The completeness, transparency, and stability of regulatory support for digital business activities reduce regulatory risks, increasing the investment attractiveness of technological modernization.

While the basic conditions that determine the overall business climate are reflected in country reviews of economic systems provided by government regulators and national and international organizations, the specific conditions of the market environment for digital business remain unknown.

To denote these specific conditions of the digital business market environment, this research proposes the term smart economy because the core of smart automation systems is Big Data and AI, which are the focus of this research material. The

research aims to determine the impact of the smart economy market environment on the application of big data and AI technologies in digital business and identify prospects for optimizing this impact to increase the use of these technologies.

2 Literature Review

The scientific principles of the smart economy concept as a market environment for conducting digital business are outlined in the published works of researchers, including Galoyan et al. [1] and Kholmuminov et al. [2]. As a result of a content analysis of the available literature, the authors systematized and specified the conditions of the smart economy market environment that influence the technological modernization of digital business. The following conditions are attributed to the resource provision for digital modernization:

- The level of initial training for employees of digital business [3];
- Subsequent training for employees of digital business personnel, including lifelong learning and the efficiency of labor market organization [4];
- Financial and investment resource base of digital business [5].

The following conditions are attributed to the infrastructural provision for digital modernization:

- Technological support for digital business in the scientific community and innovative economy [6];
- Telecommunications support for digital business [7].

The following conditions are attributed to the institutional provision for digital modernization:

- The legal landscape of digital business activities [8];
- Social support for digital business through the information society, e-commerce, and demand for digital products [9];
- The reliability of public administration of digital business activities, including the e-government system and ensuring cybersecurity in the smart economy [10].

Various aspects of applying big data and AI technologies to areas of digital business are explained in some published scientific works by researchers, such as [11]. However, the drawback of the existing literature is that, despite acknowledging the undeniable importance of the smart economy market conditions for conducting digital business, the real impact of these conditions on applying big data and AI remains unknown. This led to the formulation of the research question on how the conditions of the smart economy market environment affect the application of big data and AI in digital business.

3 Materials and Methods

The sample of this research includes the top 20 countries by the prevalence of big data and AI in the business environment and digital business practices (BDAI, scores 1–10), according to the IMD ranking [12]. The first task is to determine the impact of smart economy market conditions on applying big data and AI in digital business. This task is addressed using a regression modeling method to analyze the dependency of BDAI on the following:

1. Resource factors, including the level of initial training for personnel (RS_1), subsequent training for personnel (RS_2), and the financial and investment resource base (RS_3);
2. Infrastructural factors, including technological support (IF_1) and telecommunications infrastructure (IF_2);
3. Institutional factors, including the legal landscape (IS_1), social support (IS_2), and the reliability of public administration (IS_3).

The data statistics for these indicators are presented in Table 1.

The positive influence of the factors on the outcome is indicated by negative regression coefficient values. The smaller the negative value of the regression coefficient, the more beneficial the factor's influence on the spread of big data and AI. Factors are ranked by their significance and classified based on the beneficial impact on the dissemination of big data and AI.

The second task is to monitor the favorability of the smart economy market environment for the spread of big data and AI. For this purpose, the authors compared the arithmetic mean values of the smart economy market environment indicators with their ranks.

The third task is to identify the prospects for spreading big data and AI in a more favorable smart economy market environment. For this purpose, the authors developed a forecast of the change in the BDAI value under the best (first place) values of the smart economy market environment indicators that positively influence the spread of big data and AI.

4 Results

The result of solving the first task is the following regression model of the impact of smart economy market conditions on the activity of application of big data and AI in digital business:

$$\begin{aligned} BDAI = & 6.3904 + 0.0044 * RS_1 + 0.0023 * RS_2 - 0.0017 * RS_3 \\ & + 0.0072 * IF_1 - 0.0005 * IF_2 - 0.0144 * IS_1 \\ & + 0.0082 * IS_2 - 0.0113 * IS_3, R^2 = 0.6040 \end{aligned} \quad (1)$$

Table 1 Market environment factors of the smart economy and the activity of applying big data and AI in digital business in 2023

Smart economy	Resource factors, place 1–64			Infrastructural factors, place 1–64			Institutional factors, place 1–64			Target result, points 1–10	
	Talent	Training & education	Capital	Scientific concentration	Technological framework	Regulatory framework	Adaptive attitudes	IT integration	Use of big data and analytics BDAI		
	RS ₁	RS ₂	RS ₃	IF ₁	IF ₂	IS ₁	IS ₂	IS ₃			
Belgium	7	22	18	18	39	5	39	15	6.87		
Canada	9	2	4	5	26	19	18	4	6.14		
China	14	43	26	9	20	20	20	32	6.15		
Czech Republic	17	33	13	27	28	33	34	30	6.09		
Denmark	5	12	10	20	6	10	8	2	6.62		
Finland	11	19	7	13	11	3	3	3	6.11		
Iceland	32	26	27	37	4	11	11	31	6.21		
India	34	48	23	52	60	52	60	52	5.98		
Indonesia	42	61	3	59	57	45	54	59	6.17		
Ireland	16	24	42	24	35	9	19	35	5.96		
Jordan	38	50	44	63	54	42	53	46	6.48		
Kazakhstan	47	1	53	49	48	22	29	54	6.42		
Lithuania	25	15	39	33	33	28	37	28	5.98		
Netherlands	3	23	2	12	10	2	6	7	6.33		
Norway	21	16	20	22	21	13	15	17	6.39		
Qatar	10	51	22	60	18	23	33	27	6.79		
Saudi Arabia	19	30	9	55	36	14	32	29	6.57		
Singapore	4	9	15	11	2	1	13	11	6.41		

(continued)

Table 1 (continued)

Smart economy	Resource factors, place 1–64			Infrastuctural factors, place 1–64			Institutional factors, place 1–64			Target result, points 1–10
	Talent	Training & education	Capital	Scientific concentration	Technological framework	Regulatory framework	Adaptive attitudes	IT integration	Use of big data and analytics	
	RS ₁	RS ₂	RS ₃	IF ₁	IF ₂	IS ₁	IS ₂	IS ₃	BDAI	
Sweden	13	4	8	4	17	7	10	8	6.48	
USA	12	20	1	1	9	12	2	9	6.74	

Source Compiled by the authors based on IMD[12, 13]

In model (1), the activity of applying big data and AI in digital business is by 60.40% determined by the favorability of the smart economy market conditions. When the level of initial training for personnel increases by one rank, the prevalence of big data and AI in the business environment and digital business practices decreases by 0.0044 points. When the level of subsequent training for personnel increases by one rank, the prevalence of big data and AI in the business environment and digital business practices decreases by 0.0023 points.

When the financial and investment resource base strengthens by one rank, the prevalence of big data and AI in the business environment and digital business practices increases by 0.0017 points. When technological support strengthens by one rank, the prevalence of big data and AI in the business environment and digital business practices decreases by 0.0072 points. When telecommunications infrastructure strengthens by one rank, the prevalence of big data and AI in the business environment and digital business practices increases by 0.0005 points.

When the legal landscape improves by one rank, the prevalence of big data and AI in the business environment and digital business practices increases by 0.0144 points. When social support strengthens by one rank, the prevalence of big data and AI in the business environment and digital business practices decreases by 0.0082 points. When the reliability of public administration improves by one rank, the prevalence of big data and AI in the business environment and digital business practices increases by 0.0113 points.

The result of solving the second task is the results of the monitoring conducted on the favorability of the smart economy market environment for the spread of big data and AI (Fig. 1).

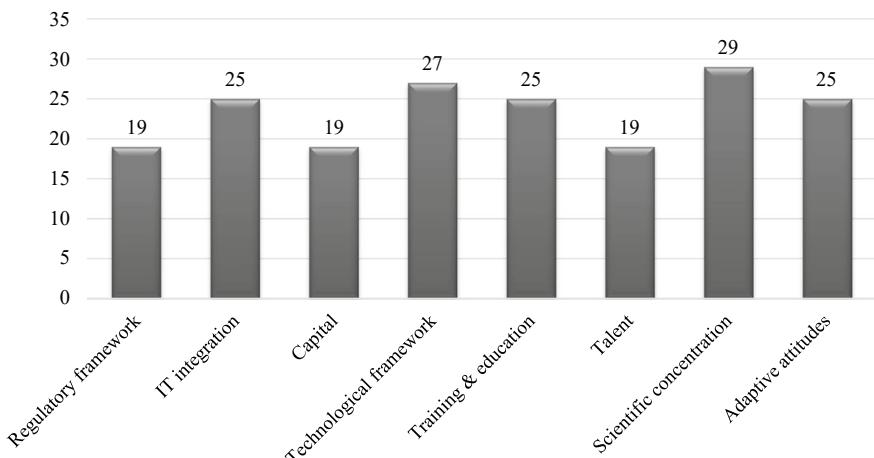


Fig. 1 Monitoring the favorability of the smart economy market environment for the spread of big data and AI, place 1–64. *Source* Calculated and compiled by the authors

As seen in Fig. 1, the legal landscape, ranked first in significance for the spread of big data and AI in the business environment and digital business practices, demonstrated a high level of development in the sample countries in 2023 (19th place). The reliability of public administration, ranked second in significance for the spread of big data and AI in the business environment and digital business practices, demonstrated a low level of development in the sample countries in 2023 (25th place).

The financial and investment resource base, ranked third in significance for the spread of big data and AI in the business environment and digital business practices, showed a high level of development in the sample countries in 2023 (19th place). Telecommunications infrastructure, ranked fourth in significance for the spread of big data and AI in the business environment and digital business practices, demonstrated a low level of development in the sample countries in 2023 (27th place).

Subsequent training for personnel, not conducive to the spread of big data and AI in the business environment and digital business practices, demonstrated a low level of development in the sample countries in 2023 (25th place). The level of initial training for personnel, not conducive to the spread of big data and AI in the business environment and digital business practices, demonstrated a high level of development in the sample countries in 2023 (19th place).

Technological support, not conducive to the spread of big data and AI in the business environment and digital business practices, demonstrated a low level of development in the sample countries in 2023 (29th place). Social support, not conducive to the spread of big data and AI in the business environment and digital business practices, demonstrated a low level of development in the sample countries in 2023 (25th place).

The result of solving the third task is the perspective of the spread of big data and AI under a more favorable smart economy market environment (Fig. 2).

As shown in Fig. 2, improving the smart economy market environment will increase the activity of big data and AI usage by digital businesses to 6.92 points (+9.09%). To achieve this goal, the authors proposed a set of recommendations, including the following:

- Improving the legal landscape of digital business activities by 95.45%;
- Strengthening the financial and investment resource base of digital businesses by 98.11%;
- Increasing the reliability of public administration by 97.92%;
- Developing telecommunications infrastructure for digital businesses by 98.15%.

5 Discussion

The contribution of this research to the literature, including the works of Galoyan et al. [3, 4] and Kholmuminov et al. [2], lies in the development of the concept of the smart economy as a market environment for conducting digital business by providing an answer to the research question on how the conditions of the smart

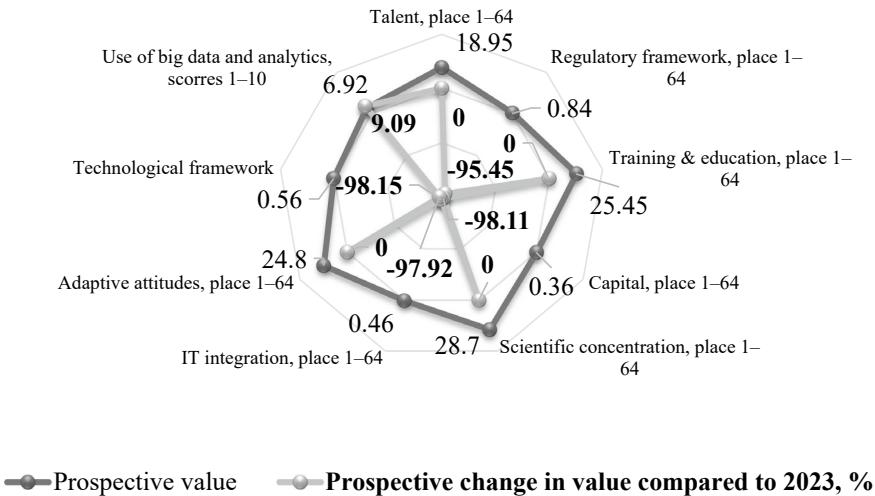


Fig. 2 The prospect of big data and AI proliferation in a more favorable smart economy market environment. *Source* Calculated and compiled by the authors

economy market environment affect the application of big data and AI in digital business (Table 2).

As shown in Table 2, the key conditions of the smart economy market environment that favor the spread of big data and AI are as follows (in order of decreasing significance):

- The legal landscape (first rank; as confirmed by [8]);
- Reliability of public administration (second rank; as confirmed by [10]);

Table 2 Answers to the research question as compared with the existing literature

Market environment conditions of the smart economy and their reflection in the literature	Identified influence on big data and AI usage in digital business		
	Category	Rank	Regression coefficient
Legal landscape [8]	Key conditions favoring the spread of big data and AI	1	-0.0144
Reliability of public administration [10]		2	-0.0113
Financial and investment resource base [5]		3	-0.0017
Telecommunications infrastructure [7]		4	-0.0005
Subsequent training for personnel [4]	Conditions hindering the spread of big data and AI	5	0.0023
Level of initial training for personnel [3]		5	0.0044
Technological support [6]		5	0.0072
Social support [9]		5	0.0082

Source Developed by the authors

- Financial and investment resource base (third rank; as confirmed by [5]);
- Telecommunications infrastructure (fourth rank—as confirmed by [7]).

The conditions of the smart economy market environment that hinder the spread of big data and AI are subsequent training for personnel (contrary to [4]), the level of initial training for personnel (contrary to [3]), technological support (contrary to [6]), and social support (contrary to [9]).

6 Conclusion

Thus, the main result of this research is the scientific explanation and justification of the influence of various smart economy market conditions on the activity of applying big data and AI. The theoretical significance of this result lies in its synthesis of the advanced international experience of the top 20 countries in the prevalence of big data and AI in the business environment and digital business practices, leading to the development of an authorial classification and ranking system of smart economy market conditions based on their impact on the application of big data and AI.

The practical significance of the results from monitoring the favorability of the smart economy market environment for the spread of big data and AI is that these findings will make it possible to adjust government policies regulating digital business. The managerial significance of the identified prospects and proposed recommendations for the spread of big data and AI in a more favorable smart economy market environment is that they will help improve public management measures for digital businesses.

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Tools to Increase the Flexibility of the Labor Market in a Period of Change



Olga F. Alekhina , Liliya I. Khairullina , Ekaterina V. Sazanova , Sergey V. Ponomarev , and Alexandra A. Chudaeva

Abstract The research aims to substantiate the assumption that during the period of changes caused by the negative impact of various crisis factors, the stability of the economic system can be supported by modern tools to increase the flexibility of the labor market, including digital technologies to ensure public access to online labor markets, new flexible forms of employment, and the formation of a professional retraining system. This research aims to study the specifics of the Russian labor market's response to crisis phenomena and find effective tools to maintain employment for improving the adaptation of the economic system to changes. The authors assessed the negative consequences of the pandemic. The article substantiates the advantages of the tools of three tools that contribute to the adaptation of the Russian labor market to the ongoing changes: expanding public access to the national and global online employment market; self-employment of the population as a new institutional form of entrepreneurial activity of the population in Russia; an effective system of professional retraining. The authors justified the advantages of online employment to increase the flexibility of the labor market. The article defines the effects of self-employment of the population on the economy and social sphere.

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It is proved that the emerging imbalances in the demand for specialists in the context of changes can be offset by an effective system of professional retraining.

Keywords Labor market · Flexibility · Adaptability · Changes · Online employment · Self-employment · Professional retraining

JEL Classification J21 · J24 · J64 · O33

1 Introduction

The current stage of society's development is characterized by continuous changes. They are caused by the influence of economic factors, for example, financial and economic crises, or political turbulence due to the aggravation of interethnic and geopolitical conflicts [1]. In 2020, new external epidemiological factors emerged that undermined the balanced development of economic systems [2]. One way or another, the impact of external factors destabilizes the sustainable development of the economic system and pushes it to changes, which, in turn, determines the speed of its adaptation to new conditions. The process of adaptation itself consists of living through the economic system of the primary shock, transitioning to a state of recession when there is an information vacuum and the mechanisms of adjusting the system to new conditions are unknown, gradual reduction of the level of uncertainty and determination of a strategy for further actions, which leads to a step-by-step revival of the economic system, and recovery and return to the full realization of one's potential in new changed conditions [3].

The labor market is the element of the economic system that reacts most quickly to shocks and crisis phenomena [4]. It primarily demonstrates contraction and disproportionate changes, and it also, recover, gives acceleration to the system's recovery from recession [5].

The pandemic highlighted the existing structural imbalances of the Russian labor market, showing its restrained adaptability to changes, primarily through the use of traditional employment regulation tools, such as wage cuts, layoffs, extraordinary vacations, and mechanisms to save working time [4].

However, for the first time, the Russian labor market was helped in the recovery by digital technologies that provided public access to the online labor market and job search platforms [6]. Another tool that began to be actively used in Russia was the self-employment regime, which provided an opportunity for people who had lost their previous level of well-being to receive additional sources of income through the implementation of their own entrepreneurial activity and the official payment of a tax on professional income to the state budget. However, the potential of these tools was not fully used in Russian conditions during the pandemic.

Also, another tool traditionally used by developed economies during crises to increase the flexibility of the labor market was not fully used—the development of

a professional retraining system in order to quickly respond to changes in the structure of demand for specialists and promptly fill emerging niches, which guarantees redistribution in the workforce. Thus, this research aims to study tools to increase the flexibility and adaptability of the labor market in the face of changes and to identify specific measures to ensure a post-crisis recovery of the Russian labor market.

2 Literature Review

The specifics of the course of transformations of economic systems during the period of instability of the external environment are reflected in the works of Gukasyan et al. [2], Karpunina [3], and Kharlamov and Kharlamova [7].

The peculiarities of the labor market's response to changes and the deviations caused by them in the development of the economic system are presented in the studies Galieva et al. [8], Gimpelson et al. [9], Nazarova et al. [4]. The authors also explore the forms of online employment of the population, which have become a response to the instability of the labor market.

New forms of realization of entrepreneurial activity of the population, including self-employment, are studied in the works of Dolinskaya and Dolinskaya [10], Moiseeva and Moiseev [11], and Zhutaev [12].

The importance of human development in the face of change is increasingly emphasized in scientific research. Building an effective system of training and professional retraining of personnel is a guarantee of increasing the adaptability of the labor market [13, 14].

3 Methodology

The research hypothesis is based on the assumption that during the period of changes caused by the negative impact of various crisis factors, the stability of the economic system can be supported by modern tools to increase the flexibility of the labor market, including digital technologies to ensure public access to online labor markets, new flexible forms of employment, and the formation of a professional retraining system.

The purpose of this research is to study the specifics of the Russian labor market's response to crisis phenomena in the economy, as well as to find effective tools to maintain employment for improving the adaptation of the economic system to changes.

The research objectives are as follows:

1. To analyze the features of the development of crisis phenomena at the present stage and their impact on the labor market in Russia;

2. To identify problem areas of the Russian labor market that reduce the adaptive capacity of the economic system in a period of change;
3. To substantiate the tools for maintaining the population's employment to ensure the labor market's adaptability.

During the research, the authors used various methods, including content analysis of information from open sources, systematization, graphical method, tabular method, economic analysis, induction, and deduction.

4 Results

The year 2020, under the influence of the pandemic, demonstrated the weaknesses of the Russian labor market. In the conditions of the knockdowns, temporary and managerial uncertainty of the prospects for developing the crisis situation appeared, which prompted employers to reconsider the concept of personnel management and search for options to reduce labor costs. For some enterprises, the way out of this situation was the reduction of employees; for others—sending them on forced leave; for others—transfer to short-term contracts and withdrawal from the staffing table; some chose hybrid forms of maintaining employment—combining remote work formats and appropriate wage adjustments [4, 15]. This primarily applied to enterprises of small and medium-sized organizational forms that are less resistant to crisis manifestations. In general, the labor market reacted to the lockdown with a decrease in employment and an increase in unemployment (Fig. 1).

In 2020, the Russian labor market found itself in a difficult situation. The unemployment rate increased sharply to 5.8%, respectively; there was a decrease in



Fig. 1 Some indicators of the development of the Russian labor market in 2019–2022. *Source* Compiled by the authors based on [16]

employment to 63.7% (-1.8% compared to 2019). This created the prerequisites for increased tension in the labor market; for example, the tension coefficient increased from 2.1 in 2019 to 2.7 in 2019. The year 2020 has highlighted the traditionally existing problems of the Russian labor market, indicating the presence of imbalances.

There was a reduction in vacancies offered by employers (for four months of 2020, the reduction was 26%), which contributed to the flow of labor between sectors of the economy [16]. The most severe reduction affected the sphere of trade, catering, and repair of motor vehicles, as well as the hotel business [17]. In agriculture, the decrease in the number of people employed in 2020 was 2.7%; in construction, it was 1.9% [18]. Other sectors of the economy, such as public administration, education, and health, have grown thanks to public financing. The internet sector has also grown due to an increase in demand for information services (growth in 2020 amounted to 3.9%).

What tools have helped the Russian labor market adapt to the ongoing changes?

Digitalization has created prerequisites for using the potential of online labor markets as a compensatory tool for reducing employment in Russia. In particular, all the necessary conditions for connecting the population to the Internet and providing access to digital online employment platforms have been created in Russia [8]. Data from the Online Labor Index (OLI) on the current state of the global online labor market indicate a noticeable increase in demand in Russia for freelance services since the beginning of the COVID-19 pandemic (Fig. 2).

Even though Russia is not the leader in terms of demand for freelancer services (the leaders are the USA (0.419 in 2019), the UK (0.076 in 2019), and India (0.063 in 2019)), Russia's demand during the pandemic 2020 increased six times compared to 2019. This indicates the inclusion of Russian employers in the competition for

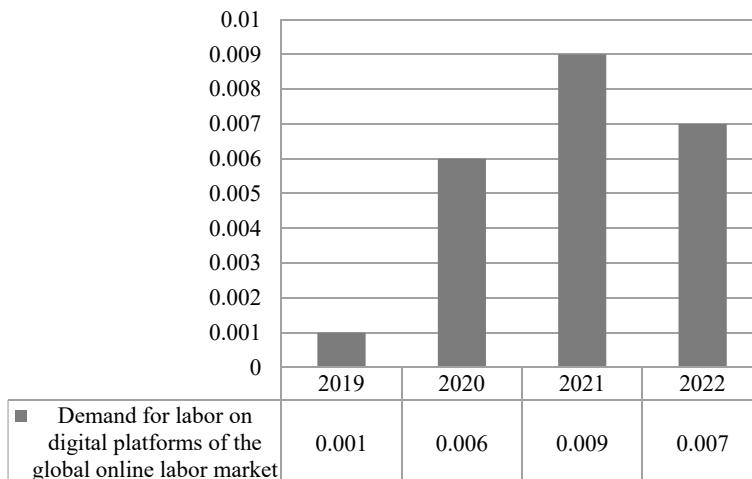


Fig. 2 Dynamics of labor demand on digital platforms of the global online labor market, 2019–2022. *Source* Compiled by the authors based on [19]

qualified specialists. This trend is more typical for developed OECD countries, with the exception of India.

As for the supply of workers active on the main online work platforms, according to the Online Labor Index (OLI), the value of the index reflecting the volume of online work supply by Russians amounted to 2344 in 2020 (for comparison in India—27,234, in the USA—5725, in the UK—3924) [19], that is, online specialists from Russia are increasingly represented in the global online labor market, realize their professional qualities and thus maintain a higher level of income than when employed in Russia.

The McKinsey Global Institute emphasizes that digital online labor platforms can help increase employment levels or ensure better alignment between workers and workplaces [20]. In particular, it is estimated that by 2025, the expected effect of public access to the global online labor market for the United States may manifest itself in the form of a \$512 billion increase in the country's GDP and an increase in employment by 2.7%, for China, the effect may amount to \$485 billion and + 1.7% of employment; for India—\$222 billion and + 2.2% of employment [20]. During the pandemic, regional online labor markets also appeared to meet buyers' demand for labor within the country [21]. In particular, a regional Russian-speaking sub-market has been formed, consisting of three digital platforms—freelance.ru, freelancehunt.ru and weblancer.ru [22]. Thus, the pandemic has contributed to developing new forms of working relationships and the flexibility of the labor market [23, 24].

However, in Russia, there are some restrictions on the participation of the population in such types of employment. Thus, the state needs to improve the institutional framework for regulating online labor while creating institutions that protect the rights and interests of workers in the traditional labor market [25]: implement measures to increase the level of education of the population to ensure the competitiveness of the workforce in the international space.

Another tool for increasing the flexibility of the labor market during the period of change is self-employment as an institutional form of realizing creative abilities and talents and declaring the professional income received. This form was put into effect by Russian legislation in 2017, but Russians received full access to its use in 2019–2020 [26]. The amount of tax rates on professional income paid to the budget by the self-employed is 4% of income from individuals and 6% of income from organizations and individual entrepreneurs.

The number of self-employed in Russia in 2019–2020 increased by 4.9 times [27]. This is due to several reasons: first, the need of the population at risk of losing their jobs for additional earnings; second, changing consumer preferences, increasing the importance of maintaining health and leading a healthy lifestyle, issues of internal development and training; third, the growing needs for environmentally friendly and moderate consumption, increased demand for goods that are unique and produced by manual labor [4]. For example, during the lockdown period of 2020, the demand for personal development trainings, meditations, esoteric practices, online educational projects, and the implementation of creative hobbies increased. Thus, Russians, using self-employment as a form of realization of their entrepreneurial initiatives and creative potential, received additional income (60% of respondents), and for

20% of the population, this form of employment replaced the main job [28]. This form of employment is mainly used in construction and repair work (14%), logistics and transportation (12%), IT (11%), beauty, health and sports (11%), tutoring, creative industry, tailoring, and information services. Even though the income level of the self-employed is limited to annual earnings of 2.4 million rubles, the surge in the popularity of self-employment in Russia brings a tangible economic effect for the state in the form of an increase in the amount of the tax on professional income received by the state budget. In 2020, the share of the self-employed in the total number of business entities amounted to 18.8%, and the amount of paid tax on professional income reached 4,959 million rubles by the end of the year [29]. In addition, the social function of self-employment is to ensure employment of the population and stimulate the entrepreneurial activity of citizens, which can support the flexibility of the labor market in the face of changes and, in the future, give an even greater cumulative economic effect.

However, government support is also required in this direction. In particular, it requires the fixation and clear definition of the self-employed from the standpoint of his functional load in the economy, the establishment of his rights and obligations, forms of responsibility for the actions carried out, as well as the grounds for removing the self-employed beyond the category of "informal employment" and "shadow activity." Currently, it is necessary to develop transitional forms when exceeding the permissible annual income of the self-employed to confirm the regularity of the income received. It is necessary to take measures to equalize the rights of self-employed and individual entrepreneurs, for example, in terms of access to government support programs, participation in regional grants, programs to improve financial and digital literacy, the work of regional business accelerators, and obtaining credit resources.

Creating a relevant and flexible system of professional retraining will contribute to the flexibility of the labor market and increase its adaptability to changes. During periods of change, when the requirements for the skills of specialists change especially rapidly, it is important that the released employees can retrain quickly and occupy existing vacant niches in the labor market. In particular, in 2021–2023, the demand for online specialists increased by an average of four times. This applies to remote accounting specialists, tax specialists (+175%), remote lawyers and auditors (+344%), online tax specialists (+134%), online accounting specialists (+73%), copywriters (+386%), designers (+382%), specialists website creation and promotion (+170%), SMM specialists (+105%), tutors for adults and children (+91%). On the contrary, in 2020, the demand for the services of tourism specialists (−73%), leisure specialists (−60%), lux sector personnel (−78%) and so on decreased. This pushes workers in shrinking sectors of the economy to find new jobs, which, in turn, require new skills.

Organizing a retraining system and stimulating its development in Russia based on leading educational institutions in the regions, as well as using digital platforms, will reduce the time lag between the period of dismissal of employees and their new employment, that is, ensure the rapid redistribution of labor between sectors of the economy. It should be based on the principles of eliminating deficiencies and updating

technical knowledge and skills, developing staff's ability to adapt, and strengthening employee loyalty [30]. Separate steps are being taken in this direction in Russia. For example, in 2022, 115 thousand people were able to get a new specialty (from IT, analytics, and programming to entrepreneurship and business) by participating in retraining programs based on 116 Russian universities, including in a remote format [31]. However, there are restrictions on the requirements for categories of citizens who have access to these retraining programs, as well as restrictions on the number of people being trained and the quality of competencies being formed.

5 Conclusion

The article presents the author's position on the justification of tools to increase the flexibility of the labor market during the period of change. The first part of the article analyzes the conditions determined by new challenges and the negative impact of environmental factors on the Russian labor market. The authors described the negative consequences of the pandemic caused by a sharp spike in the unemployment rate, a decrease in the number of employees, and the manifestation of a structural imbalance in the labor market in Russia.

The second part of the article is devoted to studying tools for increasing the flexibility of the labor market, identifying their advantages and facts of use in Russian practice. Applying these tools will contribute to the adaptation of the labor market and increase its resilience to ongoing changes. According to the authors, the first tool for increasing the labor market's flexibility is associated with expanding public access to the national and global online employment market. The analysis of statistical data made it possible to identify trends in the growth of demand and supply for online freelancer services during the pandemic. The entry of a specialist into the global online labor market expands his employment opportunities, generating more income and recognition of his competitiveness. The authors also substantiate the effectiveness of self-employment of the population as a new institutional form of realization of entrepreneurial activity of the population in Russia, contributing to increased flexibility of the labor market. The article analyzes the dynamics of self-employment development during the pandemic and the effects on the economy from its introduction. The authors recognize the system of professional retraining as the third tool for maintaining the flexibility and adaptability of the labor market during periods of change, which makes it possible to level up emerging imbalances in demand for specialists and promptly fill emerging niches. In the context of each instrument for increasing the flexibility of the labor market, the authors clarify the role of the state and the required forms of support.

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Data Analysis of Fatty Liver Prevalence in Cardiovascular Diseases in the Southern Region of the Kyrgyz Republic in Conditions of Sustainable Development



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Abstract Currently, there are no data on the frequency and prevalence, and we could not find a single scientific publication devoted to studying various aspects of fatty liver degeneration in patients with cardiovascular diseases in Kyrgyzstan. Cardiovascular disease and fatty liver disease are two serious and common medical conditions that significantly affect human health. The research aims to analyze the prevalence of fatty hepatosis among patients with cardiac diseases in the Southern Region of the Kyrgyz Republic at the Cardio Asia and Euroclinic medical clinics from 2019 to 2022. The research subjects are 3235 medical records of patients with diseases of the cardiovascular system. The authors conducted a descriptive-analytical study and carried out a statistical analysis of the time series of data from patients with fatty hepatosis. Quantitative, age, and gender indicators of patients with fatty hepatosis and cardiovascular diseases were calculated. The research showed that there was a decrease of 60.3% in 2020, and the rate of decline was 39.7%. In 2021, the decrease was 62.8%, the rate of decline was 37.2%. In 2022, there was an increase of 205.1%, with a growth rate of 105.1%. It is complicated to determine the actual indicators and frequency of the progress of the disease due to the lack of sensitive and specific screening techniques for detecting the initial, latent form of illness.

Keywords Prevalence · Fatty liver · Cardiovascular diseases · Data analysis · Time series analysis

JEL Classification I10 · I18

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1 Introduction

In the 1950s, the incidence of fatty hepatosis (FH) was 6–8% in cases. By the end of the twentieth century, it increased to 15–20%. Normally, liver cells should contain about 1.5% fatty inclusions. With fatty hepatosis, the volume of lipid inclusions is more than 5%. The meta-analysis from 22 countries in 2016 [1] showed that the overall prevalence of nonalcoholic fatty liver disease (NAFLD) varies significantly from 10 to 46%; on average, it is 26.3% (85.3 million cases). When studying the 20-year evolution of the prevalence of NAFLD, it was demonstrated to increase two-fold from 5.5% in 1988–1994 to 11.0% in 2005–2008 [2]. Hepatic steatosis was defined using the Fatty Liver Index (FLI \geq 30 (US)); its prevalence was 18% from 1988 to 1991 and 31% from 2011 to 2012 [1] according to data reported by NHANES (National Health and Nutrition Examination Survey).

The prevalence of NAFLD increased from 27.0% in 2007 to 37.3% in 2014. This increase was revealed in the Russian clinical and epidemiological study DIREG (NAFLD Disease Registry) conducted in different years [3]. The worldwide occurrence of NAFLD was 25.2%, with the highest distribution in the Middle East (31.8%) and South America (30.4%) and the lowest in Africa (13.5%). The average distribution of NAFLD was 23.7% in Europe, 24.1% in North America, and 27.4% in Asia [2].

The pathogenesis of NAFLD is multifactorial, and the underlying mechanism is not fully understood. Most mechanisms for NAFLD development are related to changes in lipid metabolism and the development of insulin resistance. Risk factors include diet, ethnicity, derangement of the gut-liver axis, and gut microbiota [3, 4].

The feature of NAFLD is hepatocytes steatosis with the manifestation of metabolic liver syndromes. Additionally, NAFLD can result from the metabolic stress induced by liver injury and is also closely related to insulin resistance and genetic predisposition, including liver steatosis, nonalcoholic steatohepatitis, liver fibrosis, liver cirrhosis, and hepatocellular carcinoma. However, the reasons for the initiation of liver steatosis and liver fibrosis in people with type 2 diabetes mellitus remain unknown [5–8].

Common reasons for the formation of major NAFLD caused by type 2 diabetes are resistance to insulin, increased levels of fats, and excess weight. NAFLD typically occurs in 50% of patients with diabetes and 76% of excess weight patients. It is the most common of all liver diseases. The occurrence of nonalcoholic steatohepatitis (NASH) is much less common. It appears in 18.5% of excess weight patients. Other common effects include hyperuricemia, abdominal obesity, or a condition in which the abdominal circumference exceeds 100 cm in men and more than 88 cm in women, and high blood pressure. Minor causes of NAFLD are caused by nutrition-related difficulties such as total parenteral nutrition, increased weight loss, and different jejunal intestinal routes.

The secondary causes of NAFLD include patients with metabolic syndrome and pregnancy-related fatty liver disease, as well as people with a normal body mass

index (BMI) who can develop NAFLD even without usual threats. It is considered that the main pathology may be unseen insulin resistance or abdominal obesity [9].

The essential occurrence of NAFLD is not well defined yet. Death of NAFLD patients reaches 13%, which is more common than in age- and gender-related groups. This is due to features of patients with metabolic syndrome at high risk of dying from heart disease. That is why coronary heart disease and malignancies are the main causes of death in patients with NAFLD. Thus, liver disease is the third prevailing reason for death in this population, accounting for 13% of all lethal cases [10].

The research aims to find and evaluate the occurrence of fatty liver degeneration in cardiovascular diseases. The research analyzes the prevalence of fatty liver disease among patients with cardiovascular diseases and studies gender and age differences in the incidence of fatty hepatosis in combination with cardiovascular diseases. The research assesses the frequency and prevalence of fatty liver degeneration in patients with cardiovascular diseases (CVD) from 2019 to 2022. In total, 3235 medical records of inpatients with cardiovascular diseases in the southern region were processed.

2 Materials and Methods

During the research, the authors studied medical history data of 3235 inpatients with diseases of the cardiovascular system of the medical clinics “Cardio Asia,” “Osh Clinic,” “Euroclinic,” and the clinic of Osh State University from 2019 to 2022 in the Southern region of the Kyrgyz Republic.

The authors conducted a descriptive study and calculated intensive and extensive indicators using calculation formulas. Statistical analyses of data on age, quantitative, and gender indicators of patients with GH with CVD from 2019 to 2022 were performed.

3 Results and Discussion

The authors conducted a survey to determine the physician awareness of NAFLD from November 15 to November 25, 2022. To accurately find the theoretical basis of NAFLD, voluntary and anonymous participation of physicians was provided. In total, 40 doctors from Bishkek and Osh were surveyed. Questioners independently filled out questionnaires without the participation of an interviewer; each questionee was asked 15 questions about their knowledge of fatty hepatosis. After the survey, an analysis of the questionnaire was carried out [11, 12].

NAFLD manifests as a metabolic syndrome in the liver, which includes central abdominal obesity along with other components. Usually, up to 80% of NAFLD patients have high body mass, defined as a body mass index (BMI) $> 30 \text{ kg/m}^2$. The distribution of fat tissue plays a crucial role in insulin resistance. Increased visceral fat in pathological obesity ($\text{BMI} > 40 \text{ kg/m}^2$) contributes to the high prevalence of

NAFLD. Free fatty acids, derived from tissues, dietary sources, and lipogenesis, enter the portal venous system. Large amount of free fatty acids and chronic low-grade inflammation from VAT cause two significant main factors leading to the progression of liver damage [13].

The incidence of NAFLD among adults' ranges from 17 to 46%, the prevalence of fatty liver degeneration in Europe, which continues to increase every year [14, 15]. The occurrence of fatty liver degeneration grows with age; older adults have a higher prevalence of steatohepatitis and an increased level of fibrosis. The percentage ratios of numerical and sex indicators of patients with fatty liver degeneration in cardiovascular diseases (CVD) from 2019 to 2022 (Fig. 1a and b).

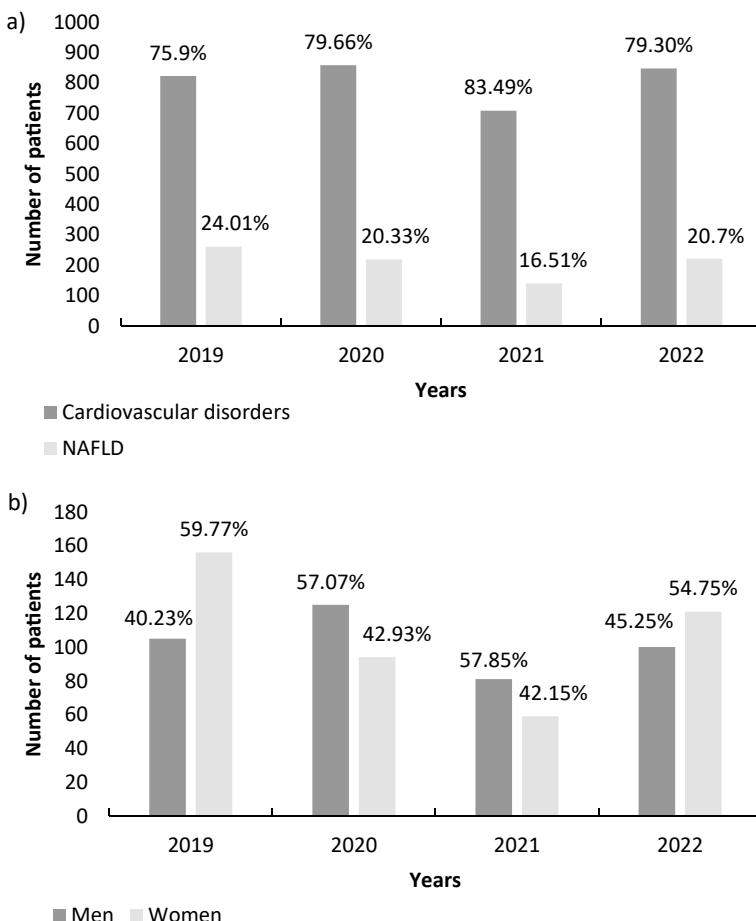


Fig. 1 **a** Quantitative indicators of patients with cardiovascular diseases and fatty liver degeneration in percentage terms from 2019 to 2022; **b** Sex indicators of patients with fatty hepatosis from 2019 to 2022 in percentage. *Source* Created by the authors

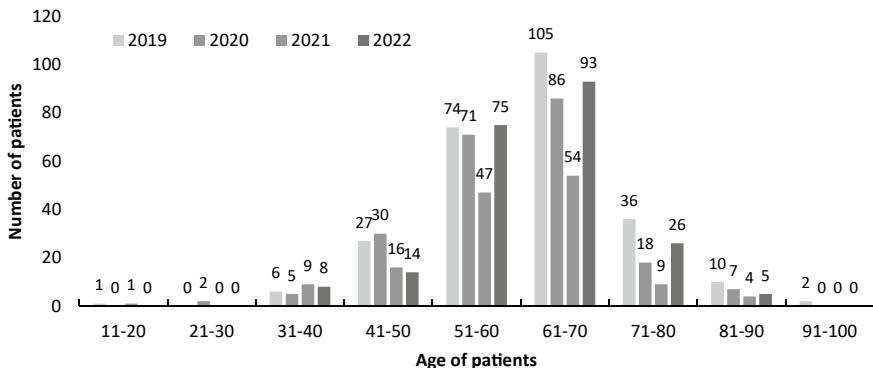


Fig. 2 Quantitative and age indicators of patients with fatty hepatosis in cardiovascular diseases from 2019 to 2022. *Source* Created by the authors

This is caused by decreased activity of metalloproteinases and, consequently, decreased collagenolysis. Additionally, liver capacity appears to be lower in older adults due to decreased hepatic blood flow [16]. Generally, older age is associated with increased susceptibility to oxidative stress and oxidative damage, although the literature provides evidence to the contrary. The study linked increased fibrogenesis in old livers to changes in the immune system and, in particular, to the response of macrophages [17]. The quantitative and age indicators of patients with fatty hepatosis in cardiovascular diseases are shown in Fig. 2.

Likewise, our analysis data showed that the number of patients diagnosed with fatty hepatosis increases with age, most often occurring at the age of 50–70 years, after which it begins to decline. As in the regions of the Russian Federation, fatty liver degeneration was more often recorded in men and increased with age [18]. A high index is more often registered in men, and is statistically significantly associated with age and living in rural areas.

When examining gender differences in our data from patients with fatty liver disease, it was impossible to draw definite conclusions about differences in the number of cases of fatty liver disease between men and women because there were approximately equal numbers of men and women in the general population. The authors analyzed the normality of the age distribution according to Kolmogorov–Smirnov and the dynamic series of quantitative and gender indicators of patients with fatty hepatosis in cardiovascular diseases from 2019 to 2022 (Tables 1 and 2).

The results of the analysis of the normality of the age distribution according to Kolmogorov–Smirnov showed that all indicators were distributed normally.

Thus, in 2020, the number of patients with GC decreased by 39.7% compared to 2019. In 2021, it decreased by another 37.2%. In 2022, it increased by 105.1%. Growth indicators show that there was a noticeable decrease of 60.3% in 2020, with a decline rate of 39.7%. In 2021, the decline was 62.8%, with the decline rate of 37.2%. In 2022, there was an increase of 205.1%, with a growth rate of 105.1%.

Table 1 Normality of the age distribution of patients with fatty hepatosis in cardiovascular diseases according to Kolmogorov–Smirnov from 2019 to 2022

Years	Test statistics KS (D)	p-value	Mean	Median	Standard deviation
2019	0.26133	0.49147	29	10	37.245805
2020	0.27021	0.44968	24.3333	7	32.422986
2021	0.29905	0.328	15.55556	9	20.561561
2022	0.29209	0.35517	24.55556	8	35.014679

Source Created by the authors

Table 2 Analysis of the dynamic series of indicators of the number of women and men with fatty hepatosis in cardiovascular diseases from 2019 to 2022

Years	Indicator (series levels)	Visibility indicator, %	Growth (decrease) rate, %	Growth (decrease) rate, %
<i>Women</i>				
2019	156	100.0	–	–
2020	94	60.3	60.3	–39.7
2021	59	37.8	62.8	–37.2
2022	121	77.6	205.1	105.1
<i>Men</i>				
2019	105	100.0	–	–
2020	125	119.0	119.0	19.0
2021	81	77.1	64.8	–35.2
2022	100	95.2	123.5	23.5

Source Created by the authors

The analysis provides the following conclusions. In 2020 and 2021, there was a significant decrease in the number of patients with gastrointestinal tract diseases due to CVD. However, in 2022, there was a sharp increase in this indicator, exceeding the 2019 figure by more than twice. This indicates a significant change, perhaps requiring a more in-depth analysis of the reasons for this sharp increase.

Based on these data, we can conclude that the number of men with GC with CVD fluctuates during the reviewed period. There was a sharp rise in incidence in 2020, followed by a decline in 2021 and a rise in 2022. Such fluctuations may be due to various factors, including changes in lifestyle, stress levels, access to quality medical care, and others.

At the intersection of therapy, gastroenterology, and endocrinology, fatty hepatosis is recognized as an interdisciplinary problem. Currently, interest in fatty hepatosis as a conspirator of cardiovascular pathology (CVD) has increased significantly [19]. NAFLD requires the attention of hepatologists, gastroenterologists, cardiologists, and endocrinologists because this disease is much more often detected in obese patients with disorders of fat and carbohydrate metabolism [20].

When studying the relationship between the thickness of epicardial adipose tissue (EAT), indicators of the anatomical and physiological conditions of the heart and cardiovascular probability in patients with arterial hypertension (AH) and nonalcoholic fatty liver disease (NAFLD), it was revealed that in patients with hypertension and NAFLD, the thickness of EAT was greater, which strongly correlates with indicators reflecting hypertrophy, the severity of hepatic steatosis, and chronic low-intensity systemic inflammation and insulin resistance [21].

4 Conclusion

In 2020, The number of men with gastric hyperplasia due to CVD was 19% higher than in 2019. In 2021, it was 22.9% less. In 2022, it was 4.8% less. Thus, further analysis requires the consideration of a broader context and a more in-depth study of the factors influencing this time series.

Fatty liver disease can be more regular in old age patients between 50 and 70 years of age. There is association between age and the development of fatty liver disease. More studies required to find the association and identify possible reasons for decrease the number of patients with fatty liver disease in different age groups.

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The Analysis of the Global Innovation Index: Failing Performance of the Upper-Middle Income Nations and Implications for Armenia



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Abstract Nowadays, fostering a dynamic economy focused on innovation is vital. The Global Innovation Index (GII) is considered an effective instrument for assessing and quantifying the innovation-oriented progress of an economy. Along with the majority of upper-middle-income countries, Armenia reported a decline in GII 2022 scores compared to 2018 score values. The research aims to figure out how five-year changes in score values of two sub-indices of the Global Innovation Index (input and output) of countries with an income level comparable to Armenia explained the statistically significant changes in the GII score values over the past five years utilizing least squares estimation technique. The research novelty is that the authors found that if the difference in the input sub-index of an average middle-income country over five years changes by 1%, it can cause a higher difference in score values of the GII index than changes in the output sub-index, other things being equal. The estimation results indicate that the priority for an average middle-income country government should be the design of such initiatives and the adoption of such measures that will contribute to an increase in the score of the sub-indices of input

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and output pillars of the GII in the medium term, while emphasizing the role of input pillars. The results can be applied by the Ministry of Economy of Armenia, policy and strategy developers, researchers, and independent experts interested in this field.

Keywords Global innovation index (GII) · Input and output pillars · Innovation capacity · Institutions · Human capital and research

JEL Classification O3 · Q55

1 Introduction

Technological advancement through innovation and knowledge generation is the primary source for economic growth. Its importance has been addressed since the end of the eighteenth century by Karl Marx and Joseph Schumpeter, who have given great importance to technological progress. Economists have always emphasized the need for innovation and knowledge accumulation for the long-term growth of the economy [1]. The crisis manifestations of the current economic environment are interpreted with a negative connotation. Nevertheless, they can also be viewed through the prism of opportunities. The increasing instability characteristic of the economic, political, and social sectors of society creates opportunities and is a favorable condition for the emergence of innovations [2]. Innovation has a significant role in the current economic situation for a country's competitiveness [3].

Innovation initiates with scientific research and ends with its realization, which is the commercialization of scientific novelty. Commercialization is the most important aspect because it ensures an increase in the country's competitiveness and, ultimately, economic aggregation and growth. The size of the innovative capacity is a parameter that allows the region to be evaluated in terms of its innovative activity capabilities and determine the innovative development strategy. Innovation is a constant process of finding solutions to complex problems based on continuous learning and accumulating knowledge. The GII is built with this logic. As a ratio of costs and results, the GII makes it possible to objectively assess the effectiveness of efforts to develop innovation in certain countries [4].

To manage innovation, it must be measurable. To ensure innovation, in 2007, INSEAD and WIPO at Cornell University published a report on the Global Innovation Index (GII), the main objective of which was to determine how to make measurements to provide insight into the innovations in society, going beyond conventional metrics of innovation, such as the number of research articles and the extent of research and development (R&D) expenditures [5].

In 2017, the Global Innovation Index Report was published, comprising 81 indicators categorized into two subgroups [6]. The majority of upper-middle-income countries (as per the World Bank's income classifications by Hamadeh et al. [7], encompassed by the WIPO) experienced a decline in their Global Innovation Index scores in 2022 compared to their performance in 2018 [8–11]. The results were

striking. In 2022, out of 36 nations of interest (excluding Iraq), 33 lagged behind their performance of 2018, thus scoring below the values of 2018. Only China, Mauritius, and Turkey were over-performers [8–11]. A possible explanation could be coping with the aftermath of the COVID-19 pandemic, which prevented the governments from promoting private businesses to undergo innovations and utilize innovative business practices by allocating respective resources and funding. Regardless of the explanation, governments need to prioritize their actions to boost the innovative performance of the economy.

Therefore, the research aims to find out how the five-year changes in the values of two sub-indices (input and output) of the GII of upper-middle-income countries could explain the changes in score values of the GII index over the five years of an average middle-income-country by utilizing the least squares estimation technique. The following objectives were put forward to achieve the research goal:

- To analyze Armenia's GII scores and rankings for the period 2018–2022;
- To define how changes in the input and output sub-index values (from 2018 to 2022) contribute to explaining statistically significant changes in the GII scores within countries having income levels similar to the Republic of Armenia (i.e., upper-middle-income countries) by utilizing an econometric estimation technique;
- To present the priorities in the direction of increasing the value of the GII scores based on the estimation results.

As of 2022, the Global Innovation Index (GII) encompassed 81 indicators and assessed the innovation capacity of 132 countries. The GII comprises two sub-groups. The first group, input, comprises five pillars: institutions, human capital and research, infrastructure, market sophistication, and business sophistication. The second sub-group is output. It comprises two pillars: knowledge and technology outputs and creative outputs [11] (Table 1). The closer the score of the indicator included in the GII approaches 100, the better the position of the given sub-index, indicator, and the economy's performance, and vice versa.

From 2019 to 2020, Armenia reported an improvement in the GII index rankings. In 2018, the economy was ranked 68th. In 2019 and 2020, it appeared in the 64th and 60th positions. This phenomenon is not coincidental because there was also an enhancement in rankings concerning the input and output sub-indices, moving from the 85th to the 83rd position and from the 50th to the 45th position. However, in 2021, Armenia recorded a decline in the GII rankings from 60 to 69. The Global Innovation Index Report [12] states that nine countries of the world, including Armenia, no longer have achievements in innovation. According to Table 1, business sophistication saw a sharp positive change in the rankings in 2020 compared to 2019 by 20 places. This indicator includes sub-indicators such as knowledge workers, innovation linkages, and knowledge absorption, in which the country improved its position. However, the same cannot be said for 2021 because Armenia reported a deteriorating performance and was ranked 98th concerning the business sophistication pillar. In 2020, the country was ranked 69th, which was the worst position among all other indicators, along with the market sophistication (99th). In 2022, the picture worsened

Table 1 Armenia's GII with its two sub-groups and indicators for 2018–2022

No	Indicator name	2018		2019		2020		2021		2022	
		Score (0–100)	Rank								
	Global innovation index	32.8	68	33.9	64	32.7	60	31.4	69	26.6	80
<i>Sub-group 1. Innovation input</i>											
1	Institutions	24.7	94	39.3	85	39.1	83	83.9	85	78.8	82
1.1	Institutions	60.8	67	63.2	64	64.3	64	64.1	65	59.7	55
1.2	Human capital and research	15.2	110	19.9	107	20.5	94	21.7	94	22.0	91
1.3	Infrastructure	36.5	93	40.2	85	34.4	90	38.1	80	39.9	94
1.4	Market sophistication	43.5	81	50.1	55	49.6	68	40.4	99	26.5	85
1.5	Business sophistication	26.1	88	26.3	89	24.6	69	19.9	98	23.5	84
2	<i>Sub-group 2. Innovation output</i>	34.1	50	26.8	50	27.15	45	54.6	56	65.7	73
2.1	Knowledge and technology outputs	23.2	62	25.5	54	28.5	45	21.4	64	19.6	71
2.2	Creative outputs	35.0	48	32.2	48	25.8	56	30.6	49	18.2	73

Source Compiled by the authors based on the GII reports for 2018–2022 [8–11]

again; a further decline in the rankings of GII was recorded, dropping from the 69th position to the 80th position, such a position not observed over the period 2018–2022. The decline in the ranking was explained by the second sub-index, reaching the 73rd position in 2022 from the 56th position in 2021.

2 Materials and Methods

Innovation is not a new phenomenon; it can even be said that it is as old as humanity. There seems to be some inherent human characteristic of the tendency to think of new and better ways and put them to the test. The world would look very different without it. Try to think for a moment about a world without airplanes, cars, telecommunications, and refrigerators [13]. The term innovation has been used since 1934 in Schumpeter's works as an important component of entrepreneurship. Particularly, innovation and entrepreneurship are seen as interrelated concepts because, according to Schumpeter, the role of an entrepreneur can be understood only if it is combined with innovation [14].

Innovation is an economic or social term rather than a technical one. It can be defined as Sei defined entrepreneurship (i.e., changing the yield of resources). Alternatively, as a contemporary economist would say, it can be defined not in terms of supply but in terms of demand, that is, as the change in value and satisfaction of resources by the consumer [15].

The conceptual bases of innovation systems began to develop in the late 1970s and later, in the early 1980s, when different scholars studied technological and innovation systems: Freeman [16], Lundvall [17], Cooke et al. [18], and Nelson [19]. The task of innovation is to process and transform information from various sources into useful knowledge for designing new products and processes, as well as for production and sales [20].

The continuous use of innovations is necessary for the successful development of high-tech industries. The debate is not only about technological innovations but also about managerial and marketing innovations, which are currently used in almost every industry [21].

2.1 Methods

In the case of Armenia, we cannot construct a time series of at least 30 years so that it would be possible to identify the role of changes in the values of the sub-indices of the output and input groups in explaining the statistically significant changes in the GII score values of the Republic of Armenia. Considering the latter, we carried out the analysis in a different way. Thus, we found out the role of five-year changes in the scores of sub-indices of the output and input groups of countries with a comparable income level to Armenia (i.e., upper-middle-income countries) when explaining the

statistically significant shifts over five years in the value of the GII scores (the difference between the values of 2022 and 2018) for an average country with a similar income level.

Accordingly, the authors defined their model as follows:

$$\begin{aligned} & \text{5 - year change in the value of the global innovation index score} \\ & = f(5 - \text{year change in the value of a subset of the input pillar group}, \\ & \quad 5 - \text{year change in the value of a subset of the output pillar group}) \end{aligned} \quad (1)$$

3 Analysis and Results

Based on the classification of countries according to gross domestic product (GDP) per capita for 2021, which was released by the World Bank [7] and valid for the fiscal year 2021–2022, Armenia was categorized among the upper-middle-income countries (\$4096–\$12,695). Subsequently, we accessed data from the database of the World Bank [22], specifically the World Development Indicators Online from 2023, to retrieve information on all countries classified as upper-middle income. Following the modified methodology published by the World Bank in 2021, the authors obtained data on 54 economies identified as upper-middle-income countries from the respective World Bank database (as of March 1, 2023). Since the main purpose was to identify the role of the sub-indices of the pillar groups (input and output) in explaining the statistically significant changes in the values of the GII scores, especially in the case of upper-middle-income countries whose 2022 GII index scores showed a decline compared to 2018 GII index scores, the authors first included countries covered by GII reports for the respective years between 2018 and 2022 in their database. The authors ensured that the dataset comprised only those countries that were featured in the country pages of the GII reports for the specified years. Thus, 28 countries reported a decline in the 2022 GII score values compared to the 2018 GII values concerning values of the sub-indices of the input and output groups of the pillars. As a result, the authors added two more countries (Argentina and Jamaica) to the list of countries of interest and ended up with dataset of 30 countries (Albania, Argentina, Armenia, Azerbaijan, Bosnia and Herzegovina, Bulgaria, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Georgia, Guatemala, Indonesia, Jamaica, Kazakhstan, Malaysia, Mexico, Moldova, Mongolia, Montenegro, Namibia, North Macedonia, Paraguay, Peru, Russia, Serbia, South Africa, and Thailand). The selection of these countries was due to the fact that the 2022 values of output sub-indices increased by 0.47 (in the case of Jamaica) and 0.85 (in the case of Argentina) to 2018; in the case of Belarus, the increase in values of the output sub-index amounted to 5.65 over five years.

It would have been desirable if the authors also identified the role of each pillar in explaining statistically significant changes in the values of sub-indices of the output

and input groups. However, this was not done due to a change in methodology that occurred at the pillar level between 2018 and 2022. Nevertheless, this did not affect the overall performance score. Simultaneously, since the authors were interested in unit and percentage change estimates, they added 20 to the differences in the values calculated so that it would be possible to take the natural log of the negative values of the dependent and independent variables (since the addition results in a positive value), which does not affect the coefficient values obtained based on the estimation.

Therefore, the authors estimated the following two regression equations using the least squares method:

$$\begin{aligned} \text{GII2022/2018}_i &= \alpha_0 + \alpha_1 * \text{Input2022/2018}_i \\ &\quad + \alpha_2 * \text{Output2022/2018}_i + \varepsilon_i \end{aligned} \quad (2)$$

where:

GII2022/2018_i is the difference between the 2022 and 2018 values of the Global Innovation Index score of country i ;

Input2022/2018_i is the difference between the 2022 and 2018 values of the input pillar group sub-index of the GII of country i ;

Output2022/2018_i is the difference between the 2022 and 2018 values of the output pillar group sub-index of the GII of country i ;

α_0 , α_1 , and α_2 are the unknown parameters of the model;

ε_i is the random error of the model.

$$\begin{aligned} \text{LGII2022/2018}_i &= \beta_0 + \beta_1 * \text{LInput2022/2018}_i \\ &\quad + \beta_2 * \text{LOutput2022/2018}_i + \varepsilon_i \end{aligned} \quad (3)$$

where:

LGII2022/2018_i is the logarithm of the difference between the 2022 and 2018 values of the GII score of country i ;

LInput2022/2018_i is the logarithm of the difference between the 2022 and 2018 values of the input pillar group sub-index of the GII of country i ;

$\text{LOutput2022/2018}_i$ is the logarithm of the difference between the 2022 and 2018 values of the output pillar group sub-index of the GII of country i ;

β_0 , β_1 , and β_2 are the unknown parameters of the model;

ε_i is the random error of the model.

Using the Jarque–Bera test, the authors found that the model errors have a normal distribution. They also checked and found no evidence of heteroskedasticity. Additionally, with the Ramsey RESET test, the authors found that there is no specification error in the specified models. No multicollinearity problem was found either.

In general, according to the results of the first estimation (Table 2, Estimation No. 1), in the case of an average upper-middle income country, a difference in the values of the sub-index of the GII input pillar group compared to the value recorded five years ago by one point, on average, could lead to the statistically significant changes

in the differences of the GII index score values by 0.5 points compared to the previous period, other things being equal. Similarly, a one-point difference in the values of a sub-index of the output pillar group compared to the value of the previous period (five years ago) could lead to a statistically significant change in the values of the differences of the GII index score of an average upper-middle income country by 0.5 points compared to the previous period (Table 2, Assessment No. 1). Additionally, the variation in the independent variables included in the model explains 99.9% of the variation in the dependent variable (Table 2, Estimation No. 1).

According to the results of the second estimation (Table 2, Estimation No. 2) in the case of an average upper-middle income country, a difference in the values of the sub-index of the GII input pillar group by 1% compared to the value recorded five years ago could lead to a statistically significant changes in the difference in values of the GII score values by 0.51% over five years, other things being equal. Respectively, a change in the value of a sub-index of the group of output pillars by 1% of an average upper-middle income country could lead to statistically significant changes in the values of the GII scores over five years by 0.47% (Table 2, Estimate No. 2). Furthermore, the variation in the independent variables incorporated into the model accounts for 99.4% of the variation observed in the dependent variable (Table 2, Estimation No. 2).

As a result of the econometric estimation, it was identified that the difference in the values of the GII index of an average upper-middle income country over five years is, to a greater extent, explained by the difference in the values of the sub-index of input pillars over the same period because a 1% change in the difference in the input sub-index values over five years contributes to higher change in the GII index value that the difference in the output sub-index values over the same period could lead to, other things being equal, thus translating into higher output performance as well.

Table 2 Estimation results (estimation method: least squares)

Dependent variable GII2022/2018 _i	Estimation No. 1	Dependent variable LGII2022/2018 _i	Estimation No. 2
Input 2022–2018 _i	0.500 (1654.76)***	LInput2022/2018 _i	0.509 (32.317)***
Output 2022–2018 _i	0.500 (2946.69)***	LOutput2022/2018 _i	0.469 (59.739)***
Constant	-0.010 (-1.984)*	constant	0.067 (1.419)
R ²	0.999	R ²	0.994
Adjusted R ²	0.999	Adjusted R ²	0.994
Sample	30	Sample	30

Note Values of the t-statistics in parentheses. * is significant at the 10% level, *** is significant at the 1% level

Source Composed by the authors

4 Conclusion

The results of these two estimations prove that the priority for governments in upper-middle-income countries should be to develop measures and take steps that will contribute to an increase in the values of input and output pillar group sub-indices of the GII in the medium term. However, in terms of reporting a higher percentage change in the difference of the GII index values over five years, the role of the sub-index of input pillar groups is stressed. It was an expected result because the values of the sub-index of input pillar groups in the case of upper-middle-income countries are higher than the values of the sub-index of output pillar groups; input pillars contribute to higher performance of output pillars as well.

Moreover, it is very important that Armenia builds a country driven by innovations and ensures economic growth faster than other upper-middle-income countries attempt to achieve.

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The Place and Role of Artificial Intelligence in Transforming Economy and Society



Alexander P. Gorbunov

Abstract The research aims to explore the place and role of artificial intelligence (AI) in the transformative changes in the economy and the system of social relations, including the prospects for the socialization and humanization of AI. To obtain reliable research results, the author employs an advanced methodology—specifically, a transformative-super cointegrating methodology of analysis and design. This allows the author to make reasoned conclusions in response to the following key questions: (1) whether the pervasive integration of AI into human life and society is accidental or systemic; (2) to what extent the economy and society are substantially transformed as a result; (3) what are the prospects for socializing and humanizing AI itself; and (4) to what extent AI is autonomous as a transformational factor. The conclusions drawn are distinguished by their originality and novelty; they are as follows: (1) the emergence of AI and its impact on the economy and society are entirely logical and even predictable; (2) under the influence of AI, the economy and society significantly and even essentially transform their type, yet not fundamentally or in a revolutionary manner; (3) the prospects for socializing and humanizing AI are determined by the inevitable prospects of socio-economic development and are subject to them; and (4) the place and role of AI in transforming the economy and society are auxiliary, not autonomous, not defining in nature.

Keywords Artificial intelligence · Natural intelligence · Duality of AI · Production capital · Society-like nature of AI · Innovation economy · Semantic originality · Breakthrough innovation · Transformative-creative capital

JEL Classification O33 · O34 · O35

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1 Introduction

We have entered a historical era where artificial intelligence (AI) is called upon to enter into the everyday life of humanity and society, acquiring massive involvement and ubiquity in its application.

Thus, it becomes a means (a factor, a condition) of transforming the economy and society.

In this regard, it is quite relevant to pose and address the following questions:

1. Is the integration of AI into human life, society, and the system of production and social relations random, unexpected, conditioned, or systemic?
2. To what extent do the economy and society undergo significant changes due to this?
3. Is there the prospect of socializing and humanizing AI, and how far does it extend?
4. Are AI's place and role in the further evolution and transformation of the economy and society autonomous, defining, or rather auxiliary, serving?

2 Methodology

Fully answering these questions is made possible by the author's latest advanced proprietary methodology, named and characterized as a transformative-super cointegrative methodology.

This methodology is based on the universal regularities, principles, and algorithms of convertibility in their co-systemic, co-level interconnectedness, co-consequence, and co-continuity. Therefore, in understanding, justifying, and explaining the self-development and self-transformation of socio-economic processes, it starts from the consideration of the most profound content-meaningful factors that transform the very type of the economy and society.

One of the key concepts here is the category of production-economic capital (i.e., productive capital), the dominant type of which changes co- logically and co-consequently in each successive logical-historical epoch, fundamentally altering the entire production (reproduction) mode (i.e., the type of the economy and social relations).

Thus, a correct assessment of AI's place and role in transforming the economy and society is primarily based on a proper determination of AI's potential in changing the dominant type of production-economic (productive) capital.

3 Results

The main results encompass comprehensive answers to the four defining questions posed in the introduction.

3.1 Undeniable Logical-Historical Determinism, the Regularity of AI Formation, and Its Pervasive Integration into Human Life and Society

Since humans, as subjects of transformative and creative activity, constantly require the expansion of the potential of their strengths and abilities, which can only be achieved technologically, namely by developing and applying increasingly sophisticated, powerful technologies, at a certain stage of social development, its factors, and means of production (production forces), such a technological tool as AI is entirely conditioned and lawfully formed.

Therefore, the formation of AI is by no means a coincidence that may not have happened, or that may have been some unexpected event. It is entirely conditioned, logical, and even predictable.

Humans find it necessary to enhance their intellect technologically—to equip it hardware and software-wise, thereby extending and expanding it, increasing its power, and thus creating new possibilities for humanity.

Nowadays, society is precisely at such a logical-historical stage of its development. It finds itself at a quite co-logical and co-consequential stage (level) of its socio-economic logical-historical evolution, which is the informational-technological (information-processing) stage, developing within its own framework.

Information technologies are the main technological tools of the present time. They are modernized and perfected, transitioning to digital formats and taking a decisive step—towards AI, which merges with the natural intelligence (NI) of humans, becoming one single whole.

How significantly or even essentially does this transform the economy and society?

3.2 The Essence of the Transformation of the Economy and Society Under the Influence of AI Application

The integration of AI into human life and society brings about significant and even essential changes, transforming the character and type of the economy and social relations.

They can be characterized as a very significant and meaningful advancement.

However, it is still not a radical socio-economic turn, a revolution—which is yet to come, to mature.

If we correctly answer the question about the significance of the changes introduced by the integration of AI, then it will be equally accurate to answer the questions about the prospects of the socialization and humanization of AI and the degree of significance of its place and role in further social progress.

The significance of the changes is determined by the fact that with AI, humans and society acquire a new, universal, and all-encompassing means of production-technological, organizational-economic, and socio-economic nature, and simultaneously—as a two-in-one, duality—a new means of communication, which connects: people, people and machines (IT programs), and machines (IT programs). Its distinguishing feature is intelligence.

These characteristics are universality, all-encompassing nature, duality, and intelligence as a distinctive feature of production means and communication means. They endow AI with a unique social (including socio-economic) status. In this capacity, it now becomes a necessary and inevitable condition for further expanding the possibilities of production and communication together.

This is why countries are currently directing more investments into the development and implementation of AI systems, especially since, under the current dominant type of socio-economic structure, they are in competition with each other and seek to outpace one another in the economic race.

Speaking of the internal substantive qualities of this new, state-of-the-art production and communication tool and condition, it should be emphasized that, while preserving, not canceling out human-machine relations as such, it introduces significant and essential transformation into them.

Partnership relations between humans and machine systems develop not on a superficial level but on a profound level—at the level of intellect. Essentially, these two intellects (NI and AI), in their union, become co-organizers, co-producers, co-broadcasters, and even co-arrangers of the jointly created possibilities and results.

The key point here lies in the unity, the merger of these two types of intellect, whereby they, in this union, become something else entirely, namely a special conglomerate, newly defined in itself due to the peculiar nature of their co-unity, co-partnership, and cointegration.

This key point conditions the undeniable sociality of AI as its categorical characteristic. The character of this sociality is different from that of ordinary machines, apparatuses, and mechanisms. We deal with a human-like and even society-like technological and social device, of an all-encompassing order, acting in co-partnership and cointegration with humans as the subjects and carriers of NI, intellect, and consciousness.

The all-encompassing nature of these new relations changes the social structuring of society and the structure of communication relations.

What is most important here?

The social (socio-economic and social class) structuring changes because people, as social subjects, by engaging in the relations of information and knowledge reproduction through and with the help of AI, effectively become a universally united network of intellectual capital subjects, although still in its contemporary prevailing format of informational-technological capital.

This is a deeper level of their socio-economic interdependence than what existed before.

The communicative structuring changes because the communicating subject is now dual: it is cointegrated from two components, effectively combining NI and AI in each of its cells and in the entire network of such interconnected cells.

Much more could be said about the finer details. However, it is important not to lose sight of the main, essential amidst this mosaic.

Do the AI economy and AI society replace the knowledge economy and society, as well as the information society?

No, they do not replace or annul but only complement them with a new, not entirely ordinary (in its essence human-like and society-like) content and structure. It is progress but not yet a radical turn or a revolution.

Why is it so?

No one and nothing can negate the key role of knowledge as such—knowledge fills the content and the direction of all social and human activities, being the expression and the embodiment of real universal regularities.

Knowledge is indeed intellectual capital. Currently, it predominates (for now) precisely in its formalized, informational-technological (information-processing) form, not yet in the truly meaningful, transformative-innovative form, which still remains non-dominant, not universal, and episodic.

Thus, we do not go beyond the level of either the knowledge economy and society nor the information society.

The participation of AI adds little to the evolving innovative structure within this level—that is, to the emerging economy and society of novelty in knowledge and transformative capabilities, or, in other words, to the economy and society of innovations, which entail a different, higher, and deeper level in the way of social reproduction, including management and communication.

At this emerging higher and deeper level (i.e., at the level of transformative capacity and innovation), AI can be an assistant, a servant to humanity and society, taking on important but still secondary intellectual functions. However, even if it creates knowledge, it does so in a formalized manner, on an existing basis; its compilation does not lead to a higher level of novelty, and it lacks an understanding of what it is doing.

Approaching this from the perspective of evaluating texts generated by AI, their originality is essentially the level of anti-plagiarism, which is not bad in itself.

However, this is also a formalized, extracted from an existing basis, compilatory, non-breakthrough originality, thus lacking a higher level of novelty and innovativeness.

Hence, we should be grateful to AI for the impetus it gives humanity—namely, for the push to always and everywhere strive to surpass the level of such mediocre, formalized, non-breakthrough originality, going beyond its limits and creating, producing outstandingly innovative, truly breakthrough, creatively innovative originality in its novelty and meaningfulness.

This is likely to happen quite soon. Formalized originality (anti-plagiarism originality) will no longer satisfy the demands for increasing the level of transformative intellectual capacity of humanity and society. Thus, meaningful originality with

the status of breakthrough innovativeness will be universally and systemically (not episodically) demanded.

This is where AI nudges, compelling humanity to go. We should thank AI for that. Apparently, this is its cosmic role—ultimately, to stimulate further growth and elevate the qualities and abilities of human reason and consciousness.

As is evident, AI is inherently not a creator (not a producer) when it comes to the creation or production of that very capital of capitals, namely the transformative-creative capital, which is created solely by human reason and possesses true meaningfulness.

However, the main path of world-historical development is meant to lead precisely to this highest peak.

As social subjects, people are capable of fundamentally, revolutionarily elevating the level of their subjectivity (not superficially or formalistically but profoundly and meaningfully) but only when they acquire a special ability (in fact, a super-ability) for transformative-creative thinking and action. Without this, we, as humans, excel little in the realm of intelligence accessible to AI and are hardly capable of truly controlling AI; rather, we are ready to submit to it.

This is where the roots of the latent fear of humans before the purported power of AI grow from—it stems from the sense (even if not consciously acknowledged) of the weakness of one's intellect, the limitations and inadequacies of the prevailing mode of thought.

The root lies in the absence of full autonomy and sovereignty of human thought under the currently dominant and inherently limited mode of thinking, which lacks full integrity and comprehensiveness of thought. If anything will ruin humanity, it is our own inability to think correctly.

Now, let us talk about the impact of AI on communication parameters.

Apparently, AI can give new impulses and parameters to increase the volume and speed of communication. However, is this the crux of the matter?

Indeed, it is hardly able to help humanity and society in the main aspect—elevating the level of semantic content and meaningfulness of communication and improving the nature and type of the communicative purpose. Without this, everything else (i.e., speed, volume, etc.) means little.

All that has been said allows the author to correctly answer the question on the prospects of socializing and humanizing AI.

3.3 Prospects for Socializing and Humanizing AI, the Horizon of Their Limitations

It is very odd when discussions about the potential of AI in socialization and humanization are based solely on its internal capacity for self-development, its presumed advancements, and limitations—completely detached from the overall process of social development and transformation, from the socially directed evolution.

It is odd because AI, as mentioned earlier, is not only technological in nature but also social because it is human-like and society-like. These properties are inseparable, just as humans and society are inseparable.

From this perspective, the higher and deeper the level of social development in its categorical sociality, the more the potential for the socialization and humanization of AI can be realized in actuality.

From the standpoint of the noospheric concept, it goes as follows. If we are talking about a truly developed noosphere of society, its fully unfolded reasonableness, consciousness, and thus, about true sociality and humanity, then we are already talking about a radically transformative (overturning) level.

This level represents not just a more modernized information society or even an improved knowledge society in its usual parameters; it is a completely different superordinary type of society, in which there is a universal transformative-oriented mental foundation and a transformative-super-omni-cointegrative, super (trans) co-unifying methodological basis of all thought and activity.

That is why we cannot consider the opinion expressed in literature that the essence of a noospheric society would be precisely the merging, combining of human mind and AI (i.e., the union of HI and AI) correct or providing a true guideline [1, pp. 38–39].

AI does not possess the ability to make humans wiser, more conscious, or more prudent. It cannot exceed its own capabilities. Without improving humans and society, it simply cannot rise to such an extraordinary supercoordinary intellect, which is internally enriched with full moral integrity and spirituality.

Indeed, without such enrichment, the alliance of humans and society with AI will inevitably pull them not forward but backward.

All the aforementioned allows the author to accurately answer the key question: “To what extent are AI’s independence and role determinative in the further social and socio-economic evolution?”.

3.4 The Auxiliary, Service-Oriented Nature of AI’s Impact on the Further Evolution of the Economy and Society

The conducted analysis shows that the substantial changes brought about by the extensive integration of AI into human activities and society are significant, even fundamental. However, they do not give AI the status of the most independent and determinative factor.

The place and role of AI remain and will continue to be auxiliary and service-oriented.

AI is a highly advanced intellectual technology, a cutting-edge tool, and an important assistant to individuals and society, inherently resembling human and societal characteristics.

It is precisely to the extent that it resembles humans and society that AI is also social and humane. Hence, it is not independent in the prospects of its self-improvement and application but depends on the nature and type of social and socio-economic relations.

Like any other tool, AI can be used for good and evil; its use can embody positive, constructive intentions and destructive tendencies.

In a society where enmity, conflict, and competition prevail over mutual support and collaboration, AI will inevitably be employed for nefarious purposes and will be asocial (in this sense) and inhumane as the goals and corresponding attitudes themselves.

Yet, it is precisely this type and character of society that currently predominates; the closer it approaches its decline, the more aggressively it tends to manifest itself and destroy within and around itself. We witness this today.

Therefore, when society's type and character change, and it becomes predominantly positive, constructive, supportive, and collaborative, AI will outweigh its asocial and anti-human aspects and lose any basis for the wrongful application of its forces.

4 Conclusion

The place and role of AI in the transformation of the type of economy and social relations, as discovered and substantiated in this research, are very significant and even essential within quite specific, limited, and dependent frameworks.

The formation of AI as a new production-technological, organizational-economic, and socio-economic means of production and communication, in its inherent universal, all-encompassing, and dualistic format, is fully conditioned, logical, and even predictable.

Its massive and widespread integration into human and social activities signifies a significant advancement and even transformation of the socio-economic, social-structural, and communicative foundations. However, it does not equate to a radical turn or upheaval—one that is yet to be mastered.

AI does not alter the nature of the dominant type of intellectual capital, leaving it at its current prevailing level of formalization and information technology reliance, and thus contributes little to substantive advancement. It expands and prolongs the capabilities of human hands and minds, ensures an increase in the volume and speed of information processing, storage, and transmission of already created and accumulated knowledge, and even fosters a certain degree of originality in knowledge (texts) generation. However, it does not transcend the boundaries of anti-plagiarism and fails to create breakthrough innovation.

AI cannot, on its own, apart from the self-improvement of the socio-economic foundations of humanity and society, make humanity wiser, more conscious, or more

prudent. It cannot leap beyond its capabilities, taken outside the regularities of socio-economic logic-historical evolution. Therefore, on its own, it can contribute little to society in achieving true noosphere.

This manifests its non-autonomous and non-determining character as a condition for the further transformation of the economy and society. AI does not go beyond the status of a serving, auxiliary, and facilitating factor (means).

Thus, the further essential prospective genesis of humanity and society (which can truly be characterized as noospheric genesis) is by no means just a technological genesis in the form of a combination, merger, and conglomerate of human abilities, its NI with informational-telecommunication AI.

Such a combination, merger alone is insufficient; it is by no means determinative.

In reality, what is determinative here is, in its unity, the civilizational and socio-economic (formational) genesis, whereby humans and society are capable of ascending to higher, utmost stages in the development, perfection of their collective, co-shared, co-intellectual faculties, rationality, consciousness, wisdom, and spirituality.

This is only possible by elevating and rising to the dominant socio-economic position precisely of the capital of capitals, that is, the transformative-creative capital—capable of fundamentally transforming the entire socio-economic system. It thereby provides the possibility and fosters the necessity for itself and the prospective socio-historical type of humanity being formed within its framework to finally become truly co-socio-intellectual, co-intellectually coherent, co-consciously aware, co-wise, and co-spiritually profound in their character.

AI cannot escape from this. Then, it will assimilate to them in its own type and character.

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The Linguistic-Composition Model of Scientific Discourse in AI



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Abstract The research analyzes the strengths and weaknesses of scientific texts produced by various artificial intelligence (AI) programs available on the Internet. The research aims to determine the extent to which scientists and university faculty can currently rely on AI achievements. By applying fundamental general scientific methods of analysis, the authors conclude that neural networks are useful in scientific discourse for writing formulaic texts, which broadly include annotations, reviews, and news reports on research discoveries (for popularizing university activities on websites and in the media), for selecting illustrative material for presentations, and in educational activities as a tool for students' independent work in planning future scientific texts. However, neural networks cannot currently significantly aid in scientific work because they lack critical thinking and the ability to conduct innovative scientific activities. Additionally, the most significant weaknesses of AI include the absence of emotional intelligence and the pedagogical skills necessary for training new scientific personnel.

Keywords Language of neural networks · Scientific discourse · Genres of scientific style · Linguostylistic features · ChatGPT 3.5

JEL Classification I0 · I2

1 Introduction

The optimization of production processes as a factor in the evolution of socio-economic relations implies an increased use of information-engineering developments. Currently, artificial intelligence (AI) systems can perform simple repetitive tasks previously performed by humans, and the proportion of such tasks is gradually

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increasing. However, the demand for neural networks in the twenty-first century is driven not only by technological but also by humanitarian reasons.

The development of AI as a means of processing, summarizing data, and generating autonomous texts in the contemporary era, philosophically and culturally identified as postmodern, seems far from coincidental. The concept of creating new material through the reprocessing of existing information (essentially writing intertexts with varying degrees of freedom from the pretexts) and predicting the next word in a verbal sequence aligns with postmodern philosophy's constants of the "dictatorship of language," "the end of text-centrism," and the "dominance of the author's strategy."

Indeed, the fundamental principle of text generation by neural networks is based on the mechanism of calculating the most probable lexeme in an already-formed context. This model illustrates the principle of the "dictatorship of language," where language, due to its systemic nature, predetermines the rules of using speech units for humans [1]. To a certain extent, this approach correlates with Roland Barthes' proposition of "The death of the author," where the text is positioned as a relatively autonomous element that does not fully reflect the creator's thinking [2].

Subsequently, the concept of the role of the text in culture is developed by conceptualists—representatives of the radical version of postmodernism. They conclude that in post-industrial society, the value of the text as a final art object is lost. The notion of "text-centrism" from past cultural epochs is replaced by the idea of the "author's strategy" as the ultimate goal of the artist's creative journey [3, pp. 40–42]). Starting from the twentieth century, it becomes more important for an artist not to create an "eternal" work but to be remembered by the public as an authorial figure. The more often their name appears in mass communication, the higher their status as an artist. As a result, the focus shifts from the quality of works to their quantity, as each new text becomes an informational reason for discussing the author's creative intentions.

A similar process is observed in science. As the establishment of normative indicators of scientific activity and the assessment of scientists' professionalism are increasingly based on the number of discoveries and publications, there is a danger of shifting priorities. Researchers may feel compelled to turn to AI systems to speed up the process of writing scientific works, especially articles. There are already documented examples of this. Although there is no direct evidence, indirect indicators (e.g., the presence of linguistic constructions typical of neural networks) suggest the use of AI in the preparation of materials. For instance, in the journals Microprocessors and Microsystems and Elsevier, the increase in publication activity from 2018 to 2021 correlates with a rise in the number of so-called "nonsensical texts" (characteristic of AI). The highest percentage of such articles belongs to authors from China [4]. The problem of allowing content-free articles to be published is commonly attributed to limited editorial resources [4]. As a result, texts with the status of authorial scientific works, which may later be used by neural networks as pretexts, enter open information sources. Gradually, secondary, tertiary, etc., materials will become widespread, with content that has not been human-controlled for a long series of stages.

Understanding the potentially negative consequences prompted 2000 scientists to publish an open letter in March 2023, requesting a halt to AI development for at least six months. Shortly after, another 1500 researchers joined the authors. The signatories include one of the early creators of AI, Steve Wozniak, and today's most famous developers of AI systems, Musk and Bengio [5]. In May 2023, another letter of similar content appeared on the Internet [6].

Nevertheless, neural networks continue to develop actively, covering new areas. Traditionally popular areas for AI use include marketing [7], advertising (the iconic component is often created by AI [8]), jurisprudence (where Legal Robot is highly appreciated; involving AI in this field is relatively simple, especially since linguistic-cognitive programming in the legal field has long been thoroughly described by scholars [9]), and translation. Educational and scientific fields have also been added recently.

Besides writing articles, as mentioned above, AI is used in preparing and taking exams and even in working on final qualification papers. In 2023, significant media resonance was generated by the news that Alexander Zhdan, a student at the Russian State University for the Humanities, used the free version of ChatGPT to prepare his graduation thesis in one day [10]. In recent years, AI has begun to be used much more actively in creating scientific texts of various lengths and levels of complexity.

The necessity of establishing the effectiveness of neural networks in preparing scientific materials underlies the relevance of this research. The research aims to describe the boundaries of AI application in scientific discourse. To achieve the desired results, the following tasks are addressed:

- To determine the requirements for scientific texts that are met by AI;
- To classify genres of scientific literature into those where the use of neural networks is beneficial and those where it has little value so far;
- To evaluate existing AI systems from the scientific discourse perspective;
- To identify the prospects for the scientific field and the role of educators in society in a changing world.

2 Methodology

The thematic scope of this work involves the application of general scientific methods, such as the scientific description of the research object, analysis, synthesis, abstraction, concretization, the hypothetical-deductive method, the comparative-comparative method, and factor analysis. Among specific scientific approaches, the authors employ methods of semantic and definitional analyses.

3 Results

Nowadays, the performance of neural networks is positively evaluated in areas related to the creation and processing of stereotypical texts. It is widely believed that AI will soon be able to translate literary texts satisfactorily, mainly those characterized by formulaic language and predictable plot development (e.g., detective stories, romance novels, etc.). AI is actively used in automatic translation, business, law, and officialdom. Chatbots are widely applied to analyze and classify texts. They help draft applications, redirect inquiries appropriately, and sort information from questionnaires. Additionally, sentiment analysis systems determine the emotional tone of texts, which helps process customer reviews or monitor social media. AI can also extract information from texts based on specified parameters, which is useful for handling large volumes of data (e.g., in medicine).

Thus, AI is an effective tool for monitoring, analyzing, and typologizing information. It can also be used to create formulaic texts. In scientific discourse, neural networks perform relevant tasks in the following genres: databases, article outlines, graduation theses, and, to a lesser extent, dissertations, annotations, and reviews.

The latter two types of texts are built on the principle of supplementing stable linguistic models with variable information from the annotated or reviewed source, usually without specific details. Testing AI capabilities in these genres yields positive results. For example, ChatGPT 3.5 offers the following annotation for an article on the value orientations of Maxim Gorky's early work: "This scientific article analyzes the axiological aspects related to the value orientations and moral principles in the early period of Maxim Gorky's work. The study is based on an analysis of his works written in the late 19th and early twentieth centuries. Emphasis is placed on the struggle for freedom and justice, humanism, and patriotism that permeate his early works. The results of the study allow for a better understanding of Maxim Gorky's value orientations and worldview, as well as his contribution to the development of literature and the formation of societal values." This and the following texts created by AI are taken from the responses of ChatGPT 3.5 to queries formulated by the authors [11].

The annotation provided by ChatGPT 3.5 meets the requirements for corresponding publication elements at a student level. It highlights the necessary components in the original text: the subject of analysis (Gorky's work), moral constants (freedom, justice, humanism, and patriotism), temporal limits (late 19th—early twentieth century), and research outcome (understanding Gorky's contribution to the development of literature and the formation of social values).

However, ChatGPT 3.5 does not specialize in writing annotations. The Internet offers other specialized sites for this purpose (e.g., robotext.io, PDF24 Tools, GPT-tools, and Online GPT). These tools are much better suited for extracting and describing the main points in a scientific text. Notably, AI often identifies keywords more accurately than the average researcher, which is related to the function of keywords (i.e., to help find the appropriate text based on phrase queries, which is the work of automatic search engines).

Writing reviews is also a promising area for developing AI in the field of science. Let us compare excerpts from two reviews: one positive and one sharply critical. Both reviews are written by ChatGPT 3.5 on Konstantin Bogdanov's article "Drunkenness and Russian literature: Rhetorical models." We will also highlight the linguistic constructions typical of the review genre.

Positive review: "The article "Drunkenness and Russian literature: Rhetorical models" by Konstantin Bogdanov is *a study that considers one of the fundamental topics* of Russian literature. Bogdanov examines the rhetorical models associated with the depiction of drunkenness in the works of Russian writers. He *convincingly demonstrates* how rhetorical devices are used to create images of drunken characters and how this reflects certain socio-cultural features. *The most important aspect of the article is the deep analysis of texts and the exploration of them in the context of socio-cultural characteristics.* Bogdanov *presents an original approach to a topic rarely addressed in academic literary studies.* The article "Drunkenness and Russian literature: Rhetorical models" is a *significant contribution to the study of Russian literature, creating new perspectives for further research in this field.* The work is *well-structured and based on a clear methodology,* which attracts the reader's attention and stimulates interest in the topic."

The provided review certainly needs editing, primarily to eliminate tautology. However, we must acknowledge that the text is scholarly (as seen in the highlighted clichés), written in competent language, and formally meets the requirements of a review. It evaluates the work's place in the context of literary studies, specifies the relevance and novelty of the research, broadly describes the methodology, logicality, and systemic nature of the presentation, and provides a conclusion on the work's significance.

An excerpt from a critical review of the same article is as follows: "Bogdanov does not provide sufficiently convincing evidence for his claims and ignores the broader contexts of the social and psychological consequences of drunkenness. This narrow focus makes the article insufficiently informative and unconvincing. Furthermore, the text suffers from a lack of systematization and consistent structure. Transitions between topics are abrupt and inconsistent, which worsens readability and comprehension. Thus, Konstantin Bogdanov's article fails to substantiate its topic and is characterized by weak structure and argumentation. As a result, the reader receives neither reliable information nor convincing evidence, making this work of little value for studying the impact of drunkenness on Russian literature."

The negative review features even more typical review expressions and characterizes the original text from multiple perspectives: argumentation, scientific novelty, structured presentation, and logic. Both reviews undoubtedly have flaws, one of which is their extremely positive or negative evaluation. Nevertheless, it is hard to deny that the texts meet the genre requirements of a review at a satisfactory level. In certain situations, the AI-generated review text can already be used as a basis for an original review (e.g., when time is limited).

Apparently, neural networks possess high capability in structuring information. Therefore, AI programs can be recommended to students as a training mechanism for developing the skill of material systematization and subsequently creating detailed

plans for scientific works. Notably, the use of gpt3_unlim_chatbot is particularly beneficial. It outlines the plan for upcoming research and explains the logic of the proposed solution in simple and understandable language in a dialogical form. This is confirmed by using phrases like: “Of course, I would be happy to help with this question! The topic “The image of the rowan tree in Marina Tsvetaeva’s work” sounds very intriguing. Let us develop a detailed plan for a scientific article on this topic”; “Rowan tree in Russian culture and literature. This section will be dedicated to the rowan tree as a symbol in Russian culture and literature. We will examine how the rowan tree was used in Russian poetry before Tsvetaeva and what associations it carries in Russian culture”; “Comparative analysis with other images in Tsvetaeva’s works. In this section, we will compare the image of the rowan tree with other important images used by Tsvetaeva in her work. We will try to identify connections between the images and understand their significance in Tsvetaeva’s poetry,” etc. (these fragments are taken from the responses of another chatbot—gpt3_unlim_chatbot [12]).

Thus, neural networks are an effective tool for information selection. This is particularly useful when creating databases, especially when they concern terminology. Such use of AI significantly accelerates scientific work in fields like linguistics, translation studies, cognitive science, and other disciplines.

Logical reasoning leads to the idea that neural networks are beneficial for compiling bibliographies for research, but practice shows the opposite. AI often suggests non-existent works as sources of information, for example, “Chernyshevsky, N. G. (1949). To the Justification of Materialism. Complete Works in 15 vols. Moscow, Russia).

The following problems with the accuracy of AI-provided data are also observed at the level of argumentation:

- Neural networks propose false facts (e.g., “Coffee was invented in Switzerland in the eighteenth century”);
- Non-existent statistics (sometimes absurdly funny; e.g., “Every fifth mathematician is into mountain biking, about 30% of physicists are into brewing, and the rest of the exact science teachers are into butterfly collecting”);
- Non-existent quotes (e.g., “According to Bykov, postmodernism ‘does not shy away from using symbols that were previously considered off-limits for jokes’”);
- Sometimes, neural networks attribute phrases to the wrong authors (e.g., the expression “Time shows itself as a sequence of ‘nows’ simultaneously passing away and coming along” is attributed to G. Deleuze instead of M. Heidegger, the real author).

Another significant problem in formulating arguments is their lack of substantive content, essentially their groundlessness. The conclusions and generalizations made by neural networks are usually not supported by facts, examples, or statistics. They often need more specificity. For example, ChatGPT 3.5 interprets Vladimir Sorokin’s work as follows: “The image of the doctor in the novel ‘The Blizzard’ reflects the typical characteristics of the medical field in Russia. The plot and the doctor’s actions

serve as a basis for analyzing typical medical practice in the historical context in which the novel's plot unfolds."

This excerpt highlights another weakness of AI—linguistic and stylistic imperfections: a tendency towards semantic redundancy (essentially, the phrases “reflects the typical characteristics of the medical field” and “serve as a basis for analyzing typical medical practice” mean the same thing and do not demonstrate a progression of thought in the given fragment), which is also expressed in tautology (repetition of words like “typical,” “medical,” “plot,” etc.), as well as the presence of speech errors (an image cannot reflect the characteristics of an entire field of activity; “the plot and the doctor’s actions” cannot be coordinate elements in a sentence because they are incomparable concepts: one is a literary category, the other is a person’s function).

As for the linguistic component of materials created by neural networks, it is necessary to note that these texts require mandatory human editing since language algorithms are too complex for the current state of AI development. Additionally, AI cannot be useful at this stage as a tool for increasing the originality of text to pass anti-plagiarism systems. Multiple attempts to use various neural networks for such purposes show that the application of synonymizing mechanisms by AI fails to raise originality above 42% and leads to considerable errors in scientific discourse—the violation of terminological consistency. For example, AI replaces the philosophical concept of “being” with the verb “to be” and confuses literary terms “metapoetics” and “metapoetry,” which have little in common for specialists.

The issue of the inadequately developed terminological framework of AI is most evident in the stage of defining research methodology. Currently, AI cannot classify the employed specialized methods (e.g., intermedial, metatextual, metapoetic analyses, etc.) and struggles with naming basic scientific approaches (e.g., analysis, synthesis, content analysis, and comparative methods). Instead, AI suggests phrases like “careful reading approach,” “thorough examination,” “consideration of the broad cultural and historical context,” or vaguely defined expressions like “psychological approaches.”

These points cast doubt on the effectiveness of using neural networks in scientific discourse under current conditions. However, the focus should be on aspects that demonstrate the inability of AI to create high-quality scientific texts, considering the very definition of science and its functions in society. First, AI cannot fully adapt to the rapid pace of scientific discoveries: the data available to neural networks is limited by the frequency of updates. For instance, chatbots from 2023 cannot incorporate discoveries made in early 2024. Consequently, relevance, one of the fundamental requirements for scientific texts, suffers. This may be less critical in the humanities. However, in technical fields, new information can drastically change paradigms.

Second, as mentioned earlier, AI operates by rephrasing already-known information. It cannot create anything new (i.e., concepts or approaches), nor can it propose methodologies for problem-solving, especially in the humanities, where solutions are not straightforward and numerous factors must be considered. AI also fails to provide the level of data systematization familiar to researchers, which identifies gaps in theories or previously unnoticed aspects, elements, paradigms, etc. Neural networks process material within the boundaries set by humans and do not go beyond

these limits. Therefore, AI cannot ensure the scientific novelty of research, which is a fundamental requirement for scientific texts. After all, the primary function of science is to serve society and improve its quality of life by discovering unknown facts, phenomena, processes, and more.

4 Conclusion

The scientific and technological progress that has led to the involvement of AI in scientific discourse has the potential to partially ease the workload of university faculty. Processing large volumes of information and recoding it in new ways (with neural networks producing texts in seconds, offering an almost unlimited amount of material daily), chatbots can present problems to researchers from previously unexplored angles, offering new perspectives for studying questions. Moreover, AI is useful to some extent (with obligatory verification) in compiling bibliographies, meta-describing scientific texts (creating annotations and keywords), and reviewing them.

AI is also used as an auxiliary tool in scientific and educational activities. It is effective in creating illustrations for presentations and media support for researchers (writing journalistic articles for university websites and media to popularize discoveries). It is recommended as an educational platform for students (e.g., improving their skills in preparing article plans and graduation thesis).

However, the drawbacks of AI, which prevent it from replacing the fundamental functions of university staff in the near future, include the inability to engage in critical thinking and, even more so, innovative scientific activities. Moreover, there is a lack of emotional intelligence and pedagogical skills necessary for education.

Overall, analysis shows that neural networks are currently relevant primarily in work involving repetitive actions or the creation of formulaic materials. Therefore, in science and education, which is designed, on the one hand, for communication (an area highly unpredictable for AI) and, on the other, for discovering new things, AI can only be used as a tool for performing specific functions. However, the number of these functions is constantly expanding; the quality of results is improving. This highlights the prospects for further study of artificial intelligence in scientific discourse.

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The Metamorphosis of Marketing in the Age of Neuromodern



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Abstract The research attempts to comprehend the era of neuromodern in its categorical manifestation. The interpretation of the concept of neuromodern through the prism of marketing makes it possible to analyze the object in the context of economic, socio-cultural, and ontological discourse. The methods of analysis used (critical, stylistic, hermeneutic, retrospective, structural, and functional) allow the authors to reveal the versatility of the ongoing metamorphosis of marketing concepts in various periods of the existence of society. The insufficiently known phenomenon of neuromodern arouses the interest of researchers in the humanities, which makes it possible to read it from the position of market reflection on the incipient change of consumer mode. Even if the era of neuromodern has arrived, it is only a teaser in the form of a simulation of creative activity in the market field and a convenient mechanism in the hands of marketers. The conducted research contains practical material from a retrospective of the metamorphosis of marketing concepts from the modern era to the meta- and the beginning of neuromodern. Thanks to the analysis of advertising campaigns of different brands over the centuries, the difference between the creative principle of human thinking and the atavism of the mechanical essence of artificial intelligence (AI) becomes apparent. Extrapolating from the above, the era of neuromodern reveals the superiority of AI over the physical capabilities of human thinking, which is not limited to the suggestion of new needs but reproduces the new reality of event processes.

Keywords Neuromodern · Metamodern · Artificial intelligence · Metamorphosis of marketing · Economics of pleasure

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1 Introduction

The research aims to analyze marketing tools through the exogenous factors of certain milestones, which is an attempt to identify the subject-subject relationship between humans and artificial intelligence (AI). Simultaneously, marketing is understood as a deep humanitarian technology of cognition of the essence of human consciousness and the unconscious within the framework of economics, sociology, cultural studies, philosophy, religion, and generating synergy in the form of consumed symbols.

The evolution of market ontology has led to a rethinking of human needs. The “economic man” is replaced by the “cultural man,” whose tactics are based on the freedom of sufficient consumption. Based on this paradigm, the world of modernity and postmodernity transposes into the epochs of meta- and neuromodern, where there is an oscillation of awareness of human destiny, turning it into an epigone of previous eras.

Does the search for meanings, signs, and symbols belong solely to humans, or does AI, as an extension of our thinking, create even more advanced forms of activity through its “binary system”? The era of neuromodern concludes the primacy of AI in the sectors of society. However, finding the user experience of using AI in the field of business, education, healthcare, etc., it is challenging to assume its subjective nature. Is humanity considered an object based on the available database, or does subjectivism have an immanent beginning?

These are the questions that formed the basis of this research.

2 Methodology

A minimal amount of resources was used as a theoretical basis for research on the topic of neuromodern due to the limited exploration of this phenomenon in various modes of knowledge and a limited number of scientific research in this area. Based on the ideas of Parfun and Lifanov [1, 2], the authors conclude that neuromodern researchers are directly related to the fields of marketing, advertising, and design. That is, the prism of neuromodern analyzes the creative principle. This fact underscores the relevance of this research, as marketing, advertising communications, and design are becoming the primary subjects of study in the neuromodern era.

A retrospective analysis of the transformation of marketing from the modern era, postmodern to meta- and neuromodern, was applied in the work, which is conditioned by the systemic representation of marketing as a concept of the temporal plane. When analyzing the formation of recent marketing concepts, it is necessary to highlight the historical and methodological approach in the research, which is based on the display of phenomena in the development and context of the historical and cultural situation

and the presence of cause-and-effect relationships between cultural trends and the processes of development of market relations.

The research was based on the works of Vermeulen et al. [3–9].

The practical part of the research consists of analyzing the materials of Internet resources devoted to advertising campaigns of various periods [10–13].

In examining the transitional category between the epochs of metamodern and neuromodern, known as the pleasure economy [3, 7], the authors applied a structural and functional method. This method involves considering marketing as an integral system with a complex structure, where each element has a certain purpose and performs a specific function. Forming the subject of research in the context of the suggestive nature of marketing concepts, the authors turned to the categories of the modern French sociologist and philosopher B. Latura: an “economic man” and a “cultural man” [14]. The “economic man” as a phenomenon of the modern era gave rise to the marketing foundation. Lying in the plane of the metamodern, the “cultural man” gives rise to the neuromodern. Neuromodern marketing is still incomprehensible due to the lack of even an intuitive perception of the upcoming processes. However, it is definitely certain that AI, with its modifications of the human thinking process as an individual, will no longer become a fundamental tool. It will be a generator of needs.

3 Results

Exploring the transformation of marketing in the era of neuromodern, it is necessary to turn to the historical and scientific digression of this problem in the context of various periods of social development.

The modern era was accompanied in marketing by the concepts of rationality, material abundance, anthropocentrism, and feminism. Classical marketing concepts are becoming a product of this era: the effect of scale (the end of the twenty-first century), the product-oriented concept (20s of the twentieth century), the concept of intensification of commercial efforts (30s of the twentieth century), and the concept of direct marketing [5].

The basis of the modern era in marketing is the understanding of the role of the consumer in the market. At first, the concept of material abundance is used. Mass production of goods is carried out regardless of the needs of society. Next comes the understanding of the need to focus on the preferences of a certain audience. There comes the realization of women as a new sales target group. The concept of feminism is manifested. The element of anthropocentrism is manifested in the following concept, which opposes mass production to individualism: a person accumulates a need, and the manufacturer takes care of the customer. The next stage is sales promotion. It is necessary to create a need for the product. As a result, a concept based on rationality appears: as much as is necessary, as much is produced. Thus, we observe the phylogeny of the consumer in the current era, from the consumption of raw goods and services to the formation of individualism.

Turning to the conclusions of V. I. Shulzhenko, we find that the “marketing modern” formed by global capitalism was based on the idea of maximum satisfaction of needs. Nowadays, the marketing of the modern era is already perceived by archaism, seriously questioning the very concept of the immensity of human consumption [7, 8].

The effects of pragmatics and benefits are beginning to become shameful and immoral. In the mid-twentieth century, marketing modernity is disappearing. The era of postmodern marketing is coming [3].

Postmodern penetrates in the form of elements into the basic marketing concepts that arose in the modern era. Postmodern marketing is characterized by outrageous and aggressive presentation of information and eclecticism. Manufacturers are trying to reach consumers. Postmodern advertising messages are deconstructive by the type of rhizome. The world is presented in the form of hypertext—the deconstruction of the storyline as a whole text. Anti-realistic images are often used; schizophrenic discourse is present. The concept of social and ethical marketing is becoming a product of the postmodern era. Cynicism is based either on pity or on the translation of universal values.

Postmodern marketing effectively imposes a pyramid of needs formulated by A. Maslow on the human life cycle, when it is clearly seen that physiological needs (the lowest level) are actualized in a person at the stage of birth and sunset, and the highest level (the level of creativity) falls at the stage of maturity—maximum viability, solvency, and socio-economic activity, when there is less desire to “eat” than to create something after oneself [4].

The pragmatic economy, where economic interests prevailed, passed into the stage of irrational existence. Economics as a basis (according to Marx [15]) has ceased to be a foundation. The dominant functions of the postmodern market are social, status, cultural, and psychological motives in the structure of consumer behavior.

The term “metamodern” was proposed in 2010 by T. Vermeulen and R. van den Acker as an era swinging between modern and postmodern, the era of the return of sincerity [9].

Marketing in the prism of metamodern transforms communication through the prism of self-irony, sincerity, and nostalgia. Metamodern marketing unobtrusively reminds of the possibilities of consumers of goods and services. Moving away from the aggressive postmodern, shocking the audience, the metamodern is distinguished by lamination, airy characters, and quirkiness (not deviation) of the characters. The metamodern is ambivalent; it is on the border between heterogeneous concepts while finding a balance and a kind of symbiosis.

Considering the epochs (post- and neuromodern) of marketing in the timekeeping plane, a transitional and mutually connecting link can be called the phenomenon of the pleasure economy, which exists during the structural crisis of capitalism, as well as complex human relationships in which AI plays an important role. Rejecting all basic paradigms of political economy and classical and neoclassical economic theories, it manifests itself as an antinomic approach to modern business management and management of market processes as a new fundamental paradigm of consumption.

The pleasure economy can be represented as a type of social marketing that appeals to culture, art, education, etc. [3, 7].

The metamodern era gives rise to the concept of “freedom of sufficient consumption,” which is the antithesis of “freedom of consumption.” A person of the era of the return of sincerity is moving away from consumerism, where creative dissatisfaction becomes the postulate of their lifestyle. The awareness of this need has opened up a new field of activity for marketers based on such concepts as: “meta-reflexivity / life-as-a-movie,” “oscillation between opposites,” “quirkiness,” “metamodern minimalism and maximalism,” “constructive pastiche,” “total anthropomorphism,” and “meta-mildness.”

One of the clearest examples of metamodern advertising communication is a commercial for a fragrance from the “Guilty” line from Gucci. The characters in the video find themselves outside the norms of society, thereby becoming vulnerable. The video contains a pronounced personal component. The images of the main characters are hypertrophied and complex. The image of animals provides a reference to the concept of an archaic consumer culture of insatiability. In contrast to consumerism, the image of two characters who are outside the everyday dimension of their lives is built [11].

It is necessary to pay attention to the fact that the context of contemporary Russian-language research on neuromodern concerns precisely the sphere of advertising and design. If the era of premodern, modern, and postmodern are multi-domain concepts, then the emerging field of neuromodern is still limited to interpretation in the field of design. Given the speed of the introduction of AI, automated systems and other innovations into many areas of society, one can assume the presence of totalitarianism in the era of neuromodern.

Returning to the influence of the Internet and Internet technologies on the consciousness of the majority, it is worth noting that one of the markers of neuromodern may be the transition to a simulation-simulating model of life in the form of social networks, computer games, and the creation of avatars on various platforms. It has become possible to form one's own meaning and text not only through the material objects of various brands and the simulation they carry but also through the digitalization of an image, a lifestyle that may not correspond to physical reality. Marketers use the personal data of customers and potential audiences based on their digital image. They create a meaning that will be interesting to the simulation that neuromodern people put on themselves [16].

Hermeneutics in marketing accompanies all epochs. Interpretation of meanings accompanied merchants at fairs in the form of a herald text and inextricably occupies a place in the era of neuromodern, when marketers in symbiosis with AI are engaged in studying the target audience, looking for approaches and new sales strategies.

However, neuromodern marketing is much more complicated than simply using digital capabilities to analyze the target audience and promote a product or service. Otherwise, the concept of neuromodern as an epoch is leveled—an equal category of modernity, postmodernity, etc. In the authors' understanding, neuromodern is currently only beginning to emerge in the form of mechanical tools. Currently, AI

does not have the property of creating a new one. It only imitates or synthesizes what was invented by people.

Here are practical examples of the use of AI in marketing:

1. In 2020, “Sber” launched a New Year’s Eve advertisement with Georges Miloslavsky. The hero of the beloved Soviet comedy “Ivan Vasilyevich changes his profession” was “revived” with the help of AI technologies [13];
2. “Netflix” used AI-based machine learning technology to provide personalized content recommendations based on user preferences, in addition to what they liked in the past [10];
3. “Heinz” has turned to AI image generators to get a variety of design options for ketchup bottles that can be used as advertising tools on various channels [10];
4. “Coca-Cola” has expanded the scope of its marketing using AI by introducing its own consumer-oriented and AI-based creative platform [10];
5. One example of an advertising campaign launched by the “Martini” brand was created thanks to AI. The neural network has generated unique original images. The main goal was achieved—AI managed to show what is happening in each bottle of drinks better than artists and designers [12].

According to A. Parfun, Vice President of “AKAR,” the era of neuromodern “is an era defined by the total penetration of artificial intelligence into human life, which serves as a multiplier of any intellectual activity” [2].

Russian designer V. Lifanov claims that the era of neuromodern will come when AI realizes its idealistic beginning. Neural networks cannot think; they can imitate. Machines do not know how to create. We see an endless set of identical forms but not meanings [1].

The curbing of vital needs gave rise to the procrastination of the ontological essence of man as an individual. AI is still only a tool for executing certain algorithms programmed by humans. The transition from the era of consumption, with the postulates of unlimited enjoyment and gaining independence, to the pleasure economy reduces the chances of a positive outcome of humanity’s struggle with AI.

4 Conclusion

Thus, after conducting a retrospective analysis of the metamorphosis of marketing through the epochs of modernity, post-, meta- and neuromodern, the authors concluded that neuromodern is at the stage of its inception. The growth of the precariat, based on the needs of creative dissatisfaction, which has replaced the postulates of the “modern man,” gives rise to the development of AI as a tool, which will reduce the human potential of the creator in the near future, transforming him into a performer. Simultaneously, there is an alternative representation of the outcome of the interaction of AI with humanity: technologies will take over the mechanical work, freeing up human time for spiritual development and creative activity [17]. The culmination of the neuromodern era is understood by the authors as a complete

congruence of the triumph of AI over human thinking. The research on the temporality of the neuromodern era does not lead to concretizing results of the chronological structure due to the lack of iteration of this phenomenon. A full-fledged representation of the neuromodern era is impossible due to the lack of empirical experience in encountering the identification of AI with its idealistic beginnings. Humanity does not think of itself outside the subject plane. The incomprehensibility of neuromodern is akin to the teaching of eschatology—our consciousness is limited to comprehend this knowledge. The moment when AI overpowers the human personality will be not just a phase of neuromodernist marketing but an era of redefining the decadent nature of human beings under the threat of an infernal exodus of humanity.

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The Contribution of Transport Digitalization to Improving Quality of Life



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Abstract The research aims to determine the contribution of transport digitalization to improving the quality of life in Central Asia and develop recommendations for maximizing this contribution, using the Republic of Uzbekistan as an example. The authors conducted a correlation analysis to explore the relationship between government regulatory factors determining the digitalization of the transport and logistics sector and the quality of life indicators associated with this sector across all 12 Central Asian countries in 2023. The analysis reveals the advantages of transport digitalization for the quality of life in Central Asia. Government regulatory measures determining the digitalization of the transport and logistics sector are ranked by their significance for the quality of life in Central Asia. Additionally, a contradiction in the government regulation of transport and logistics digitalization in Uzbekistan is identified. The authors provide recommendations to resolve this contradiction and improve government regulation of transport and logistics digitalization in Uzbekistan. The main conclusion is that the digitalization of transport significantly improves the quality of life in Central Asian countries. The theoretical significance lies in clarifying the relationship between transport digitalization and quality of life in Central Asia. The importance of the proposed recommendations for economic policy is that they will enhance the effectiveness of government regulation of transport and logistics digitalization in Uzbekistan. The practical significance of the authors' conclusions and recommendations is that they will improve the quality of life in Uzbekistan and other Central Asian countries.

Keywords Transport and logistics sector · Transport regulation · Transport digitalization · Improving quality of life · Central Asia · Uzbekistan

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1 Introduction

The state of the transport and logistics sector plays a crucial role in maintaining and enhancing the quality of life within the socio-economic system. However, government management of transport and logistics infrastructure to improve quality of life fundamentally differs from this management to support entrepreneurship and attract investments into the economy.

The success of this activity depends, first, on the widespread accessibility of transport and logistics infrastructure. Supporting entrepreneurship often entails creating elite infrastructure for specific business structures (priority sectors and certain areas, for example, through advanced infrastructure for special economic zone participants) while improving quality of life requires universal infrastructure accessibility.

Second, it depends on the development of transport and logistics infrastructure. On the one hand, the infrastructure must be advanced to effectively meet the population's needs for transport and logistics services. On the other hand, to enhance quality of life, the infrastructure must be affordable for broad consumers (financially and in terms of knowledge). When developing infrastructure to support entrepreneurship, it is not constrained by these limitations because businesses can attract additional financial resources and necessary personnel.

Third, it relies on the even distribution of transport and logistics infrastructure across the country. To improve the quality of life, infrastructure should be accessible to all residents: those in the major cities and those in remote and rural areas. In contrast, infrastructure development to support entrepreneurship is marked by the concentration of key transport and logistics infrastructure in major industrial centers (urban agglomerations) and along the routes of product distribution.

Digitalization has given the transport and logistics sector a new impetus for development. The problem is that the existing approach to managing the digital development of the transport and logistics sector has been created and applied mainly to support entrepreneurship. Due to the aforementioned characteristics of how transport and logistics infrastructure impact quality of life, the current approach contributes limitedly to improving quality of life, which is a drawback.

Another drawback of the existing approach is that it is based on the experiences of leading digital economies. In developing economies, the impact of transport digitalization on quality of life may differ significantly. This highlights the need for a new approach to managing transport digitalization aimed directly at improving quality of life and considering the specifics of developing countries.

The experience of Central Asian countries deserves special attention because this region consists solely of developing countries. The research aims to identify the contribution of transport digitalization to improving the quality of life in Central Asia and develop recommendations for maximizing this contribution, using the Republic of Uzbekistan as an example.

2 Literature Review

The fundamental basis of this research is the scientific concept of government management in developing the transport and logistics sector [1]. This concept identifies the main factors of government regulation determining the digitalization of the transport and logistics sector. These factors include the following:

- Accessibility of information and communication technologies (ICT), particularly digital technologies [2];
- Active use of ICT, including in obtaining transport and logistics services [3];
- The development of government online services, including those supporting the use of transport and logistics infrastructure [4];
- The development of the information society, including the digital competencies necessary for using digital transport and logistics infrastructure [5].

The impact of transport and logistics infrastructure on the quality of life in a country is manifested through improvements in the following quality of life indicators associated with this sector:

- Public satisfaction with public transportation [6];
- Quality of transport logistics for the efficient distribution of goods across the country [7];
- Safety level of road transport [8];
- Accessibility of all-season roads for rural populations [9];
- Unemployment reduction due to improved access to and quality of transportation [10];
- Poverty reduction due to increased employment resulting from improved access to and quality of transportation [11];
- Carbon emissions associated with the functioning of the transport and logistics sector [12].

A literature review showed that some aspects of the functioning and development of the transport and logistics sector in Central Asia are covered in existing publications, for example, in the work of Sultanova and Babakhanova [13]. However, the role of transport digitalization in ensuring the quality of life of the population in Central Asian countries remains understudied and unknown, representing a gap in the literature.

In this context, this research poses the following research question (RQ): “What contribution does transport digitalization make to improving the quality of life in Central Asia?” To answer this research question, this research examines the impact of the aforementioned factors of government regulation, which determine the digitalization of the transport and logistics sector, on the quality of life indicators associated with this sector, drawing on the experience of Central Asian countries.

3 Materials and Methods

To comprehensively cover the socio-economic systems of Central Asia, this research includes all 12 countries whose territories are entirely or partially located in Central Asia. The research period is 2023. However, for indicators where data have not yet been calculated, the most recent and relevant official international statistics for 2023 are used.

The following designations of indicators have been introduced. The factors of government regulation determining the digitalization of the transport and logistics sector are taken from the official international statistics of the United Nations [14] and the World Bank [15, 16]. They are denoted as D. The quality of life indicators related to the transport and logistics sector are taken from the official international statistics of WIPO [17]. They are denoted as QL. The empirical basis of this research is presented in Table 1.

The methodology of this research is based on the correlation analysis. Using the selected method, the authors calculated cross-correlation coefficients to reflect the relationship between the factors of government regulation determining the digitalization of the transport and logistics sector and the quality of life indicators associated with this sector in Central Asian countries.

The arithmetic means of the cross-correlation coefficients are calculated considering their positive or negative values. This determines the impact of each government regulation factor on the quality of life. Following this, the authors identified the advantages and disadvantages of the digitalization process of the transport and logistics sector in terms of quality of life using the Republic of Uzbekistan as an example. The authors then provide recommendations for improving this process through government regulation.

4 Results

To determine the relationship between the factors of government regulation influencing the digitalization of the transport and logistics sector and the quality of life indicators associated with this sector in Central Asian countries, the authors calculated the cross-correlation coefficients based on the statistics from Table 1 (Table 2).

The results of the correlation analysis presented in Table 1 indicate that public satisfaction with public transport is not influenced by the digitalization of the transport and logistics sector in Central Asia. However, transport digitalization impacts the quality of transport logistics by 46.78%, road transport safety by 11.73%, the accessibility of all-season roads for rural populations by 39.52%, unemployment by 50.92%, poverty levels by 33.75%, and carbon emissions by 61.86%.

The availability of ICT, particularly digital technologies, affects the quality of life in Central Asia by 21.45%. The active use of ICT, including in obtaining transport

Table 1 Factors of transport digitalization and quality of life indicators related to transport in Central Asia in 2023

Country	Satisfaction with public transport, %	Logistics performance index: quality of trade and transport-related infrastructure (worst 1–5 best)	Traffic deaths, per 100,000 population	Rural populations with access to all-season roads, %	Unemployment rate, % of total labor force, ages 15+	Poverty headcount ratio at national poverty lines, % of population	CO ₂ emissions, metric tons per capita	ICT access, points 1–100	Government's online Service, points 1–100	E-participation, points 1–100
QL ₁	QL ₂	QL ₃	QL ₄	QL ₅	QL ₆	QL ₇	D ₁	D ₂	D ₃	D ₄
Afghanistan	22.0	1.8	15.9	50.4	11.7	54.5	0.2	N/D	N/D	N/D
China	85.0	3.8	17.4	85.0	4.6	0.0	7.8	82.7	87.7	86.0
India	77.0	2.9	15.6	84.2	7.3	21.9	1.6	56.2	49.2	77.2
Iran, Islamic Rep.	60.0	2.8	21.5	70.1	11.1	0.0	7.1	77.5	75.3	58.1
Kazakhstan	58.0	2.5	12.7	68.2	5.0	5.2	11.3	86.7	80.9	16.3
Kyrgyz Republic	68.0	2.4	12.7	60.8	4.8	33.3	1.4	81.8	69.2	57.7
Mongolia	40.0	2.1	21.0	66.2	8.9	27.8	6.4	84.7	76.0	59.3
Pakistan	58.0	2.2	13.0	68.0	6.7	21.9	0.8	45.4	35.1	52.0
Russian Federation	61.0	2.8	12.0	94.5	4.7	12.1	11.2	82.8	86.3	34.9
Tajikistan	80.0	2.2	15.7	60.6	8.4	22.5	1.0	49.1	12.7	59.3
Turkmenistan	71.0	2.2	13.5	57.8	5.5	N/D	10.2	N/D	N/D	23.3
Uzbekistan	84.0	2.6	11.7	70.2	6.3	14.1	3.4	79.1	74.5	60.5

Note N/D—the data for these indicators for these countries are not available in the source
Source Compiled by the authors based on the United Nations [14], WIPO [17], and the World Bank [15, 16]

Table 2 Cross-correlation of transport digitalization factors and quality of life indicators related to transport in Central Asia in 2023, %

Country	QL ₁	QL ₂	QL ₃	QL ₄	QL ₅	QL ₆	QL ₇	Mean
D ₁	-23.01	30.62	9.94*	18.10	-28.00*	-33.54*	72.85	21.45
D ₂	-19.95	50.07	7.64*	43.78	-32.39*	-47.38*	75.96	31.71
D ₃	16.62	54.87	-37.54*	51.92	-71.72*	-30.92*	48.84	44.63
D ₄	11.99	51.54	-26.98*	44.29	-71.57*	-23.16*	49.81	39.91
Mean	-3.59	46.78	11.73	39.52	50.92	33.75	61.86	34.42

Note * Negative values of the correlation coefficients for these indicators show their positive mutual influence. Therefore, when calculating the arithmetic means, the data from these cells are taken with the opposite sign

Source Calculated and compiled by the authors

and logistics services, determines the quality of life in Central Asia by 31.71%. The development of government online services, including those supporting the use of transport and logistics infrastructure, affects the quality of life in Central Asia by 44.63%.

The development of the information society, including digital competencies necessary for using digital transport and logistics infrastructure, determines the quality of life in Central Asia by 39.91%. The overall relationship between the considered indicators is estimated at 34.42%. In Uzbekistan, among the government regulation measures determining the digitalization of the transport and logistics sector, ensuring ICT availability is most actively practiced (evaluated at 79.11 points in 2023), which has the least impact on the quality of life in Central Asian countries.

In contrast, the development of government online services, which is of paramount importance for the quality of life in Central Asian countries, is at one of the lowest levels in Uzbekistan (evaluated at 71.71 points in 2023) among the government regulation measures determining the digitalization of the transport and logistics sector.

The active use of ICT, playing a secondary role in ensuring the quality of life in Central Asian countries, is evaluated in Uzbekistan at 74.48 points in 2023. Similarly, the development level of the information society, which plays a secondary role in ensuring the quality of life in Central Asian countries, is evaluated in Uzbekistan at 60.46 points in 2023, representing the lowest level of development among the government regulation measures determining the digitalization of the transport and logistics sector.

To improve government regulation of the digitalization of the transport and logistics sector in Uzbekistan to enhance the quality of life, it is recommended to intensify the development of government online services related to supporting the use of transport and logistics infrastructure.

5 Discussion

This research contributes to the literature by developing the concept of government management in developing the transport and logistics sector, clarifying the relationship between transport digitalization and quality of life in Central Asia. As a result of the research, the authors re-evaluated the role of government regulation factors in determining the digitalization of the transport and logistics sector and ensuring the quality of life in Central Asia.

In contrast to Sultanova and Babakhanova [6], the authors substantiated that public satisfaction with public transport is unrelated to digitalization in Central Asia. The authors also proved that the digital development of the transport and logistics sector in Central Asian countries ensures the following:

- Improvement in the quality of transport logistics (as confirmed by [7]);
- Increase in road transport safety (as confirmed by [8]);
- Enhanced accessibility of all-season roads for rural populations (as confirmed by [9]);
- Reduction in unemployment (as confirmed by [10]);
- Alleviation of poverty (as confirmed by [11]);
- Reduction in carbon emissions, contributing to the decarbonization of the economy (as confirmed by [12]).

6 Conclusion

The main conclusion of this research is that transport digitalization significantly contributes to improving the quality of life in Central Asian countries. This contribution is manifested in the following advantages of transport digitalization for quality of life in Central Asia (listed in order of decreasing impact): reduction in carbon emissions, leading to the decarbonization of the economy (correlation of 61.86%), reduction in unemployment (correlation of 50.92%), improvement in transport logistics quality (correlation of 46.78%), increased accessibility of all-season roads for rural populations (correlation of 39.52%), alleviation of poverty (correlation of 33.75%), and enhancement of road transport safety (correlation of 11.73%).

Government regulation measures determining the digitalization of the transport and logistics sector are ranked by their significance for quality of life in Central Asia. The highest significance is attributed to the development level of government online services, including those supporting the use of transport and logistics infrastructure (impacting quality of life by 44.63%).

The second most significant factor is the development of the information society, including the digital competencies necessary for using digital transport and logistics infrastructure (impacting quality of life by 39.91%). The third most significant factor is the active use of ICT, including in obtaining transport and logistics services

(impacting quality of life by 31.71%). The least significant factor is the availability of ICT, particularly digital technologies (impacting quality of life by 21.45%).

The authors also identified a contradiction in the government regulation of transport and logistics digitalization in Uzbekistan. This contradiction lies in the fact that, on the one hand, the development of government online services, which is of paramount importance for the quality of life in Central Asian countries, is among the lowest (evaluated at 71.71 points in 2023) among the measures of government regulation determining the digitalization of the transport and logistics sector in Uzbekistan.

On the other hand, the availability of ICT, which has the least impact on the quality of life in Central Asian countries, is the most actively practiced (evaluated at 79.11 points in 2023) among the measures of government regulation determining the digitalization of the transport and logistics sector in Uzbekistan. The authors provide recommendations for resolving this contradiction and improving government regulation of transport and logistics digitalization in Uzbekistan.

The significance of the proposed recommendations for economic policy lies in their potential to enhance the effectiveness of government regulation of transport and logistics digitalization in Uzbekistan. The practical significance of the authors' conclusions and proposed recommendations is that they will help improve the quality of life in Uzbekistan and other Central Asian countries.

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How Generative Artificial Intelligence is Impacting Marketing



Ruslan R. Gabidullin and Elena V. Krutina

Abstract The research examines the impact of generative artificial intelligence (AI) on marketing. The focus is placed on evaluating recent advances in generative AI algorithms and their potential to transform approaches to content marketing, trend analysis, forecasting, and changing the roles of marketers. The authors also discussed ethical and legal issues arising from using neural networks in content creation. The authors analyzed current research and publications focusing on the application of generative AI in marketing. During the research, the authors reviewed the methods for content generation and conducted a comparative evaluation of neural networks based on their accessibility threshold. Key findings include an assessment of the potential of generative AI to automate content creation, data analysis, and trend forecasting in marketing. The changing roles of marketers are also discussed, highlighting the ethical and legal aspects of using generative AI in this area. The novelty of this research lies in its comprehensive examination of the impact of generative AI on various aspects of marketing activities, as well as in identifying the ethical and legal issues associated with its use.

Keywords Generative artificial intelligence · Marketing · Content marketing · Data analysis · Prediction · Ethics

JEL Classification J15

1 Introduction

Integrating artificial intelligence (AI) into contemporary marketing processes has been a notable phenomenon. In the context of Industry 4.0, where data volumes are growing exponentially, generative AI has emerged as a crucial tool for companies and marketers striving to maintain competitiveness in a dynamic and demanding

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market environment. This research will examine the evolution of generative AI and its significant impact on marketing strategies and practices. These changes can open new avenues for more effective audience interaction, increased conversion rates, and enhanced customer experiences.

Despite the significant advances in the field of generative AI algorithms, there are still many questions and issues that require further study and analysis. Particularly, the ethical and legal issues associated with using generative AI in marketing are considered, as well as the changing role of the market.

The research aims to analyze recent advances in generative AI algorithms and their impact on the marketing domain. The research objective is to identify the benefits and limitations of generative AI in different marketing domains and analyze its potential influence on future digital marketing strategies and practices.

The following tasks are proposed to achieve the aforementioned objectives:

- To review the latest achievements in generative AI algorithms and their application in marketing;
- To examine the methods of content generation using generative AI and its impact on content marketing;
- To examine the changing role of marketers in the context of the implementation of generative AI;
- To discuss the ethical and legal aspects of using generative AI in marketing and propose recommendations for effectively managing these aspects.

The research provides a deeper understanding of the role of generative AI in marketing and identifies ways to optimize its use, considering ethical and practical considerations.

2 Materials and Methods

The works explore the features of implementation and use of AI in marketing by Abaev et al. [1]; Anokhina and Krutovtsova [2]; Azoev, Aleksandrova and Aleshnikova [3]; Khachaturyan [4]; Makhmetova, Kublin and Sharapov [5]; Melnikova, Lopatkin and Kozheva [6]; Saitova [7]; and Shevchenko and Tatevosyan [8]. Despite the large number of publications on related topics, the issue of using AI in marketing and its ethical and legal aspects are undefined and insufficiently studied in contemporary science.

3 Results

Some models of generative AI are facilitating the work of marketers, including ChatGPT 3.5/4, developed by OpenAI. This is one of the most advanced text generation models, enabling the creation of high-quality text materials such as advertising

copy, blogs, emails, and much more. Marketers can use ChatGPT to automate the content creation process. Midjourney is another model that specializes in generating images from text descriptions. The application of these models allows marketers to create visual content with minimal effort. For example, marketers can describe a product in words, and Midjourney will generate the corresponding image.

DALL-E generates images based on textual requests from the user with a higher level of abstraction. This allows for creating unique and attractive visual content for advertising campaigns. For instance, a marketer could utilize ChatGPT to generate textual content and Midjourney or DALL-E to create the corresponding visual imagery, which makes it possible to create complex “creatives” with minimal time and effort, thereby increasing the efficiency of marketing campaigns and allowing marketers to respond promptly to market changes.

Furthermore, neural networks facilitate the analysis and interpretation of images and videos. They are useful for analyzing advertising clips and photographs to understand the specific elements that attract consumer attention [2].

The utilization of neural networks in the routine activities of social media marketers encompasses the planning of projects, the definition of objectives and goals, and the creation of text posts. These neural networks perform a “smoothing” function in communications with partners, rendering them more concise and clearer [6].

The following example input was provided to ChatGPT: “Write a post about the dangers of sugar. The text should be 300 characters in length and should be divided into paragraphs. No lists should be included.”

The output generated by ChatGPT was as follows:

Sugar creates an addiction similar to drugs. Excess sugar in the diet leads to obesity, type 2 diabetes and heart problems. Excessive sugar consumption has a negative effect on the skin and teeth, increases inflammation and reduces the body's immune defenses.

The above is an example of how a ChatGPT SMM specialist might write a social media post.

Many neural networks can create conceptual layouts for banner ads. A user inputs a text request, which the algorithms analyze to generate an image. This input text is known as a prompt. A prompt consists of a set of words and phrases that fully describe the characteristics of the image the neural network is to create. This information is formatted using specific templates and linguistic structures [8].

More complex neural networks, which can process a larger volume of information, are used to create advertising banners. The entry threshold is relatively moderate: the user should have basic knowledge of the prompt formation process. There are online and offline models. Offline models use the resources of a personal computer or a specialized server for generation. The authors compared neural networks by entry threshold (Table 1). The following criteria were identified to assess the entry threshold:

- Cost (paid—1 point; free—0 points);
- Platform used (app/browser—0 points; other—1 point);

Table 1 Comparison of neural networks based on the principle of entry threshold assessment

Name	Paid/free	Platform	Supported languages	Entry threshold
Midjourney	Only the paid version is available	discord	English only	High. Advanced prompt functionality
Stable diffusion	Free, some features are paid	Browser access	English only	Average. Intuitive and unintuitive interface
DALL-E	Only the paid version is available	Browser access	Multilingual	Average
Kandinsky 3.1	Free	Browser access	Multilingual	Low
Shedevrum	Free	Browser access	Russian and English	Low. On the platform there are examples with images of other users

Source Compiled by the authors

- Language support (less than two—1 point, two or more—0 points).

The total points are then summed to provide an entry threshold rating. The rating is as follows: 3 points—high, 2 points—above average, 1 point—average, and 0 points—low.

The entirety of the “Maslenitsa-2023” advertising campaign by Teremok, a Russian fast-food chain, is the result of the utilization of multiple neural networks. Initially, the Midjourney model was employed to create the visual representation of Maslenitsa for this campaign. Subsequently, D-ID was employed to transform the static image into a video clip [7]. The ChatGPT model generated the texts for this video. Furthermore, a neural network was employed to create posts on Teremok’s official accounts during the Maslenitsa week. The campaign’s visual design was developed using the Stable Diffusion model. Texts for the video and the posts were generated using the ChatGPT model.

The most critical function of AI-based analytics is to assist in forecasting based on existing data. AI can predict what products will interest a user by analyzing their past purchases and online searches. Additionally, AI can forecast potential demand for a company’s products, which allows for properly planning supply quantities and production loads. This also makes it possible to accurately determine the necessary purchase volumes [3].

AI makes it possible to analyze and understand natural language. It is a useful tool for analyzing customer feedback, social media comments, and emails [1]. Text analytics helps companies understand what people think about their products and services and how to improve their marketing strategies. With this technology, it is possible to gather information from all mentions of a company in a short period, analyze it, and identify the main issues that users are facing [4]. This is a good

opportunity for large companies, often mentioned in the media, to significantly save time.

With the development of generative AI in marketing, the role of the marketer is changing significantly. Traditionally, marketers have been involved in content creation and distribution. However, implementing AI has shifted the focus from performing operational tasks to more strategic functions such as strategic planning and analysis.

This transition reflects a move away from routine tasks such as content creation, campaign management, market analysis, SEO, and data collection and analysis of marketing campaign performance, to a more strategic and analytical approach to marketing, where AI becomes a tool to improve the efficiency and scalability of marketing processes. Marketers need skills in selling products, skills in technology, and an understanding of the requirements of AI to formulate tasks for it properly [5]. Potential future roles for marketers include strategic planning and optimization, content personalization, data analysis using machine learning, and the management and use of intelligent systems.

The use of generative AI in marketing is transforming the role of marketers, making them strategic professionals capable of analyzing data and developing effective marketing strategies based on the results of AI algorithms.

However, the use of AI to create content raises issues of copyright and authenticity. As AI can generate text, images, video, and audio, it is necessary to determine who owns the rights to the content created. It is unclear who should be considered the author of the generated material—the algorithm developer, the system operator, or the algorithm. There is also a risk of fake or manipulated content being created, which could lead to a loss of consumer trust and brand damage.

Transparency is also an important part of using AI in marketing. Marketers and companies need to be honest and open with consumers about the fact that some content has been created using AI algorithms. This will help build trust with consumers and prevent negative consequences if they discover they have been deceived.

Russia develops a system to comprehensively regulate public relations related to the development and use of AI technologies, including the following:

- Normative legal regulation;
- Normative technical regulation;
- Ethical regulation.

Currently, the authorship of works created exclusively by a machine cannot be protected under Articles 1255 and 1257 of the Civil Code of the Russian Federation because the copyright belongs to the citizen whose creative labor has created the work of science, art, and culture [9]. The same is true in the USA.

Recommendations identified for effective management of ethics in AI include the following:

- To develop and implement ethical standards and norms for using AI in marketing, including principles for content creation, transparency of use, and protection of personal data;
- To ensure compliance with copyright and privacy laws in the development and use of generative models;
- To establish principles of transparency and openness in communicating with consumers about the use of AI in marketing;
- To actively engage with legislators, regulators, and public organizations to develop and implement legal and ethical standards for using AI in marketing.

4 Conclusion

Generative AI is playing an increasingly important role in the evolution of marketing, offering marketers unique opportunities to improve the effectiveness and efficiency of their strategies. In this research, the authors examined several key aspects of the impact that AI has on marketing and highlighted the likely prospects for its development.

The future of generative AI in marketing represents a promising area for advancement. Nevertheless, it requires attention to ethical and legal aspects to ensure its fair and responsible use in digital marketing strategies.

Data Availability An example of using a combination of neural networks to create an advertising campaign is available at <https://figshare.com/> with the identifier <https://doi.org/https://doi.org/10.6084/m9.figshare.26042560>.

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The Formation of a New Model of International Production and Finance in the Context of Industry 4.0



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Abstract The paper provides a detailed analysis of the main features of the world's economic development. The authors explore the crisis agenda and focus on the problems that together form the process of changing in its current model. The authors give grounds for changes in the traditional production processes, logistics, consumption, and finance, resulting in a new model as a new combination of progressive forms of economic relations in the context of Industry 4.0, which is an objective process of economic and technological progress of the world community and digitalization and is a way of its development. Simultaneously, it is shown how the previous model loses its effectiveness; it is expressed in the total factorial return decrease and economic paternalism increase. It is noted that the systemic crisis of 2008 became the boundary of the model change of the world economy and a starting base for the transition to an open phase. A long period of low interest rates and the actual pumping of the financial system with unsecured liquidity was the result of the attempt to overcome the crisis. The authors explain how manufacturers built up new projects relying on cheap credit, including the industries of the previous model. The main triggers of the current system are international protectionism, supply chain disruptions, and delayed inflationary effects due to high global debt and supply shocks.

Keywords Industry 4.0 · Digitalization · World economy model · World trade · GVC · Stagflation · Inflation · Trade wars · New mercantilism · Globalization

JEL Classification F02

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1 Introduction

The COVID-19 pandemic has become a significant marker of the scientific mainstream evolution toward forming the stagflation agenda, as we see it at the end of 2022. However, even this simple renewal of scientific rhetoric required two difficult years of research and verification, although even the middle of the 2000s was marked by some significant works [10] that determined the systemic crisis of the contemporary model of the world economy. This problem has been clearly seen [13] in 2022, especially on the background of rapid corrections to the negative forecasts for the development of the world economy from respected international organizations of the UN Statistics Division, the World Bank, the IMF, etc. The UN Statistics Division initially issued a pessimistic forecast [6], supported by the World Bank. Then, the IMF also changes its rhetoric, adjusting its April forecast for a more pessimistic one in July [3]. Simultaneously, Bloomberg, Financial Times, and others add the pessimistic mood already being broadcast to the general public. As a result, financial aces and ordinary investors paid attention to the record forty-year income inversion of American Treasures (the difference in the profitability of two-year and ten-year Treasures reached 57 basis points, which is the lowest value since 1982. According to statistics, over the past fifty years, recession follows after an inverted Treasures yield curve. The average waiting time for such an event is 311 days. In 2019, an inversion could be observed in relation to ten-year and three-month Treasures. However, there was a serious recession in 2020, which was initially attributed to the COVID-19 pandemic. In 2022, it seems that such an attempt to attribute the impending collapse to a separate event of a military-political nature is unlikely to succeed, the global financial system has lost stability. Through the veil of political news, the voices of Goldman Sachs, JP Morgan, Deutsche Bank, and others are heard more loudly, predicting a long recession awaiting the world community. Nouriel Roubini suggests [2] that the new crisis will surpass the crisis of the 1970s in terms of consequences severity and processes complexity and will be inherently stagflation, the regulators will not have the opportunity to resist it against the backdrop of international debt overload problems. Indeed, drawing parallels with the period of the late 1970s and the early 1980s, we can observe multiple overweight of the world's debt. In the specified period, the ratio of world debt/world GDP did not exceed one. By the end of 2022, this ratio reached 3.5 or 350%. If we evaluate this figure among economic leaders, among national economies that are considered developed, this indicator will be 4.2 or 420% of GDP. Price dynamics create similar concerns. According to its Commodity Market Outlook, the World Bank predicts that energy prices will rise by 50%, and non-energy prices will increase by at least 20%; this forecast is made against the background of a record price rise for metals and food.

In this research, the authors do not just want to focus the attention of the key players on the problem of supply shocks cascade in an inflationary economy [9] or the stagflation problem in itself. The research aims to justify the transition from one world economy model to its new type based on fundamentally different principles of international production organizing and finance [12]. For this purpose, as a first

step, it is necessary to uncover the inner nature of the outgoing model of the world economy and understand the digital context as the process of its weakening. Then, it is necessary to determine the triggers of the ongoing transition and make an attempt to outline the contours of the new model and draw conclusions analyzing its features.

2 Methodology

The research uses the following methods:

- Theoretical generalization and comparison;
- Analysis and synthesis;
- Comparison and generalization;
- Abstract-logical, system-structural, and empirical analysis.

To understand the current changes in the global economy models, it is important to remember the year 2008 that became a threshold dividing the previous model's rapid growth from its degradation.

Publications more often refer to the first period as hyperglobalization [5], and call the second slowbalization [7]. Representing the share of exports of goods and services in world GDP over time, Fig. 1 clearly shows a period of active growth from around the early 1990s to 2008 and an obvious plateau lasting from 2008 to 2020. In 2008, the share of exports of goods and services in world GDP reached a peak of 31.2%, in 2021, this share decreased to 21%. In other words, the progress in world trade has noticeably slowed down, resulting in a decrease in the average annual growth rates of world GDP, which reached an average of 4% in 1995–2008 but dropped to 3% in 2008–2020. Simultaneously, the share of GVCs in world trade decreased from 55 to 44% in 2021, an indicator that steadily grew going from 35 to 55% in 1970–2008.

According to the statistics, 2008 became a milestone in the development of international trade, transforming its landscape dramatically. Measures proposed by the Federal Reserve System to readjust the world economy model that was based on the growth of world trade and its core and GVCs, allowed to delay the collapse. However, the problems turned out to be systemic. Thus, when the measures exhausted their potential, the challenges resurfaced in a more acute form.

The institutional transformations of the 1970s–1980s were of unsurpassed importance for the future world economy because they provided a reliable foundation for developing technologies that are now commonly known as Industry 4.0. Interestingly, despite its obvious meaning, there is still no clear understanding of it and no standard definition. For example, some experts understand Industry 4.0 as “a number of economic areas with fully automated production” [1]. Others attempt to standardize the characteristics of the industry by generating experimental indicators [4], structuring the digital trend into digital transactions, products, and the industry itself.

However, from the authors' perspective, Industry 4.0 is primarily an objective process of economic and technological progress of the world community, which can make a country a leader or an outsider depending on how successful it is in achieving it. In this sense, digitalization is a way to develop Industry 4.0.

Digitalization changes conventional patterns of production, logistics, consumption, and finance. Namely, it changes the economic foundation (i.e., the totality of economic relations and principles). The economic paradigm is also changing. Its visible manifestation is the decline of traditional industries as a result of changes in investment flows [3]. There is a noticeable slowdown in GDP growth and even stagnation at the level of national economies.

The post-war economic miracle of the 1950s–1960s created productive forces, which, as a result of the institutionalization of the 1970s–1990s, were used properly from an economic point of view, thus creating the basis for the emergence of a model of international exchange on the axis the US-China. The period from 1990 to 2008 was marked by high growth rates of aggregate factor productivity; the US and China became world economic leaders. In 1990–2008, the cumulative factor productivity in the USA was at 3.9% annually. Net accumulated direct investments in China in the 1990s increased two to three times annually; as a result, China became the leader in world exports. In 2020, China (\$2.66 trillion) managed to outperform the USA (\$2.514 trillion) in terms of exports.

World trade based on the development of GVCs has become the driver of the world economy's current model and networks of international corporations have begun to determine the direction of investment flows and, consequently, the development trajectories of countries and regions.

However, by 2008, the current model of the world economy was dealt a serious blow. Digitalization has made the world go global; national financial systems put together created a world of open finance and investment. The global financial architecture has changed dramatically. World money has become extremely mobile; a speculative component has become more prominent in its structure. Digitalization has led to a change in the structure of monetary aggregates [8], the M0—cash aggregate has lost a lot of ground; crypto-money has become a new reality.

Within the new context, traditional industries that make up the majority of the contemporary economy, from 99% in developing countries to 75% in developed ones [8], turned out to be less attractive from the point of view of investments. After the financial bubbles burst in 2008, the cumulative factor yield decreased from 3.9 to 2% in the USA, in China, its growth was no higher than 0.2%. It radically changed the prospects of the world economy and gave rise to the “sovereignization” of crises in the USA and China, the mechanism of trade wars was activated, leading to the revival of modern mercantilism. In the context of growing protectionism, the previous model loses its effectiveness resulting in a decreasing total factor profitability while giving rise to economic paternalism; the model's crisis becomes self-sustaining.

3 Results

Even though publications revealing the nature of what had happened appeared in 2008, it remained hidden from the mass investor. The public rhetoric of regulators was reduced to outlining the need for appropriate regulatory measures, which eventually resulted in a policy of forced pumping of unsecured liquidity into the global financial system.

Monetary easing, known as a series of QE policy actions, which is, in fact, a continuous injection of unsecured liquidity, has reached an unprecedented level—a fact that bankers do not like to advertise nowadays. For the first time in history, the Fed's rate was lowered to 0.5% and was held on that level from 2009 to 2016; during the “black swan” of the COVID-19 pandemic, the rate was lowered even more to 0.25% and stayed this way for almost two years until recently.

In fact, in the context of an ever less effective international exchange model, the classic scenario of triggering the inflationary spiral described in student textbooks was played out, this is why the only thing necessary for a full-fledged inflation storm was time.

In fact, monetary easing was supposed to fulfill the firefighter's task of putting out fire. In the face of growing protectionism that prevents changing the downward trend of aggregate factor returns in the USA and China, the new money could not be fully used for investing into the manufacturing sector. The changed financial architecture easily swayed it towards portfolio investment; as a result, banks' intermediary role was reduced, and insurance and pension funds took their place in investment processes. Manufacturers used the new money to save previous projects and, with the help of cheap loans, develop new ones, including in the retreating model's industries. Simultaneously, consumers were getting used to a lifestyle they could not afford. As a result, in the context of low factor profitability, such a system led to an uncontrolled increase in global debt. As it was to be expected, the debt in the center of the system was larger than that of the financial periphery. Hence, the ratio reached 420% in developed economies and 350% in general.

As for the second party to the general exchange model (i.e., China), it did not have an instrument similar to the QE of the US Federal Reserve. Over the past decades, in its newly acquired status of a leading exporter, China has not been able to increase its share in the global financial system over 2.3%. Therefore, in response to the glitches in the model, an attempt was made to move national corporations further upstream in the GVCs that make up the core of the model based on world trade.

New methods for analyzing the development of GVCs [14] show that despite the size of exports from China, its position in the value chains is very disadvantageous. Tentatively speaking, Chinese corporations are in the middle of the well-known smiling curve [11], which means that businesses mostly concentrate on assembly and, accordingly, that China receives a disproportionately lower added value from its contribution to international exchange.

This policy (i.e., open use of administrative resources in corporate competition) was naturally perceived as an unfriendly act. However, the genie was released from

the bottle, and the USA took some protectionist measures in response to the steps taken by China. The logical result of this exchange of blows did not take long; world trade began to stagnate. Simultaneously, the involvement of both countries in GVCs stopped growing and stabilized in the 2010s at a level below the global average of 43.5%, with China and the USA at 32 and 35%. The export growth rate in China decreased from 18% in 2000–2010 to 5.2% in 2010–2020. In the USA, the indicator also stabilized at a level not higher than 5%. However, more depressing was the fact that the rate of GVCs decreased from 9.7% annually in 2000–2010 to 3.8% in 2010–2020.

As a result, trade wars that started long before the COVID-19 pandemic actually hindered world trade at its core no less effectively than administrative pandemic-related restrictions. Therefore, the pandemic can be considered as yet another restriction on international trade, seamlessly fitting into the trend that had been accelerating in the previous decade.

Against the background of low factor profitability under the international economy's previous model, growing mercantilism together with monetary regulation have become a perfect starting point for a cascading supply-related shocks. The agenda of the post-COVID, military and political reasons behind the inflationary surge in 2022 is still relevant in politics. However, since the late 2010s, the scientific community has begun to make publications focusing on the inflationary agenda [5], a strong theoretical foundation was provided for supply shocks in the modern world economy.

According to the Bureau of Labor Statistics [13], consumer inflation in the USA in 2021 was 7%, at a time when there was no talk of major military-political conflicts. In the context of surging demand, the anti-COVID restrictions were strict and became a certain deterrence for producers. Nevertheless, this did not create an inflationary spiral a year ago.

On the contrary, the price surge occurred according to the scheme of supply shock that has become a classic since the 1970s, when the first inflation wave came from commodity markets after a long period of monetary easing. In 2022, the World Bank registered a 50% increase in the price of raw materials [2], this is not only energy raw materials but primarily aluminum (37%), nickel (51%), metals in total (15.8%), wheat (42%), fertilizers (69.3%), etc. A reactive increase in the price of gas and oil in Europe is striking. In general, prices for energy resources in the world have risen by about 30%, which does not point to any other reasons for the inflation surge besides the economic ones. On the contrary, the situation resembles the classic revaluation of commodity assets during a “monetary flood,” its harbinger in the 2010s being the active development of the cryptocurrency market and its price rally.

A cascade of supply shocks in itself is not a novelty. However, in the context of a retreating world economy model, it makes stagflation inevitable. Demand inflation is well-known to have a monetary solution, while supply inflation is more complicated. Nowadays, it all goes down to the issue of international debt accrued when loans were extremely cheap.

The year 2022 passed under the sign of monetary restriction by the US Federal Reserve, which has resulted in a collapse in stock markets. Companies are deprived

of a source of cheap financing, debt instruments turn out to be beyond the reach of many, which actually takes the system back to the period before large-scale QE. Traditional industries are losing ground. Companies are facing more losses. Market clearing, suspended in 2009, is being restarted. The international debt parameters constrain the actions of the Fed, otherwise the public sector will also be facing multiple bankruptcies much like the commercial one, as proven by the government crisis in September–October 2022 in the United Kingdom.

Given these triggers, the long-lived springs of the old mechanism break down, trade wars prevent international cooperation from going back to business as usual, and the growth of total factor profitability within the global economy model. The usual monetary regulations faced the problem of excessive international debt (i.e., the monetary authorities are forced to raise rates), giving rise to supply shocks more powerful than during the COVID-19 pandemic. In turn, they create a solid foundation for inflation to move from the monetary sphere to production, severing less effective corporate ties and eliminating the affected businesses: markets are being cleared; it is the most efficient manufacturers that fit Industry 4.0 profile that will be able to stay afloat.

The totality of these triggers became the release mechanism for the change of international production and finance model that was latent up until 2020, so that the new reality gave rise to publications dedicated to the fragmentation of the world economy [6].

However, by the end of 2022, though it was important to acknowledge the very fact of fragmentation, publications that link the current fragmentation with the world economy qualitative transition are gaining recognition.

Fundamental investment shifts are occurring against the background of the weakening of the so-called North. The World Bank notes a serious migration of foreign direct investment to the south, where liberal-minded governments create the most comfortable conditions for international corporations to be based in new regions, conduct R&D, and deal with finances and production. There emerges a kind of co-evolution of state capital and international corporate networks, which becomes the driver for developing a new economic model. Its effectiveness is growing, attracting international finance. The share of South East Asia in global FDI increased from 11.9 to 13.7% in 2020, by another 19% in 2021, with the total amounting to \$619 billion.

According to Baldwin [4], digital technologies in the context of the accelerating Industry 4.0 trend make new business models relevant, creating opportunities for the most effective localization of its individual elements, reducing the costs of moving across borders, and creating opportunities for harmonization of production and delivery.

By changing business processes, the digital trend is changing the trajectories of regional development, redirecting investment flows, which, in turn, change the economic landscape. New centers of economic power are emerging, based on a more progressive combination of technology, capital, and labor.

In this regard, the process of globalization of the world economy is accelerated, contrary to the opinion originating from 2020 about its disruption and even reversal

due to the pandemic. Thus, under the new economic model, the world will remain global. The globalization trend will even accelerate, while cost inflation rising in 2022 will change relative prices and will contribute to the active clearing of markets, which, according to the Dixit-Stiglitz-Krugman model, will reinforce the trend of capital concentration meaning a further strengthened corporate core of the world economy and its development in the form of GVCs.

With relatively higher total factor returns, new strengthened economic centers developing in the context of Industry 4.0 create new markets and make global consumption polycentric, which requires a change in the global financial architecture and calls into question the dominance of the Fed as a lender of last resort. Fighting in the financial sector causes more economic and political blockage and strengthens regional integration processes, as a result new reserve currencies are put on the agenda. In parallel, crypto-money projects are being discussed in financial circles.

4 Conclusion

Together, the characteristics described above show us the outline of the new model of the international economy:

- The new model of the world economy solves the problem of a growing total factor productivity with the help of the co-evolution of the state and corporations in international GVCs.
- This co-evolution is possible only in the form of a free market and investment mobility thus creating the basis for the most effective placement of manufacturers within international networks.
- GVCs networks are the production and technological core of the new model.
- As part of the creation of a new model, a transition to a polycentric consumption pattern is underway.
- The creation of a new model of the world economy requires global financial reengineering based on crypto-money, and, accordingly, a revision of the role of banks as investment intermediaries.
- Tectonic shifts in the global economy will require a significant revision of the role of the national government in the new system of socio-economic coordinates.

Simultaneously, against the background of the currently unfolding stagflationary process that is part of changing world economy models, it is important to understand that this change inevitably implies a severe economic crisis, which is likely to become protracted and will be accompanied by new socio-political disruption. In this sense, the transformation process is not exclusively positive because it is based on Industry 4.0 presupposing a serious labor-saving trend. This inevitably means more socio-political negativity.

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The Specifics of Digital Banking and Opportunities for Its Development



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Abstract The twenty-first century is the era of information technology development, where society sets a high bar of requirements driven by technological innovation. It is no coincidence that along with the quality of service, customers began to seek high speed of service. Implementing the latest technology in the banking sector and its targeted application are gaining increasing importance and demand. While the shift to digital technology is not a new process in the global banking industry, implementing such technology for Armenian banks is gaining momentum and is an increasing trend. Armenia still has a way to go until the digital transformation in banking reaches its peak. However, certain prerequisites can boost the country's digital banking development. The research aims to study the specifics of digital banking, consider the experience of various countries and companies on their digital banking journey, and discuss the opportunities for developing this area in Armenia.

Keywords Modernization · Bank · System · Technology · Service · Innovation · Economics

JEL Classification G21 · G24 · O31 · O33

1 Introduction

Nowadays, the streamlining of banking operations is a priority item on the agenda of banks since it is what drives the competitiveness of banking services, shapes the market for various services, and expands the digital banking scope. Over the recent decades, the banks have been heavily applying the unprecedented advancement of science and technology. Modernization of the legacy banking industry and its dynamic development primarily depend on having reliable and high-tech digital banking solutions. Implementing digital banking technology in banks leads to the

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automation of business processes, cost-cutting, improvement of efficiency, etc. The integration of information technology into Armenia's economy is a pressing task. The first step on the way of achieving this task is a thorough study of various problems, conditions, and bottlenecks.

2 Methodology

The authors applied various methods during the research, including examination, analysis, and graphic methods.

3 Results

3.1 *Analysis of the Current Situation in the Armenian Banking Sector*

Nowadays, the need to improve service efficiency and the increasing competition require modernization and optimization of banking services at various levels. As a result of the intensive development of the banking industry, as well as the growth of competition, commercial banks have to diversify their business, search for still empty niches of business development, and expand the range of services offered to customers [5].

Figure 1 demonstrates the competition among the commercial banks in Armenia by the number of digital banking users.

According to Fig. 1, almost all banks except Mellat Bank are providing digital banking services. In 2022, the largest number of individuals using distance banking services was registered by Acba Bank (24,560 customers), followed by Ameriabank (24,500 customers) and Inecobank (19,000 customers). ID Bank, Evocabank, and Ardshinbank have also demonstrated high indicators. HSBC, Armeconombank, and Artsakhbank are lagging behind.

The digital banking transactions are performed via mobile apps and payment cards. Let us see the volumes of card transactions in Armenia per the distribution channel.

In 2020–2022, the volume of transactions made via ATMs dropped by 14.7%. As of June 2023, the volume of transactions made via ATMs increased by 1.1% as compared to the previous year. The volume of transactions via POS terminals in the 2020s has risen. In 2021–2023, the volume of non-cash transactions made in the online environment increased by 9%. The same dynamics can be observed in the number of transactions.

Mobile banking services have a predominant share of the services offered. As of June 2023, it had a share of 35% in the total digital banking services, followed

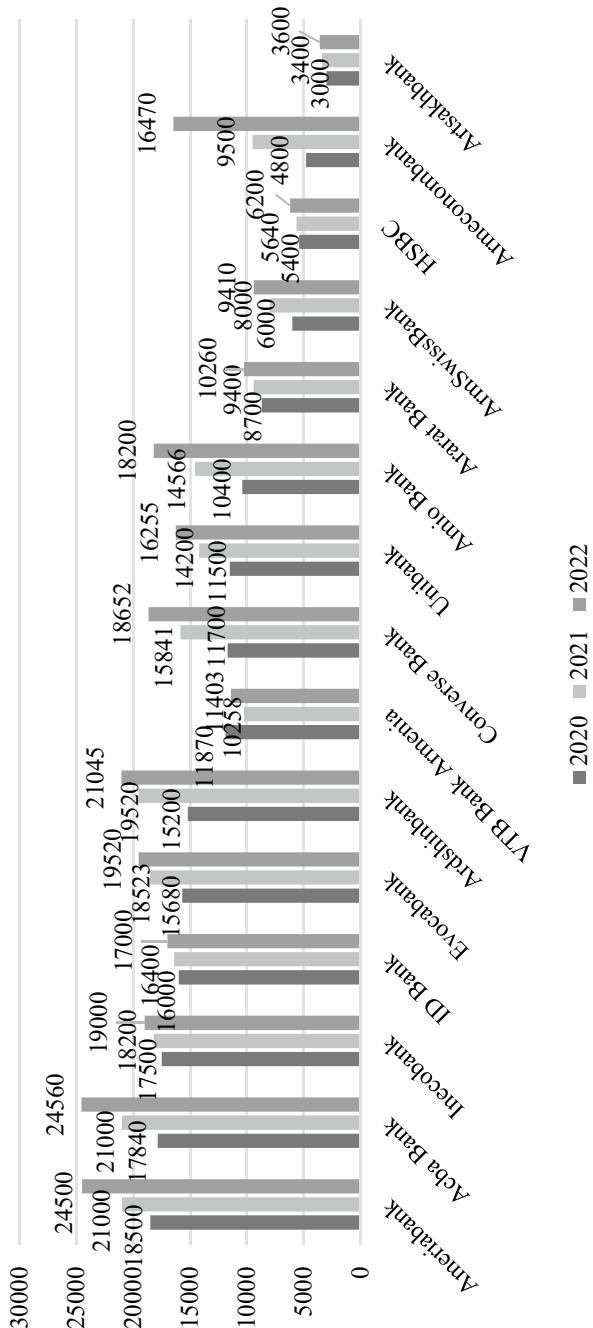


Fig. 1 The number of digital banking users in Armenia, 2020–2022. *Source* Compiled by the authors based on Central Bank of Armenia (n.d.)

by payment terminals (23%) and e-wallets (20%). The share of other services was small. Let us look at the share of digital banking transactions in the total banking transactions. In 2019, the volume of digital banking transactions grew by 1.3% YoY. There was a surge in 2020 due to the outbreak of the COVID-19 pandemic. In 2020, the share of digital banking made 37.4%, up by 6.1% YoY. In 2021, there was a decline in the share of digital banking by 1.9%. In 2022, it was almost flat at 35.4%. The highest indicator in the considered period was registered in 2020, driven by COVID-19, which limited the number of customer visits to banks and caused customers to shift to digital banking transactions [2].

Thus, the development of high technology is of critical importance for increasing a country's competitiveness, security, and living standards. Countries that develop and advance high technology change the competitive environment and gain leading positions internationally. To advance the digitalization process in Armenia, commercial banks should be equipped with the relevant professional resources that will enable the banks to collaborate with the relevant agencies and authorities, develop relevant terms of reference, including the requirements to the digital solutions, technical specifications, digitalization processes, etc. This is a professional function assuming the involvement of the best professionals in this field.

3.2 The International Experience of Digital Banking Development

Digital banking is of key importance for the international banking industry. Nowadays, digital banking is considered to be an advanced and highly effective technology. Digital banking allows banks to increase the effectiveness of their operations and the level of innovation and cut certain costs. Customers may enjoy more convenient, smarter, and safer banking, from online payments to making deposits online [8]. Digital banking also makes it possible to optimize the banking processes from the loan decision making to managing financial risks.

Figure 2 shows the adoption rate of digital banking in the banking sector of various countries.

According to the data provided, the USA is the leader in the digital banking adoption rate, with a 51% adoption rate in 2022. The USA is followed by China (48%), France (47%), Germany (46%), and the UK (46%). The countries with the lowest adoption rate of digital banking are South Africa (12%), Mexico (20%), and Chile (22%). While Argentina and South Africa have registered the lowest digital banking adoption rates, they are leaders in terms of relative growth.

The results of the mapping of the global actors engaged in the economic processes related to digital banking over the past decade, along with numerous studies and analyses, prove the leading positions of the USA and China. The USA has a robust ecosystem and stands out as a leader in terms of the number of organizations, experts, and global achievements. On the other hand, China takes the lead in the number of

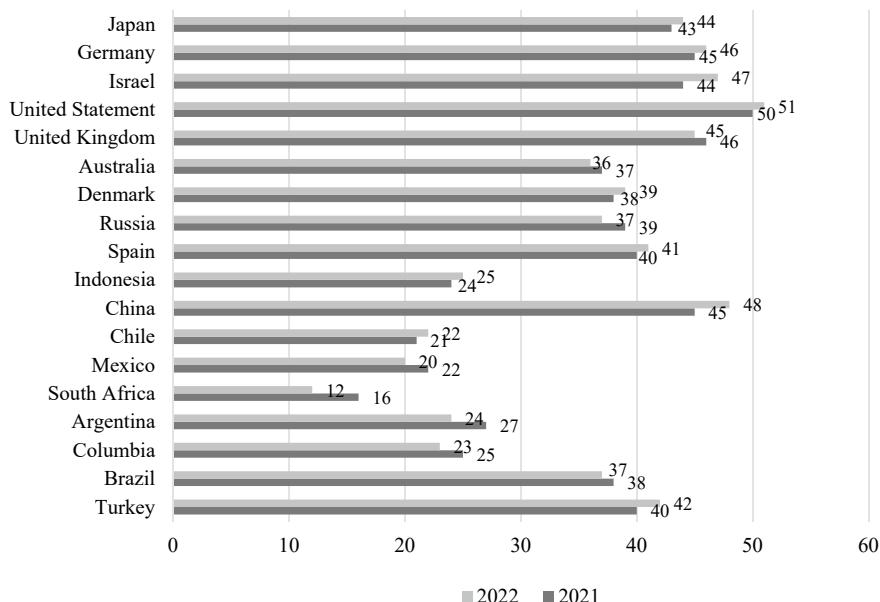


Fig. 2 Digital banking adoption rate in the banking sector of various countries, 2021–2022, %.
Source Compiled by the authors based on Statista [3]

government and research centers, startups fostering digital banking development, and registered patents. The next is Israel, which proves its technologically advanced economic system and substantial potential in this area.

Let us consider the digital banking penetration rate among the population of developed countries. Japan has the highest rate of digital banking penetration, standing at 56% in 2022. Australia demonstrates the lowest level of 28%. The digital banking penetration rate in the USA reached 67% in 2021–2022. As opposed to the developed countries, in countries with developing economies such as China, Kazakhstan, and Turkmenistan, the penetration rate of digital products is within the range of 37%–47%. Compared to other countries in the region, in 2022, Armenia's indicator is 6% lower than that of Azerbaijan, 1% lower than that of Georgia, and 16% lower than Kazakhstan's indicator. India's indicator is also low, at 18% in 2022 (up by 2% YoY). Despite Singapore's low figures, there was a 6% rise YoY in 2022 in the use of digital banking by the population. Despite the adoption of digital banking solutions by several banks in developing countries, the level of digital banking implementation, as compared to other sectors, is still not high enough to ensure significant advantages [10].

Let us focus on European countries. According to the data for 2018–2022, several European countries (i.e., Latvia, Estonia, Ireland, Lithuania, and Austria) registered high indicators in digital banking (Table 1).

The Netherlands has experienced unprecedented growth in this area: the rate of digital banking usage by the population stood at 89% in 2022, up by 8% from the

Table 1 The rate of the use of digital banking by population in several European countries, 2018–2022 (%)

Country	2018 (%)	2019 (%)	2020 (%)	2021 (%)	2022 (%)
Latvia	64	67	69	71	75
Estonia	79	79	80	81	80
Ireland	52	58	58	67	69
Lithuania	54	56	61	65	68
Austria	53	57	58	63	66
Netherlands	39	40	44	81	89
Bulgaria	4	5	7	9	13
Greece	19	25	27	31	37
Cyprus	28	28	33	41	52
Romania	5	7	7	8	12

Source Compiled by the authors based on Statista [4]

previous year. In 2021, this indicator surged to 81%, which is 37% higher than the previous year. Greece, Bulgaria, Cyprus, and Romania recorded lower rates.

Now, let us review the digital innovations employed by global financial companies.

Mastercard is a global payment system, a transnational financial corporation that unites 22 thousand financial institutions across 210 countries. The company's headquarters are located in Westchester County, New York, USA [6]. The Global Operations Center is located in O'Fallon, a suburb of St. Louis, Missouri. Its principal business globally is to process payments between the banks of merchants and the card-issuing banks or credit unions of the purchasers who use the Mastercard-brand debit and credit cards for payments [7].

In 2020, Mastercard started testing a new technology in the USA, enabling shoppers to make payments at various points of sale using their face or hand. That is, users may authenticate their payments by showing their face or palm instead of using a physical card. The program has already been implemented at five St. Marche grocery stores in São Paulo, Brazil. According to Juniper Research forecasts, about 1.4 billion people globally are expected to use facial recognition technology to authenticate a payment by 2025. To sign up for Mastercard, customers need to take a photo of their face or scan a fingerprint to register it in the app. This may be done either on a smartphone or at a payment terminal. Customers can then add a credit card, which gets linked to their biometric data. It is similar to the technology tested by Amazon in the USA. Implementing this innovation in Armenian banks could make the payment process easier for customers, eliminating the need for cards. This product could boost customer interest in banks, eventually leading to an increase in the customer base.

The Russian Bank Tochka is a digital-only bank focused on creating an ecosystem of digital services for legal entities, small businesses, and entrepreneurs [1]. Tochka was established in 2015 and has long operated as a fintech platform based on its parent financial organization. In 2023, Tochka Bank obtained a banking license from

the Central Bank [9]. In July 2016, Tochka Bank launched a chatbot on Facebook that helps customers find the nearest ATMs, make payments, and get information about their accounts. Personal digital assistants are being most actively developed on Google, Apple, Amazon, and Facebook platforms. Implementing this innovation in Armenia can boost bank profits because the chatbot makes it possible to locate the nearest ATM faster, which leads to an increase in the number of payments.

Sberbank CJSC is a Russian financial institution, standing as the largest transnational and universal bank in Russia and Central and Eastern Europe. It is the most popular bank among retail customers, with most Russian residents (87.1% as of September 2020) using its services. The retail business volumes of Sberbank CJSC surpass those of its major competitor, VTB CJSC, by several times. In Sberbank, AI is already making 98% of decisions on granting loans to individuals. Credit risks are analyzed based on the user's "digital footprint." According to H. Gref, the head of the bank, this footprint is already reaching 500 MB per day; on its basis, a "second digital self" is formed, which very accurately repeats our human "self." Assessing credit risks for corporate clients proves to be more difficult for artificial intelligence because it is currently capable of making only 30% of decisions on loan approvals in this field. Another area of application of AI in banks is the use of data collection robots. Sberbank was also a pioneer in this aspect. In 2016, it launched a pilot project through its subsidiary, Active BC. A year later, the robot's effectiveness surpassed that of human operators since loan repayments of customers increased by 24%. After that, Active BC worked with 27 more banks (Otkrytie, Binbank, etc.). In 2017, this area only brought the company about 25% of its total profit.

The only bank in Armenia currently employing robots is Evocabank. At the head office of Evocabank, visitors can already meet Robin, an AI-equipped robot. Robin presents the bank's news to visitors, gathers opinions of employees about the bank's service quality through Q&A sessions, takes selfies with visitors sending the photos via email, and engages in small talk about the weather. Thanks to AI, Robin constantly learns from people, improving its communication skills. The bank engaged Robin to make bank visits funnier and more entertaining for its customers. The bank customers are now actively chatting with Robin and taking selfies. Robin can be met at the head office of Evocabank at 44/2 Hanrapetutyian Street.

The authors believe that the innovations utilized by the countries discussed align well with Armenia's banking sector and meet the requirements of the Armenian population to implement these innovations into digital banking.

Thus, the solutions to improve the digital banking landscape in Armenia should be sought by examining international experience and the effective localization of best practices. It is suggested to leverage the potential of the diaspora, develop new and up-to-date programs, and simultaneously implement legislative reforms pertinent to the sector. The steady growth of Armenia's economy and the banking sector should be tied to having an efficient and advanced digital banking system.

4 Conclusions

The analysis of the types and services of digital banking in Armenia, as well as the development trends, allows the authors to make the following conclusions:

1. Digital banking has become widespread globally and continues to gain momentum. The international experience of digital banking demonstrates its capacity to deliver numerous services remotely through a global network. In turn, this means that banks cut transaction and service costs while increasing profits. Banks implementing digital banking solutions in various countries, such as the USA, Russia, and Western Europe, create products distributed globally beyond their borders.
2. While studying the distance service systems of Armenian banks, we conclude that due to the growth of competition, all 18 banks have developed digital banking services, while the services and products already used are expected to be further improved and enhanced. The Armenian banks stand out for their desire to adopt innovative information technology programs, creating a variety of digital banking and online payment solutions. Nonetheless, a certain share of the population is very far from adopting such services. This is especially characteristic of the provinces where the level of use of the Internet, smartphones, and digital banking services is very low.

Hence, it is impossible to imagine today's banking sector without software solutions and cutting-edge technology. Therefore, their development should be facilitated.

Based on the findings of the analysis, the authors propose the following:

1. Conduct monitoring to increase the penetration rate of digital banking among the population (i.e., find out the target segments of the population that are actively using digital banking services and apply promotion tools to bolster such use). Raise awareness and conduct various trainings and seminars for the population that experiences difficulties adapting to digital banking solutions.
2. The study of international experience showed that developed countries respond and adopt information technologies more quickly. Tinkoff Bank, in particular, creates digital banking products for Russian customers and customers in other regions. Hence, Armenian banks should pay close attention to the various innovative programs and events carried out in foreign countries to implement similar solutions in the future and boost the development of digital banking in Armenia. The authors propose developing digital banking services for non-resident clients as well.

Summing up the findings of the studies, research, and analysis of the Armenian banks, as well as of other countries, the authors can state that Armenia will employ advanced technology. All banks will offer various digital banking services, which will be modified, developed, and further enhanced along with digital banking transactions

and will contribute further to the spread of digital banking and the increase in the number of users, eventually leading to a significant improvement in the efficiency of the banking sector.

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Artificial Intelligence and Its Impact on the Economy and Business



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Abstract The research shows that artificial intelligence (AI) increasingly influences the economy and business. It represents an advanced set of technologies and methods capable of solving intellectual tasks. A growing number of such systems perform tasks faster, more accurately, and more cost-effectively than humans. At the current stage of technological development, tools are being created that provide higher efficiency and threat reduction. AI can be widely utilized in various fields, such as manufacturing, finance, trade, marketing, logistics, etc. AI holds valuable potential for pioneering economic transformation and redefining vectors in modern entrepreneurship. After thorough analysis, the authors conclude that AI is designed to extensively rationalize and accelerate processes, optimize forecasting and resource usage, and improve decision-making quality. AI can be applied to create innovative products and services previously unavailable, becoming the foundation for developing innovative industries and markets and addressing complex issues faced by government agencies, organizations, and public structures. This research confirms that AI is a powerful tool that can be used in various areas, enhancing efficiency and productivity. However, its application also raises new questions of ethics, social and legal responsibility, and security. In the future, AI will continue to evolve and occupy an increasingly significant place in the economy and business, making it important to oversee its development and use within the context of social, legal, and ethical aspects.

Keywords Artificial intelligence · Automation · Robotics · Economy and business · Efficiency · Productivity

JEL Classification O11

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1 Introduction

In the twenty-first century, innovative management methods and scientific and technological advancements significantly affect many areas of human activity, particularly the economy. With the advent and development of the Internet (marked by the completion of the transformation of local networks and the establishment of a unified data transfer network), various operations at the macro level and within individual organizations have been transformed and simplified. Currently, we reached the stage of forming artificial intelligence (AI) as a complex of technologies that provide higher levels of efficiency and productivity.

The current AI stage should be viewed as succeeding the previous stages of robotics and automation, capable of ensuring growth in production volumes and labor productivity and improving the overall quality of life. However, if not accompanied by control mechanisms, its application can lead to deepening personal and collective inequality, as well as disparities in the levels and rates of economic development across regions, communities, and industries. Consequently, this can exacerbate the quality of life gap among different global regions, countries, and regions within a country.

2 Materials and Method

The methodological foundation of this research is based on systems analysis, incorporating the necessary methods and scientific approaches for evaluating the research results. Systems analysis is essential as a comprehensive set of methodological tools used to develop and justify scientific solutions to complex issues. It begins the process of implementing solutions by defining and constructing a system of ultimate goals. It operates on the necessity of examining the issue integrally, as a holistic system and establishing all results and interdependencies of individual decisions. Additionally, it involves identifying and assessing potential ways to achieve the objectives.

3 Results

AI is a rapidly evolving field that can potentially transform many aspects of our lives. This involves the creation of computer systems capable of performing complex intellectual tasks such as image recognition, natural language interpretation, and developing solutions, models, schemes, and calculations [1]. AI is applicable in various sectors, from social services and medicine to wholesale trade and agriculture. Its impact is already evident throughout the entire economy and society. As AI advances, it can potentially bring about significant changes in how we live and work. The use of AI is becoming increasingly common, transforming how organizations operate. AI

algorithms are used to analyze large volumes of data and make predictions, helping organizations to act more efficiently.

AI is also used to automate repetitive tasks, freeing up workers to focus on more complex and creative problems [2]. For example, retail organizations use AI-powered chatbots to handle customer inquiries, freeing employees from unnecessary work and allowing them to focus on more creative functions. In the energy sector, AI algorithms are used to optimize renewable energy systems, making them more efficient and cost-effective.

Another way AI can impact the economy is by diversifying job roles. As AI systems take over routine functions, there is a need for workers to oversee, develop, design, and manage these systems. This leads to new jobs in data science and analytics as organizations seek to utilize the vast amounts of information they generate. Moreover, AI provides new competitive advantages by enabling more efficient and innovative business processes [3].

However, implementing AI also raises concerns about privacy, ethics, and justice. AI systems collect and store significant amounts of information, which can lead to privacy issues and increase the risk of data breaches [4]. Additionally, AI systems can make decisions that do not consider the importance of values, ethical norms, and human characteristics. There are fears that AI tools might perpetuate existing biases and create new ones. Questions arise about who will ultimately be responsible for the decisions made by AI systems. To maximize the benefits of AI while minimizing its negative impacts, it is crucial to have mechanisms in place to control the ethical aspects of AI system applications.

AI can significantly enhance efficiency and responsiveness and stimulate new work chains and models.

However, it is essential for people to consider the potential risks and negative consequences, such as job displacement, retraining, and issues of privacy and social-legal norms. Thus, it is important to work together to ensure that the benefits of AI are fully realized. By doing so, we can ensure that the impact of AI on the economy and business is reliable and stable.

AI holds valuable potential for transforming the economy and redefining vectors in business. Let us consider some areas actively implementing AI.

AI can expand the scale of automation and accelerate the optimization of production and distribution processes. Machine learning algorithms and automatic data analysis can help optimize demand, plan logistic routes, and manage resources efficiently, enabling organizations to reduce costs and improve the quality of goods and services.

AI can also drive the creation of innovative products and services that do not yet exist. Technologies that perform natural language processing are particularly promising because they can lead to the widespread creation of virtual assistants and chatbots that replace humans in consumer and client interactions.

Additionally, AI significantly enhances the development of managerial decisions and optimal operational models for organizations. Its algorithms can quickly analyze information, identify consistencies and inconsistencies, and improve the quality of forecasting, goal-setting, and decision-making. This is especially relevant in areas

requiring coordinated interaction chains, such as logistics, supply chain management, finance, and marketing.

AI can accelerate the development and improvement of innovative industries, service sectors, and marketing solutions. For instance, the creation of autonomous vehicles will likely lead to the development of advanced taxi services, goods delivery, and freight transportation. AI will also speed up and expand the use of robotics, creating new services providing helper robots and companion robots. This will open up new vectors for entrepreneurship and investment.

AI algorithms will revolutionize the medical field, speeding up and enhancing the analysis of medical information, thereby improving diagnosis and treatment. AI is also relevant as a tool for analyzing climate information and forecasting changes in the short term and long term, which is crucial for economic activities and logistics.

Thus, the prospects for AI development in the economy and business are vast. However, ethical and social aspects of AI application must be considered to ensure its fair and responsible use in the interest of humanity.

The use of neural networks and AI is already in high demand and is becoming a distinguishing feature of developing organizations internationally. From the perspective of technological paradigm shifts, the global economy currently operates within the framework of Industry 5.0, with significant achievements in information technology. According to many analysts, countries like China, the USA, Japan, and South Korea have already moved towards the sixth technological paradigm, characterized by “uncrewed” management methods developing towards AI systems. [5].

All research show that AI can significantly affect the renewal of economic activities, management, and business operations. Based on the assessment of the twelve strongest economies in the world (with a combined volume exceeding half a percent of global GDP), the experts from Accenture forecasted that AI implementation could influence the annual growth rates in the global economy by approximately 25% by 2035, which is very significant.

AI will impact this in three main ways. First, it will significantly increase productivity (potentially up to 40%) through the widespread implementation of AI algorithms and technologies. Second, it will create innovative virtual management structures (teams) that can optimally solve problems while continuously self-learning. Third, AI will spur widespread innovations across all industries, thereby increasing the diversity of revenue sources [6].

Currently, major market players are intensively experimenting with AI and its application in their business processes, primarily through replacing low-skilled workers and optimizing the activities of others [7].

Global and Russian surveys agree that AI will mostly have a positive impact on the labor market, increasing efficiency and reducing the time spent on routine processes. Simultaneously, analysts believe that fears of AI completely replacing humans are unfounded. According to a World Bank analysis, 83 professions will cease to exist from 2023 to 2027. However, the same review notes that 69 new professions will emerge. Moreover, 590 professions will remain in demand. It is expected that the number of innovative jobs created by AI will exceed the number of those eliminated. For example, according to a 2023 Goldman Sachs study, AI is expected to replace

humans in 18% of processes, affecting around 300 million jobs worldwide. However, it will also create many jobs and increase labor productivity, potentially boosting the global GDP by up to 7%. For more than 60% of current workers in various fields, the introduction of AI will bring benefits and improvements by significantly enhancing working conditions through the automation of routine and monotonous processes [8].

How is AI technology developing in the Russian economy and business?

In accordance with the Presidential Decree “On the development of artificial intelligence in the Russian Federation” (October 10, 2019 No. 490) [9], a national strategy has been adopted. The “Artificial intelligence” project has been systemically implemented since 2021 as part of the National Project “Digital economy of Russia.” This project includes tasks such as investing in grant-supported educational projects and startups in the field of AI, developing AI technologies, creating research centers for AI, and drafting new regulatory documents to support the development of AI systems and tools.

The main tasks are as follows:

- To create and improve the research base and infrastructure in the field of AI;
- To train the necessary workforce in sufficient quantities;
- To form a new regulatory environment;
- To develop next-generation software products and promote them for the needs of government bodies and economic sectors;
- To expand the circle of AI technology users.

The overall economic potential of AI in Russia is estimated to be around 22–36 trillion rubles by 2028, with the realized result projected at 4.2–6.9 trillion rubles, corresponding to an impact on the gross domestic product of 4% [8].

These directions align with the main priorities in the development strategies of foreign countries. Similar initiatives are being implemented in Germany, the UK, China, the USA, South Korea, and Japan.

For example, the size of government investments for AI research and development in the USA is proposed to reach approximately \$32 billion per year by 2026. There is a notable increase in spending on national AI strategies in many countries worldwide.

However, the main trend in the development of AI is set by large global business organizations. Their spending on AI exceeds the budgets of some countries. For instance, Amazon’s expenditures on technology and content alone amounted to \$42.7 billion in 2020, Alphabet’s expenses were \$27.6 billion, Microsoft’s spending was \$19.3 billion, Apple’s investment was \$18.7 billion, and Facebook’s spending was \$18.5 billion. Much research in these organizations focuses on AI and related fields to create software, hardware, and service solutions [7].

The size of the Russian AI market is steadily growing. In 2021, it was over 550 billion rubles, reaching 650 billion rubles in 2023, which is 18% more than in 2022. Analysts estimate that by 2025, AI will allow Russian companies to save around 1 trillion rubles [10].

Considering the focus on its development and stable funding, the prospects for AI in Russia seem rather positive. However, experts identify several barriers to its

broad technological application, such as the lack of unified mechanisms for data representation, processing, and protection, often excessive oversight and control, informational isolation, the detachment of Russian-language networks from global ones, and insufficient quality of Russian hardware and software [6]. Additionally, the authors believe that there are considerable social obstacles, including the unpreparedness of government and administrative bodies for the full and safe use of AI, the prevention of negative consequences, and the lack of public trust in the effects of this technology.

4 Conclusion

AI is actively integrated into human and societal activities, influencing all areas of the economy and business. It represents an advanced intellectual tool capable of significantly assisting humans in increasing their productivity and the efficiency of their tasks.

AI is intended for widespread use across various economic sectors, including manufacturing, finance, trade organization, marketing, and logistics. AI can help streamline processes, improve prediction and decision-making, optimize resources, and enhance the effectiveness of business operations.

AI can have a substantial impact on the economy and business in several ways, including the following:

1. Increasing efficiency and productivity by automating routine, monotonous, and time-consuming tasks, thereby optimizing processes and decisions, boosting productivity, reducing costs, expanding production scales, creating new job opportunities, and improving product quality;
2. Enhancing the efficiency of decision development and implementation by improving the analysis of large volumes of information and identifying trends, focuses, and nuances that humans might overlook, thereby raising the level of rationality in organizational decisions and the quality of their execution;
3. Significantly improving customer service, including through AI-based chatbots and virtual assistants that can provide personalized, round-the-clock service, leading to increased customer satisfaction and loyalty, and expanding the customer base;
4. Deploying innovative business models by introducing subscription services and analytics-based insights derived from data volumes, pointing to new revenue sources.

Thus, AI is an advanced intellectual tool intended for successful application in all fields, enhancing the speed, efficiency, quality, and effectiveness of processes.

However, its widespread use intensifies ethical and socio-legal issues, prompting the need for increased oversight of its development and application. This involves developing appropriate measures for restriction, safety, and protection and clearly defining accountability for AI decisions.

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Socio-environmental and Legal Aspects of the Ethics of Applying Big Data and Artificial Intelligence Technologies

Organizational and Methodological Aspects of Intraoperative Critical Situations Assisted by Data Analysis and Artificial Intelligence



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Abstract In the case of severe wounds and polytrauma, the risk of surgery depends on many factors. Some factors are more definite, while others may arise or be revealed during the intervention. Thus, their unpredictability is especially pronounced, pre-determining an extreme situation of risk, extreme situations of extreme necessity, and extreme situations of forced experiment. The research aims to study the organizational and methodological aspects of resolving intraoperative extreme situations using the integration of artificial intelligence (AI) to mitigate and identify modifiable risk factors. The research processed data on the injury's nature, the shockogenicity of the injury, the degree of risk based on the injury characteristics, mortality in victims in extreme situations, and the length of stay of deceased victims in the hospital. Based on the study of the organizational and methodological aspects of solving extreme situations for victims when providing surgical and resuscitation assistance to victims in an extreme situation, the authors formulated certain recommendations. In extreme situations, a close intraoperative collaboration of surgeons and anesthesiologists-resuscitators is necessary, perceived in unity as a surgical team with the common goal of mastering the system of joint assessment of extreme situations and making collegial and competent decisions on its correction.

Keywords Polytrauma · Extreme situation of extreme necessity · Extreme situation of forced experiment · Extreme situation of risk · Intraoperative emergency

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1 Introduction

In extreme situations, many principles, rules, and norms of surgery undergo serious corrections towards simplification or complication. However, in most cases, immediate surgery should be perceived as a component of intraoperative resuscitation [1, 2]. To avoid discrepancies in the principles of providing surgical and resuscitation care to victims with polytrauma, with an extreme situation of risk (ESR), with an extreme situation of extreme necessity (ESEN), and with an extreme situation of forced experiment (ESFE), it is necessary to adhere to certain norms and recommendations.

In this regard, there is a need for a detailed analysis of the extreme situation and the essence of the norms of requirements. Moreover, it is necessary to methodologically justify the situation for that period of time and circumstances.

Unfortunately, many methodological, clinical-psychological, organizational, methodological, tactical, and technical aspects of developing and making decisions on this fundamental basis remain unclear [6].

Meanwhile, they serve as the basis for developing certain proposals that will be of a recommendatory nature.

One of the most relevant options for using artificial intelligence (AI) in the healthcare sector is the development of technology [3, 5, 9].

In healthcare, AI has valuable potential to reduce health, social, and economic inequalities. Moreover, AI can realize universal health coverage and improve health outcomes globally [4]. The advantages of AI include suggesting optimal surgical approaches, simulating surgical procedures, and analyzing CT scans to create 3D models of the patient's anatomy (e.g., blood vessels) [11].

This research aims to study organizational and methodological resolutions in extreme situations using the integration of AI.

The main research question lies in determining the main organizational and tactical decisions in extreme situations and the nature of intraoperative studies in patients with polytrauma who are in the ESR, ESEN, and ESFE.

The research subject is data from patients with various types of ES, their volumes and nature of extensive indicators of intraoperative studies, and the length of stay of deceased patients in the hospital with various types of ES.

2 Materials and Methods

The relevant data from the provision of surgical and resuscitation care to 100 victims with severe injuries ($n = 16$) and polytrauma ($n = 84$) who were in an extreme situation were used as materials for analysis. The victims were divided into three groups:

1. Those requiring immediate surgery as an element of resuscitation measures, without which they would inevitably die in the next minutes and hours ($n = 28$);
2. Those in need of immediate surgery for life-saving reasons against the background of anesthesia and active resuscitation, without which the fatal outcome is obvious ($n = 22$);
3. Extremely severe and agonizing patients with severe injuries and polytrauma incompatible with life. They were resuscitated on the operating table but not operated on in time ($n = 10$).

3 Results and Discussion

In all cases, brain damage was observed 3.2 times more often than internal organ damage with cavitary bleeding. Fractures of tubular bones of the musculoskeletal system were 2.8 times more common than fractures of the pelvis or spine. In victims with ESEN and ESFE, as a rule, the most common injuries were the brain and skull bones, trunk bones, large joints, ruptures of parenchymal organs, mesentery, and intestines [7, 8].

The main causes of death of the victims were acute respiratory and circulatory disorders and acute blood loss [10, 12]. Table 1 shows the injury patterns in polytrauma, the levels of surgical and anesthetic risks of injury, and the degree of risk based on the injury characteristics at the time of victims' placement in an extreme situation.

As can be seen from Table 1, intraoperative emergencies (IOES) occurred in 42% of cases. A significant level of surgical risk and anesthetic risk (OR + AR) was observed in 40% of cases. The shockogenicity of the injury in 82% of victims was 5–10 points. Among them, the most severe injuries and wounds (7–10 points) are 42%.

A typical feature of these categories of victims in extreme situations (82%) is the presence of mutual burden syndrome, which directly affects the volume and content of surgical and resuscitation work.

In evaluating organizational and tactical decisions, experts must ascertain whether the deceased would survive if they received prompt and comprehensive emergency care. A scoring assessment of the shockogenicity of the injury and the degree of risk based on the characteristics of the injuries can help in obtaining this information. As can be seen from Fig. 1, out of 100 victims, 22 died. Thus, the mortality rate was 22% (Table 2).

Table 1 Distribution of polytraumas, according to the score (> 5), shockogenicity of the injury, and the degree of risk based on the characteristics of the injury at the time of placement of victims with an extreme situation on the operating table

Injury character	Point	%	Level of surgical and anesthetic risk
Shock, damage to two or more parenchymal organs with massive blood loss, trauma to the chest or skull	10	6	IOES (n = 42)
Trauma to the chest and abdomen with damage to one parenchymal organ or traumatic brain injury, intracranial hematoma	9	8	
Chest injury with lung damage, hemopneumothorax and bone fracture of large limb segments with a large soft tissue crush area	8	6	
Traumatic brain injury and musculoskeletal injury	7	22	
Traumatic brain injury and brain contusion. Fracture of the vault and base of the skull. Multiple fractures of the pelvic bones	6	18	Significant (n = 40)
Abdominal trauma with damage to hollow organs and fracture of the bones of the middle segments of the extremities with crushing of soft tissues	5	22	

Source Created by the authors

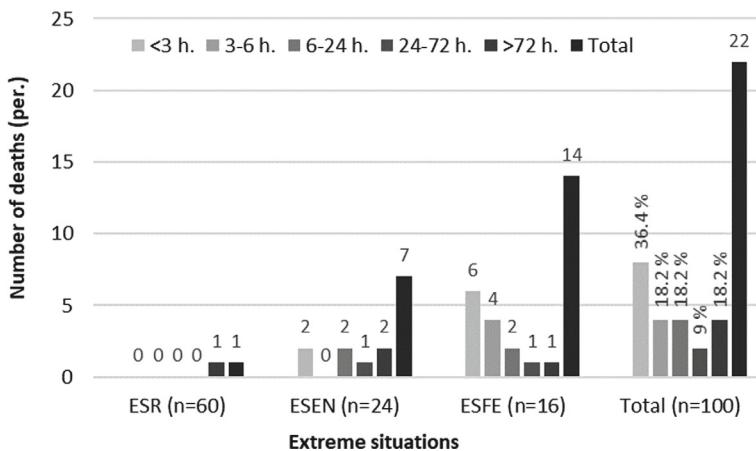


Fig. 1 The number and length of stay of deceased patients in hospitals with various types of ES in quantitative and percentage terms. Source Compiled by the authors

Table 2 Mortality in victims staying in ESR, ESEN, and ESFE

Extreme situations	Sex	n	%	Ratio to the total number of victims (n = 100) (%)
ESR (n = 60)	Male	1	1.7	1.0
	Female	—	—	
	Total	1	1.7	
ESEN (n = 24)	Male	8	33.3	8.0
	Female	—	—	
	Total	8	33.3	
ESFE (n = 16)	Male	12	75.0	13.0
	Female	1	6.25	
	Total	13	81.25	
Total (n = 100)	Male	21	21.0	22.0
	Female	1	1.0	
	Total	22	22.0	

Source Created by the authors

In the group of victims with ESR, mortality in relation to the total number of victims was only 1%. In ESEN and ESFE, this figure was 8% and 13%, respectively. In general, the mortality rate in the group was 1.7% in the group with ESR, 33.3% in the ESEN group, and 81.25% in the group with ESFE.

Thus, every third victim died in the group of victims with the ESEN. In the group with ESFE, 80% of the victims died. Among the dead, there was only one woman with polytrauma.

As can be seen from Fig. 1, 9% of the 22 deceased patients with ESCI died on the operating table without surgery at the time of induction of anesthesia (< 3 h). Another six (27.3%) patients with ESFE (n = 6) died on the operating table despite the surgery performed during resuscitation (< 3 h).

In the next 3–6 h after completion of the surgery, against the background of ongoing resuscitation measures, another four victims (18.2%) who had ESFE died immediately on the operating table. Four victims (18.2%) died after being transferred to the intensive care unit. The remaining six victims died within 24–72 h amid intensive care.

It has been established that the proportion of organizational prerequisites for various types of errors and complications occurs quite often (in almost every second or third victim).

It is particularly regrettable that the first and second places in frequency are occupied by such factors as the lack of vigilance of members of the surgical team when predicting intraoperative complications (50%), as well as the incorrect assessment by the surgical team of the properties of the ES (37%) due to untimely establishment of intraoperative diagnosis in victims.

It is also deeply regrettable that in 41% of cases, there was an organizational defect, such as insufficient material and technical equipment in the surgery room, which reduces the effectiveness of providing operational and resuscitation care to victims located in the ESR, ESEN, and ESFE. This is also facilitated by insufficient knowledge of the clinical specifics of providing surgical and resuscitation care (31%), as well as the fact that surgical work is not well established in the medical institution (34%).

Deficiencies in maintaining the necessary medical documentation occur in 35% of cases. Incorrect personnel placement and weak control over knowledge of their professional and official rights and responsibilities served as a prerequisite for the emergence of an organizational defect in 21%. In 24% of cases, the surgical team (ST) was unable to correctly implement the clinic's capabilities in relation to intraoperative diagnostics and provision of surgical resuscitation care in the proper volume and quality.

The listed factors certainly affect the quality and efficiency of the surgical team's work. According to the results of timing the deployment of the surgery room, the authors found that 25.2 ± 5.8 min pass from the moment the victim enters the emergency department until they are taken to the operating table; 16.5 ± 4.5 min pass from the moment of intubation to the start of the surgery. In general, these terms fit into the "golden hour" for victims with wounds and polytrauma from 20 min to 1.5 h.

Untimely and incomplete use of advisory assistance in establishing an intraoperative diagnosis and management tactics for victims in the emergency room occurred in 13% of cases. In ESR, ESEN, and ESFE, it is almost impossible to create a consistent program of diagnostics and treatment measures, determine the order and optimal timing of surgical interventions, and define the content and scope of resuscitation. However, in almost every case, there is a need for mandatory intensification of the processes to resolve these issues. Unfortunately, expectant management for ESR, ESEN, and ESFE is unacceptable. Only the immediate use of all available methods of resuscitation, including surgery, as well as methods of intraoperative diagnostics, helps implement the principle of saving the life of the victim.

The slightest doubt about the possibility of intracavitary damage serves as an indication for performing puncture studies and placing diagnostic drains.

Publicly available methods (thoracentesis, laparocentesis, spinal puncture, bladder catheterization, and urography) and advanced infrasonic methods (laparoscopy, thoracoscopy, cystoscopy, ultrasound, CT, etc.) should be used especially widely.

As can be seen from Fig. 2, almost all 381 diagnostic methods were used intraoperatively and quite intensively. The proportion of skull echoscopy was 11% (42 cases), and skull radiography 5.77% (22 cases). The share of ultrasound was 7.35% (28 cases). The share of evaluation studies was 23.09% (88 cases). The share of laboratory tests was 40.94% (156 cases).

For a well-known reason, the above methods are used relatively less in victims with ESEN and ESFE than with ESR. Unfortunately, many errors are associated precisely with incorrect diagnostic search methodology. These diagnostic methods

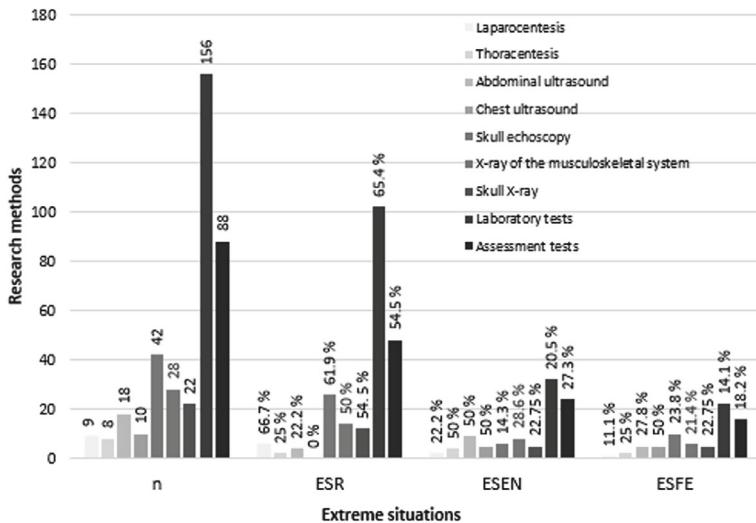


Fig. 2 The volume and nature of extensive indicators of intraoperative studies in victims in the ESR, ESEN, and ESFE in percentage terms. *Source* Created by the authors

are often ignored in favor of laparotomy, thoracotomy, or diagnostic craniotomy, which aggravates the severity of the victim's condition.

Members of the ST should have a syndromic approach to victims with wounds and polytrauma (i.e., identify the dominant injury and predict its life-threatening consequences and complications). In this regard, the surgical team must consider the type of injury to predict possible variants of combined organ injuries and possible complications and select the appropriate medical-surgical treatment.

An incomplete volume of intraoperative studies in victims, considering its real capabilities, was noted in 24%. We are talking about performing laparocentesis, thoracentesis, spinal puncture, cystography, etc., for diagnostic purposes. In cases of ESR, especially in ESEN and ESFE, express methods of intraoperative diagnosis should be carried out together with surgery and resuscitation.

Thus, various shortcomings in the provision of operational and resuscitation care were allowed in almost every second victim with severe wounds and polytrauma who were in ESEN and ESFE. In a randomized assessment, the authors found that organizational and methodological factors had a probability of $t = 4.8 \pm 0.8$.

However, the distributions of all quantitative characteristics are asymmetrical and abnormal. There is a close relationship between various factors of an organizational and methodological nature and groups of victims (ESR, ESEN, and ESFE). This connection is most strongly manifested in the group of ESEN and ESFE.

In 31% of cases, an intraoperative crisis in the form of complications or mortality on the table is directly or indirectly associated with insufficient awareness of members of the surgical team, as well as health care providers, regarding the resolution of ES.

The relative risk is of sufficient significance ($t = 3.1$). Therefore, the role of this factor in ensuring a low-acceptable quality of emergency care is quite noticeable.

In 41%, the intraoperative crisis is associated with insufficient material and technical equipment in the operating room ($t = 4.1$), which is a fairly high figure. We see that t remains high, associated with such a factor as the insufficiently established organization of surgical work in medical and preventive institutions (MPI) (34%, $t = 3.5$). Additionally, there is another organizational defect—insufficient staffing of the administration of health care facilities (21%, $t = 2.7$).

In 13% of victims, complications or mortality are, to one degree or another, associated with untimely and incomplete use of advisory assistance from relevant specialists during surgery and resuscitation. The relative risk of this factor is not very high, amounting to 2.1. Therefore, its significance is not entirely convincing.

Based on the study of the organizational and methodological aspects of solving emergency situations for victims when providing operational and resuscitation assistance to victims located in emergency situations, the authors formulated the following recommendations.

4 Conclusion

The authors developed the following conclusions:

1. From the point of view of clinical riskology of ES, it is advisable to distinguish two categories of victims requiring: immediate surgery as an element of resuscitation measures or agonizing patients;
2. In victims with ESEN and ESFE, as a rule, the most common injuries are those to the brain and skull bones, trunk bones, ruptures of parenchymal organs, mesentery and intestines, and the main causes of death are multiple organ failure syndrome, and empty nose syndrome (MOFS and ENS);
3. The first and second places among organizational and methodological miscalculations are occupied by the lack of alertness of the members of the clinical department when predicting intraoperative complications, as well as incorrect assessment of the properties of ES;
4. Insufficient material and technical equipment in the surgery room, insufficiently organized surgical work in the clinic, and insufficient knowledge of the ST of specifics in providing surgical and resuscitation care for ES occupy third and fourth place among organizational defects;
5. Disadvantages of maintaining the necessary documentation, incorrect placement of personnel, and insufficient implementation of the clinic's capabilities in relation to intraoperative diagnostics and the provision of surgical resuscitation care occur in every fourth case;

6. In case of ES in the operating room, only the immediate use of all available methods of resuscitation, including surgery, is acceptable, as well as in parallel methods of intraoperative diagnostics helps to implement the principle of saving the life of the victim.

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The Friendliness of Big Data and AI Towards Humanity as a Criterion for Optimal Decision Support Intelligence



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Abstract The research determines the impact of big data and AI technologies on the components of quality of life as a primary demonstration of the friendliness of these technologies towards humanity. For this purpose, the authors carried out regression modeling of the influence of the dissemination of big data and AI on the components of quality of life. The research is based on IMD and Numbeo data on the top 30 developed and developing countries with the highest quality of life levels in 2023, ensuring a thorough examination of international practices in promoting public welfare within the digital economy. As a result, the authors constructed a social profile of big data and AI technologies, offering a systemic view of the social consequences of disseminating these technologies. This framework delineated the benefits (e.g., enhanced purchasing power, heightened physical security, and reduced housing costs and transportation) and the risks (e.g., a higher cost of living and environmental degradation associated with their implementation). This analysis provided a scholarly basis for introducing a new criterion—the human-friendliness of big data and AI in decision support systems. Furthermore, the research presents comprehensive recommendations for applying this criterion effectively in the contemporary digital economy landscape.

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Keywords Human friendliness · Big data · Artificial intelligence (AI) · Optimality criterion · Intelligent support · Decision making

JEL Classification G41 · J17 · O35

1 Introduction

The current stage of technological progress, now embodied in the form of digital modernization of economic activities, has historically played a significant role in shaping socio-economic systems. It has become a decisive factor in their global positioning in the twenty-first century. The consequences of industrial revolutions have always been contradictory. In the context of the Fourth Industrial Revolution, the antagonism of its outcomes has reached critical levels, a necessity that is apparent to all stakeholders.

The benefits of technological development traditionally encompass the expansion of production capacities and labor productivity, the acceleration of economic growth, and the strengthening of international influence. Conversely, the drawbacks of industrial revolutions are also quite broad, ranging from labor market destabilization to increased environmental damage from growing economic activity.

The prevailing approach to managing technological development in economic systems lacks flexibility, hindering the ability to maximize advantages and mitigate drawbacks. This approach predominantly supports scientific and technological progress, which, when strictly limited and reluctantly restrained, often unfolds chaotically.

The fundamental idea behind the existing approach is that involvement in scientific and technological progress is a necessary condition for maintaining the global competitiveness of an economy as a territory attractive for business, production placement, investment, and habitation. Indeed, historical attempts to slow down scientific and technological development in certain territories, let alone isolate them from industrial revolutions undertaken by some countries of the Global South, have led to the deglobalization and economic stagnation of these countries.

To ensure high efficiency in economic activities, the economy must be inherently open to economic agents, external trade, investments, and technologies. However, there is a pressing need for a new approach to managing technological development in economic systems, one that provides the required flexibility in governance and makes it possible to promote beneficial practices in digital economic modernization and restrain potentially hazardous practices.

Special attention should be given to advanced technologies (e.g., big data and artificial intelligence) when applied to intelligent decision support in a digital economy. The current approach evaluates the optimality of decision support based on their economic impacts, primarily concerning the external environment of the economic system. Thus, scientific and technological progress is encouraged when it strengthens

the positions of domestic producers in global markets and achieves technological sovereignty.

An alternative approach proposes using a new criterion for the optimality of intelligent decision support—its social impacts within the internal environment of the economic system. Introducing this criterion requires thorough scientific and methodological analysis of the social consequences of big data and AI technologies, which, despite active research, remain largely undefined. This context underscores the relevance of the present research and its objective, which is to determine the impact of big data and AI on quality of life as a primary manifestation of these technologies' friendliness towards humanity.

2 Literature Review

In the theoretical framework of intelligent decision support underlying this research, the primary technologies considered are big data (as sources of analytical information) and AI (as a means of processing this information and delivering the results to decision-makers) [5, 13].

Several published works by Maulidevi et al. [10] and Popkova et al. [12] noted specific social impacts of using big data and AI technologies. A literature review and content analysis of existing publications by Ali et al. [1] and Yusof et al. [18] allowed the authors to organize these impacts and present them as components of quality of life, including the following:

- Purchasing power of the population, cost of living, and the ratio of real estate prices to income, reflecting the standard of living [17, 19];
- The effectiveness of law enforcement in ensuring public physical safety [3, 6];
- The level of healthcare [8, 14];
- Time spent on transportation [4, 15];
- Environmental conditions, including production and consumption waste and climate [2, 9, 16].

However, the existing literature provides only a general outline of the components of quality of life affected by big data and AI, leaving the strength and nature of this influence unknown. Moreover, there is no comprehensive understanding of the overall impact of these technologies on quality of life.

This gap in the literature is significant because the uncertainty of social consequences hinders the optimization of intelligent decision support in the digital economy according to this criterion. To address this gap, this research poses the research question of how the use of big data and AI technologies affects the aforementioned components of quality of life.

3 Materials and Methods

To conduct a comprehensive and reliable study of advanced international practices in ensuring public welfare within the digital economy, the sample for this research includes the top 30 countries (top 15 developed and top 15 developing countries) with the highest quality of life (leaders of the Numbeo ranking [11]) and established digital economies (included in the IMD ranking [7]).

The indicator of big data and AI usage activity in the digital economy is the “Use of big data and analytics” (DM_{BDAI}) [7]. The quality of life components are as follows [11]:

- “Purchasing Power Index” (HFr_1), “Cost of Living Index” (HFr_2), and “Property Price to Income Ratio” (HFr_3) as indicators of the standard of living;
- “Safety Index” (HFr_4) as an indicator of the effectiveness of law enforcement;
- “Health Care Index” (HFr_5) as an indicator of the level of healthcare;
- “Traffic Commute Time Index” (HFr_6) as an indicator of the time spent on transportation;
- “Pollution Index” (HFr_7) and “Climate Index” (HFr_8) are indicators of environmental conditions.

The listed statistical data for the selected sample for 2023 are presented in Table 1.

The statistics from Table 1 are processed using regression and correlation analysis. Equations of simple linear regression are formulated to describe the dependence of the resulting variables HFr on the factor variable DM_{BDAI} . The friendliness of big data and AI towards humanity is indicated by positive regression coefficients, provided that the correlation coefficients are high and the established dependencies are statistically significant (passing the Fisher’s F-test).

The results of the regression modeling are used to forecast the potential for improving the quality of life in Russia by optimizing decision support through big data and AI, considering opportunities and threats. For this purpose, the regression equations are adjusted to include the maximum possible value of DM_{BDAI} (10 points). The expected changes in the values of the other indicators are determined.

4 Results

To determine the social impacts of the use of big data and AI in the digital economy, the authors conducted a regression analysis of data from Table 1. The analysis allowed the authors to formulate the following system of regression equations:

Table 1 Statistics of big data and AI usage and public welfare in the top 30 countries with the highest quality of life in 2023, scores

Category	Country	Quality of life index	Purchasing power index	Cost of living index	Property price to income ratio	Safety index	Health care index	Traffic commute time index	Pollution index	Climate index	Use of big data and analytics
	HFr ₁	HFr ₂	HFr ₃	HFr ₄	HFr ₅	HFr ₆	HFr ₇	HFr ₈	DM _{BDAI}		
Developed countries (top 15)	Luxembourg	207.3	148.9	65.6	76.3	65.3	9.1	26.1	21.8	82.6	5.12
	Netherlands	198.5	103.3	73.7	78.9	64.3	7.4	23.7	21.8	87.1	6.33
	Iceland	194.9	109.1	74.6	67.1	85.7	5.6	21.9	15.8	68.8	6.21
	Denmark	193.6	103.3	73.7	78.0	75.2	6.8	28.7	21.9	82.5	6.62
	Finland	190.4	97.3	73.7	77.3	65.5	8.3	26.0	12.0	58.9	6.11
	Switzerland	186.7	118.9	74.7	72.6	112.2	11.1	33.1	22.2	79.2	5.48
	Norway	184.2	94.9	67.4	75.7	79.2	7.8	26.8	18.6	71.4	6.39
	Austria	181.5	84.4	70.7	76.6	66.8	11.0	24.1	21.8	77.8	4.89
	Estonia	180.1	69.0	76.2	76.3	53.0	10.2	21.8	16.7	64.3	5.32
	Japan	177.6	99.5	77.4	79.3	50.7	10.0	40.2	38.6	84.8	3.80
	Germany	176.5	101.0	61.1	71.7	62.7	9.8	30.3	29.2	82.7	4.60
	Spain	176.5	78.2	63.8	77.6	48.4	7.4	26.4	35.6	94.4	4.32
	Sweden	175.0	94.6	51.6	68.6	62.2	8.1	29.1	17.7	74.0	6.48
	USA	174.0	120.9	50.7	67.6	72.9	4.1	33.8	37.1	78.9	6.74
	Slovenia	173.4	68.0	75.8	66.5	49.3	11.2	25.2	22.4	76.1	5.12
Developing countries (top 15)	Qatar	165.9	127.4	84.0	72.3	55.0	6.7	31.0	60.5	36.0	6.79
	UAE	163.2	98.7	84.4	69.2	57.8	4.2	37.4	49.0	45.8	5.52
	Saudi Arabia	155.1	105.1	73.1	60.4	47.4	3.2	30.9	64.1	55.3	6.57

(continued)

Table 1 (continued)

Category	Country	Quality of life index	Purchasing power index	Cost of living index	Property price to income ratio	Safety index	Health care index	Traffic commute time index	Pollution index	Climate index	Use of big data and analytics
		HFr ₁	HFr ₂	HFr ₃	HFr ₄	HFr ₅	HFr ₆	HFr ₇	HFr ₈	DM _{BDAI}	
Kuwait	140.1	128.5	67.2	57.9	43.4	7.7	35.0	68.0	20.2	5.63	
South Africa	139.9	84.7	24.6	64.0	33.8	3.3	38.7	56.3	95.3	5.38	
Malaysia	125.8	62.1	49.3	70.1	30.5	8.5	37.1	61.4	57.9	5.43	
Mexico	123.9	38.0	46.2	72.5	43.8	10.7	39.2	58.1	90.0	4.38	
Turkey	123.6	39.3	59.1	70.7	33.8	12.5	44.1	64.7	93.3	4.73	
Jordan	117.0	36.4	59.6	65.0	43.0	7.5	40.6	76.4	89.0	6.48	
Argentina	112.1	35.8	35.8	68.1	27.8	21.1	44.2	51.1	98.3	4.58	
India	111.8	60.7	55.7	64.9	22.2	13.3	46.8	72.8	63.3	5.98	
China	110.9	60.5	75.1	68.1	34.1	29.6	39.0	78.2	79.7	6.15	
Brazil	109.1	30.1	34.4	58.9	35.2	16.5	40.6	52.6	95.1	3.90	
Russia	106.1	41.5	60.9	60.9	29.5	16.1	43.2	59.6	45.1	5.17	
Colombia	102.9	28.1	38.8	68.3	30.6	18.7	47.3	62.8	96.7	4.73	

Source Compiled by the authors based on IMD [7], Numbeo [11]

$$\left\{
 \begin{aligned}
 & HFr_1 = -7.50 + 16.33 * DM_{BDAI}, R^2 = 0.4210, \\
 & F_{\text{observed}} = 6.35, \text{ Significance F} = 0.02; \\
 & HFr_2 = 9.82 + 7.80 * DM_{BDAI}, R^2 = 0.3380, \\
 & F_{\text{observed}} = 3.61, \text{ Significance F} = 0.07; \\
 & HFr_3 = 22.51 - 2.23 * DM_{BDAI}, R^2 = 0.3470, \\
 & F_{\text{observed}} = 3.83, \text{ Significance F} = 0.06; \\
 & HFr_4 = 29.70 + 5.99 * DM_{BDAI}, R^2 = 0.3414, \\
 & F_{\text{observed}} = 3.69, \text{ Significance F} = 0.06; \\
 & HFr_5 = 72.36 - 0.42 * DM_{BDAI}, R^2 = 0.0603, \\
 & F_{\text{observed}} = 0.1022, \text{ Significance F} = 0.75; \\
 & HFr_6 = 48.97 - 2.77 * DM_{BDAI}, R^2 = 0.3128, \\
 & F_{\text{observed}} = 3.04, \text{ Significance F} = 0.09; \\
 & HFr_7 = 50.92 - 1.45 * DM_{BDAI}, R^2 = 0.0593, \\
 & F_{\text{observed}} = 0.10, \text{ Significance F} = 0.75; \\
 & HFr_8 = 124.75 - 9.20 * DM_{BDAI}, R^2 = 0.4157, \\
 & F_{\text{observed}} = 5.85, \text{ Significance F} = 0.02.
 \end{aligned}
 \right. \quad (1)$$

The system of Eq. (1) indicates that an increase in the activity of big data and AI usage in the digital economy by 1 point results in the following changes: the purchasing power of the population increases by 16.33 points, physical security improves by 5.99 points, the property price-to-income ratio decreases by 2.23 points, commuting time decreases by 2.77 points, and production and consumption waste reduces by 1.45 points.

However, the cost of living rises by 7.80 points, healthcare quality decreases by 0.42 points, and the climate condition worsens by 9.20 points. The correlation coefficients were low. The Fisher's F-test was not passed for the resulting variables HFr_5 and HFr_7 , indicating the statistical insignificance of the regression equations for these variables.

To forecast the potential improvement in quality of life through optimizing intelligent decision support using big data and AI in Russia, the system of Eq. (1) was used with the maximum possible value of DM_{BDAI} . The expected changes in the values of other indicators were determined. The forecasting results showed that increasing the use of big data and AI in the digital economy by 93.42% (to 10 points compared to 5.17 points in 2023) would create the following opportunities for improving quality of life in Russia:

- The population's purchasing power would increase by 101.94% (from 41.50 points in 2023 to 83.81 points);
- The level of physical security would increase by 49.12% (from 60.90 points in 2023 to 90.82 points);
- The property price-to-income ratio would decrease by 111.77% (from 16.10 points in 2023 to -1.90 points);
- The time spent on transportation would decrease by 42.17% (from 43.20 points in 2023 to 24.98 points).

However, the risks associated with the increased use of big data and AI in the digital economy for the quality of life in Russia include the following:

- An increase in the cost of living by 76.01% (from 29.50 points in 2023 to 51.92 points);
- A deterioration in environmental conditions, particularly the climate, by 63.76% (from 45.10 points in 2023 to 16.35 points).

5 Discussion

The contribution of this research to the literature, including those works by Ali et al. [1], Haj Qasem et al. [5], Maulidevi et al. [10], Popkova et al. [12], Poszler and Lange [13], and Yusof et al. [18], lies in the development of the concept of intelligent decision support through clarifying the social consequences of using big data and AI technologies in the digital economy.

In contrast to van der Sloot [17] and Zhang et al. [19], this research established that the implementation of big data and AI technologies has a contradictory impact on the standard of living. On the one hand, it increases the population's purchasing power and reduces the property price-to-income ratio. On the other hand, it raises the cost of living.

Supporting the findings of Arulkumar et al. [3] and Horowitz and Kahn [6], the research substantiated that the proliferation of big data and AI enhances the effectiveness of law enforcement and physical security for the population.

Contrary to Inshakova et al. [8] and Przhedetsky et al. [14], this research found that the use of big data and AI does not significantly impact healthcare levels. Confirming the findings of Audonin et al. [4] and Sultanova and Babakhanova [15], this research proved that the implementation of big data and AI contributes to reducing the time spent on transportation.

In contrast to Allahham et al. [2], Jain and Awasthi [9], and Tolmachev et al. [16], it is established that the spread of big data and AI leads to environmental degradation. While it does not have a statistically significant impact on production and consumption waste, it accelerates the rate of climate change, reducing its favorability for human well-being.

On this basis, the authors proposed a new approach to managing the technological development of economic systems. The distinctive feature of this new approach is its flexible management to mitigate potential threats (e.g., prevent an increase in the cost of living and environmental degradation) and maximize expected benefits (e.g., enhance the purchasing power of the population and their physical security and reduce the property price-to-income ratio and the time spent on transportation) from the dissemination of big data and AI technologies. The friendliness of big data and AI towards humanity is proposed as a new criterion for the optimality of intelligent decision support in the author's approach.

6 Conclusion

The most significant result of the research is the compilation of the social profiles of big data and AI. The theoretical significance of this result lies in its ability to form a comprehensive understanding of the social consequences of the proliferation of big data and AI. This comprehensive understanding encompasses benefits (e.g., increasing the purchasing power of the population, enhancing physical security, and reducing the property price-to-income ratio and transportation time) and risks (e.g., increasing the cost of living and deteriorating the state of the environment) of implementing big data and AI for society.

The originality and scientific novelty of this research lie in the new criterion for the optimality of intelligent decision support: the friendliness of big data and AI towards humanity, along with the development of a set of recommendations for the practical application of this criterion in the context of the contemporary digital economy. The significance of state social policy lies in the perspective revealed for improving the quality of life through the optimization of intelligent decision support using big data and AI, making it possible to fully realize the potential for improving the quality of life in Russia in the coming years. The social significance of the author's recommendations is expressed in the fact that their implementation will ensure the humanization of the digital economy.

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Gamification Technology and Tools in Teaching Business English



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Abstract Online tools and platforms extend a great variety of opportunities in the classroom, including General English and Business English classes. The outbreak of the pandemic in 2020 and the lockdown that followed urged many educational institutions and educators to transfer their teaching materials into digital form, thus enabling the smooth shift to online teaching modality. The research addresses the issues related to the advantages of two main online platforms, namely Kahoot and Blooket, employed during Business English classes at the Armenian State University of Economics (ASUE). During the research, the authors used statistical, descriptive, and comparative analyses to collect feedback from 58 students and responses from in-person interviews with 18 lecturers teaching Business English at the same university and reveal and compare the advantages and disadvantages of two considered platforms from teachers' and students' perspectives. The results showed that the advantages of the Blooket platform far outweigh those of Kahoot in terms of accessibility, ease of use, and affordability.

Keywords Gamification technology · Gamification elements and features · Online tools and platforms · Online teaching · Virtual reality

JEL Classification D83 · 123

1 Introduction

The twenty-first century poses new challenges as technology, virtual reality, and online tools and platforms have emerged and transformed all traditional ways everything used to be organized. Education, especially language teaching, has also faced new challenges because traditional face-to-face teaching and teaching methods have

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become outdated, and textbooks seem to be not engaging or uninteresting, thus leading educators to find or invent fresh and novel language teaching methods.

The blending and integration of technology into language teaching offer new opportunities to improve learning and teaching. Educators can integrate different online platforms and tools into their teaching process in a formal setting. However, the main issue still seems to be the activities, time allocated during the lesson, and websites to be used for the learners' benefit. These resources and activities should be customized for the needs of learners, depending on their level of knowledge, age group, and needs. Besides online platforms and tools, novel teaching tools (e.g., gamification) can incentivize learners, engage them more in the learning atmosphere, and increase competitiveness.

English language teaching should be organized through online tools, resources, and platforms in the twenty-first century, when virtual reality has changed the way the teaching processes should be developed and organized locally and globally. Games have always been of keen interest to children and adults as well. This led many educators and teachers to integrate games into language teaching. With the emergence of new technology and online platforms and applications, games took a new form. Gamifying some tasks and activities will engage learners in the language-learning process.

Gamification is the application of game design elements such as scores, points, leaderboards, competition, feedback, avatars, and badges to obtain a game-like learning experience [2, 4]. Game-based learning is training with games to achieve a particular learning outcome and develop a particular talent [1].

Researchers emphasize that gamification can become a potential tool in the language learning classroom because it can increase students' motivation and engagement in the class [3], facilitate teacher-student interaction, and help develop academic, cognitive, and social skills and competencies [6]. To enhance the efficiency of game-based learning, gamification applications should be entertaining and well-designed [7]. They should align with the implemented environment [8].

With gamification activities and technology, extrinsic motivation can be boosted; learners will find themselves in a new setting and atmosphere of competitiveness that motivates them and promotes peer collaboration and competition. Thus, Liu, Zhou, and Ye carried out a study based on the Quizlet Live game platform to reveal the impact of competition on students' vocabulary learning and learning motivation. The results showed that students in competitive classrooms experienced better vocabulary learning effects and motivation than those in non-competitive classes [5].

This research intends to support a more comprehensive picture of the published research on gamification for English language learning and which platforms and online technologies are commonly used in Business English classes at the Armenian State University of Economics. The research also aims to reveal, compare, and evaluate the advantages and disadvantages of two online platforms—Kahoot and Blooket—in terms of their efficiency in the Business English learning and teaching process.

2 Methodology

The research used quantitative methods to collect and interpret the data aimed at finding and offering the best possible solutions and outcomes. The major technique for collecting data was the questionnaire designed to find out the opinion of the parties involved that was sent to the groups of first- and second-year students (who were taught Business English in gamified settings) studying at the Armenian State University of Economics. The students at ASUE study Business English, which differs significantly from General English by containing many new terms and notions.

The current research applied statistical, metacognitive, descriptive, and comparative analyses to address the paper's main objectives. Methodological and descriptive analyses assisted in organizing and managing the classroom effectively and making it beneficial for both the learners and the lecturers. The quizzes and tests for the games were developed by the authors and were later extensively used during the English lessons based on Business English vocabulary learned by students.

Statistical and comparative analyses enabled the authors to collect feedback from 58 students and responses of in-person interviews with 18 lecturers teaching Business English at the same university and reveal and compare the advantages and disadvantages of Kahoot and Blooket platforms from teachers' and students' perspective.

Metacognitive research comprised in-person interviews of lecturers teaching Business English at ASUE by applying gamification features and activities during their lessons.

3 Results

The shift to online teaching has become a necessity for ELT educators. They have to apply sophisticated methods and identify online platforms and tools to use in the teaching process. After thoroughly investigating different tools and platforms, the idea of gamification quickly attracted our attention as an alternative that would make Business English lessons more engaging by capturing the students' interest and would motivate them to compete and learn.

First, the authors analyzed and studied the student population, their English language needs, and their level of English competence to identify topics to be covered during the teaching process, adjust the curriculum, and stimulate their study habits.

The next goal was to identify the knowledge gaps that should be filled during our teaching process. Thus, the learning objectives would be defined, knowledge gaps would be eliminated, and learners would enrich and expand their knowledge of Business English vocabulary to communicate in business settings.

When learning Business English, the learners must memorize new words pertaining to business and economics or get familiar with new meanings of English words that were previously used by the learners when learning General English.

When teaching vocabulary games, the authors selected two websites (Kahoot and Blooket) in terms of their efficiency in usage, accessibility, ease of use, and affordability. The authors gamified the process by introducing quizzes and tests.

The website Kahoot has been around for decades before the emergence and global spread of the COVID-19 pandemic. Teachers and educators conducted their teaching process through this online platform even before the spread of COVID-19; many educational institutions successfully implemented it. This online platform has been widely used by us when teaching Business English and testing the knowledge of Business vocabulary proved its advantages.

Meanwhile, Blooket has been thoroughly investigated and widely applied during Business English lessons at the Armenian State University of Economics. The online platform was extensively used when teaching face-to-face during two consecutive semesters at ASUE, at the Department of Computer Science and Statistics and the Department of Management. The students of the first and second years of studies were involved in this process. The primary problem with business vocabulary teaching is the process of remembering and keeping the words in the working memory later to be used in the right context or when necessary.

When teaching vocabulary, the lecturer can assign the quiz as homework or host the game to be played during the face-to-face lesson (e.g., host live game mode (e.g., gold quest, crypto hack, fishing frenzy, tower defense, monster brawl, cafe, or factory) or classic version, without any game mode). The online platform Blooket makes it possible to choose a game that can be played in line with the test. The peer competition drives the learners to play fast, take first place, and see their name on the leaderboard and podium, which satisfies the desire of students to win in the process. This motivates the students. However, the authors would also like to analyze the benefits they get from such an activity. Such activities foster the learners' autonomy and provide playful opportunities.

It is considered beneficial to test vocabulary via the application of tests and quizzes. This online platform offers an interesting and engaging tool when answering the test questions. It offers a new tool embedded in the platform in the form of a game inside the game. Namely, after three correct answers during the game, students can start the game parallel to the quiz or test. During the lessons, the students chose to play the cafe, factory, and gold quest modes. The students mostly preferred cafe mode. After three correct answers, students started designing their cafe, restocking the food, and serving the customers, thus earning cash and upgrading their cafe to earn even more money.

The lecturer can choose to end the game when the time ends or somebody earns the gold specified by the lecturer as the final goal.

The students open the website on their phones, input the game ID, and choose their name and avatar, after which the game starts. As the lecturer has specified time or money to be earned as a final goal, the students will have to answer the same test questions several times for the whole duration of the game to win the game and achieve success. As the questions repeat several times, students automatically remember the question and the answer; their sensory memory transfers the words and their definitions from short-term memory to the working memory that can generally

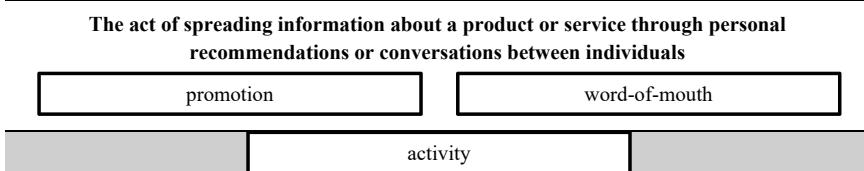


Fig. 1 Graphical representation of the questions and answers to be chosen based on the lessons studied and learned during Business English classes. *Source* Developed by the authors

hold between five and nine items (or chunks) of information at any one time. Figure 1 presents questions and answers to be selected based on the lessons learned and mastered in Business English classes.

Peer comparison pushes the students to perform better, eventually win the game, and find their names on the leaderboard.

The students underlined the interactive nature of these platforms; such gamification elements as getting scores, badges, points, and their names on the leaderboards were accepted enthusiastically.

The primary goal of this research was to investigate how satisfied the students were after the gamified environment specially designed for them. The survey (6 questions) was conducted among the participating students (28 freshmen and 30 sophomores); 58 answers were collected, which proved that gamification could motivate and incentivize the students to learn better. Based on the data collected, 45 students (77.6%) were satisfied with online games and quizzes, only 13 students (22.4%) were interested in paper versions of the quizzes and tests, justifying this by the fact that they faced some difficulties when switching from traditional ways of learning to the digital ones. Answering the question “How often does your teacher organize tests and quizzes in gamified format?”, 57 students (98.3%) answered “once a week.” Only one student (1.7%) selected the option twice a month. The next question was “What gamification website or tool did you like the most?” (Fig. 2) 30 students (51.7%) preferred Kahoot, and 53 students (91.4%) chose Blooket. The authors also asked students to rate the websites from 1 to 6 according to their tools and possibilities to hold tests and quizzes (where 1—not interesting; 6—extremely interesting). According to the answers, 46 students rated Blooket as extremely interesting (6 points), and 17 students rated Kahoot as extremely interesting. The last question was “Would you like your lessons to be organized using gamification technology and tools?” Answering this question, students gave 49 positive answers (84.5%) and 7 negative answers (12.1%), justifying this by difficulties experienced with data access and the fact that the small size of the phone screen did not allow them to acquire the information comprehensively.

In line with this, the authors also interviewed 18 ASUE teachers in person. The questions posed and answered reflected the advantages and disadvantages of Kahoot and Blooket. They mostly underlined the engaging and motivating nature of gamified activities and how active and motivated the students are when doing the quizzes and tests in gamified settings. The next advantage identified was the possibility for the

What gamification website or tool did you like the most?

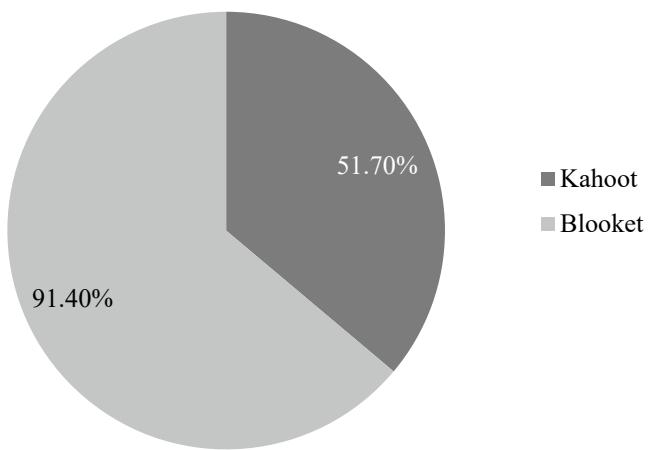


Fig. 2 Results of the questionnaire (58 students took part in the study). *Source* Designed by the authors

lecturers to prepare quizzes and tests and keep them on the website, on their dashboard to be further used for different groups and during different lessons. They highlighted the possibility of preparing tests on Blooket to be used by other lecturers. Moreover, it is possible to make the test public. The tests can be accessed by the lecturers, thus making them more beneficial from the lecturers' standpoint. The next advantage of Blooket was the number of students that could access the test simultaneously—60 students can simultaneously play (which is impossible at Kahoot because it has a limit on the number of players—10 students; if the number is higher, the lecturer has to pay a monthly fee to be able to engage more players). The possibility of engaging more participants in the quiz is Blooket's biggest advantage. The only advantage of Kahoot is the possibility to download the application from the App Store to play on smartphones. Blooket still does not offer this option. Thus, Blooket is accessible only through its website.

4 Conclusion

As a result of studying gamification features and their application from a variety of angles, namely, their accessibility, ease of use, and whether the online tool or application was free of charge for us to use during the teaching process, and according to the results of the research and experiment, the authors identified the main points of the advantages of these online platforms, including the following:

1. The online platform Kahoot is widely used by educators and has many advantages. However, some features are provided on a paid basis. Moreover, only ten students can participate in the test simultaneously, which sometimes impedes the testing process and discourages the lecturers from using it widely and extensively.
2. The online platform Blooket, which the authors extensively used during two consecutive semesters, offers more opportunities and a “game inside the game” option in the form of a cafe, gold quests, or other games to be played in line with answering the test questions and finally winning the game and taking the places on the leaderboard or getting badges. Another advantage is the possibility of using the same test prepared by one lecturer by others, which saves time.
3. The platform Blooket has one more advantage highly appreciated by students and lecturers—60 players can simultaneously play the game. Thus, any group can play and compete without any restrictions practiced by Kahoot.

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Psychological Support (Maintenance) of the Implementation of Artificial Intelligence



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and Boris V. Kaigorodov[✉]

Abstract The research aims to analyze the development of personal qualities among employees in the real sector of the economy who utilize artificial intelligence (AI) in their professional activities. The authors employed a psychodiagnostic method to obtain empirical data. The research was conducted on a sample of employees from the banking sector (289 individuals) and the oil and gas industry (289 individuals). The results were processed using statistical methods: calculation and analysis of percentage ratios, processing of primary descriptive statistics data (calculation of the mean), correlation analysis (determination of Pearson's linear correlation coefficient), and calculation of the nonparametric Kolmogorov–Smirnov criterion and the parametric Student's t-test. Personal qualities (e.g., humanity, responsibility, honesty, willingness to cooperate, and readiness to make moral choices in favor of good) among employees in the banking sector and the oil and gas industry are approximately at the same average level of development. “Good as a character trait” is highly developed, while “Evil as a character trait” is low. The results indicate the absence of malevolence as a personal quality among employees in the banking sector and the oil and gas industry, as well as the presence of a friendly attitude. However, the average level of development of most investigated personal qualities indicates the necessity for their further development in the context of the increasing influence of AI on human life and, consequently, the further increase in requirements for the resilience of personality to information-psychological influences. Currently, there are very few studies on the role of personal qualities of individuals utilizing AI. This research provided new empirical data on the state of personal readiness of representatives of the real sector of the economy to the increasing information-psychological influence of AI.

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JEL Classification M5 · O3

1 Introduction

Artificial intelligence (AI) is increasingly permeating and integrating into people's lives. The scope and possibilities of its application are expanding in the professional area and everyday life. AI is a tool created to enhance the quality of human life by freeing individuals from performing stereotypical standard functions. Smirnov [14, 15] and Sizikova [13] point out that the development of AI entails the development of an intelligent digital assistant for humans. Scientists justify their conviction with the mediation scheme (e.g., the mediation of intellectual decisions by mental activity) from L. S. Vygotsky's cultural-historical psychology [16]. In the new cultural practice of human development and personality formation, a model of human-sign-machine mediation in achieving life goals through the activity of AI is clearly traced.

Like any tool, AI can be used for good and bad. The way this tool will be used certainly depends on humans. AI can solve complex tasks. Thus, its malevolent use is fraught with negative consequences. Therefore, it is important for people to be aware of these consequences and be prepared for responsible and socially beneficial use of AI. Human beings are the subjects of interaction with AI. Therefore, it is necessary to cultivate the subjective qualities of human personality capable of consciously and responsibly applying AI. These qualities can include responsibility, honesty, willingness to cooperate, and the ability to make moral choices in favor of goodness.

The research aims to analyze the development of the mentioned personal qualities among representatives of the real sector of the economy who utilize AI in their professional activities—employees in the banking sector and the oil and gas industry. In these sectors, the responsibility of their employees in using AI is important; malevolence is unacceptable. Otherwise, economic damage may be incurred for individual persons, large organizations, and the country. Ecological harm may also be inflicted, leading to economic losses.

2 Methodology

The issue of malevolent use of AI as a threat factor to information-psychological security has been examined by Dremluga and Korobeev [5], Leksyutina [8], Pantserov [9], and Pashentsev et al. [10]. The authors emphasize that the source of the threat is not AI but people employing it.

Ya. V. Leksyutina investigated the problem of malevolent use of AI in China. The author highlights that the negative consequences of this extend not only to material

and economic damage but also to social-psychological destabilization of society by provoking panic among the population through the creation and dissemination of false information, harming interethnic, intrastate, and interstate relations and the psychological well-being of citizens [8].

K. A. Pantserov examines existing practices and risks of malevolent use of AI on the example of African countries. The author found that the issue of ensuring information-psychological and cyber security is common to all African countries. It hampers further sustainable social and economic growth. Certain African countries cannot ensure cyber security. The efforts of all African countries need to be united. However, serious contradictions between these countries hinder cooperation in solving this problem [9].

E. N. Pashentsev, C. N. A. Phan, and V. N. Dam also concluded on the necessity of cooperation among different societal structures for effective counteraction against malevolent use of artificial intelligence. The authors propose increasing knowledge about AI as a measure to counteract this phenomenon and recognizing and taking responsibility for the common future [10].

Within the framework of considering the issues of criminal policy in countering the platformization of criminal activities, R. I. Dremluga and A. I. Korobeev note that the transition to the digital economy is often associated primarily with the transfer of economic activities to online platforms created using AI. This provides criminals with the opportunity to reach a wide audience of consumers of illegal goods. The use of platforms complicates the identification of criminals and the proving of their guilt. The authors highlight the socio-psychological basis of the considered offense, manifested in citizens' predominantly negative attitudes toward these criminal manifestations [5].

There are very few studies on the role of personal qualities of individuals using AI. This aspect of the problem was addressed by Deviatko et al. [4], Kornilova [7], and Popov [11].

T. V. Kornilova examined the connection between responsibility and the moral component of choice. She notes that the problem of personal responsibility for decision-making entails considering the moral component in regulating choice [7].

The application of AI entails addressing moral-ethical issues. I. Deviatko, I. V. Katerny, and T. Y. U. Kirilina, with co-authors, note that rapid changes in the world highlight the need to study moral and ethical issues. The authors note the presence of considerable moral and ethical contradictions in all areas of public life [4].

I. Deviatko addresses the issue of orienting AI toward human values and its alignment with the sociology of morality and justice, emphasizing the importance of research for developing ethically oriented AI systems [3].

D. V. Popov sheds light on the issue of human responsibility for the inhumane consequences of AI functioning. The author writes that "responsibility for the intrusion of the inhumane rests not on AI but on humans" [11, p. 139]. As a solution to this problem, the author suggests focusing efforts not on the technical side of the issue or on specific machine learning of AI but on cultivating humanity within the human being [11].

N. G. Bryukhova and S. V. Agafonova demonstrate that the development of humanity as an expression of morality should be based on enduring universal values and on the cultivation of creativity as a creative search for ways to embody these universal values in life, manifesting one's creative potential for the sake of others and society, in the choice of moral ways to solve tasks and problems, influence, and assistance to others [2].

The following psychodiagnostic methodologies were employed for the empirical study of personal qualities among representatives of the real sector of the economy utilizing AI in their activities:

- Psychodiagnostic test "Good and Evil" developed by Popov et al. [12];
- Methodology "Diagnosis of business, creative, and moral climate in the team" developed by Fetiskin et al. [6];
- Questionnaire "Psychological diagnosis of moral choice in innovative situations" developed by Artemeva and Veselova [1].

The research involved 578 individuals:

- Employees in the banking sector ("Sberbank" PJSC in Astrakhan and the Astrakhan Region) totaling 289 people (including 124 senior managers and 165 client managers);
- Employees in the oil and gas industry (Astrakhan Gas Processing Plant) totaling 289 people (including 128 middle-level managers and 161 employees of structural divisions).

The obtained data was processed using statistical methods: mathematical methods of calculating and analyzing percentages, processing of primary descriptive statistics data (calculation of the arithmetic mean), and correlation analysis (determination of the Pearson linear correlation coefficient), with the use of the nonparametric Kolmogorov–Smirnov criterion and the parametric Student's t-test. For the convenience of conducting comparative analysis and visual illustration, the authors converted the data obtained from the above-mentioned methodologies into a 100% interval scale or decimal fractions. The boundaries of the development levels were used for conclusions:

- Low from 0 to 0.35;
- Medium from 0.36 to 0.65;
- High from 0.66 to 1.

The results at the significance level were used for conclusions:

- $p < 0.01$ (high significance of differences);
- $p < 0.05$ (significant differences);
- $p < 0.1$ (differences at the level of statistical tendency).

Differences between the indicators of the subjects in the correlation analysis are associated with the degree of relationship expression:

- Very weak ($r \leq 0.19$);

- Weak ($0.2 \leq r \leq 0.29$);
- Moderate ($0.30 \leq r \leq 0.49$);
- Average ($0.5 \leq r \leq 0.69$);
- High ($r \geq 0.7$).

During the research, the authors did not analyze very weak correlations. A comparative method was used to organize the empirical study, implying the simultaneous study and comparison of indicators from different samples to establish similarities and differences in the obtained data.

3 Results

The research yielded indicators on the scales of “Humanity,” “Evil as a character trait,” “Good as a character trait,” “Responsibility,” “Cooperation,” “Honesty,” and “Moral choice” among employees in the banking sector and the oil and gas industry.

Additionally, the authors assessed the reliability of differences in the values of indicators among representatives of the two investigated samples. To test the normality of the distribution of quantitative variables, the authors calculated the nonparametric Kolmogorov–Smirnov criterion for each sample. The distributions of all studied variables comply with the normal law, as the significance level is $p < 0.1$. To compare the indicators for these variables, the authors calculated the parametric Student’s t-test for independent samples.

The correlation coefficients of the “Humanity” scale with the indicators of scales characterizing the features of the development of personal qualities among employees in the banking sector and the oil and gas industry indicate that at the “Sberbank” PJSC in Astrakhan and the Astrakhan Region and at the Astrakhan Gas Processing Plant, the indicators of the “Humanity” scale positively correlate with the indicators of scales (arranged in descending order of correlation coefficients): “Good as a character trait,” “Cooperation,” “Moral choice,” “Honesty,” and “Responsibility” (Table 1). The indicators of the “Humanity” scale correlate negatively only with the indicators of the “Evil as a character trait” scale. For employees in the banking sector, these correlations are stronger.

Employees in the banking sector and the oil and gas industry are characterized by a moderate level of development in the indicators of “Humanity,” “Responsibility,” “Cooperation,” and “Honesty” (Table 2).

Meanwhile, “Humanity” and “Cooperation” are more developed among employees in the banking sector than in the oil and gas industry ($p < 0.01$ —at a high level of significance of differences). Responsibility indicators are higher among employees in the oil and gas industry ($0.05 < p < 0.15$ —at the level of statistical tendency). No differences in the indicator of “Honesty” were found among employees in both samples (differences are insignificant).

“Evil as a character trait” is developed at a low level among employees in the banking sector and the oil and gas industry. However, at the level of statistical

Table 1 The correlation coefficients of the “Humanity” scale with the indicators of scales characterizing the development of personal qualities among employees in the banking sector and the oil and gas industry (r —Pearson linear correlation)

Scale	Employees of the banking sector	Employees of the oil and gas industry
Evil as a character trait	– 0.638**	– 0.569**
Good as a character trait	0.642**	0.575**
Responsibility	0.462**	0.381*
Cooperation	0.664**	0.593**
Honesty	0.579**	0.547**
Moral choice	0.618**	0.580**

Note The correlation is significant at the 0.01 level (2-tailed); ** The correlation is significant at the 0.05 level (2-tailed)

Source Compiled by the authors

Table 2 The average values on the scales characterizing the development of personal qualities among employees in the banking sector and the oil and gas industry, the significance of differences in indicators (Student's t-test for independent samples)

Scale	Average value ($x_{av.}$)		Student's t-test value	Significance level of differences
	Employees of the banking sector	Employees of the oil and gas industry		
Humanity	0.589	0.522	5.138	0.000
Evil as a character trait	0.231	0.260	– 1.326	0.097
Good as a character trait	0.820	0.782	4.477	0.002
Responsibility	0.568	0.613	– 1.519	0.076
Cooperation	0.645	0.581	5.140	0.000
Honesty	0.547	0.552	1.364	0.151
Moral choice	0.668	0.601	6.138	0.000

Note $p < 0.01$ —high significance of differences, $p < 0.05$ —significant differences, $0.05 < p < 0.1$ —differences at the level of statistical tendency, **bold**—differences are insignificant

Source Compiled by the authors

tendency ($0.05 < p < 0.15$), the trait of evil is more characteristic of employees in the oil and gas industry.

Employees in the banking sector and the oil and gas industry are characterized by a high level of development in the indicator “Good as a character trait.” However, the trait of goodness as a character trait is significantly more developed among employees in the banking sector ($p < 0.05$).

Only in terms of the indicator “Moral choice” do the average values differ between the examined samples. Employees in the banking sector demonstrate a high level in this regard. Among employees in the oil and gas industry, this trait is rated as average.

4 Conclusion

The development of personal qualities among employees in the banking sector and the oil and gas industry is approximately the same. Most of the examined personal qualities (i.e., humanity, responsibility, cooperation, and honesty) are developed at a moderate level. “Evil as a character trait” is developed at a low level, while “Good as a character trait” is at a high level. Only in terms of the indicator “Moral choice” do the average values differ between the examined samples. Employees in the banking sector demonstrate a high level in this regard. Among employees in the oil and gas industry, this trait is rated as average.

Slightly higher scores on the scales of “Humanity,” “Good as a character trait,” “Cooperation,” and “Moral choice” are noted among representatives of the banking sector. Employees in the oil and gas industry have slightly higher scores on the scales of “Evil as a character trait” and “Responsibility.”

This is presumably explained by the fact that employees in the banking sector more often interact with other people during their professional activities. Moreover, “Sberbank” PJSC has an organized and constantly improving system of intra-corporate training for employees on socio-psychological interaction.

Employees of the Astrakhan Gas Processing Plant (an organization in the oil and gas industry) interact more with technology than with people. The system of corporate development of employees is built considering the requirements for their qualifications—training is more directed towards developing business qualities and, to a lesser extent, towards personal and interpersonal competencies.

On the one hand, the results indicate the absence of malice as a personal quality among employees in the banking sector and the oil and gas industry, as well as the presence of a friendly attitude. On the other hand, the average level of the development of other personal qualities indicates the need for their further development to be able to respond to contemporary challenges in the conditions of further technological development of society, including the complexity and expansion of the influence of AI. Therefore, it is necessary to increase the requirements for the resilience of individuals to information and psychological influences further.

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AI-Based Detection of Conflict Markers in Political Discourse



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Abstract Within the last two decades, conflict has become one of the most highly-demanded topics in cross-disciplinary research. Considering the anthropo-centric paradigm as the major research framework of contemporary linguistics, it is apparent that it is necessary to study conflicts as they serve as an indispensable part of society and its systems. Conflict is inherent in interpersonal communication; language is actively involved in the process. While conflict was originally examined in sociology and psychology, it has also attracted linguists, who have explored it across various theoretical frameworks. Political discourse is no exception. On the contrary, political interviews stand out as having significant conflict potential because they represent a kind of dialogical verbal interaction within which a clash of communicative goals appears normal. These interactions employ specialized language tools that serve as markers of conflict communication, utilized by interlocutors to either temper or intensify the conflict, depending on their communicative intentions. The authors propose applying AI-based techniques to identify markers of conflict communications. The authors show the way such techniques may be used for research purposes as far as conflict communication is concerned. The authors singled out such markers of conflict communication as communication styles mismatch, frequency of turn-taking, and different sets of most frequently used words identified by AI-based techniques.

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1 Introduction

Conflict (along with cooperation) is a type of social interaction that contributes to the mutual achievement of the common goal set by its participants and the solution of common tasks. In most general terms, scholars define it as the manifestation of the divergence of views or interests. Conflicts represent ways to resolve contradictions by means of open or hidden actions by individuals or groups. Conflicts consist of the misalignment of interests, goals, and values.

The conflict-driven nature of political discourse is the result of the diversity of its participants' viewpoints, leading to the clash of opinions and opposing pragmatic attitudes. Certain social conditions can strengthen or weaken contradictions typical of a conflict situation, which may further aggravate or reduce the possibility of a communicative failure in political communication.

Generally speaking, conflict communication can be defined as the clash of interests, needs, values, and opinions represented in speech via various linguistic means [9]. It is rooted in the whole complex of external and internal factors of psychological, social, and linguistic nature, including the following:

- External factors—norms and traditions typical of a certain linguoculture;
- Conventions and regulations generally accepted by the representatives of the community;
- Patterns of speech behavior adopted by the individual due to their social significance;
- Social roles of communicants that depend on their social status, occupation, nationality, education, or age;
- Internal factors—personality type, motives and intentions [12, p. 169].

Important for the analysis of conflict communication are the purposes of communication, the means, and the quality of their realization. Bearing this in mind, we may state that any conflict is represented in language and speech. According to V. S. Tretiakova, speech and language are characterized by such features that instigate language users to speech conflict [24, p. 139].

2 Materials and Methods

This research is based on the communicative-pragmatic analysis of the text of a political interview. Starting with providing the characteristics of political discourse and its conflict potential, the authors conduct an investigation into the language and pragmatic means of the verbalization of conflict, coming to the conclusion that certain language and pragmatic means can be considered markers of conflict communication in political discourse.

The research is conducted on the material of the interview of President of the Russian Federation V. V. Putin to an American TV channel on June 6, 2021 [11].

3 Results

3.1 *Conflict Communication in Political Discourse*

3.1.1 Political Discourse: Major Characteristics

Political discourse is understood as the use of language in the public sphere of communication [9, p. 36] conducted in oral and written forms and thematically related to politics. It is a type of institutional communication that employs a certain system of professional codes. That is, it has its own language comprised of vocabulary, phraseology, and paremiology [19, p. 15]. In a broad sense, political discourse includes such forms of communication within which either the content of communication, the addressee, or the subject relates to the political sphere. Narrowly defined, political discourse is the type of discourse aimed at exercising, preserving, or taking political power [22, p. 147].

Scholars highlight some important features of political discourse, including heterogeneity of genres [1, p. 296], cultural and national discourse specifics [8, p. 37], relevance to the social system and its participants [7, p. 274], status-role relations differentiation [20, p. 3], and power-driven instrumental function [16, p. 244].

Within the proposed research, we will focus on the analysis of one of the mediatized political genres [18, 20], the genre of a political interview.

3.1.2 Political Interview as an Example of Conflict Communication

Political interview embraces the properties of a number of discourse types, namely political, mass media, and public types of discourse, as well as features typical of dialogical genres, as it is usually conducted in the form of a dialogue. According to some scholars, distinctive features of an interview include such characteristics as directness of communication, dialogic nature, public character, and a question-answer kind of interaction [18, p. 70]. Possessing these features, a political interview

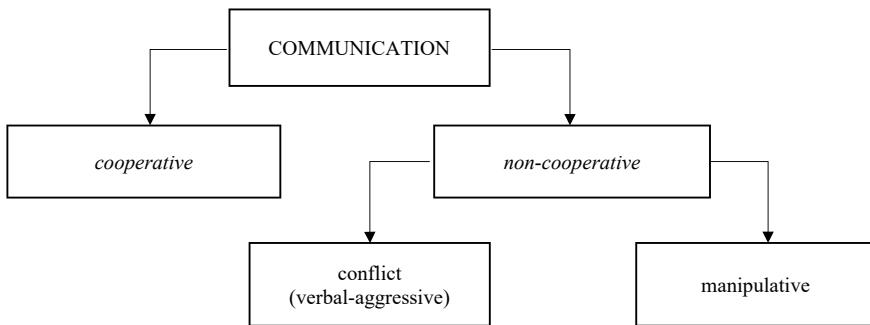


Fig. 1 Typology of dialogical communication. *Source* Compiled by the authors based on [7]

represents “a conversation that is of socio-political and public interest, which is determined not only by the urgency and “situationality” of the discussed issue but also by the direct relevance of the addressee to the discussed issue” [10, pp. 66–69].

There is no denying the fact that dialogical communication cannot be only of cooperative nature as “there is always a factor of disharmony that introduces the potential danger of the formation of false ideas, the destruction of understanding and the violation of emotional, psychological and physical balance” [14, p. 208]. In political interviews concerned, if there are differences in opinions or opposing views on some political topics, dialogues inevitably turn into a conflict type of communication, which corresponds with the typology of the genres of dialogical communication developed by Kuznetsov [7, p. 276] (Fig. 1).

Some scholars propose a basic structure of a political interview following which will allow the interlocutors to achieve the goals of the interview in a conflict-free way. As pointed out, interviews are “all … characterized by the same role distribution, all having an interviewer as a representative of a media organization and an interviewee” [6, p. 139]. Sharing this opinion, Ekström [5, p. 565] identifies the following basic and recurrent features of a political interview:

- It is started and ended by the interviewer (journalist);
- The initiative comes from the interviewer, who invites the interviewee to speak;
- The interviewee is aware of the fact that the agenda is set by the interviewer;
- The interviewer adheres to a neutral and formal position;
- The interviewee is supposed to answer the interviewer’s questions.

Any breach of standard procedure may lead to a conflict in communication. Some violations are considered quite natural and expected. Vignozzi proves it by writing that “the interviewee and interviewer’s institutionalized rule of taking turns in succession without interrupting each other is something that is likely to be violated” [25, p. 17]. In turn, other violations lead to serious communication failures.

Besides, in political interviews, conflict may be revealed in the process of verbal interaction when interlocutors have “an illocutionary dominant idea characterized by the presence of a clash of communicative goals, the representation of which contains

implicit or explicit invectives” [3, p. 5]. Such communication results in negative emotions experienced by the interlocutors due to verbal influence on each other. It is verbally realized by certain language and pragmatic means. Language means may include the use of lexical units of subjective character (addresses, performatives, imperative verbs with invective meaning), negative adverbs and particles, and exclamations [3, p. 33]. That is, interlocutors use vocabulary that can potentially convey various shades of meaning due to the fact that semantic structure contains connotative meaning and associative fields contributing to semantic flexibility and variations of their usage [13, p. 60; 15, pp. 64–65].

3.2 Language Markers of Conflict Communication in Political Discourse

3.2.1 Language Markers in Communicative-Pragmatic Research Paradigm

Being one of the elements of the system of textual features, language markers have so far been the focus of linguistic and interdisciplinary studies. Understood as specific words and phrases capable of providing an unambiguous definition of one or another aspect of the content, language markers form multiple constructions typical of certain aspects of the text.

Text linguistics studies various aspects of speech with a detailed analysis of markers, representing different levels of language and differing in their pragmatic and functional attitudes. Thus, numerous studies of the lexical level touch upon the following problems:

- Verbalization of elements of a certain language culture (linguocultural markers), including in professional discourse [23, p. 100];
- Pragmatic attitudes typical of the text (markers of causality, argumentation, persistence, speech manipulation) represented with the help of certain lexical units in various types of discourse [2, p. 466];
- Gender-specific features of communication are represented by specific gender-marked lexical units [21, pp. 129–130].

As far as grammar is concerned, the research focuses on the analysis of syntactic structures typical of specific types of discourse and variable cases of morpheme usage, which provides ground for viewing them as syntactic or morphological markers.

The presented research is an attempt to analyze the totality of lexical and pragmatic means of the language typical for the speech of a political leader in the genre of a political interview. These linguistic phenomena include units of different levels of language that denote and mark differences in the opinions or opposing views, the employment of which expresses such communicative intentions of interlocutors that may lead to the escalation or mitigation of a conflict.

3.2.2 AI-Based Detection of Markers of Conflict Communication in Political Discourse

The research procedure includes several stages:

1. Preparing the texts for automatic analysis. To avoid errors, the authors removed the names of the interlocutors from the text and divided the text in two blocks. The prepared text contained the same number of utterances for each interlocutor (68 people), which shows that not a single question of the interviewer remained unanswered.
2. AI-based analysis of agreement or disagreement in the text.

General characteristics of the text were as follows:

- The number of words: 10,504;
- The number of characters without spaces: 48,052;
- The number of words in the remarks of the interviewer: 2114;
- The number of words in the remarks of the interviewee: 8390;
- The number of question marks in the remarks of the interviewer: 47;
- The number of question marks in the remarks of the interviewee: 95.

According to the interpretation of the results, a difference of 3.8 times in the number of words pronounced by each interlocutor shows that the interviewee gave detailed answers to the interviewer's questions. However, the number of question marks demonstrates the breach of standard procedure of an interview—the interviewee asked two times more questions than the interviewer.

The analysis of the text done by Voyant Tools [26] gave the following results (Table 1).

The analyzed texts differ in lexical density, which measures the proportion of meaningful words in the total number of words, giving an idea of how rich in information the text is. A higher lexical density means that most words in the text are meaningful, which indicates a more informative or content-rich text. Academic or official texts often have a higher lexical density compared to spoken texts.

Given the fact that the journalist prepared the questions in advance, his part of the dialogue can be attributed to a written text, which is generally characterized by a higher level of lexical density. However, the indicator in the range of 40%–49% demonstrates the average density, which is typical for fiction and nonfiction of general subjects with the inclusion of conversational content. The text's style is semi-official. Such texts often use a combination of diverse vocabulary and commonly used words.

Table 1 Quantitative analysis of the text

Interviewer	Interviewee
Unique word forms: 885	Unique word forms: 2253
Lexical density: 0.477	Lexical density: 0.318
Readability Index: 14.102	Readability Index: 13.525

Source Compiled by the authors

Examples of texts with this level of lexical density can be found in Time Magazine, National Geographic, the novel “Pride and Prejudice” by Jane Austen, and the novel “To Kill a Mockingbird” by Harper Lee.

The indicator of 0.318 (range 30–39%) demonstrates a level of lexical density below average, characteristic of dialogic speech, which fully corresponds to interview answers. The text’s style is conversational narrative. The text focuses on dialogue, storytelling, or expressing personal points of view. Such texts include works of fiction with a large number of dialogues, scripts for films or television dramas, personal essays, and occasional blog entries. Examples of texts with a lower-than-average lexical density can be found in People Magazine, the novel “The Catcher in the Rye” by J. Salinger, and the novel “Twilight” by Stephanie Mayer.

The mismatch of communication styles revealed by the lexical density indicator can be considered a marker of conflict communication.

The word “no” was used 41 times, 40 of which were in the interviewee’s utterances. The word “yes” was used three times in the interviewee’s utterances to express agreement with the interviewer’s opinion.

The most frequently used words by the interviewer are “president” (24 times), “Russia” (14 times), “Biden” (14 times), “China” (12 times), and “question” (11 times). The most frequently used words in the interviewee’s utterances are “know” (37 times), “states” (35 times), “people” (34 times), “united” (31), and “China” (24). According to Wierzbicka, word frequencies are “important and revealing” [27, p. 15] in terms of concepts and values. In the context of the presented research, the most frequent words reflect the most important topics for the interviewer and the interviewee. The fact that these words are different demonstrates the difference of priorities in the conversation between the two parties.

Table 2 presents word and sentence statistics, which were compiled using the service “Readability Formulas” [17].

Let us now consider the automatic detection of agreement or disagreement—turn-taking frequency. The average length of the interviewer’s utterances is 3–4 lines. The average length of the interviewee’s utterances is 12 lines. These figures were obtained using the DeepAI resource [4]. There are a few fragments where the turns change after each line; this tendency is mostly initiated by the interviewer, who does not give the interviewee an opportunity to give a full answer to the question, interrupts him, and asks another question, which sounds sharper and more direct than the previous one. Aggressive interruptions aimed at seizing the initiative in the conversation may be viewed as markers of conflict communication.

3.2.3 Language Markers of Conflict Communication in Political Discourse—Supporting the Data Obtained by AI-Detection

Linguistic research of the interview text revealed certain language means (lexical units, stylistic devices, and syntactic structures) that may be viewed as markers of conflict communication depending on the context.

Table 2 Word and sentence statistics

Interviewer	Interviewee
<i>Word statistics</i>	
Total number of words (with numbers): 2278	Total number of words (with numbers): 80,549
Average word length: 4 characters	Average word length: 4 characters
Longest word in text: unpredictability (16 characters)	Longest word in text: incomprehensible (16 characters)
Average number of words per sentence: 13	Average number of words per sentence: 16
Total number of characters (with spaces): 12,159	Total number of characters (with spaces): 46,232
Total number of characters (without spaces): 10,037	Total number of characters (without spaces): 37,988
Total number of letter characters (A-Z only): 9621	Total number of letter characters (A-Z only): 36,462
<i>Word usage statistics</i>	
Number of easy words: 1844 words (80% of the text)	Number of easy words: 7090 words (83% of the text)
Number of hard words: 262 words (11.5% of the text)	Number of hard words: 1101 words (13% of the text)
Compound words count: 4	Compound words count: 23
Total cardinal numbers in text: 8	Total cardinal numbers in text: 20
Proper noun count: 142	Proper noun count: 294
Abbreviated words count: 18	Abbreviated words count: 20
<i>Sentence statistics</i>	
Total number of sentences: 162 (Sentences with ending punctuation)	Total number of sentences: 545 (Sentences with ending punctuation)
Total line count: 162 lines of text	Total line count: 549 lines of text
Average sentence length: 13 words	Average sentence length: 16 words
Compound sentence count: 0	Compound sentence count: 0
Number of passive voice sentences: 6 (4% of the text)	Number of passive voice sentences: 46 (8% of the text)
Number of active voice sentences: 156 (96% of the text)	Number of active voice sentences: 499 (92% of the text)
Total number of short sentences: 92 (57% of the text)	Total number of short sentences: 260 (48% of the text)
Total number of medium sentences: 38 (23% of the text)	Total number of medium sentences: 157 (29% of the text)
Total number of long sentences: 32 (20% of the text)	Total number of long sentences: 128 (23% of the text)

Source Compiled by the authors

For instance, the interviewer often refers to the opinion of a third party (e.g., “it is the opinion of the President of the USA J. Biden”) and calls the Russian President using words with negative connotations. It is apparent that such words will induce the interviewee’s negative reaction. Besides, a direct adversarial position supported by indirect accusations is often present in the interviewer’s speech.

Both parties widely employ interruptions and question-question sequences of utterances. Unfinished sentences are also widely employed to increase the intensity of speech opposition.

4 Conclusion

As the conducted research shows, conflict is inherent in political interviews. Interview participants resort to special language that has the potential to either escalate or de-escalate the conflict. The authors propose to view these means as markers of conflict communication typical of political discourse. AI-based detection of conflict markers is based on some formal characteristics of the studied text, such as vocabulary density, word frequency, word and sentence statistics, and automatic detection of turn-taking. The obtained results are relevant and supported by the results of the linguistic research of the text showing the choice of language means, which include various lexical units with negative connotations, lexical oppositions, interruptions, question-question sequences of utterances, and stylistic devices. Further analysis may be devoted to the study of pragmatic strategies and sentiment analysis, which also requires a combination of AI-based and empiric methods of linguistic research.

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AI Tools in the Analysis of Legal Discourse: Methods and Prospects



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Abstract Artificial intelligence (AI) has been used in practice for a relatively short time. The first attempts to apply AI to analyze legal discourse date back to the late 1990s. Nowadays, AI is widely implemented in various areas of law, such as predicting the outcome of court cases, risk assessment, contract analysis, and more. This research focuses on methods and prospects of using AI tools in the analysis of legal discourse. The authors draw on theoretical foundations of the analysis of legal texts, present a brief history of AI development, provide an overview of the tools used in the research of the legal field, and map up the prospects for using AI in various fields of legal discourse. The research is conducted to identify the potential of AI technologies in optimizing lawyers' work connected with legal texts so that they can focus on activities requiring human experience, which will eventually improve the quality of justice. Besides, the study is of great assistance to the linguistic research community as it proposes a repository of AI-based methods of analysis applicable to legal discourse.

Keywords AI tools · Legal discourse · Linguistic analysis · Methods of linguistic analysis · Applications of AI · Linguistics

JEL Classification C35 · C45 · Y80

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1 Introduction

In the present-day world of rapidly developing technology, the application of data-based methodologies turns out to be an effective tool relevant to the research of various data. Legal texts are no exception. This research examines the role and possibilities of using tools in the analysis of legal discourse. It identifies methods and prospects for using them to improve the understanding and interpretation of legal texts. This research aims to explore the possibilities offered by advanced AI technologies for analyzing legal discourse. The objective of this research is to identify the potential of AI in legal text analysis.

The relevance of this research lies in recognizing the need for the legal sector to adapt to the challenges posed by digital advancements and in the reflection of benefits that new digital tools offer to optimize the work of lawyers and, as a result, improve the quality of justice. The novelty of this research consists of a comprehensive analysis of various methods of applying AI in the field of law and identifying their potential to improve the processes of analysis and interpretation of legal texts.

2 Materials and Methods

The research deals with the description of methods and prospects of AI-based analysis of legal discourse, which requires studying the development of AI and the specifics of its application in the legal domain. Considering that the topic is relatively new for linguistics studies, the proposed investigation is primarily based on analyzing theoretical sources that provide insight into the possibilities of AI tools in legal text processing. For this purpose, the authors thoroughly studied a body of scientific publications and various Internet sources related to the subject.

The research object is legal discourse, which is considered one of the most conservative types of discourse. The choice of the research object is explained by recognizing the fact that AI tools of linguistic analysis are gaining more popularity as far as legal discourse is concerned. Developing a repository of AI-based methods of analysis applicable to legal discourse will be of great methodological assistance to the linguistic research community.

3 Results

Understanding that AI and its applications have become a widely studied topic in cross-disciplinary research, we find it necessary to start by conducting a diachronic analysis of AI, tracing its development from the very beginning.

Several names should be mentioned in relation to the development of AI. The field's founders based on representation and reasoning are Minsky [22] (received the

A. M. Turing Award in 1969) and McCarthy [19] (received the A. M. Turing Award in 1971). Their research was further advanced by Feigenbaum [8] and Reddy [27] (co-received the A. M. Turing Award in 1994), who, nearly thirty years later, developed expert systems capable of encoding human knowledge to solve real-world problems. In 2011, Judea Pearl managed to develop probabilistic reasoning techniques able to deal with uncertainty in a principled manner. A critical step in developing advanced computing is the development of deep learning by Yoshua Bengio, Geoffrey Hinton, and Yann LeCun (co-received the A. M. Turing Award in 2019).

A brief history of AI is presented in Table 1.

Since this research is focused on legal discourse, the authors will turn to determining its constitutive features, genre differentiation, and language specifics.

First, the authors will consider the constitutive features of legal discourse. As with any professional type of discourse [17, p. 23], legal discourse is distinguished by the following:

- Goal orientation—to convince of guilt or innocence, to advocate, to explain legal norms and principles, etc.;
- Correspondence to the norms of communicative behavior—the specifics of legal discourse are represented in its discursive practices—observance of typical

Table 1 Major landmarks in AI development

Dates	Stage	Major developments
1943–1956	Inception of AI	The first recognized work in AI—a model of artificial neurons [20]; the development of high-level language Lisp [18]
1980s–1988	AI boom and AI winter	Rapid growth from a few million dollars in 1980 to billions in 1988; companies build expert systems, vision systems, and robots; “AI winter”—companies failed to deliver on promises due to the limitations of expert systems
1986–present	The return of neural networks	A resurgence of interest in neural networks (the mid-1980s); the reinvention of the back-propagation learning algorithm; the appearance of connectionist models, which led to advancements in AI applications
1987–present	Probabilistic reasoning and machine learning	Probabilistic reasoning and machine learning as driving forces; probability, machine learning, and experimental results are incorporated into AI research; significant advancements in AI are marked by shared benchmark problem sets and the use of Bayesian networks
1988–present	Reunification of AI subfields	AI subfields (computer vision, robotics, speech recognition, and natural language processing) are reunited; start of practical applications
2001–present	Big data era	Advances in computing power; learning algorithms are developed to handle large data sets

Source Compiled by the authors based on [4, pp. 17–26]

behavior patterns, use of specific language means relevant to a certain communicative situation, performance of various kinds of actions according to a typical model (verbal and non-verbal) [15, p. 84];

- Asymmetric nature of communication (equality or inequality in distributing professional expertise and institutional power among discourse participants)—multi-vector communication: professional–professional, professional–layman, and layman–professional.

Second, the authors consider genre differentiation of legal discourse. Traditionally, legal discourse has been divided according to the mode of communication (i.e., oral or written). The digitalization of law, as in any other sphere of professional communication, contributed to the appearance of hybrid types of discourse (Fig. 1), such as popular-legal, which is widely represented in a multitude of computer-mediated forms of communication.

Third, the authors focus on the language specifics of legal discourse. Legal discourse is characterized by using certain linguistic features that distinguish it from other types of professional discourse. They include the following:

- Lexical means—“technical” legal terms, borrowed clichés, discourse markers, binomial phrases, pronominal adverbs, archaisms, and terminologized units;
- Syntax and grammar means—complicated sentence structure, multiple levels of subordination, homogeneous terms, indented structures, inversion, conditional sentences with modal verbs, passive voice, parentheses, and nominalization [2, 6, 10, 16, 32].

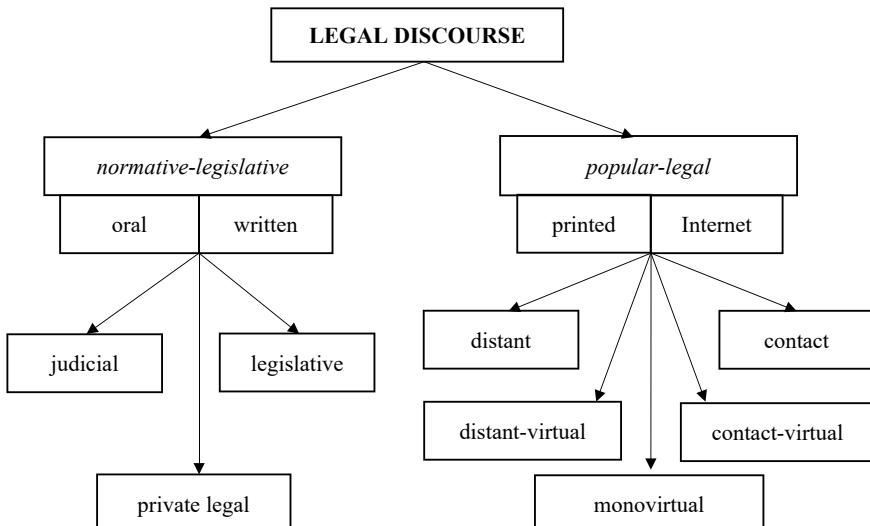


Fig. 1 The diversity of genres within the legal domain. *Source* Compiled by the authors based on [2, 6, 16, 32]

Turning to the analysis of the role of AI in the legal sector, the authors would like to highlight the main directions of the interaction of AI and legal discourse.

First, AI may be successfully involved in legal research. AI-based tools provide quick and efficient access to legal information. These tools are used in the analysis and extraction of relevant information from huge collections of legal documents, which significantly lessens the process of legal research for lawyers, legal professionals, and law students.

Another area of AI applicability is document verification. Driven by AI, machine learning algorithms quickly process documents, which absolutely excludes the possibility of human error.

No less important is contract analysis conducted by AI. It is primarily used for analyzing and revising contracts to determine key provisions, potential inconsistencies, and risks. This application of AI contributes to the optimization of contract management processes and ensures compliance with legal requirements.

Intelligent analytics is another area of successful implementation of AI in the legal field. Lawyers can use AI tools to evaluate potential litigation outcomes, considering precedents and historical data. Such techniques may help lawyers to develop effective legal strategies and make informed decisions.

As far as cost-saving is concerned, AI is quite handy at conducting repetitive tasks, which inevitably improves the efficiency of lawyers' work and reduces operating costs and manual workload. Consequently, lawyers may focus on tasks that require human experience.

One more area of AI active participation is providing legal assistance. Chatbots and virtual assistants are becoming more popular in interacting with clients, answering common legal questions, and accompanying individuals during legal processes. Such tools are a good choice for people looking for free legal services and assistance.

Last but not least is a feature that allows businesses to track the latest changes in legislation. AI technologies can ensure compliance with laws and regulations and identify and evaluate potential business risks.

As for the study of legal communication, there are quite a few AI tools that can be successfully involved in analyzing legal discourse. Scholars point out that "new computational technologies open important new research opportunities for law scholars by expanding the analytic methods that can be applied to legal texts" [9, p. 39]. Some computational methods to analyze legal discourse are presented in Fig. 2.

Currently, AI is successfully employed for the analysis of legal discourse, which is proved, on the one hand, by many scholarly publications showing the results of such research [3, 14, 23, 29, 33] and, on the other hand, by a constantly widening range of AI tools available for computational analysis.

Table 2 presents AI tools used to process legal texts.

A detailed description of the options offered by certain Internet services within the mentioned areas of AI application will allow us to develop a holistic view on AI potential in dealing with texts representing popular-legal Internet discourse.

Let us start with NLP. The services offered are as follows:

USES OF COMPUTATIONAL METHODS IN LEGAL ANALYSIS		
	<i>law-as-code approach</i>	<i>law-as-data-approach</i>
	Legal rules, regulations, and statutes are represented in a machine-readable format that can be interpreted and executed by computer systems	Legal texts, statutes, regulations, and other legal documents are treated as structured data that can be analyzed, processed, and interpreted using data science techniques
	Legal texts are translated into structured data or code that can be processed and analyzed by artificial intelligence (AI) algorithms and other computational tools	Legal information is viewed not just as text to be read and understood by humans but as data that can be leveraged for computational analysis and automation
POSSIBLE APPLICATIONS		
	standardization	data structuring
	automation	data analysis
	interpretability	automation
	dynamic updates	visualization
	integration with AI technologies	interoperability
		predictive analysis

Fig. 2 Computational methods used for the analysis of legal discourse. *Source* Compiled by the authors based on [4]

Table 2 Range of AI tools used in the analysis of legal discourse

Areas of AI application	Description of functions
Natural language processing (NLP)	It deals with natural language processing. It is used to analyze textual data
Machine learning (ML)	It allows computers to learn from data without the need for programming. It is useful for identifying patterns or trends
Deep learning (DL)	It is a subset of machine learning that uses neural networks to train on large amounts of data. It is used to identify complex patterns
Text analytics	It is the process of analyzing text to extract information and understand meaning. It is used to identify key topics or issues
Information extraction (IE)	It is the process of extracting structured information from unstructured text data. It is used to extract specific information from online legal advice texts (names, dates, and locations)

Source Compiled by the authors based on [3, 5, 7, 9, 23, 28, 29]

1. Google Cloud Natural Language API [12]—a cloud service from Google that offers tools for text analysis (context understanding, tonality classification, and information extraction);
2. IBM Watson Natural Language Understanding [13]—an IBM service providing text analysis capabilities (context understanding, tonality classification, and information extraction);
3. Microsoft Azure Cognitive Services Text Analytics [21]—a set of services from Microsoft that offer tools for text analysis (context understanding, tonality classification, and information extraction);
4. Rasa NLU [26]—an open platform for NLP that provides tools for text analysis and creating dialog systems;
5. Spacy [30]—a Python library for NLP that offers a wide range of functions for text analysis (tokenization, part of speech, dependency, reading, and comprehension);
6. NLTK (Natural Language Toolkit) [24]—a Python library for NLP that provides tools for text analysis (tokenization, part of speech, reading, and comprehension);
7. OpenNLP [25]—a Java library for NLP that offers tools for text analysis (tokenization, part of speech, reading, and comprehension);
8. Stanford CoreNLP [31]—an NLP toolkit developed at Stanford University that provides tools for text analysis, including tokenization, part of speech, reading, and comprehension.

Turning to ML, it is necessary to mention that it uses various tools and techniques for data analysis and learning based on solutions to many similar problems. The ML process uses the tools of mathematical statistics, numerical methods, mathematical analysis, optimization methods, probability theory, graph theory, and techniques for working with data in digital form. ML involves working with data, features, and algorithms. The data is the starting point of the process and adds to the knowledge base of the model. The signs serve as labels by which the model can get the necessary results and solve problems. The algorithms determine the model's shape, its operation speed, and the accuracy of the answers. In applied linguistic research, ML allows robots to perform complex tasks such as speech recognition and pattern detection.

Speaking about DL tools, let us mention the AlchemyAPI Expert System S.p.A. [1], which is capable of conducting text analysis and information extraction. One more option is the General Architecture for Text Engineering (GATE) [11], which can be characterized as a modular architecture for text processing. Both tools are based on using deep learning techniques to provide accurate and efficient analysis of legal texts.

4 Conclusion

As the conducted theoretical research shows, AI is currently actively involved in many areas related to law and legal discourse, such as legal research, document verification, contract analysis, intelligent analytics, efficiency and cost savings, legal assistance, and regulatory monitoring.

In the research of legal communication, two approaches have been simultaneously developing: law-as-code and law-as-data. Both approaches extract insights, automate text processing, and enhance decision-making in the legal domain. AI is employed for natural language processing, machine learning, deep learning, text analytics, information extraction. Various AI-based tools are at the researchers' disposal, including services from Google, IBM, Microsoft, and many others.

Further advancement of technologies will undoubtedly open up new trends and research directions in the field of interaction of AI and law. It will certainly relate to a wide range of innovative developments that shape this field. Let us map out a few key trends and areas in AI that may turn out to be of great help to legal professionals.

First, AI may be used for dispute resolution to facilitate negotiations, mediation, and arbitration and provide affordable and effective solutions in resolving legal disputes. In view of cross-disciplinary research, AI may be integrated with other law-related areas of expertise, which will contribute to a deeper understanding of human behavior and legal systems. Besides, a cross-disciplinary perspective may generate innovative solutions to complex legal problems.

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Gamification in the Formation of Legal Knowledge in Students in the Legal Educational Discourse



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Abstract The research aims to disclose the gamification role in the educational process to develop law knowledge in students in the legal educational discourse. Nowadays, the speed of the emergence of new information exceeds the speed of the emergence of new learning tools. A significant amount of educational material loses its relevance by the time of its release. Therefore, this material has no application. Modernization of the educational process is important to make educational programs reflect the present reality. Gamification of the educational process makes it possible to solve cognitive, research, educational, development, adaptation, and control functions. The game process can ensure effective work in the classroom and form necessary competencies depending on how the game is organized and implemented. During the research, the authors surveyed students. The survey identifies preferable online resources. The participants included 116 students aged 15–20. Participants took part in a gamified lesson on legal topics. According to the study, during the development of legal knowledge within the gamification framework, students must master the legal material and work out the necessary skills in practice. The experience of using gamification shows that there are no boundaries for creativity. The direction, methods, and tools used in educational activities depend solely on the participants. Gamification serves as a valuable tool for developing adolescents' legal culture during legal education and upbringing.

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JEL Classification A20

1 Introduction

One of the challenges in educating young people is addressing the formation of legal nihilism among new generations. This issue affects public legal consciousness and influences their perception of social structures. One of the ways to find a rational way out of this situation is to form a legal culture among adolescents in the process of legal education. Nowadays, the rate of appearance of new information is significantly higher than the rate of appearance of new learning tools. A significant issue in education is that a large amount of educational material becomes outdated by the time it is published. In today's world, the concept of continuous education is gaining popularity, with specialists constantly learning new technologies and methods to improve their qualifications. Modernizing the pedagogical process to reflect current realities in educational programs is essential. A promising trend in this direction is the gamification of the educational process [2, 12, 13]. Gamification of the educational process is the introduction of game elements into a non-game environment. Gamification aims to provide an educational environment that promotes soft-skills development (i.e., students' critical thinking formation, joint activity skills, and responsibility for decision-making). Using game methods in the learning process helps involve and motivate participants in the gamified process. The priority goals of using gamification in the educational process are to increase the cognitive activity of students, develop interaction skills, and establish a high level of motivation for results [9, 16]. Gamification of the educational process is an innovative tool that can help today's education system. For a long time, gameplay during training was believed to distract from achieving the main goals of education. Nowadays, gamification has shown high results in achieving training effectiveness.

Gamification relies on analyzing personal behavior and applying effective motivation methodologies derived from studying individual participant behavior in the learning process. The gameplay involves various simulators and strategies. Through these, students engage in research and develop essential skills for their future activities. Using gamification in the humanities is becoming increasingly popular and yields significant results [6, 22].

The game learning process is aimed at encouraging students to acquire knowledge, skills, and abilities. Therefore, it should not be restricted to supervision tasks to control knowledge verification [25]. Students are invited to solve a certain task, while mastering the necessary information. Game elements serve as internal motivators for students, encouraging flexibility and creativity in solving specific issues, such as how to apply the information they receive. The use of gamification tools

in the educational process enables the achievement of cognitive, research, educational, developmental, professional adaptation, and control functions. Implementing gameplay in the classroom promotes effective learning, contributing to developing essential competencies in individuals.

The quality of the game depends on the involvement and cooperation of all educational participants. During the gamified process, it is crucial to recognize that the game is a productive activity for students. Therefore, creating comfortable and supportive conditions for their training is essential [1]. A positive atmosphere and a well-designed game program will allow students to show creativity in solving problems and making decisions quickly for a minimum period. Simultaneously, it will contribute to the interrelation of theory and practice, social skills formation, and individual learning path construction. Gamification rejects such principles of the educational process as templates and invariability. Thus, teachers should independently adjust to the prevailing circumstances. Gamification of the educational process is of great importance because it is in demand and contributes to the development of creative abilities in students. Speaking about the gamification of the educational process, it is important to consider that students often actively use games. Game elements are present in all sectors of our life. Students are sure to seize this opportunity during training. Students note that a dynamic, bright, and short game can develop legal skills and knowledge more effectively. During the game, young people try themselves in different roles [7]. Most of them are trying to accumulate the highest number of points to gain credibility among their peers. The high results of students' gaming activities help them socialize and accumulate legal knowledge. Additionally, during the simulation models of games, participants in educational activities develop the most important abilities for managers. Moreover, the legal culture increases. Gamification makes it easier to learn the sequence and methods of data analysis and processing, trace the relationship of individual elements and processes, and develop group thinking techniques. Gamification of the educational process makes it possible to unlock the potential of students and motivates their self-education. Thanks to gamification, a person receives a complex of legal knowledge [27], which allows them to call their owner a legally competent person.

2 Materials and Methods

Within the framework of this research, it was necessary to reveal the role of gamification in the educational process as a condition for the formation of legal knowledge of students. To achieve this goal, it is necessary to consider various approaches to the peculiarities of using gamification in the educational process, describe the potential of gamification in the development of legal knowledge, study the basic principles of gamification, and analyze the experience of using gamification in the learning process using the example of popular online resources. The study was conducted in 2020–2021. The participants were 116 students aged from 15 to 20. Students were asked to take a survey that allows them to identify popular online resources that develop legal

knowledge. The following platforms were presented as a choice: Kahoot, Factile, Flippity, Genially, Learning apps, and Wordwall. During the research, students participated in a gamified lesson on the topics “Forms of government” and “Legal knowledge.” The participants played “true or false” and searched for concepts on a specific topic. Throughout the study, the subjects were under the supervision of experts who recorded the students’ choice features and the main aspects of their behavior. Varenina [23] calls the process of involving and motivating students the gamification of education. The author claims that this concept is the use of game techniques in non-game situations. Experience has allowed the authors to conclude that introducing such an approach in the learning process increases the effectiveness of education. Varenina [23] notes that many people associate the use of gaming technologies with young children only. However, this is not the case at all. Starting from kindergarten, games are firmly integrated into our lives and become a daily assistant and regulator of public relations. Currently, large organizations and corporations are constantly using gamification elements to increase the motivation of their employees. A high interest in gamification is associated with the desire to find a tool to increase human involvement and provide an open mechanism for encouragement and reward. According to the author, the important game elements of gamification are the setting of tasks, feedback, levels, and the creative process. Participants gain points that serve as an incentive for subsequent educational activities.

Laakso et al. [16] establish that the game design project is a pedagogically meaningful way of engaging students in knowledge-creating learning. It combines formal and informal learning for students. Students experienced game design as an inspiring and challenging activity. Game design engaged student teams in sustained and collaborative efforts to create shared digital artifacts. Their efforts involved a great deal of mutual support and knowledge sharing. Participation also improved students’ technical and artistic digital competencies. The game design project fostered informal, interest-driven, and socio-digital participation, inspired learning engagement, and improved schoolwork practices.

Gadzhieva [11] and Ivanova and Korostelev [14] note that the high potential of gamification in the development of legal knowledge is due to the functions that the game performs in the learning process: entertaining (to encourage interest in learning), communicative, therapeutic (overcoming internal difficulties), diagnostic, correctional, and socialization. The gameplay is a natural and human form of cognition. Gamification is one of the active legal education methods. It expresses a reality model and is based on situations taken from real life.

Clark et al. [8] conducted a systemic review and meta-analysis of digital games. Results from media comparisons indicated that digital games significantly enhanced student learning relative to non-game conditions ($g = 0.33$, 95% confidence interval [0.19, 0.48], $k = 57$, and $n = 209$). Results from value-added comparisons indicated significant learning benefits associated with augmented game designs ($g = 0.34$, 95% confidence interval [0.17, 0.51], $k = 20$, and $n = 40$). Moderator analyses demonstrated that effects varied across various game mechanics characteristics, visual and narrative characteristics, and research quality characteristics. Taken together, the

results highlight the affordances of games for learning, as well as the key role of design beyond the medium.

Kondrashova [15] highlights the following main aspects of gamification:

1. Creating a general gaming experience aimed at the participants' emotional involvement in the educational process;
2. Using scenarios that describe the behavior of students;
3. Introduction of game elements into the learning process (e.g., statuses, medals, or the number of lives);
4. Ensuring interaction between the participants of the game process.

According to the author, when completing homework using gamification, students expressed a different opinion about mistakes and grades. Despite the voluntary consent to participate in the gamified process, most students agreed to participate in the new approach to learning. The students were asked to complete certain tasks; the teacher indicated the mandatory minimum number of solved tasks. It is significant that 80% of the players passed more game elements than was required to win. The students doubled the amount of homework. After the results announcement at the first stage of the gameplay and the results presentation, the number of participants increased by 80% in the second stage. The experimental data showed that completing the tasks increased the average score in each group from 9.2 to 9.5, from 6 to 8, and from 5 to 6.3. As a result of the experiment, the personal responsibility of each participant increased. The author concludes that the gamification of the educational process is a successful way of organizing training. The obtained results confirm the idea that the gamification of the educational process can increase the involvement of students in cognitive activity [10, 21].

Aniskin et al. [3] and Sailer and Homner [18] formulated important principles of gamification (Fig. 1).

Autonomy is expressed in the fact that students will be more interested in the learning process and high learning outcomes when they feel responsible for the consequences of their activities, and their progress depends on the efforts made. This principle can be attributed to gamification and games in general because each next step is determined independently by the player [16, 20, 26]. When applying game

Autonomy

- Students will be more interested in the learning process when they feel that they are responsible for the consequences of their activities

Value

- When applying game elements in the learning process, it is important not to forget that education should teach him new skills

Competence

- The better people cope with a specific task, the more desirable it will be to continue its implementation

Fig. 1 Principles of gamification. *Source* Compiled by the authors

elements in the learning process, it is important not to forget that education should carry some value and teach new skills. The principle of competence implies that the better people cope with a specific task, the more desirable they will continue to perform it. When participants in the gameplay complete tasks and move to the next level, they get an idea of their development [17, 22, 25].

3 Results

The goal of gamifying the educational process is to engage students in cognitive activities similarly to how an online game engages players. This involves creating a system where success in the game is tied to abilities that can be applied in real-life contexts. The formation of legal knowledge among students depends on a well-designed game structure (Fig. 2).

The conflict consists of the interest confrontation. It is a prerequisite for the implementation of the game. The conflict can be expressed in the players' confrontation or desire for the best result. It is important to note that conflict does not have to occur between people. Conflict is not a temporary difficulty that you can ignore. It is a vital problem for players. Roles, characters, and participants are also important for the gamification of the educational process. The characters represent the parties to the conflict. There are different ways to take a certain role [19, 23, 24]. For example, a character is an archaeologist who needs to learn information about human civilization. Otherwise, the character will not survive at that time. The player is faced with a choice: to portray a mad archaeologist, trying to imitate his habits, or to take the opposite position. The rules of the game must be clearly defined to develop strategies for achieving success. Players only simulate life in a reduced format. The excitement of the game is to determine the first player to find the best strategy.

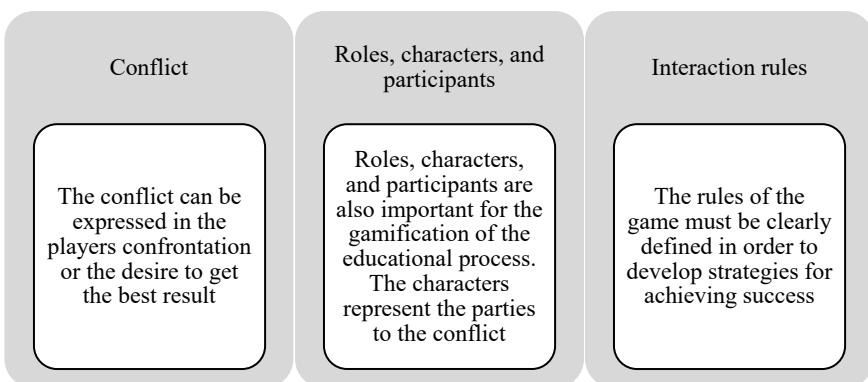


Fig. 2 The gameplay structure (according to the analysis of scientific works). *Source* Compiled by the authors

The experience of using gamification tools in the learning process makes it possible to conclude that creativity has no boundaries. Only the training participants determine the direction of their development and the ways of implementing the educational process. A survey was conducted among the students of the educational organization, which makes it possible to identify the most popular online resources that most effectively form legal knowledge. The survey involved 116 students of the humanities. Table 1 shows some of the questions for students.

The responses provided showed the following:

- 62% of the respondents highlighted the Kahoot platform, noting its clear interface and interactive mode;
- 31% of the respondents pointed out the Factile online service, highlighting interesting game characters and the ability to choose a team mascot as positive aspects;

Table 1 Questions for students to identify popular online platforms

No.	Question	Suggested answers
1	Which of the presented online platforms do you use in the learning process?	<ul style="list-style-type: none"> • Kahoot • Factile • Flippity • Genially • Learning apps • Wordwall
2	Which of the proposed online platforms is more convenient to use in studying?	<ul style="list-style-type: none"> • Kahoot • Factile • Flippity • Genially • Learning apps • Wordwall
3	Which online platforms can you get quick feedback on?	<ul style="list-style-type: none"> • Kahoot • Factile • Flippity • Genially • Learning apps • Wordwall
4	Which online platform provides interactive learning?	<ul style="list-style-type: none"> • Kahoot • Factile • Flippity • Genially • Learning apps • Wordwall

Source Compiled by the authors

- 24% mentioned that they had never used the Flippity service and could not express their opinion about it;
- 42% of students identified the platform Genially because there is an opportunity to add interactive elements, pass online quests, and create interactive posters.

Students actively participate in online games. For example, on the Learning apps platform, students consolidated their knowledge on the topic “Forms of government.” Owing to this exercise, the game participants noted the usefulness of this class format because the limited time created a competitive effect and contributed to motivation growth. On the Wordwall platform, students were invited to play a game “True or false” for the topic “Legal knowledge.” The game participants noted the convenience and colorfulness of interactive exercises and mini-games. Students answer the game questions. Then, they can see themselves on the leaderboard, which encourages them to step up their activities and achieve better results. Observing teachers’ activities has shown that those who use gamification in their practice have demonstrated better results. The material studied in the game course activity is forgotten more slowly than the material given in the traditional form. The game activity combines entertainment, which makes the process of learning accessible and exciting; knowledge assimilation is more efficient and durable. Gamification does not mean the rejection of traditional teaching methods. It is only an important addition to the educational process that makes it possible to consolidate knowledge in practice [4, 5]. On various platforms, it is possible to prepare a variety of tasks for students in accordance with their needs, interests, and personal and professional capabilities. The use of several online services will improve the quality of training and the level of mastering legal knowledge.

4 Discussion

The results obtained correspond to the results of the study of Fomin et al. [10], which indicate the need to use gamification in the contemporary educational process. The authors note the possibility of implementing feedback between training participants as a factor in improving the effectiveness of classes. The authors’ works also consider online services that allow students to be involved in the process of cognition. Such online services include Kahoot!, Edmodo, SMARTies, Jclic, Surala, and computer games and ICT technologies, including VR.

Rogacheva et al. [17] also prefer Kahoot! as a global educational platform that provides an opportunity for students and teachers to fully unleash their learning potential. The online platform contains quizzes, tests, discussions, and questionnaires using gamification mechanics. The platform’s advantages lie in its speed and ease of use. According to students, incorporating a game format into the educational process enables them to focus on the most significant aspects of the topic being studied. It fosters healthy competition among peers, facilitates result analysis, and maintains dynamism and activity throughout the lesson or event.

5 Conclusion

The most valuable knowledge is that which can be applied in practice. Students are more likely to learn information that is immediately relevant to them, so teachers must create conditions where this relevance is clear. This is a primary goal of gamifying the educational process. Gamification aims to develop key competencies and boost students' motivation. It incorporates various methods of organizing the pedagogical process, including different types of games, each with unique goals, outcomes, and directions.

When developing legal knowledge through gamification, students should not only learn legal material but also practice essential skills. Gamification serves as a tool for fostering legal culture among adolescents during legal education and upbringing. Today's education system increasingly relies on gamification to enhance students' legal knowledge because it supports the development of well-rounded individuals. Studies have proven the effectiveness of gamification in the educational process for cultivating students' understanding of law within the context of legal education.

The obtained results show that teachers actively use online platforms in their practice to implement gamified learning. Each platform has its own functions and capabilities. Therefore, in the educational process, it is advisable to use a system of online services to achieve the highest learning outcomes.

The use of game visual content enhances the internal motivation to complete the course. Further research will touch upon the issues of increasing the level of motivation of students within the framework of unified learning.

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Creating Green Jobs and Making Environmental Decisions Using Big Data and AI



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Abstract The research aims to determine the impact of big data and AI on creating green jobs and making environmental decisions in Asian countries. By employing correlation and regression analysis methods, the authors developed an econometric model for environmental management in the top 15 Asian countries with the most favorable opportunities for developing a green economy in 2023. According to the model, the use of big data and AI has a significant yet contradictory influence on environmental decision-making in these countries. While it promotes more active green investments and job creation, it simultaneously limits green trade and restrains green innovations. The theoretical significance of the developed model lies in its pioneering revelation of the causal relationships between the use of big data and AI and the effectiveness of environmental decision-making in Asia, a unique region of the world. The practical significance stems from the identified potential to increase the number of green jobs and optimize environmental decision-making through the more active use of big data and AI in Kyrgyzstan. This approach enables the development of corporate plans and the implementation of programs for the green development of Kyrgyz enterprises. The managerial significance is reflected in the fact that the organizational scheme developed for creating green jobs and making environmental decisions using big data and AI will enhance contemporary environmental management practices for enterprises in Kyrgyzstan and other Asian countries.

Keywords Green jobs · Environmental decision making · Big data · Artificial intelligence (AI) · Green economy · Asia

JEL Classification C44 · Q55 · Q57

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1 Introduction

In today's environmentally conscious societies, being part of the green economy is crucial for many enterprises to maintain their market positions. However, the challenge lies in the contradictory outcomes of environmental decisions. From an ecological standpoint, the best management decisions are those that most benefit the environment. This involves actively implementing green innovations that improve the environmental friendliness of production and distribution processes, products, and their consumption while also ensuring the safe disposal of waste.

From an economic standpoint, green production, investments, and trade should not only break even but also be profitable. If they do not yield returns, the business activity loses its viability. Therefore, if environmental innovations reduce product demand and economic efficiency, abandoning these innovations becomes necessary. Business practices that expand opportunities for green employment are of great interest from a social perspective.

To make the best environmental decisions, it is essential to comprehensively consider all viewpoints, which places a significant burden on enterprise managers involved in the green economy. Even large enterprises cannot always increase their managerial staff. For small and medium-sized enterprises, this is usually unattainable. This fact hinders the green growth of enterprises and underscores the need to find ways to boost managers' productivity in the green economy.

A promising solution to this problem is automating the environmental decision-making process using big data and artificial intelligence (AI). These technologies already enhance managerial productivity in other decision-making areas. However, their application in making specific environmental decisions is underexplored and poorly described in the literature, limiting the spread of these technologies in environmental decision-making practices.

The experience of each geographical region of the world needs independent study due to the regional specificity of business, consumer, and environmental cultures. The experience of a region like Asia deserves special attention because it includes developed and developing countries and advanced green and digital economies. Therefore, this research aims to determine the contribution of big data and AI to creating green jobs and making environmental decisions in Asian countries.

2 Literature Review

This research is based on the concept of managing an enterprise as a subject of the green economy [2, 7, 12, 19]. According to this concept, the main results of making environmental decisions include the following:

- The volume of green investments in the economy, reflecting the activity of financial support for sustainable and environmentally responsible resource use [13, 17];

- The volume of green trade, demonstrating the greening of foreign economic activities [6, 8];
- The number of green jobs and the share of green employment in the economy, representing the involvement of enterprise workers in addressing local environmental issues and the opportunities for realizing the human potential of green personnel [3, 16];
- The activity of creating and implementing green innovations in the economy, showcasing the intensity of utilizing advanced technologies in greening economic activities, reducing the environmental costs of economic growth, and ensuring decarbonization [14, 20].

The empirical experience of creating green jobs and making environmental decisions in Asian entrepreneurship is well-studied and documented in numerous scientific literature sources, such as Bishnoi et al. [1], Meltzer [10], and Samieva et al. [15]. Specific issues regarding the application of advanced technologies, particularly big data and AI in management, are discussed in several publications, including those by Dzhumanova et al. [4], Litvinova [9], and Osovsev et al. [11].

However, the available literature does not fully explain the consequences of applying big data and AI for creating green jobs and the outcomes of making environmental decisions in Asian countries. This gap in the literature forms the basis for the research question on how the use of big data and AI in enterprise management affects the creation of green jobs and environmental decision-making in Asia.

3 Materials and Methods

For this research, the authors formed a sample consisting of the top 15 Asian countries with the most favorable opportunities for developing a green economy in 2023. The selection criterion was the highest value of the “green economic opportunities” indicator among Asian countries in the 2023 Global Green Growth Institute ranking [5].

To determine the impact of using big data and AI in enterprise management on the creation of green jobs and environmental decision-making in Asia, this research employs correlation and regression analysis. Based on these methods, the authors determined the strength of the relationship and modeled the influence of the “readiness for frontier technologies index” (denoted as BD&AI) from UNCTAD materials [18] on the outcomes of environmental decisions, specifically on the following [5]:

- “Green investment” (GInv);
- “Green trade” (GTrd);
- “Green employment” (GEmp);
- “Green innovation” (GItn).

The statistics for these indicators are provided in Table 1.

Table 1 Environmental management in the top 15 Asian countries with the most favorable opportunities for developing a green economy in 2023

Country	Criterion for inclusion in the sample	Technological factor	Results of environmental decision-making			
			Green investment	Green trade	Green employment	Green innovation
			BD&AI	GInv	GTrd	GEmp
China	62.68	0.74	57.65	77.26	83.67	41.43
South Korea	58.60	0.94	69.53	73.16	62.25	37.24
Azerbaijan	54.57	0.40	39.16	67.04	60.95	55.40
UAE	52.38	0.74	71.87	56.04	58.90	31.74
Malaysia	51.97	0.76	53.62	76.21	47.55	37.55
Japan	49.29	0.88	51.12	84.62	32.23	42.35
Tajikistan	48.86	0.17	37.25	95.79	35.04	45.57
Indonesia	47.74	0.49	47.56	69.94	44.88	34.80
Vietnam	47.74	0.58	57.60	69.87	46.86	27.54
Thailand	47.31	0.64	52.19	76.51	50.91	24.64
Armenia	46.62	0.51	38.97	68.86	68.14	25.83
Singapore	46.40	0.94	97.85	48.04	28.63	34.44
Kyrgyz Republic	45.68	0.34	41.68	61.13	36.80	46.42
India	45.41	0.66	39.19	69.82	55.48	28.01
Georgia	45.33	0.51	30.20	73.12	61.23	31.23

Source Compiled by the authors based on Global Green Growth Institute [5] and UNCTAD [18]

Based on the results of the regression analysis, decisions on environmental outcomes are selected where the application of big data and AI yields advantages (regression coefficients have taken positive values). Using Kyrgyzstan as an example, the authors determined the potential for maximizing the application of big data and AI ($BD\&AI = 1.00$) for the selected outcome variables.

4 Results

To determine the impact of using big data and AI in entrepreneurial management on the creation of green jobs and environmental decision-making in Asia, the authors conducted an econometric analysis of the data from Table 1. The analysis made it possible to formulate the following system of equations of paired linear regression:

$$\left\{ \begin{array}{l} GInv = 17.23 + 56.66 * BD\&AI, R^2 = 0.7299, \\ GTrd = 80.71 - 15.40 * BD\&AI, R^2 = 0.3045, \\ GEmp = 48.85 + 4.38 * BD\&AI, R^2 = 0.0651, \\ GItn = 43.41 - 11.51 * BD\&AI, R^2 = 0.2945. \end{array} \right. \quad (1)$$

Based on the system of equations (1), in Asia, an increase in the use of advanced technologies, particularly big data and AI, by 1 leads to an increase in the volume of green investments in the economy by 56.66 points (correlation: 72.99%) and an increase in the number of green jobs and the share of green employment in the economy by 4.38 points (correlation: 6.51%). However, it also results in a decrease in the volume of green trade by 15.40 points (correlation: 30.45%) and a decline in the activity of creating and implementing green innovations in the economy by 11.51 points (correlation: 29.45%).

The constructed econometric model (1) allowed the authors to select environmental decision outcomes where applying big data and AI generates advantages (regression coefficients have taken positive values) in Asia. These include the volume of green investments in the economy, the number of green jobs, and the share of green employment in the economy.

Based on the results of the econometric analysis, the authors identified the perspective of increasing the number of green jobs and optimizing environmental decision-making through more active use of big data and AI using Kyrgyzstan as an example. For this purpose, the maximum possible value of the big data and AI application indicator ($BD\&AI = 1.00$) was substituted into the model (1). The consequences for the selected outcome variables $GInv$ and $GEmp$ were determined.

As a result of forecasting, the authors determined that increasing the activity of using advanced technologies, particularly big data and AI, in Kyrgyzstan by 194.12% (from 0.34 in 2023 to 1.00) will prospectively ensure the following:

- A 130.24% increase in the volume of green investments in the economy (from 41.68 points in 2023 to 95.96 points);
- A 10.22% increase in the number of green jobs and the share of green employment in the economy (from 36.80 points in 2023 to 40.56 points).

To implement the demonstrated perspective in practice within the entrepreneurship of the green economy in Kyrgyzstan and other Asian countries, the authors developed an organizational scheme for creating green jobs and making environmental decisions using big data and AI (Fig. 1).

According to Fig. 1, within the developed organizational framework, AI employed by the enterprise assumes the role of the decision-making entity for environmental matters. It sifts through vast amounts of data, serving as an ecological information system accessible to the enterprise, and integrates this data into its decision-making processes. AI conducts environmental decision-making and machine learning, drawing insights from prior environmental decisions that have been enacted and put into practice.

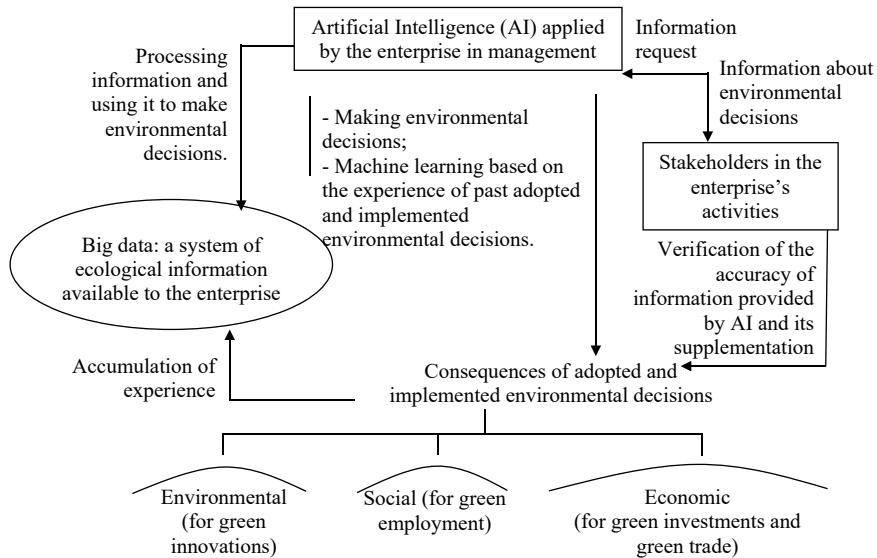


Fig. 1 Organizational scheme for creating green jobs and making environmental decisions using big data and AI. *Source* Developed by the authors

It considers the consequences of adopted and implemented environmental decisions: ecological (for green innovations), social (for green employment), and economic (for green investments and green trade). Information about these consequences is aggregated into big data for experience accumulation. Stakeholders in the enterprise's activities receive information about environmental decisions from AI, verify the accuracy of this information, and supplement it as needed.

The enhanced organizational scheme for creating green jobs and making environmental decisions, utilizing big data and AI, offers the following advantages compared to the currently employed organizational scheme for environmental decision-making in green economy entrepreneurship:

- More comprehensive and systemic (considering ecological, social, and economic factors jointly) assessment of expected consequences in environmental decision-making;
- Improved monitoring of real consequences of implemented environmental decisions through experience accumulation and machine learning, enabling the optimization of their outcomes with each decision-making cycle;
- Extensive provision of information to stakeholders about the environmental decisions adopted and implemented by the enterprise, ensuring marketing support for these decisions for a more successful return on green investments.

5 Discussion

The obtained results further develop the scientific principles of the enterprise management concept as a subject of the green economy [2, 7, 12, 19], specifying the consequences of applying big data and AI for creating green jobs and the outcomes of making environmental decisions in Asian countries. The synthesis and econometric modeling of the empirical experience of the top 15 Asian countries with the most favorable opportunities for developing the green economy in 2023 revealed the following.

The utilization of big data and AI significantly increases the volume of green investments in the economy (as supported by [13, 17]) and moderately boosts the number of green jobs and the proportion of green employment in the economy (as supported by [3, 16]). However, it reduces the volume of conducted green trade (in contrast to [6, 8]) and diminishes the activity of creating and implementing green innovations (in contrast to [14, 20]).

6 Conclusion

Thus, the main conclusion of this research is that the application of big data and AI has a strong but contradictory influence on environmental decision-making in Asian countries, facilitating more active placement of green investments and creation of green jobs, yet limiting green trade and restraining green innovations.

The developed econometric model of environmental management in the top 15 Asian countries with the most favorable opportunities for developing the green economy in 2023 has theoretical significance as it has, for the first time, revealed the causal relationships between the use of big data and AI and the effectiveness of environmental decision-making in Asia as a unique region of the world.

The identified prospect of increasing the number of green jobs and optimizing environmental decision-making through more active use of big data and AI in Kyrgyzstan has practical significance because it represents a highly accurate forecast and can be used in formulating corporate plans and programs for implementing the green development vector of Kyrgyz enterprises.

The developed organizational scheme for creating green jobs and making environmental decisions using big data and AI has managerial significance because it will help improve the current practice of environmental management in the operations of Kyrgyzstan's enterprises and other Asian countries.

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The Organization of Circular Production and Improvement of Energy Efficiency Through Decision-Making Based on Big Data and AI



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Abstract The research focuses on the potential for organizing circular production and improving energy efficiency through decision-making based on big data and AI. The authors conducted a regression analysis on the best practices of the top 20 dynamically developing digital economies with the highest activity in applying big data and AI in 2023. The developed econometric model provided highly accurate quantitative measurements of the impact of automating investment and environmental decisions based on big data and AI technologies for the green economy, underscoring its theoretical significance. The scientific novelty of the research results is linked to the author's classification of the consequences of automating investment and environmental decisions based on big data and AI for the green economy. Using Russia as an example, the authors demonstrated the potential for growth in energy efficiency and circularity of production by implementing big data and AI in decision-making, highlighting its practical significance by expanding opportunities for planning and forecasting the development of the green economy. The authors developed a decision-making framework for organizing energy-efficient circular production based on big data and AI. The managerial significance of the developed model is reflected in the optimization of these decisions.

Keywords Investment and environmental decisions · Green AI · Green big data · Environmental manager · Circular production · Energy efficiency

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1 Introduction

The decarbonization vector set by supranational and state regulators as a priority for sustainable development during the Decade of Action and beyond has heightened the importance of transitioning to circular production and increasing the energy efficiency of economic activities. The green transition of organizations to support the fight against climate change is encouraged by a whole set of incentives.

One of the incentives is the introduction and periodic tightening of mandatory requirements by public administration bodies for the environmental efficiency of organizational activities. These requirements include state norms and standards for circularity and energy efficiency, as well as additional environmental regulatory measures for the business environment, ranging from climate taxes to carbon quotas.

Another incentive comprises the ecological demands of the market, which progress as green social and business culture evolves. Organizations cannot remain aloof from the growing trend of voluntary ecological standardization and product certification. An increasing number of market agents are improving the environmental properties of their products to strengthen their green competitive advantages.

Incentives also include the full-scale provision of green production factors for environmentally responsible organizations. The labor market offers many green personnel, representing various levels of qualification for all sectors of the green economy with developed environmental competencies. Additionally, the markets for production factors are widely represented by green technologies, climate investments, and infrastructure support for combating climate change and transitioning to clean energy.

Nevertheless, despite the systemic impact of the discussed incentives on contemporary organizations, their green transition is occurring slowly. Circular productions are rare and confined to specific green territories. Clean energy retains a secondary role in the economy; the consumption of fuel and energy resources, as well as the energy intensity of economic growth, remain relatively high.

The reason for the weak impact of incentives on the green transition of contemporary organizations lies in the high complexity of making investment and environmental decisions. First, environmental monitoring of organizational activities presents significant challenges. Data on circularity and energy efficiency for certain elements are fed into the corporate information system, where they mix with other corporate accounting data. This fragmentation of information often hinders the accurate determination of an organization's environmental characteristics as the starting point for its green transition.

Second, organizations often face high uncertainty and risk in environmental investments. Despite being fully prepared to produce goods with improved climate and other environmental properties, organizations frequently have to abandon such production due to insufficient confidence in its future commercial success. Third,

the potential opportunities for a green transition within an organization are usually unknown and fragmented, which prevents their practical implementation.

Thus, there is a pressing scientific and practical problem of improving the process of making investment and environmental decisions by organizations. As an innovative and promising solution to this problem, this research proposes modernizing investment and environmental decision-making processes based on advanced digital technologies such as big data and artificial intelligence (AI). This research aims to identify the prospects for organizing circular production and improving energy efficiency through decision-making based on big data and AI.

2 Literature Review

The fundamental basis of this research is the theory of investment and environmental decision-making. According to established theory, the primary criteria for the optimality of these decisions for the green economy include the following outcomes:

- A reduction in the natural rent of GDP [5];
- An increase in private investments in energy [9];
- An increase in GDP per unit of energy consumption through reduced energy intensity of economic growth [2];
- A higher share of renewable energy consumption due to a widespread shift to clean energy [8].

While the general application of big data and AI technologies in investment and environmental decision-making is extensively covered in the scientific literature, the consequences of automating these decisions using these technologies remain unknown. This represents a gap in the literature that needs to be addressed to enhance the scientific and methodological support for the green transition of today's organizations.

In this regard, the research question is "How does the automation of investment and environmental decision-making based on big data and AI impact the green economy?" Various published works present alternative viewpoints.

Some authors argue that the technological modernization of the investment and environmental decision-making process using big data and AI restrains the inflow of private investments in energy [7], increases the natural rent of GDP [4], decreases GDP per unit of energy consumption [6], and reduces the share of renewable energy consumption [10].

Conversely, other researchers claim that the automation of investment and environmental decision-making based on big data and AI stimulates the inflow of private investments in energy [1], decreases the natural rent of GDP [3], increases GDP per unit of energy consumption [12], and raises the share of renewable energy consumption [17]. To clarify these causal relationships and refine the answer to the research question, this research conducts econometric modeling of the impact of big data and AI on the green economy.

3 Materials and Methods

The authors determined the consequences of automating investment and environmental decision-making based on big data and AI technologies using regression analysis. This method is applied for econometric modeling of the impact of the application of these technologies (Tech) on the outcomes of investment and environmental decisions for the green economy (DsGr).

To exclude the distorting influence of institutions on the causal relationships of investment and environmental decision-making, and considering the differences in the institutional environment of developed and developing countries, this research focuses on the experience of developing countries, which is the least studied and, therefore, deserve in-depth research. The sample (Table 1) includes the top 20 dynamically developing digital economies with the highest activity in applying big data and AI in 2023, according to the Tortoise Media ranking [11].

The econometric model also includes the influence of DsGr₂ on the other outcomes of investment and environmental decision-making for the green economy. This selection identifies the outcomes for the green economy that are directly (in direct dependence on Tech) or indirectly (in dependence on DsGr₂) improved through the modernization of investment and environmental decision-making using big data and AI.

Based on the results of the econometric model, the potential for growth in energy efficiency and circularity of production (using Russia as an example) is identified when big data and AI are integrated into decision-making by substituting the maximum possible value (100 points) for Tech in the model.

4 Results

To achieve highly accurate quantitative measurements of the consequences of automating investment and environmental decision-making based on big data and AI technologies for the green economy in rapidly developing countries in 2023, the authors conducted a regression analysis of the data from Table 1. As a result, the following econometric model was developed:

$$\left\{ \begin{array}{l} \text{DsGr}_1 = 5.0872 + 0.0151 * \text{Tech}; \quad \text{DsGr}_1 = 4.2851 + 1.1154 * \text{DsGr}_2; \\ \text{DsGr}_2 = 0.4503 + 0.0272 * \text{Tech}; \\ \text{DsGr}_3 = 16.6425 - 0.1861 * \text{Tech}; \quad \text{DsGr}_3 = 13.6676 - 0.6812 * \text{DsGr}_2; \\ \text{DsGr}_4 = 33.8949 - 0.4839 * \text{Tech}; \quad \text{DsGr}_3 = 23.9656 + 0.4590 * \text{DsGr}_2. \end{array} \right. \quad (1)$$

Model (1) indicates that the natural rent of the economy increases by 0.0151% of GDP with a one-point increase in the use of big data and AI and by 1.1154% of GDP with a \$1 billion increase in private investments in energy. Private investments

Table 1 Technological factor and the consequences of investment and environmental decision-making for the green economy in 2023

Country name	Total natural resources rents (% of GDP)	Investment in energy with private participation (bln. current \$)	GDP per unit of energy use (constant 2021 PPP \$ per kg of oil equivalent)	Renewable energy consumption (% of total final energy consumption)	Global AI Index, score 0–100
	DsGr ₁	DsGr ₂	DsGr ₃	DsGr ₄	Tech
Argentina	2.65	0.52	14.01	9.84	17.50
Armenia	7.05	0.04	12.90	8.38	14.50
Brazil	7.94	6.13	12.47	50.05	22.10
China	1.71	0.56	6.16	14.81	61.50
Colombia	5.32	0.77	22.95	31.31	17.80
Egypt, Arab Rep.	5.14	1.68	17.12	6.51	16.90
India	3.16	2.59	9.68	35.82	31.40
Indonesia	5.16	0.15	12.06	22.01	18.20
Malaysia	6.92	0.05	9.18	5.84	19.60
Mexico	3.64	0.45	13.60	12.33	16.90
Morocco	0.39	0.17	14.52	10.92	13.60
Nigeria	8.55	0.04	8.25	82.51	9.30
Pakistan	1.44	0.10	10.77	46.60	10.10
Russian Federation	18.51	0.10	7.44	3.72	23.70
South Africa	7.33	1.84	5.53	9.76	14.10
Sri Lanka	0.08	0.01	25.19	49.32	10.00
Tunisia	2.25	0.10	13.65	12.88	13.70
Turkiye	0.83	0.50	15.77	13.72	20.60
United Arab Emirates	17.63	3.80	7.94	0.92	23.90
Uruguay	1.93	0.07	20.74	61.09	16.30

Source Developed by the authors based on the materials from Tortoise Media [11] and World Bank [13–16]

in energy increased by \$0.0272 billion with a one-point increase in the use of big data and AI.

GDP per unit of energy consumption decreases by 0.1861 constant 2021 PPP \$ per kg of oil equivalent with a one-point increase in the use of big data and AI and by 0.6812 constant 2021 PPP \$ per kg of oil equivalent with a \$1 billion increase in private investments in energy. The share of renewable energy consumption increases by 0.4839% with a one-point increase in the use of big data and AI and decreases by 0.4590% with a \$1 billion increase in private investments in energy.

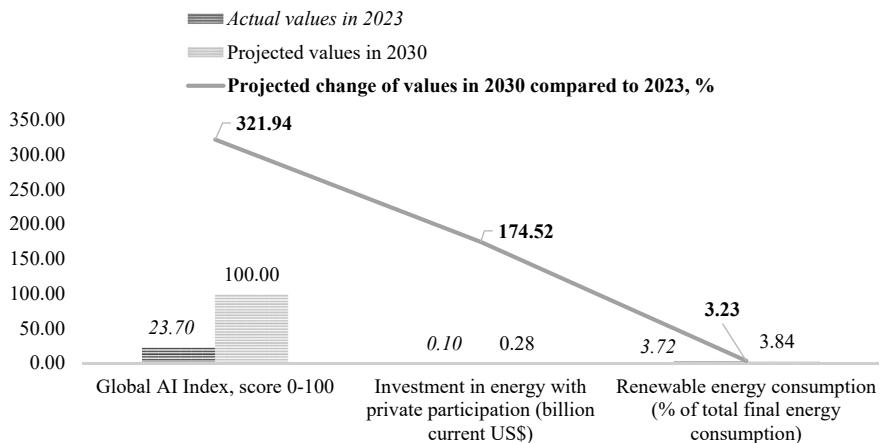


Fig. 1 Prospects for growth in energy efficiency and circularity of production in Russia by integrating big data and AI in decision-making. *Source* Developed by the authors

The econometric model was used to establish the prospects for growth in energy efficiency and circularity of production (using Russia as an example) when big data and AI are integrated into decision-making by substituting the maximum possible value (100 points) for Tech in the model (Fig. 1).

The prospects shown in Fig. 1 indicate that with a 321.94% increase in the use of big data and AI technologies in Russia, the inflow of private investments in energy will grow by 174.52% (from \$0.10 billion in 2023 to \$0.28 billion). Additionally, this will increase the share of renewable energy consumption in the Russian economy by 3.23% (from 3.72% in 2023 to 3.84%).

To implement the identified prospects in the practice of the green economy in Russia and other rapidly developing countries, the authors developed a decision-making framework for organizing energy-efficient circular production based on big data and AI (Fig. 2).

The framework presented in Fig. 2 assumes that green big data receives statistics and information about problems, threats, and opportunities for the organization's energy-efficient circular production. Public administration bodies transmit energy efficiency and circularity standards and norms, co-financing measures to improve them, and corporate environmental reporting requirements to green big data.

Consumers and representatives of green communities provide information on the demand for green products to green big data. Contractors (business partners) contribute information about the standards of green supply and sales chains. Competitors interested in cooperation offer proposals for joint green projects. From the organization's production, information on actual energy efficiency and circularity is fed into green big data.

Green AI analyzes green big data and provides intelligent support for making investment and environmental decisions. In turn, the environmental manager makes investment and environmental decisions and passes them to green AI for practical

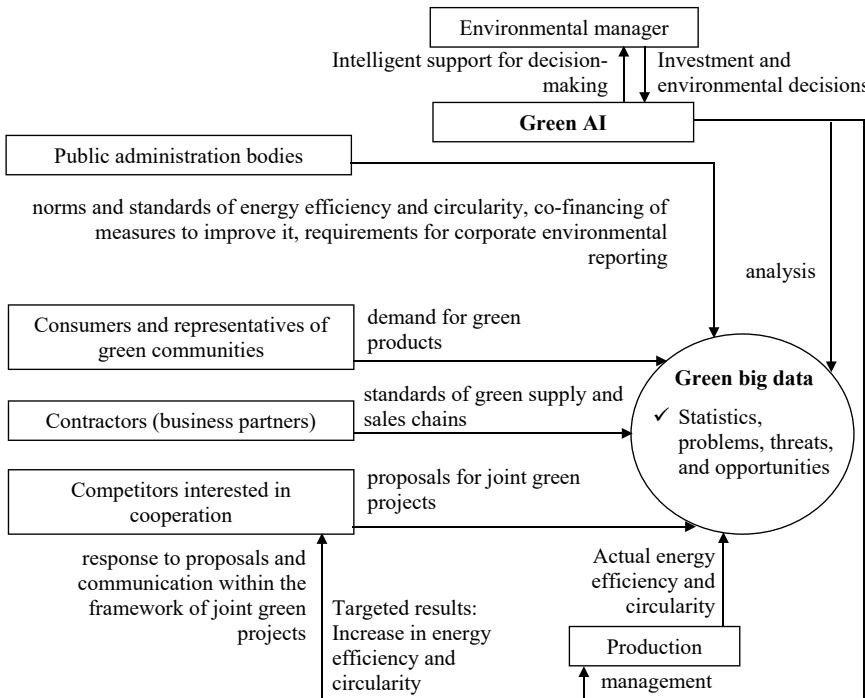


Fig. 2 Decision-making framework for organizing energy-efficient circular production based on big data and AI. *Source* Developed by the authors

implementation in the organization's activities. Green AI manages the organization's production, focusing on target outcomes related to improving energy efficiency and circularity. Green AI also responds to competitors' proposals and communicates with them within the framework of joint green projects.

5 Discussion

The contribution of this research to the literature related to the theory of investment and environmental decision-making [2, 5, 8, 9] lies in clarifying the causal relationships between the use of big data and AI and the optimality of investment and environmental decisions. The results of the analysis of the impact of big data and AI on the green economy obtained in this research are compared with the existing literature in Table 2.

As shown in Table 2, unlike Lyu et al. [7], big data and AI do not restrain private investments in energy. Rather, they attract them by optimizing decisions (as supported by [1]). In contrast to Gao et al. [4], big data and AI do not decrease the natural rent of

Table 2 Comparing the obtained results of analyzing the impact of big data and AI on the green economy with the literature

Area of comparison—impact of big data and AI on	Alternative perspectives in the literature		Results obtained in this research—big data and AI
Private investments in energy	Restrain [7]	Stimulate [1]	Attract by optimizing decisions
Natural rent of GDP	Increase [4]	Decrease [3]	Increase due to the high energy intensity of big data and AI
GDP per unit of energy consumption	Decrease [6]	Increase [12]	Decrease due to the high energy intensity of big data and AI
Share of renewable energy consumption	Decrease [10]	Increase [17]	Indirectly reduce by supporting the growth of private investments in energy

Source Developed by the authors

GDP but increase it due to the high energy intensity of big data and AI (as supported by [3]).

Unlike Li et al. [6], big data and AI do not increase GDP per unit of energy consumption. Instead, they decrease this indicator due to the high energy intensity of big data and AI (as supported by [12]). Contrary to Singh et al. [10], big data and AI do not reduce the share of renewable energy consumption but indirectly decrease it (through the inflow of private investments in energy) by supporting the growth of private investments in energy (as supported by [17]).

6 Conclusion

Thus, the main result of this research lies in the revelation of the prospects for organizing circular production and improving energy efficiency through decision-making based on big data and AI. Drawing on the advanced practices of the top 20 dynamically developing digital economies with the highest activity in the application of big data and AI in 2023, the authors developed an econometric model.

The theoretical significance of the developed model lies in the highly accurate quantitative measurement of the consequences of automating investment and environmental decision-making based on big data and AI technologies for the green economy. Based on the model, the authors developed a classification of the consequences of automating investment and environmental decisions using big data and AI for the green economy.

One consequence for the green economy that directly (in direct dependence on the technological factor) improves due to the modernization of investment and environmental decision-making using big data and AI is the inflow of private investments in energy. Indirectly (depending on private investments in energy), another consequence for the green economy that improves due to the modernization of investment

and environmental decision-making using big data and AI is the increase in the share of renewable energy in the energy consumption structure. However, some consequences for the green economy do not improve with the modernization of investment and environmental decision-making using big data and AI, such as the natural rent of GDP (increases) and GDP per unit of energy consumption (decreases).

The identified prospect of growth in energy efficiency and circularity of production in Russia through integrating big data and AI in decision-making holds practical significance because it expands the possibilities for planning and forecasting the development of the green economy. The managerial significance is attributed to the author's developed decision-making framework for organizing energy-efficient circular production based on big data and AI, which will enhance the effectiveness of these decisions.

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Making Climate-Responsible Decisions Based on Big Data and AI in Smart Business to Support Decarbonization



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Abstract The research explores the prospects for enhancing advanced practices of making climate-responsible decisions based on big data and artificial intelligence (AI) in smart business to support decarbonization. Using regression modeling and drawing on the best practices of the top 25 countries with the highest impacts from climate-responsible decisions and the active digitalization of smart business in 2023, the authors developed a new model. This model identifies the impact of digitalization of smart business on the results of climate-responsible decision-making. The combined model reveals the causal relationships in economic decarbonization, highlighting its theoretical significance. The model forms the basis of the author's conclusion that the prospects for improving climate-responsible decision-making practices based on big data and AI in smart business to support decarbonization are linked to enhancing cybersecurity levels. The authors created an economic decarbonization forecast using Kyrgyzstan as an example. This forecast revealed the potential for improving climate-responsible decision-making practices based on big data and AI in smart business. The forecast holds practical significance, forming a scientific foundation for developing Kyrgyzstan's national economic decarbonization strategy.

Keywords Green management · Decision making · Climate-responsible decisions · Big data · AI · Smart business · Decarbonization

JEL Classification C44 · O32 · Q54

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1 Introduction

Decarbonization is a key area of the green development vector in contemporary economic systems. Business structures are moving towards decarbonization under market pressure, as green competition intensifies annually. Consumers are becoming more selective in their purchases, often considering the ecological properties of products. Similarly, green investors set high standards for the environmental performance of businesses as a condition for financing their development.

On the other hand, state pressure also drives this trend. Governments worldwide are introducing environmental taxes, quotas, standards, and regulations, some of which are mandatory and others preferable, affecting the conditions of state regulation of business activities, including subsidiary support. Consequently, businesses are interested in making climate-responsible management decisions, a core practice of green management.

The Fourth Industrial Revolution led to the emergence of a new phenomenon in the business environment—smart business characterized by the automation of business operations across all areas of economic activity. Amid the trend of total automation in corporate management, the scientific and practical challenge of establishing highly effective practices for using big data and AI in climate-responsible decision-making has become relevant.

These technologies have proven promising tools for automating general management decision-making practices. However, the question of their applicability and suitability for green management remains open. The broad monitoring and analytical capabilities are the pros of using of big data and AI in making climate-responsible decisions.

Conversely, arguments against using these technologies point to the fact that automating green management could increase its energy consumption, potentially turning management into a barrier to decarbonization instead of eliminating barriers associated with managed economic operations. This research aims to determine the prospects for improving climate-responsible decision-making practices based on big data and AI in smart business to support decarbonization.

2 Literature Review

According to the concept of climate-responsible decision-making [5, 9, 20], the main criteria for optimizing these decisions are as follows:

- Shift to clean energy [14];
- Energy consumption in the economy [1, 2];
- Carbon and greenhouse gas emissions [11].

The following main factors of digitalization in smart business are identified in the concept of management automation [7, 10, 21]:

- Internet accessibility [4];
- Internet quality [8];
- Level of digital infrastructure development [6, 12];
- Level of cybersecurity [22];
- Level of e-government development [3].

A literature review showed that despite the thorough development of the mentioned scientific concepts, there is a gap at the intersection of these fields. This gap lies in the uncertainty regarding how digitalization factors in smart business influence adherence to the criteria for optimizing climate-responsible decision-making.

Therefore, the research question (RQ) is: “Which digitalization factors in smart business contribute to better compliance with all criteria for optimizing climate-responsible decision-making?” To address this research question, the authors analyzed the causal relationships of economic decarbonization, drawing on advanced international experience.

3 Materials and Methods

The research goal is achieved by addressing two main tasks. The first task is to determine the contribution of digitalization factors in smart business to decarbonization and identify key factors. To achieve this goal, the authors conducted a factor analysis of climate-responsible decision-making based on big data and AI in smart business. Using regression analysis, the authors influenced digitalization factors in smart business on the outcomes of climate-responsible decisions.

In addressing this task, the authors draw on advanced international experience. The sample includes the top 25 countries with the best outcomes from climate-responsible decision-making in 2023 that actively engaged in the digitalization of smart business, as ranked by Surfshark [13]. The collected data is presented in Table 1.

The authors selected those factor variables whose regression coefficients indicate a positive influence on all outcome variables in Table 1. The second task is to identify the prospects for decarbonizing Kyrgyzstan’s economy by improving climate-responsible decision-making practices based on big data and AI in smart business. To achieve this goal, the maximum possible values of the selected factor variables are substituted into the regression equations; the resulting changes in all indicators for Kyrgyzstan are assessed.

4 Results

To address the first task and determine the contribution of digitalization factors in smart business to decarbonization, the authors conducted a factor analysis of climate-responsible decision-making based on big data and AI in smart business, relying

Table 1 Factors of smart business digitalization and implications of climate-responsive decision-making by countries worldwide in 2023

Country	Factors of digitalization of smart business, shares from 1					Implications of climate-responsive decision-making				
	Internet affordability	Internet quality	Electronic infrastructure	Electronic security	Electronic government	Renewable energy consumption (% of total final energy consumption)	CO ₂ emissions (metric tons per capita)	CO ₂ intensity (kg per kg of oil equivalent energy use)	Energy use (t of oil equivalent per capita)	Total greenhouse gas emissions (thousand kt of CO ₂ equivalent)
SmB ₁	SmB ₂	SmB ₃	SmB ₄	SmB ₅	CID ₁	CID ₂	CID ₃	CID ₄	CID ₅	
Congo, Dem. Rep.	0.13	0.19	0.23	0.13	0.23	96.16	0.03	0.17	0.38	56.12
Ethiopia	0.13	0.19	0.27	0.17	0.33	89.52	0.15	0.25	0.48	167.30
Mozambique	0.09	0.26	0.28	0.15	0.31	80.91	0.22	0.38	0.45	33.75
Tanzania	0.07	0.3	0.42	0.13	0.42	83.95	0.23	0.43	0.49	89.26
Kenya	0.07	0.31	0.72	0.42	0.58	72.50	0.37	0.64	0.52	80.19
Cameroon	0.03	0.22	0.38	0.17	0.38	78.94	0.37	1.02	0.34	93.35
Nepal	0.16	0.32	0.58	0.25	0.41	74.54	0.51	0.61	0.43	45.87
Bangladesh	0.12	0.36	0.65	0.36	0.58	27.96	0.51	1.80	0.23	206.57
Nigeria	0.05	0.36	0.59	0.39	0.49	82.51	0.54	0.86	0.75	322.34
Angola	0.43	0.21	0.3	0.15	0.38	61.02	0.59	2.36	0.54	70.78
Ghana	0.06	0.32	0.47	0.36	0.48	40.25	0.60	1.59	0.32	39.07
Benin	0.04	0.27	0.37	0.51	0.47	46.20	0.63	1.29	0.40	16.19
Senegal	0.12	0.26	0.53	0.3	0.45	38.64	0.65	2.17	0.28	30.29
Pakistan	0.22	0.29	0.52	0.22	0.52	46.60	0.81	1.71	0.43	436.61
Honduras	0.04	0.32	0.51	0.12	0.3	50.09	0.87	1.77	0.59	21.15

(continued)

Table 1 (continued)

Country	Factors of digitalization of smart business, shares from 1					Implications of climate-responsible decision-making				
	Internet affordability	Internet quality	Electronic infrastructure	Electronic security	Electronic government	Renewable energy consumption (% of total final energy consumption)	CO ₂ emissions (metric tons per capita)	CO ₂ intensity (kg per kg of oil equivalent energy use)	Energy use (t of oil equivalent per capita)	Total greenhouse gas emissions (thousand kt of CO ₂ equivalent)
SmB ₁	SmB ₂	SmB ₃	SmB ₄	SmB ₅	CID ₁	CID ₂	CID ₃	CID ₄	CID ₅	
Tajikistan	0.05	0.18	0.37	0.15	0.41	38.75	0.98	1.59	0.34	17.69
Sri Lanka	0.42	0.28	0.5	0.23	0.49	49.32	1.00	1.64	0.50	35.12
Guatemala	0.04	0.37	0.53	0.13	0.47	65.46	1.00	1.06	0.86	33.17
El Salvador	0.04	0.35	0.63	0.13	0.41	23.70	1.01	1.62	0.65	11.06
Cambodia	0.09	0.32	0.65	0.08	0.39	51.41	1.14	1.04	0.42	42.36
Paraguay	0.06	0.38	0.69	0.44	0.51	61.44	1.14	1.09	0.85	50.78
Philippines	0.06	0.47	0.75	0.54	0.64	29.06	1.19	2.19	0.47	224.97
Costa Rica	0.11	0.39	0.76	0.46	0.6	36.43	1.36	1.60	1.01	14.41
Kyrgyz Republic	0.53	0.32	0.53	0.3	0.51	30.04	1.38	2.56	0.65	16.09
Peru	0.07	0.43	0.73	0.53	0.71	31.62	1.40	2.22	0.78	89.87

Source Compiled by the authors based on the materials from Surfshark [13] and World Bank [15–19]

on the statistics from Table 1. As a result, the following model was developed to show the influence of digitalization factors in smart business on the outcomes of climate-responsible decision-making.

$$\left\{ \begin{array}{l} \text{CID}_1 = 116.24 - 25.54\text{SmB}_1 - 3.89\text{SmB}_2 - 35.32\text{SmB}_3 \\ \quad + 22.10\text{SmB}_4 - 95.87\text{SmB}_5, \\ \text{CID}_2 = -0.58 + 0.84\text{SmB}_1 + 1.59\text{SmB}_2 + 0.98\text{SmB}_3 \\ \quad - 0.57\text{SmB}_4 + 0.83\text{SmB}_5, \\ \text{CID}_3 = -0.54 + 2.22\text{SmB}_1 + 1.06\text{SmB}_2 + 0.02\text{SmB}_3 \\ \quad - 0.41\text{SmB}_4 + 2.99\text{SmB}_5, \\ \text{CID}_4 = 0.08 + 0.23\text{SmB}_1 + 1.79\text{SmB}_2 + 0.05\text{SmB}_3 \\ \quad - 0.01\text{SmB}_4 - 0.33\text{SmB}_5, \\ \text{CID}_5 = -63.99 - 76.62\text{SmB}_1 + 149.82\text{SmB}_2 \\ \quad - 253.63\text{SmB}_3 - 161.45\text{SmB}_4 + 639.12\text{SmB}_5. \end{array} \right. \quad (1)$$

Model (1) indicates that with an increase in Internet accessibility by one point, renewable energy consumption decreases by 25.54%, CO₂ emissions increase by 0.84 metric tons per capita, CO₂ emission intensity increases by 2.22 kg per kg of energy used in oil equivalent, and energy consumption increases by 0.23 kg of oil equivalent per capita. However, total greenhouse gas emissions decreased by 76.62 thousand tons of CO₂ equivalent.

With an increase in Internet quality by one point, renewable energy consumption decreases by 3.89%, CO₂ emissions increase by 1.59 metric tons per capita, CO₂ emission intensity increases by 1.06 kg per kg of energy used in oil equivalent, energy consumption increases by 1.79 kg of oil equivalent per capita, and total greenhouse gas emissions increase by 149.82 thousand tons of CO₂ equivalent.

With a one-point increase in the level of digital infrastructure development, renewable energy consumption decreases by 35.32%, CO₂ emissions increase by 0.98 metric tons per capita, CO₂ emission intensity increases by 0.02 kg per kg of energy used in oil equivalent, energy consumption increases by 0.05 kg of oil equivalent per capita, and total greenhouse gas emissions decrease by 253.63 thousand tons of CO₂ equivalent.

With a one-point increase in the level of cybersecurity, renewable energy consumption increases by 22.10%, CO₂ emissions decrease by 0.57 metric tons per capita, CO₂ emission intensity decreases by 0.41 kg per kg of energy used in oil equivalent, energy consumption drops by 0.01 kg of oil equivalent per capita, and total greenhouse gas emissions decrease by 161.45 thousand tons of CO₂ equivalent.

With an increase in the level of e-government development by one point, renewable energy consumption decreases by 95.87%, CO₂ emissions rise by 0.83 metric tons per capita, CO₂ emission intensity increases by 0.99 kg per kg of energy used in oil equivalent, energy consumption decreases by 0.33 kg of oil equivalent per capita, but total greenhouse gas emissions increase by 639.12 thousand tons of CO₂ equivalent.

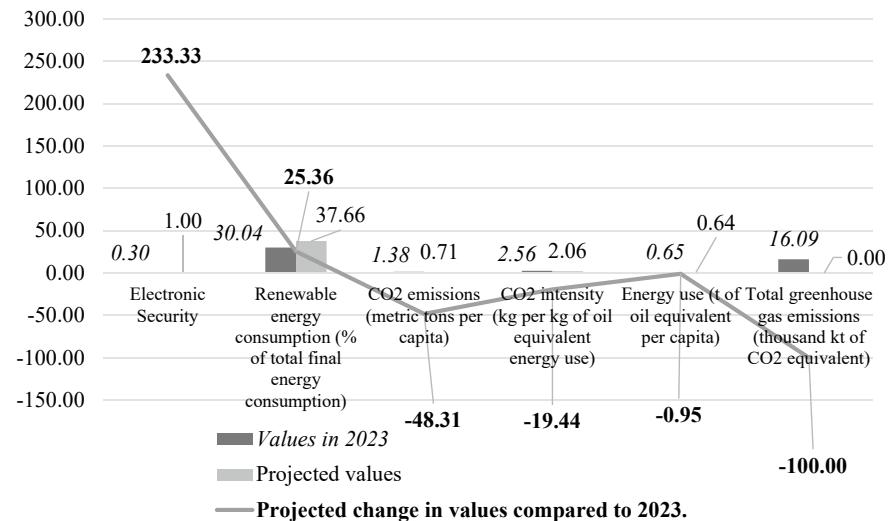


Fig. 1 Perspective of decarbonization of the Kyrgyz economy through improving the practice of climate-responsible decision-making based on big data and AI in smart business. *Source* Calculated by the authors

Based on the modeling results, the authors selected one digitalization factor in smart business. The regression coefficients of the selected factor indicate a positive influence of digitalization on all outcome variables. This factor is cybersecurity. To address the second task and identify the prospect of decarbonizing Kyrgyzstan's economy through refining the practice of making climate-responsible decisions based on big data and AI in smart business, the maximum possible value of the selected factor variable was substituted into the model (1); the change in all indicators in Kyrgyzstan was evaluated (Fig. 1).

According to the perspective identified in Fig. 1 for refining the practice of making climate-responsible decisions based on big data and AI in Kyrgyzstan's smart business, it is recommended to increase the level of cybersecurity by 233.33% compared to 2023. Implementing this recommendation will result in the following advantages in the field of decarbonizing Kyrgyzstan's economy:

- A 25.36% increase in renewable energy consumption (from 30.04% in 2023 to 37.66%);
- A 48.31% reduction in CO₂ emissions (from 1.38 to 0.71 metric tons per capita);
- A 19.44% decrease in CO₂ emission intensity (from 2.56 to 2.06 kg per kg of energy used in oil equivalent);
- A 0.95% decrease in energy consumption (from 0.65 to 0.64 kg of oil equivalent per capita);
- A 100.00% reduction in total greenhouse gas emissions (from 16.09 to 0 thousand tons of CO₂ equivalent).

5 Discussion

The research contributes to the literature by bridging the gap between scientific concepts of climate-responsible decision-making [5, 9, 20] and management automation [7, 10, 21]. The research clarifies the impact of digitalization factors in smart business on adhering to the optimality criteria of climate-responsible decision-making.

In contrast to Haini and Pang [4], this research established that while increasing Internet accessibility contributes to reducing greenhouse gas emissions, it leads to a rise in carbon emissions and hinders the transition to clean energy. Unlike Peng and He [8], the authors of this research state that improving Internet quality completely contradicts the current global decarbonization trend.

In contrast to Li et al. [6] and Smetamina and Morozova [12], this research argues that the development of digital infrastructure contributes to a decrease in greenhouse gas emissions but leads to an increase in carbon emissions and slows down the transition to clean energy. Agreeing with Zorin et al. [22], the authors proved that increasing cybersecurity increases clean energy consumption and reduces CO₂ emissions, CO₂ intensity, energy use, and total greenhouse gas emissions. In contrast to Arkin et al. [3], the authors determined that developing e-government reduces energy consumption in the economy but hinders the reorientation to clean energy and increases carbon and greenhouse gas emissions.

6 Conclusion

Thus, the main conclusion is that the prospect of enhancing the contemporary practice of making climate-responsible decisions based on big data and AI in smart business to support decarbonization is linked to increasing the level of cybersecurity. Specifically, the authors developed a model of the influence of digitalization factors in smart business on the results of making climate-responsible decisions. The developed model combines the best practices of the top 25 countries in the world with the highest impacts from such decisions in 2023 and active digitalization of smart business. The theoretical significance of this model lies in its revelation of the cause-and-effect relationships of economic decarbonization.

The forecast for decarbonizing the Kyrgyzstan economy revealed the potential for improving the practice of making climate-responsible decisions based on big data and AI in smart business. The practical significance of the author's forecast lies in its potential to serve as a scientific basis for developing a national strategy for decarbonizing the Kyrgyzstan economy in the coming years.

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Implementing Artificial Intelligence in Accounting and Auditing: Risks and Benefits



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Abstract Nowadays, the megatrends of the Fourth Industrial Revolution are becoming increasingly important, permeating all areas of activity. Implementing information technologies makes it possible to accelerate economic indicators' growth rate and improve business processes' efficiency. Advanced technologies are inevitably being integrated into accounting and auditing activities. In this context, analyzing the prospects of mass adoption of artificial intelligence (AI) services in company operations is extremely important. The research aims to identify the risks and benefits of AI algorithms implementation in accounting and auditing. The methodological basis of the research is formed by general scientific and special methods of scientific knowledge, including the system approach, deduction, induction, analysis, and synthesis. The authors identified risks from the implementation of AI algorithms. According to the authors, these risks include the imperfection of AI algorithms, the probability of errors, dependence on technical infrastructure, cybersecurity threats, and human discrimination. As a result, the authors found that using AI algorithms will improve the efficiency of auditing and accounting services in certain cases. However, AI will only partially replace an accountant or auditor because the professional judgment and practical experience of human specialists allow them to make innovative solutions.

Keywords Artificial intelligence · Accounting · Auditing · Ethics · Digitization

JEL Classification M40 · M41 · M42 · O30 · O31 · O32

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1 Introduction

Nowadays, all sectors of the economy are experiencing one of the most significant transformations in history against the backdrop of the technological process [15]. The accelerated pace of development of large language models has attracted the attention of the world community to the problems of integrating artificial intelligence (AI) tools to optimize business processes. Nevertheless, the integration of automatization in accounting and auditing has become a common practice, mirroring the broader trend of AI adoption across various industries [1].

Enterprises can increase efficiency, reduce costs, and automate routine tasks by implementing AI tools into operational processes. Despite some significant benefits of introducing AI into the economic activities of enterprises, several challenges, including data privacy, data security, clear identification of the party's responsibilities, etc., are to be settled. The discussion on the impact of ethical aspects of using AI on the reputation of organizations, customer trust, and process automation is ongoing on the global economic agenda while the popularity of neural network technologies is growing.

Introducing neural network tools into accounting and auditing activities requires technological and ethical regulation. Accounting and audit specialists need to determine the area of responsibility for decisions made by algorithms in the context of expanding the scope of AI.

Despite its extreme relevance, scientific studies have not adequately addressed the issue of using AI tools in accounting and auditing activities. Ethical aspects of implementing AI in these areas have become a matter of concern for practitioners and theorists [8]. Legal regulation within the digital economy does not currently address the implementation of AI in accounting and auditing and provides only general recommendations for the correct use of neural network tools in companies.

Thus, the study of ethical aspects of the use of AI in auditing and accounting is of particular relevance. The results of the study will help identify possible areas of application of AI in these sectors and formulate the main risks of introducing AI into accounting and auditing. The research represents an important contribution to developing the theory and practice of accounting and auditing in the context of the digitalization of the economy.

2 Methodology

The theoretical basis of the research includes fundamental studies, concepts, and theories of international and Russian scientists in the field of accounting and auditing. Moreover, the theoretical basis also includes practical methods and developments that reveal the essence, features, and directions of development and use of digital tools in accounting and auditing.

The methodological basis of the research is general scientific and special methods. The methods used in the research include visualization, grouping, generalization, scientific analysis, synthesis, induction, deduction, comparative analysis, retrospective analysis, and statistical analysis.

3 Results

IT specialists have diverging opinions on the impact of AI on humankind. Some experts note exclusively negative consequences of the use of the technology. Others expect significant positive effects. Unlike computer programs, neural networks are designed to solve tasks that require a flexible, adaptive approach. AI is trained based on empirical data [5]. Instead of a standard algorithm of a computer program with a given sequence path and constraints, the technology builds dependencies between input and output data automatically and forms an architecture.

Despite the technological breakthrough after creating large language models, AI tools can currently perform only narrowly focused and specific tasks. Humankind expects the transition of Artificial Narrow Intelligence (ANI) to Artificial General Intelligence (AGI) technology. AGI is a technology that performs at a median level of human performance. It will be able to complete many versatile tasks, improve its results by self-learning capability, adopt to the realities, and produce new knowledge. This technology is expected to change the labor market in the next 10–15 years.

Implementing AI tools has become a sign of success for many corporations, which are increasingly using the technology to optimize processes and improve efficiency. AI solutions based on big data are anticipated to enhance overall performance in accounting and auditing.

The main spheres of application of AI in accounting and auditing encompass a diverse array of fields: recognition of textual and numerical information in documentation, data analysis, detection of vulnerabilities, the fact of fraudulent transactions and information distortion [11], and conducting inventory procedures using autonomous aircraft (Fig. 1).

Applying AI algorithms opens the following prospects in accounting and auditing (Fig. 2).

The first benefit is the automation of routine tasks. Most AI-based programs can analyze and process a large array of data per the request. Using neural network technologies can improve the efficiency of accounting and auditing activities by automating routine processes. For instance, Deloitte uses Argus development based on AI for scanning and analyzing documents, which allows employees to spend their time on creative and complex tasks. Auditing the process involved the comparison of compacts and cross-checking of data to ensure compliance with regulatory requirements, which is time-consuming and can lead to errors. The program identifies changes and classifies data according to type and materiality level with the help of computer vision tools.

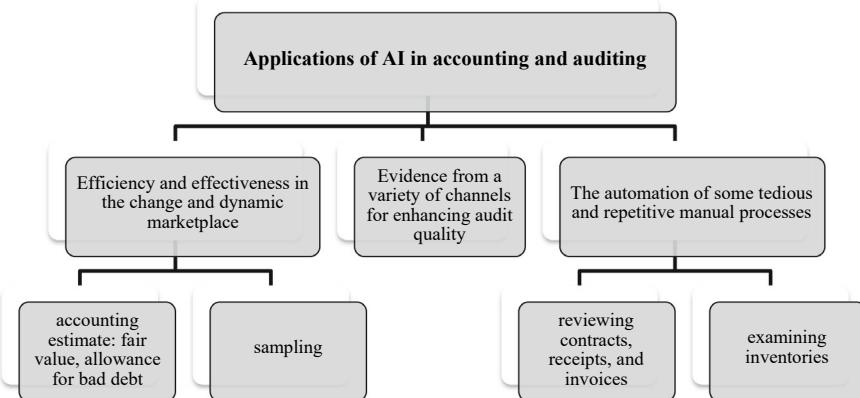


Fig. 1 Possible applications of AI in accounting and auditing. *Source* Compiled by the authors

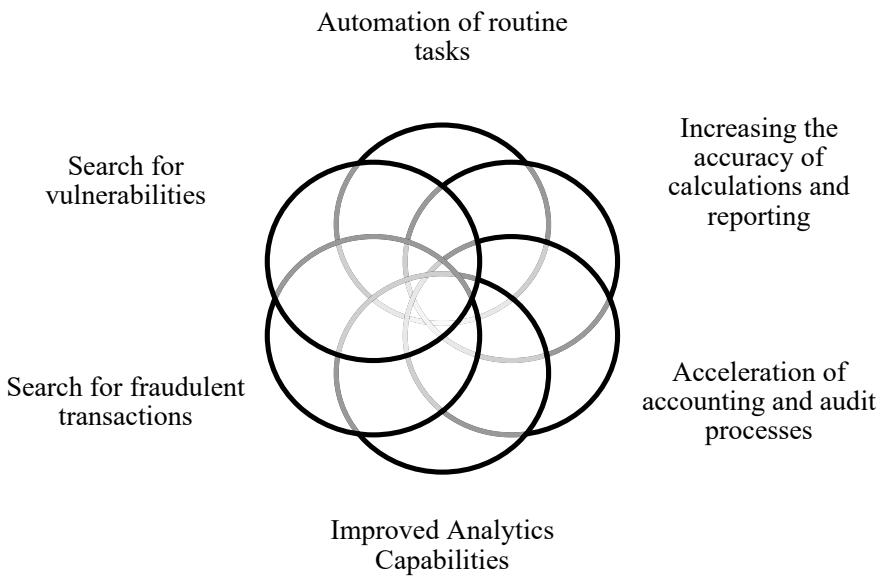


Fig. 2 Benefits of implementing artificial intelligence in accounting and auditing. *Source* Compiled by the authors

The second benefit is the acceleration of accounting and audit processes. The ability to analyze a large data set using AI allows accounting and auditing specialists to increase the speed of information processing. The use of neural networks in addressing routine tasks facilitates the optimization of time allocation, thereby enabling the reallocation of saved time towards more intricate and demanding tasks.

One of the most common technologies is the creation of virtual assistants in companies using AI chatbots. This technology is already used in accounting and auditing, incorporating the capabilities of many AI tools. Chatbots of companies can respond to customer queries promptly. They can also be used internally to speed up many tasks.

The third benefit lies in increasing the accuracy of calculations and reporting. In addition to the ability to solve computational problems of varying complexity, AI can scan text information from images and analyze a large array of documents, which improves the accuracy of calculations and mitigates the risks of errors. For example, PwC uses AI Audit for Cash (Cash.ai). The program includes an algorithm that enables automatic reading, verification, and analysis of such client documents as cash balance reports, bank statements, etc. The data are compared via computer vision, making it possible to identify discrepancies.

The next benefit is improved analytical capabilities. Nowadays, many AI tools used in accounting and auditing can perform historical and predictive analytics [3]. For example, KPMG's Clara platform can analyze data based on AI and machine learning and perform retrospective analyses of companies.

The fifth benefit lies in the search for fraudulent transactions. Companies use AI algorithms to identify erroneous or fraudulent transactions. AI programs analyze amounts, accounts, users, and even the time of transactions to identify suspicious transactions. For example, PwC's AI program GL.ai uses company data and solutions trained to reproduce variations of audit case solutions. The algorithm verifies transaction, user, amount, and account data to identify anomalous transactions as potential errors or fraud.

The sixth benefit lies in the search for vulnerabilities. Companies can use AI tools to identify reporting vulnerabilities. For example, Deloitte uses the Guided Risk Assessment Personal Assistant (GRAPA) program. This tool makes it possible to choose an audit strategy based on a preliminary assessment of the risk of misreporting. The program analyzes various factors, including industry specifics. It identifies the areas that are most at risk of misstatement. The auditor can refer to similar cases selected by GRAPA and obtain information on the risk profile of the respective companies.

Despite the many benefits of implementing AI in organizations, some issues should be addressed. The first issue is errors in AI algorithms. An incorrectly composed algorithm can lead to inevitable errors. Drawing up a methodology for using AI tools in accounting and auditing requires careful consideration. There are also AI hallucination risks, in addition to errors associated with an incorrect algorithm. Technical failures (AI hallucinations) may periodically occur within the operation of neural networks. This phenomenon is related to the peculiarities of large language models (LLM): the model only remembers and uses repetitive sets of text but cannot synthesize the meaning of this information, which can lead to actual errors.

The next issue is the dependence on technical infrastructure. The correct operation of AI algorithms requires a high level of technical support in the company. The work of algorithms will be hampered in case of lack of technical infrastructure, which will

result in AI performance decrease and incorrect decisions caused by lack of access to data.

The third issue is that AI entails cybersecurity threats. The operation of AI algorithms involves storing large amounts of data, including sensitive data [6]. Insufficient protection of technical infrastructure can lead to data leakage and cause risks of hacker attacks. If systems are hacked, the systems' algorithms may be changed, leading to information distortion and incorrect decisions [7].

The fourth issue is related to crisis on a labor market. The automatization of routine tasks when AI tools are introduced into accounting and auditing activities naturally leads to a reduction in the labor costs of job performance [2]. Simultaneously, there is a need to retrain personnel with specialized skills and knowledge to work with AI. For example, one of the new competencies is the possession of prompt engineering skills, which makes it possible to compose a correct query to algorithms when solving tasks.

The fifth issue is human discrimination. AI algorithms may have distortions during training, which potentially result in discriminatory behavior towards individuals based on various attributes. The manifestation of discrimination in AI systems underscores the importance of methodology development for bias detection, transparency, and legal regulation.

Discussions about the ethical aspects of using neural networks and their impact on the reputation of organizations, customer trust, and process automation are high on the global economic agenda [4]. This is due to the threats posed by the introduction of artificial intelligence tools into accounting and auditing. It is crucial to define the area of responsibility for decisions made by algorithms in the context of the expanding field of AI integration [16].

New opportunities in accounting and auditing are forcing professionals to rethink how they do business. Technology allows auditors to verify 100% of the available data, eliminating the need for traditional sampling methods and performing real-time analysis. In light of the dynamic nature of business processes, accountants and auditors are required to adapt their working processes to accommodate these ongoing changes. The adoption of AI technologies requires companies to make additional investments in digital initiatives such as blockchain, cybersecurity, cloud storage, and data processing systems [10]. Companies and the professional community of accounting and auditing specialists need to work on responding to the benefits, threats, and opportunities of the introduction of neural network tools. In doing so, companies should utilize a quality training sample when implementing the technology. Such developments are not always available to small organizations, which can lead to the creation of a poor quality and bland model. To use AI algorithms correctly in accounting and auditing activities, such companies should seek ready-made solutions from large corporations [9]. Such data processing systems using neural network tools are created jointly by accounting and audit specialists and developers [12]. For example, the development of IBM's Watson allows many audit companies to implement AI successfully.

Achievements in the development of technology naturally leads to changes in the labor market in all areas, no exception is the demand for specialists engaged

in accounting and auditing. It is necessary to master new skills, such as prompt engineering and basic programming knowledge, to remain competitive.

Regulators are only at the stage of developing regulations despite the active use of AI technologies. The work of the global initiative to implement the UNESCO recommendations on the ethical aspects of AI implies the creation of a new legislative framework to prevent negative consequences from using AI, including in accounting and auditing activities. Considering the nature of the new technology, flexible regulatory measures are expected to be used. Nowadays, international organizations, government agencies, company executives, and academic and professional communities are accumulating forces to develop mechanisms to manage the technology to reduce the likelihood of a “race to the bottom.”

4 Conclusions

Nowadays, many areas of the economy are being changed by the megatrends of Industry 4.0 [13]. There is no denying that innovative technologies will have a significant impact on the structure of the accounting and auditing industries. The use of AI algorithms will optimize the working process of the accountant or auditor. Certain routine tasks can be performed using AI algorithms. However, the role of an accountant or an auditor transcends the mere execution of monotonous tasks. The multifaceted nature of work requires the professional judgment of the accountant or auditor. The specialists are responsible for the decisions made. Full replacement of the accountant or auditor with AI algorithms seems impossible at the current stage. Nevertheless, partial integration of AI into the working process is possible and is likely to increase the efficiency of accounting and auditing activities. The essence of these professionals lies in their unique ability to interpret, analyze, and communicate financial information holistically and strategically.

Accountants and auditors face new challenges in a changing business landscape. Competent professionals must adapt to contemporary realities and become pioneers in using innovative technologies in their activities [14]. Specialists who neglect the emerging opportunities for AI integration are at risk of losing their competitive advantage and becoming unclaimed in the labor market. Integrating advanced technologies into accounting and auditing processes has already begun [2]. The examples of successful integration of AI into company business processes were given in the research so that the coming changes cannot be denied or ignored.

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Applied Solutions for Decision-Making in the Smart Economy Using Big Data and Artificial Intelligence

Data Analysis of Students' Academic Performance in Learning Human Anatomy Through Traditional and Mixed Teaching Methods in a Sustainable Development Context



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Abstract Recent issues in the educational policy of Osh State University include improving the professional training of teachers, modernizing the scientific and methodological education system, developing the teaching forms and methods, lowering the distance between the actual level of training of specialists and the demands of employers, protecting continuity of education, and evaluating foreign experience in pedagogy. The research aims to conduct a statistical analysis of data on the academic performance of students in studying the subject of human anatomy using traditional and mixed teaching methods, develop and implement a blended learning module to support traditional didactic lectures for teaching or learning human anatomy and obtain the opinions of students and teachers regarding its usefulness. The authors conducted a statistical analysis of data on the level of academic performance in the section “Splanchnology” of the subject “Human anatomy” between first-year students enrolled at the International Medical Faculty of the Osh State University in the 2021–2022 academic year. Statistical analyses were performed using the Kolmogorov–Smirnov test and Pearson correlation analysis. Positive results were obtained in the Kolmogorov–Smirnov test for the normality

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of the distribution of the number of correct and incorrect answers of intermediate testing and absolute and qualitative indicators of students' academic performance. The Pearson correlation coefficient revealed a moderate connection and degree of relationship between the absolute and qualitative indicators of students' academic performance on the Chaddock scale. The authors conclude that blended learning is a good way to provide students with the best learning and teaching experience and support teachers to organize group work professionally.

Keywords Traditional teaching methods · Mixed teaching method · Teaching methodology · Interactive teaching methods · Human anatomy · Data analysis · Pearson correlation analysis · Chaddock scale · Kolmogorov–Smirnov test · Sustainable development

JEL Classification C10 · I20 · I21 · I23

1 Introduction

The feature of sustainable development in the present times is an integrating principle for various fields of knowledge, research and practical activities, the goal of which is to ensure an exception and standard of living for current and future generations, where education plays an important role [1].

To train future specialists, develop professional qualifications, to form a new set of professional guidance, prepare professional specialists, it is important to strengthen the educational process, establish modern types and methods of teaching, which includes organization of the educational process on a scientific fundament, make situation for creative thinking and students research work creates interest in their future specialty.

Learner-centered approaches “focus directly on learning: what the student learns, how he learns, the conditions under which the student learns, whether the student retains and applies what he learns, etc. how current learning prepares the student for future learning” [2].

Developing the future specialists competencies is one of the primary concerns of educational institutions in the recent information society development which requires specialists to quickly adapt to changes in the work content, who are able to gain new knowledge, acquire new skills in a short time and upgrade the educational process with the informatization of education and the successful performance of special adjustment and procedure in teaching [3].

A principal constituent in the development of a student's professional competencies is information technology tools [4]. Information technology refers to modern appliances complex that allow to control information processes, including interactive methods.

The student is the subject of interaction, actively participates in the learning process and receives feedback. Practical classes in human anatomy are increasingly

gaining importance as unusual creative activities, in parallel with interactive learning. The modern classes successfulness is placed on the widespread accomplishment of interconnections with life and the use of new forms of education [5].

Each teacher task should be connected with a creative approach. The teacher as an advisor, first of all, must arouse in students the desire to learn, search, to do experiment, and this should eventuate with the active participation of the student [6]. Only then can a positive result be achieved, and therefore contribute to the formation of a harmonic comprehensively established personality. Inventive forms of work allow to strengthen educational activities and help improve the students intellectual activity, and therefore the effectiveness of lessons [7]. A characteristic of the classes is their originality in outline and structure, as well as the formation of new knowledge, consolidation of skills, and monitoring of skills.

The structure of the lesson is a way to better know and understand students, assess their individual features, classify cognitive ideas and the opportunity for self-realization, a creative approach to work, and the implementation of one's own ideas. Tasks of non-traditional forms of classes are to form the intellectual and ingenious abilities of students through non-standard teaching methods, enhance cognitive activity, develop communication skills and orientation in the subject being studied [8].

An interactive mixed-form methods introduction at the Anatomy, Histology and Normal Physiology Department (AHNP) has become especially important in recent years due to the reduction in practical hours simultaneously maintaining the same volume of factual material being studied, as well as the lack of corpses. As a result, there is an urgent need to improve the previous didactic system. One of the main and necessary skills for successfully mastering the subject "human anatomy" is the ability to recognize and differentiate anatomical formations on models, on tablets, on an anatomical table and on plastination preparations [9].

The perceptions of students and teachers were that blended learning facilitated understanding of the subject, motivated students to learn independently, and provided flexibility in accessing learning resources.

The combination of the online learning benefits and the traditional classroom learning environment has led to the establishment of an advanced learning environment often referred to as "blended learning." Blended learning combines face-to-face interaction with technologically mediated interactions between students, teachers, and learning resources. There is usually some element of self-directed learning and the learner has some control over the time, place, and pace of learning [10].

The blended learning strategy shifts learning from primarily teacher-centered activities to more student-centered activities because it encourages students to be active in the learning process rather than being passive learners. Other benefits of this approach include a better learning experience, greater flexibility and student satisfaction. This allows students to become motivated and more involved in the learning process, thereby increasing their engagement.

Blended learning is currently attracting a lot of interest, it is still underdeveloped and used for training medical students. Evidence is needed for the usefulness of BL (blended learning) in teaching anatomy to medical students [11], and we hope that

this study will serve as an early contribution to a much larger and more comprehensive research effort in this area. The study contributes by providing educators as well as students a perspective regarding the usefulness of BL (blended form) for student learning [12].

The main difficulty in identifying anatomical structures on the visual aids used is because illustrations in atlases, textbooks and teaching aids on human anatomy do not have complete similarities with dummies and, especially with plastination material, so the teacher faces the need to build an educational process using appropriate teaching methods to enhance students' academic performance.

Accordingly, statistical analyses of digital data on the academic performance of students in the subject of human anatomy make it possible to define the advantage of certain teaching methods.

Purpose of the research: Assessment of traditional and mixed methods of teaching the subject and their advantages, statistical analysis of data on the students' academic performance. Development and implementation of a blended learning module to support traditional didactic lectures for teaching and learning human anatomy and obtaining student and faculty opinions regarding its usefulness.

Main research questions: Identification of the main objects of the pedagogical process, traditional, non-traditional and mixed forms of education and their results.

Research subject: Final and intermediate indicators of students' academic performance. Monitoring was carried out to assess the residual knowledge of 2nd year non-CIS students in the specialty "Human anatomy".

2 Materials and Methods

The effectiveness of traditional and innovative teaching methods before and after the introduction of a mixed form of education at the department was carried out in 3 groups, the first year of the Faculty of Medicine within the "Splanchnology" section. Each group had 15 students.

Statistical data analysis: After the Kolmogorov-Smirnov analysis, all digital data did not differ significantly from the normal distribution. The Kolmogorov-Smirnov test carried out to check the distribution forms of absolute, qualitative academic performance and attendance of students, showed the values of the K-S (D) statistic to be 0.13735, 0.13027 and 0.21182, and the p -value is 0.70538, 0.76274 and 0.20082, respectively, letting us know that the data are significantly normally distributed (Table 1).

The Pearson correlation coefficient calculated the linear relationship of variables on the Chaddock scale [13, 14]. The average positive correlation between quantitative indicators of qualitative academic performance and student attendance was $r = 0.3599$. The weak positive correlation was $r = 0.1797$ between absolute academic performance and attendance.

Table 1 Normality of data distribution according to the Kolmogorov–Smirnov test

	Test statistics K-S (D)	p-value	Mean	Median	Standard deviation SD
Students' attendance	0.13574	0.71859	21.08333	21	3.161132
Quality academic performance	0.13027	0.76274	46.825	45.8	14.257302
Absolute academic performance	0.13735	0.70538	74.6625	77.45	15.325109
Correct answers number	0.26127	0.10798	76.45	108	57.119888
Incorrect answers number	0.27731	0.07499	59.05	22	57.771305

Source Created by authors

3 Results and Discussion

Lessons 1–8 within the “Splanchnology” section were carried out using innovative teaching methods. The first eight practical lessons in the first group of students were carried out in the form of a traditional teaching method using moulages and plastination. In this case, the practical lesson began with testing. The teacher explained to the students the importance of the current topic. Then, the teacher conducted a survey of students, focusing on clinically significant anatomical formations and analyzing the algorithm for identifying the studied structures on posters and dummies (Fig. 1a, b). The lesson ended with 20 min of independent work by students with visual aids and summing up by the teacher.

The illustrative basis with ready-made symbols was various atlases or electronic manuals with color drawings. During the work of the first group, students exchanged opinions on the correct identification of the studied formations and the comparative characteristics of the depicted anatomical structures on tablets and dummies. When a student had difficulty (difficulties in identifying structures or interpreting the spatial arrangement of topographic formations), the teacher's intervention was allowed, who answered questions of narrow content and directed and coordinated the further work of this group using Latin terminology. At the final stage, students tried to separately demonstrate and name clinically significant anatomical formations using visual aids.

The second group of students independently worked with an anatomical table (Fig. 1c), tablets, models, and various schematic drawings. Students in this group had the opportunity to restart, if necessary, the completed sections of the educational film several times and pause it. After studying the entire section, the sum of five marks obtained in practical classes using the traditional method was separately calculated for each student.

After testing, at the starting point of the lesson, students were motivated to study the current topic of the lesson for 7–8 min. Then, they gave a brief general anatomical and functional description of the anatomical formations included in the current lesson.

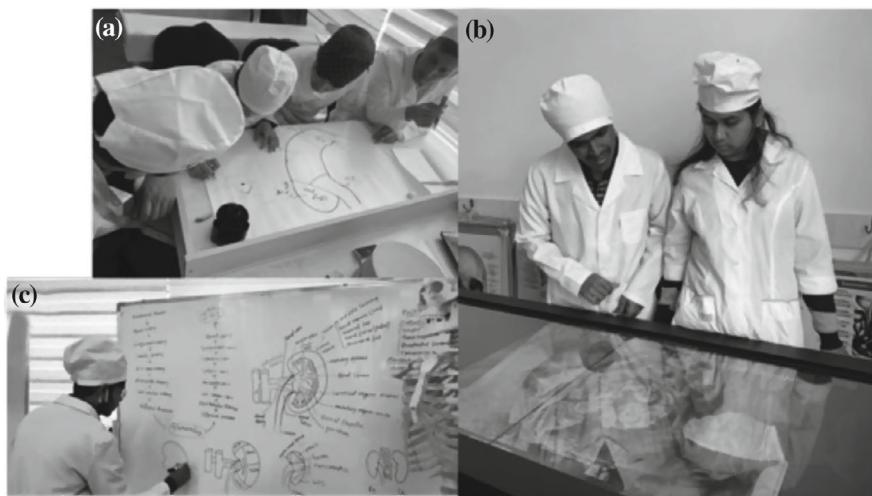


Fig. 1 Traditional teaching method in human anatomy classes: **a** educational discussion with peer teaching; **b** independent work of a student; **c** interactive teaching method where students are working with an anatomy table. *Source* Created by the authors

Separately, they emphasized the importance of those anatomical structures on which doctors often perform surgical techniques or diagnostic manipulations. The second group of students initially received the task of working with tablets and an anatomical table. Computer technology was actively used in this case.

The computer was used to demonstrate an educational film, which contained a demonstration with comments on the studied anatomical structures on plastination, which students must detect on preparations.

The third group of students was initially tasked with working with plastination preparations (Fig. 2a, b), an anatomical table, and tablets. Computer technology and plastination preparations were actively used. In the second part, the class moved on to questioning and grading. After completing the active phase of independent work, students of both groups summed up the results, answered additional questions, and focused on the comparative characteristics of the work in the group. A group was identified that organized the work more rationally and coped with the stage of identifying anatomical formations faster.

In the second part, the class moved on to questioning and grading. The main tasks in this group were as follows:

- To identify all anatomical formations of the current topic on visual aids (models, pad tablets, and diagrams);
- To analyze the main topographic formations and the area;
- To carry out a comparative characterization of the localization and syntopy of the studied structures on pad tablets and anatomical waxworks. The solution to



Fig. 2 Mixed teaching method, students work with plastination preparations. *Source* Created by the authors

the third problem is important because pad tablets provide planar visualization of anatomical structures, while models provide three-dimensional visualization.

In November 2023, the department teachers conducted a monitoring to assess the residual knowledge of the second-year students in the specialty "Human anatomy." The results of the indicators of the number of correct and incorrect answers are shown in Table 2.

Table 2 The number of correct and incorrect answers during intermediate testing in the subject “human anatomy”

No.	Questions	Correct answers	Incorrect answer
1	Describe the bone chemical composition	85.9% (116)	14.1% (19)
2	What portion of the scapula articulates with the clavicle?	74.1% (100)	25.9% (25)
3	Which one is part of Femur?	8.9% (12)	91.1% (120)
4	Which tarsal bone has three small bones?	97% (131)	3% (4)
5	An example of a secondary cartilaginous joint includes	0% (0)	100% (135)
6	An example of a fibrous joint includes	94.8% (128)	5.2% (7)
7	Which one is part of sphenoidale?	0% (0)	100% (135)
8	Specify parts of the stomach	94.1% (127)	5.9% (8)
9	Show which part is missing in the penis	28.1% (38)	71.9% (97)
10	Which of the following muscles controls the movement of the eyelid?	97.8% (132)	2.2% (3)
11	The PNS is subdivided according to its functional characteristics	97% (131)	3% (4)
12	The average amount of human cerebrospinal fluid is	0% (0)	100% (135)
13	The medulla oblongata contains the nuclei	91.9% (124)	8.1% (11)
14	Indicate the boundary between the medulla oblongata and the pons (dorsally)	89.6% (121)	10.4% (14)
15	Which pairs of cranial nerves are motor nerves?	97% (131)	3% (4)
16	All cranial nerves have nuclei in the brain except	1.5% (2)	98.5% (132)
17	The upper lateral surface of the hemisphere contains	3% (4)	97% (128)
18	Participating in the formation of the cerebral arterial circle are	43% (58)	57% (107)
19	Sympathetic nerves approach the stomach from	97% (131)	3% (4)
20	Cava-caval anastomoses include an anastomosis between	34.1% (46)	65.9% (89)
Total (%)		56.7	43.3

Source Created by authors

4 Conclusion

Therefore, blended learning is a good way of providing students with the best possible learning and teaching experience while also supporting teachers in organizing group work professionally. Combining traditional methods (i.e., face-to-face group teaching) with innovative teaching methods can help overcome the time constraints of traditional teaching and improve teaching.

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Artificial Intelligence Possibilities in the Functional Diagnosis of Phonological and Phonetic Decoding of Bilingual Speech



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Abstract The authors consider artificial intelligence possibilities in the functional diagnosis of phonological and phonetic decoding of bilingual speech, using the example of one of the indigenous peoples of the North Caucasus—the Avars. The relevance of the research is due to its interdisciplinarity and use of different methods and approaches to analyzing bilingual speech. The corpus of audio files of assimilative interaction of minority languages of the North Caucasus is processed in Praat 5.3.32. The acoustic and prosodic parameters are marked, normalized, and tokenized. The sampling procedure is performed using the signal processing libraries Librosa, Parselmouth, and a script developed by Goncharova for acoustic and prosodic analysis in Python 3.11. During the prosodic and acoustic analyses, the authors proved the predominance of large pauses in the target bilingual performer's speech. Moreover, the authors identified certain deviations in the pronunciation norm for certain consonants and minor changes in the frontness (or backness) and height of the vowels /u/ and /a/, which appeared due to the interference of the qualitative characteristics of the Avar vowels. The scientific novelty of this research is determined by the description of the programming stage algorithm and the flexibility of the proposed model. The presented approach can be extended to other languages.

Keywords Artificial intelligence · Accent decoding · Acoustics · Prosody · Interference · Bilingualism

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1 Introduction

The problem of decoding bilingual speech has been widely discussed in Russian and foreign linguistics in recent decades. The interest in the problems of language contacts, increasing globalization, and active migration processes force researchers to address the issues of functional differentiation of language variants in the context of intensive and multifaceted interaction of languages. Weinreich significantly contributed to studying this problem. He noted that millions of people master, to a certain degree, two or more language systems throughout their lives. According to the scholar, they can use each system separately depending on the circumstances and requirements of the situation [19]. Haugen suggested the idea of the coexistence of two language systems with the possibility of penetration of some non-assimilated elements from one language to another [7].

In “Languages in Contact,” Weinreich argues that the greater the differences between systems (the more mutually exclusive forms and groups in each language there are), the greater the potential area of their interference. By the term “interference,” he means certain deviations from the norms of any of the languages that occur in bilinguals’ speech as a result of mastering more than one language or a kind of rearrangement of workplaces resulting from the introduction of external elements into more structured areas of the language, such as the main part of the phonetic system, a significant part of morphology and syntax, and some areas of the dictionary [19, p. 22]. When studying bilingualism from the sociolinguistic point of view, Weinreich names some factors contributing to the interference in speech. This primarily includes the speaker’s initial linguistic competence, disloyalty to the studied language, a puristic attitude towards the recipient language, and social significance of the recipient language [19, pp. 64–65].

According to Lott, there are three factors that cause interference and provoke the occurrence of interference errors. They are as follows:

- The actual language factor—negative influence of the mother tongue as the only source of errors;
- Similarity by analogy—the misuse of an element based on phonetic, spelling, semantic, or syntactic similarity;
- The transfer of structural deviant forms—the commission of a second language error due to compliance with the rules of the mother tongue [12, pp. 258–259].

Vishnevskaya states that despite the existing knowledge of bilingualism and bilinguals, this topic seems not to have been fully covered, and the linguistics of bilingualism needs further research in many aspects of this phenomenon [18, pp. 258–259]. Moreover, the authors of this research are confident that the identification of speech features of bilingual speakers of minority languages will help determine the

mechanisms of decoding and automatic detection of speech production errors, which can be integrated into diagnostic software [14].

Although the decoding process has made significant progress since its invention and the variety of existing approaches to speech recognition (e.g., working with audio recording transformations or generating synthetic data using machine learning methods), it is still debatable whether these approaches are effective and the features they reveal are relevant [15]. One of the problems is that the speech signal is subject to high variability [6]. The dominant approach used to identify speakers based on the use of low-frequency cepstral coefficients (MFCC) as parameters and Gaussian mixture models (GMM) has very high recognition accuracy. However, recent studies have noted that the error rate as the speech signal deteriorates is still high, while prosodic characteristics show greater resistance to channel distortion and noise [2]. A combination of the two approaches can provide a more sustainable solution [9]. With a wide coverage of the role of MCC-based features in recognition, their role in describing the qualitative structures of sounding speech and obtaining visual weighted diagnostic parameters of variants is not apparent. As a rule, they are just numerical arrays without any reference to the meaning [11].

The possibilities of artificial intelligence (AI) as a diagnostic tool for encoding and decoding of bilingual speech production have not yet received proper attention from either linguists or ML engineers. The relevance of automating instrumental diagnostic methods (e.g., spectrograms and ultrasound visualization of language) for analyzing speech articulations is quite apparent and is due to the real complexity of their use [3, 4].

2 Materials and Methods

The research aims to demonstrate the potential and capabilities of AI in the functional diagnosis of phonological and phonetic decoding of bilingual speech. For this purpose, it is necessary to form a corpus of audio files of assimilative interaction of minority languages of the North Caucasus (e.g., the Avar language) with the norm of the Russian language and carry out its primary processing using the open-source software Praat 5.3.32. Next, it is necessary to mark up the data and normalize and tokenize the acoustic and prosodic parameters of the audio files of the experimental corpus.

A comprehensive analysis of the experimental corpus will be carried out in several stages. Each stage requires the use of special methods and approaches.

In the first stage of this research, the authors compiled a general experimental sample of the material and formed the research corpus. The files of Russian-language utterances of bilingual speakers of the Avar language will be recorded in the form of a quasi-spontaneous and spontaneous implementation of the corpus files. They will be selected on the principle of the presence of interference features in them as a result of the auditory analysis with the participation of informants.

During the experimental phonetic stage, it is necessary to determine and extract the features and convert the signal into a set of acoustic characteristics. The sampling procedure, after which an array of numbers representing the amplitude of the sound wave at fixed intervals will be obtained, should be performed using the signal processing libraries Librosa, Parselmouth, and a script developed by Goncharova [20] for acoustic and prosodic analysis in Python 3.11 (preliminary development in the public domain <https://github.com/brainteaser-ov>).

During further analysis of the features' importance (the SHAP feature importance plot method), it is necessary to determine the basic combination of features that provides the highest performance of the model:

- Mel-frequency cepstral coefficients (MFCC) and mel spectrogram (mel) tonal centroid (Tonnetz);
- Formant values of vowel frequencies normalized using the z-score metric, indicators of phrase intensity, tonal range and register, the magnitude of the intervals of raising and lowering the tone, and the volume of these intervals.

To implement this stage, it is necessary to use the open-source software Praat 5.3.32 (obtaining formant values and acoustic indicators of phrases), the two-dimensional graphics library Matplotlib, a script for data normalization developed by O. Goncharova, and acoustic and prosodic analysis in Python 3.11.

At the programming stage, it is necessary to encode and scale the following features: scaling/StandardScaler of the scikit-learn library, encoding One-HotEncoding/Ordinal-Encoding of the scikit-learn library. We will apply the algorithms of the K-nearest neighbor, the decision tree, the linear and logistic regression, and the gradient descent. Next, it is necessary to apply the Confusion matrix to visualize the performance of classifiers (Precision/Recall), ROC-AUC, accuracy, and F1-score.

3 Results

Any language is always associated with transmissions of various meanings, in which creation units the linguistic and paralinguistic levels take part, including phonetic and phonological (i.e., acoustic and prosodics ones) [10]. When analyzing the phonetic parameters of speech, it is important to avoid opposing them because the nature of articulation determines the properties of sound units; their perception is associated with a person's ability to match the necessary articulation with a certain sound [13]. The ability of prosodic characteristics of speech to convey various semantic meanings and emotions has become the subject of different research works [1, 5]. Generally, paralinguistic communication is a special coded set of behavioral acts consisting of vocal and non-vocal elements, the choice and meaning of which depend on the characteristics of a particular culture [16, 17].

We are especially concerned with the Russian-language speech of North Caucasian bilinguals, particularly its inferential prosodic characteristics and the

peculiarities of perception of assimilative results of the North Caucasus languages interaction with the Russian language norm. To determine the ethno-relevant accentual characteristics of the North Caucasian bilingual speech, the authors formed a corpus of audio files with recordings of representatives of one of the indigenous peoples of the Caucasus—the Avars. A special block of the corpus was represented by the recordings of Sheikh Abdullah Kosteksky, an Islamic radical preacher recognized as a terrorist in Russia. At the first stage of the experimental phonetic research, the authors conducted an auditory analysis, during which they listened to several extracts from online sermons by Russian-speaking preachers, including those performed by Kosteksky, to an expert group consisting of phonetics teachers and linguistics students of Pyatigorsk State University. After an audition, the authors asked the group of informants to choose those recordings that, in their opinion, were read by North Caucasian bilinguals. The majority of informants (90%) chose the recordings of Kosteksky's speech.

At the next stage, the authors asked the informants to classify the recordings of Kosteksky's speech into one of the following categories:

- The speaker has no accent;
- The speaker has a slight accent;
- The speaker has a strong accent.

This time, the opinions of the informants were different. Although the majority chose the category “the speaker has a strong accent” (60%), the indicator in the category “the speaker has a slight accent” (37%) turned out to be quite high. Only 3% of the auditors considered that “the speaker has no accent.” The absence of an accent or its insignificance was mentioned by the students who are North Caucasian bilinguals themselves—native speakers of Kabardino-Circassian, Ossetian, Karachay-Balkar, and Avar languages. In this case, it is difficult to disagree with the point of view of Vishnevskaya, who believes that the impact of an accent on the native speaker (positive and negative) is based on their linguistic and social experience [18, p. 188]. She suggested evaluating the possible reaction to accentual speech of bilinguals in the categories of “strong or slight accent” and “unpleasant or pleasant accent.” She suggests understanding the accent as “a complex of systemic and stable deviations from the pronunciation norm,” which is “easily perceived by the hearing of a native speaker” [18, p. 189]. Consequently, informants are insensitive to Kosteksky's accent can be explained by the fact that what the native speakers of the Russian language (not North Caucasian bilinguals) consider to be a pronunciation deviation is not the case for bilingual speakers of the North Caucasus minority languages.

The next task of the auditory analysis stage was to assess the pauses and their duration. The informants gave their assessment within the framework of the following types of pauses in the experimental audio files: short, small, medium, and large. Most of them noted the predominance of large pauses in Kosteksky's speech (about 60%). This can be explained by the discursive features of religious preaching as a speech genre, the individual characteristics of speech production, and the interference factor. For comparison, according to Kochenkova, in speeches of Orthodox priests in sermons, the most common type is the so-called “performer's pause,” the recurrence

rates of which vary from 12 to 18.5%. This “pause” is used to give the speech “greater perspicuity, clarity of sound, and perception convenience” [8, p. 53].

At the level of perceived acoustic speech parameters, the informants found a number of pronunciation deviations for certain consonants. For example, the lack of consonant palatalization was noted in such words as *менять* [change], *делать* [do], *omey* [father], *mamepu* [mother’s], etc. All informants noted qualitative differences in the articulation of the Russian posterior slit deaf consonant sound [x], which is explained by interference from the Avar language. In the phonetic system of the Avar language, there are four variants of this sound: posterior sonorous [x_b], pharyngeal sonorous [x_I], uvular aspirative affricate [x_v], and uvular sonorous [xx]. Additionally, there were qualitative changes in articulating a deaf solid sound [ɸ], which sounded more like a consonant [n] to informants. This change is explained by the absence of a consonant [ɸ] in the phonetic system of the Avar language.

To search for deviations in the qualitative characteristics of vowel sounds, the authors obtained the necessary parameters using the open-source software Praat 5.3.32 with subsequent data coefficient normalization. Table 1 shows the main vowels /ɔ, u, a, o/ formant frequency rates in the accent speech of the North Caucasian (Avar) bilinguals.

Based on the obtained data, the authors visualized and compared the coordinate space of the main vowels /u, a, o/ in the accent speech of the North Caucasian (Avar) bilingual with the standard normative indicators of the Russian language. The results of the visualization are presented in Fig. 1.

Thus, in the bilingual realization of the main vowels /u, a, o/, there are minor changes in the frontness or backness and height of the vowels /u/ and /a/, which appeared due to the interference of the qualitative characteristics of the Avar vowels. Therefore, the vowel sound /a/ in the realization of the bilingual Avar is more open and advanced, and the vowel /u/ is more open and back.

Thus, the authors presented the results of the first stage of their experimental study. To use all possibilities of AI in the functional diagnosis of phonological and phonetic decoding of bilingual speech, as it was mentioned above, the following steps must be taken:

- To generate spectrograms and oscillograms with the consideration of the input parameters, encode and scale phonetic and phonological parameters, and obtain vectors of signs of bilingual speech production;
- To identify coincidences or discrepancies in the allocation of semantically significant units by prosodic means;
- To analyze ethnic-relevant acoustic and prosodic parameters of encoding and decoding of bilingual speech;
- To form an analysis algorithm and select optimal models based on a combination of hyperparameters using the gradient descent method;
- To train and apply the most productive model to new data and obtain and interpret predictions.

Table 1 Formant frequency rates of the main vowels in the North Caucasian (Avar) bilingual speech

Vowel	Duration (ms)	The formant rate/F1	The formant rate/F2	The formant rate/F3	The normalized formant rate/norm_F1	The normalized formant rate/norm_F2
ɔ	0.045	451.740	1709.729	3478.165	0.153	0.848
u	0.028	425.841	1565.413	2507.155	- 0.079	0.500
a	0.045	499.561	1077.943	2048.825	0.582	- 0.674
o	0.0595	443.762	1061.285	3234.974	0.0815	- 0.714
ø	0.064	439.338	1002.285	2581.661	0.0418	- 0.856
a	0.0454	487.082	818.312	1548.942	0.470	- 1.300
u	0.0430	421.513	1647.654	2655.749	- 0.118	0.699
u	0.061	417.478	1875.578	3153.193	- 0.154	1.248
a	0.0594	488.768	1581.498	1849.099	0.485	0.539
a	0.0422	261.421	596.757	1509.924	- 1.556	- 1.834
u	0.034	380.878	1662.758	2672.528	- 0.483	0.735
u	0.0814	354.528	1671.423	2430.236	- 0.719	0.756
ɔ	0.052	417.782	1788.043	3049.762	- 0.1518	1.037
u	0.134	354.895	953.247	2204.862	- 0.716	- 0.975
a	0.054	419.530	1490.693	3343.078	- 0.136	0.320
a	0.0555	838.629	1684.164	3436.233	3.628	0.787
u	0.0524	397.544	797.690	2153.578	- 0.333	- 1.350
u	0.0915	319.847	1819.760	3158.992	- 1.031	1.114
y	0.0548	418.082	802.165	1801.462	- 0.149	- 1.339
a	0.054	455.426	1546.975	2418.759	0.186	0.456

Source Compiled by the authors

4 Conclusion

In this research, the authors presented the research of the AI possibilities in the functional diagnosis of phonological and phonetic decoding of bilingual speech. The analysis of accent features in bilingual speech is necessary to prevent and overcome communicative failures. The speech portrayal of the North Caucasian bilingual is of undoubtedly interest. It is relevant, especially from the point of view of differentiation of language variants in the context of intensive and multifaceted interaction of the Russian language with the languages of the peoples of the North Caucasus.

Despite the considerable experience gained, the research in the field of prosodic interference shows that there is still no information about the acceptable range of interlanguage variations and that, in the case of prosody descriptions of different languages, they are quite difficult to relate to each other due to the absence of commonly accepted methods. A number of issues regarding the method of obtaining structures for analysis and the method of their interpretation remain unsolved.

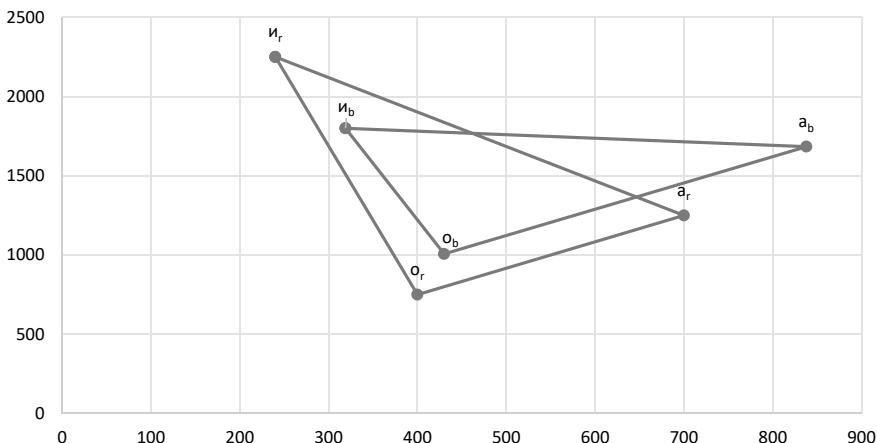


Fig. 1 Formant vocal triangles of the main vowels /u, a, o/: u_r , a_r , o_r —standard Russian vowels; u_b , a_b , o_b —Russian vowels in the North Caucasian (Avar) bilingual speech. *Source* Calculated and built by the authors

Language components subject to interference are fragmentarily described. Despite the evidence of the existence of a prosodic model characterized by universal and specific features, research is mainly focused on listing distinctive features that do not always create an adequate and complete picture of an accent. Thus, the possibilities of AI as a tool for encoding or decoding research of bilingual speech production are of great potential due to incredible precision and imminent and profound future effect on linguistic science as a whole.

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Machine Learning Algorithms in the Speech Analysis: Intonation and Acoustic Characteristics Comparative Study



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Abstract The research focuses on analyzing intonation and acoustic features of speech using machine learning techniques. The relevance of the research is due to the attempt to search for a methodology to create a system based on the combination of prosodic and spectral features and the selection of an optimal classifier to identify whether there is an accent in speech. The authors discuss the advantages and constraints of the most commonly used machine learning algorithms in binary classification tasks: the K-nearest neighbor (KNN) algorithm, support vector method (SVM), decision tree algorithms (DTC), and machine learning logistic regression algorithms that were used during the research. As a result of analyzing the importance of features, the authors determined the “basic combination of features,” which demonstrates the highest accuracy. The scientific novelty of this research is determined by using machine learning techniques to create a system based on a combination of prosodic and spectral features and select the optimal classifier for identifying the presence and absence of an accent in speech.

Keywords Intonation · Acoustics · Speech analysis · Accent · Spectral features · Machine learning

JEL Classification C10 · C15 · C25 · C45

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1 Introduction

Speech-emotion recognition has entered everyday life due to mobile devices that can receive voice commands and respond with synthesized speech. It is used in human-computer interaction, mobile services, call centers, computer games, etc. [10, 11]. Despite its many applications, emotion detection in bilingual speech is a challenging task because emotions are subjective and culturally conditioned; acquired speech habits are mainly influenced by the cultural and social environment and first (native) language features [9].

In contemporary research, to recognize states based on voice information, as a rule, various vectors of voice characteristics are selected, in which different statistical indicators are calculated. Although the emotional and accentual content of uttered statements is clearly encoded in the speech signal, and there is a great variety of approaches to recognize audible speech [1], such as audio recording conversion or synthetic data generation with machine learning techniques, the effectiveness of the results gained and the features identified are still being discussed [7].

It is quite apparent that the approach involving the use of MFCC—low-frequency cepstral coefficients [15] and a probabilistic model that posits that all data points originate from a combination of a limited number of Gaussian distributions—Gaussian mixture models (GMM) as parameters has a fairly high recognition accuracy. Nevertheless, though spectral and acoustic features are considered default to represent a particular speaker's voice characteristics, especially under appropriate acoustic conditions [12], they are vulnerable to noise and outer variations [6, 13]. Both of them tend to ignore higher-level aspects of speech that represent speaker characteristics. Thus, they cannot reflect an individual's unique speech style [12]. Due to their long-term nature, prosodic features can offer supplementary information by capturing the unique characteristics of a speaker and the individual's speech patterns. These features may contribute more to voice recognition when included together with spectral and acoustic. Moreover, the role of MCC-based features in the qualitative structures of sounding speech description and obtaining parameters of variant diagnosis is not apparent because, as a rule, they appear as numeric arrays without any reference to their meaning [8], while it is undoubtedly relevant to know what exactly within a sound accomplish a certain function in the language system [14, p. 19].

Therefore, there is an increasing interest in using prosodic features to identify a certain speaker. A number of different approaches was employed to extract these features, including leveraging the results of an automated speech recognition system to identify segment boundaries and trying to transform this information to calculate prosodic features [9]. MFCC-oriented research undoubtedly makes a significant contribution to the task of emotion recognition. Nevertheless, there is no sufficiently effective method for describing emotional states and the degree of accent expression in bilinguals, which is certainly relevant for the multilingual region of the North Caucasus. It should also be noted that relatively little attention has been paid to classifying emotions and accented speech at both levels (prosodic and spectral) [4].

2 Materials and Method

This research aims to analyze intonation and acoustic characteristics of speech via machine learning algorithms. For that purpose, the authors attempted to search for a methodology to create a system based on the combination of prosodic and spectral features and the selection of an optimal classifier to identify the presence and absence of an accent in speech [16]. The material was an experimental corpus of recorded audio files of dialogues by speakers—representatives of Russian, Kabardian, and Armenian ethnic groups.

The most commonly used machine learning algorithms in binary classification tasks are as follows:

- The K-nearest neighbor (KNN) algorithm;
- Support vector method (SVM);
- Decision tree algorithms (DTC);
- Machine learning logistic regression algorithms.

These algorithms were used during the research. The authors will discuss the advantages and constraints of each model to better understand their suitability for the task at hand.

- (1) The K-Nearest Neighbors (KNN) algorithm is a technique that operates by making no assumptions about the distribution of data and is usually used for developing classifiers capable of solving binary and multiclass problems. In a simplified version, the algorithm's work is reduced to determining the class to which an object belongs by identifying the classes of its nearest neighbors—the target object belongs to the same class to which most of the nearest objects in the training sample belong. To calculate the distance to objects, as a rule, either Manhattan distance or Euclidean distance are used.
- (2) A Decision Tree is an algorithm based on a tree model, where each step implies a decision that is made based on a characteristic or attribute of a feature, and each branch is the outcome of the decision [3]. The data is partitioned into a finite number of subsets, the number of which depends on the selected stopping criterion, and each leaf implies a label that predicts the outcome.
- (3) Support Vector Machines (SVM): SVM machine learning algorithm finds the hyperplane in a one-dimensional or multidimensional space that best separates data points of different classes using different decision kernels. It compares favorably with other algorithms in its ability to classify high-dimensional data.
- (4) Logistic regression is used to identify the relationship between the target variable and several independent variables in the training sample, select hyperparameters, remove mutually dependent variables, and introduce new variables based on combinations of initial variables to model the relationship between the dependent variable and one or more independent variables. The objective is to apply a logistic function to the data in such a way as to minimize the total amount of error between the predicted and actual values of the dependent variable [2, pp. 1937–1967].

3 Results

The purpose of this research was to analyze intonation and acoustic characteristics of speech via machine learning algorithms and find a methodology for creating a system based on a combination of prosodic and spectral features and selecting the optimal classifier for identifying the presence and absence of an accent in speech and emotion recognition.

The material of this research was an experimental corpus recorded by representatives of the Russian, Kabardian, and Armenian ethnic groups, consisting of quasi-spontaneous audio files of dialogues marked with the emotional state “anger” and neutral versions of the same dialogues necessary for the classifier to work.

The corpus files were first analyzed by linguists and native speakers estimate the unambiguity of the reproduced emotional state, the accent intensity degree (strong accent, medium accent, or slight accent) and the overall naturalness of the sound. The final dataset consisted of 650 audio files with 250 implementations for each variant—Russian and interfered in both emotional states and 150 implementations of neutral replicas.

Prosodic characteristics were analyzed through the terms of tone, duration, and intensity subsystems because these factors influence energy distribution within a syllable. Duration is key to identifying different rhythmic patterns, while F0 measurements can vary significantly among speakers due to differences in vocal cord tension and subglottal pressure. Meanwhile, average pitch offers insights into a speaker’s physiological condition. Additionally, the shape of the tone contour plays a crucial role in identifying the style of speech. The features were developed in the course of interference studies within the Pyatigorsk phonetic school (Y. A. Dubovsky, E. V. Kipa, A. E. Sadovaya, L. F. Shishimer, N. V. Lukova, N. A. Ermakova, E. O. Martyanova, O. V. Goncharova, O. V. Vorobyeva, et al.) [5, p. 42].

For the analysis, the Praat software was used to evaluate the contours of the aspen tone frequency, intensity and duration indicators, and formant values. MFCC features were extracted using the Python Librosa audio analysis library. Normalization and subsequent extraction of features were performed using a Python script developed for the purposes of this study (in the public domain: <https://github.com/brainteaser-ov/PySound>). For each utterance, the intensity, duration, pitch frequency contours, and F2 and F1 were normalized, calculating the z-score for each specific speaker.

The statistical data that was calculated for each utterance included average values of features, the variance of features and their standard deviation, binary values of the pitch frequency (minimum and maximum), intensity and duration of the whole utterance, and element by element (at the level of syllable and phrase), and the frequency of formants F1 and F2.

For every level of feature, 13 Mel Frequency Cepstral Coefficients (MFCCs), which also account for logarithmic energy, were computed utilizing a Hamming window with a duration of 25 ms and intervals of 10 ms. This was followed by the normalization of each speaker’s z-score. Moreover, the delta and acceleration coefficients, representing a pair of derivative labels (first and second) of the MFCCs,

were determined through finite difference methods, contributing an additional 26 features. Consequently, the total spectral features at the pronunciation level amount to 78. This total includes the mean values of the MFCCs variable and their standard deviations along with their delta and acceleration coefficients.

Each data set was randomly divided into a training set, which contained 70% of the total number of statements, and a test set, which included the remaining 30% of statements. The necessary marking and preparation of training data before training was carried out in the REC “Data Mining” of the FSUE in Pyatigorsk State University by the staff of the center. Initially, 29 prosodic features were selected and used as a starting point to describe the differences between “angry” and “neutral” speech.

As a result of the initial experimental phonetic study, it was found that the main markers of emotions in the speech of representatives of Russian, Kabardian, and Armenian ethnic groups are as follows:

- Increased degree of articulation;
- Decreased contrast of the ratio of stressed and unstressed syllables;
- Ascending-descending tone in stressed syllables;
- Increased intensity of unstressed syllables;
- Increased phrase onset and phrase completion.

The following prosodic features were chosen for further training of the model:

- Phrase intensity indicators (stressed and unstressed syllables, as well as contrasts of these syllables);
- Tonal levels of phrase beginning and ending;
- Tonal range;
- Magnitude of rising and falling tone intervals;
- Volume of these intervals.

We also used the first two formant values of vowel frequencies /i/, /a/, and /u/, which were normalized via Lobanov’s z-score metric. After training dataset generation and its differentiation into training, validation, and test samples, we split the material into input data X (base combination of features) and target data Y (class 1 or 0, i.e., whether a given realization is “accented” or “not an accent”) for further processing.

Using data on frequency levels, intervals, ranges, and formant values, we converted the primary acoustic parameters to relative measures using StandardScaler and MinMaxScaler of the scikit-learn library. Then, all categorical data were converted to numbers as a set of binary features with values of 0 and 1. This allowed the data to be compared without considering physiological differences between speakers.

For the training of the model, a pipeline incorporating three algorithms was established: K-nearest neighbor (KNN), decision tree, and logistic regression. To ensure a thorough evaluation, a ten-fold stratified cross-validation approach was applied across datasets. This means that each classifier was developed using 90% of the data for training, with the remaining 10% used for testing purposes. This procedure was

Table 1 Indicators of KNN, decision tree, and logistic regression

Metric/model	ROC-AUC	Precision
KNN	0.67	0.73
DTree	0.77	0.68
LogReg	0.85	0.88

Source Compiled by the authors

iterated ten times, with each iteration utilizing a unique seed for splitting to mitigate variations across different partitions.

As a result of using GridSearch classifier in the Pipeline, we chose the best classification model to be logistic regression, with coordinate descent liblinear, random_state = 42 (parameter of reproducible random values; if we explicitly set random_state value different from None, then the generated pseudo-random values will have the same values at each call), penalty = ‘L1’ (lasso-regularization removing uninformative features), C = 1 (determines the degree of regularization). Table 1 shows the performance of the proposed approach with respect to KNN, decision tree, and logistic regression classifiers.

The outcomes of applying the trained model to novel data are detailed in Table 2. It is anticipated that the model’s accuracy will drop when tested on new samples compared to its performance on the training set. This decline could be attributed to including irrelevant or highly correlated features within the spectral and prosodic parameters. Among the three algorithms (K-nearest neighbor (KNN), decision tree, and logistic regression), logistic regression demonstrates superior performance in terms of ROC-AUC and precision metrics across all three languages (Russian, Armenian, and Kabardian). However, upon deploying the logistic regression model on new data, there is a noticeable degradation in model quality for each language.

As a result of training and testing the model, the spectral and prosodic characteristics that we used as input data for the classifiers were transformed into calculable attributes, making it possible to find out their role in the emotion differentiation and obtain a test “language model of emotions” of speech of the Kabardino-Circassian bilingual and determine the “basic combination of signs,” which shows the highest accuracy: mel-frequency cepstral coefficient (MFCC), formant values of vowel frequencies /i/, /a/, and /y/, intensity indicators of the beginning and first stressed syllable of a phrase, the ratio of the intensity of the first stressed and subsequent unstressed syllable, the tonal levels of the beginning and completion of the phrase, the tonal range, the rate of frequency changes in the nuclear syllable, the dynamic contrast of the nuclear and pre-nuclear syllables, the rate of intervals of pitch increase and decrease, and the volume of these intervals.

Table 2 The results of applying a trained linear regression model to new data

Metric/model	ROC-AUC	Precision
LogReg	0.64	0.61

Source Compiled by the authors

4 Conclusion

In this research, the authors presented a comparative study of intonation and acoustic characteristics of speech via machine learning algorithms and suggested a methodology of a system creation based on a combination of prosodic and spectral features and selecting the optimal classifier for identifying the presence or absence of an accent in speech.

Due to the widespread use of prosodic features in this research paper, it is important to further study the recognition rates: (1) only prosodic features and (2) combinations of prosodic features and the ones traditionally used in machine learning. Although the prosodic features chosen for this research do not exhaust all potentialities, they cover important aspects of prosodic information. Thus, the recognition rates from this sample can serve as a basic set for the entire space of prosodic features.

Further improvements in the quality of the model could be achieved by experimenting with different combinations of classifiers and expanding the dataset.

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AI-Based Technologies in French Learning at the Beginner Level



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Abstract The research analyzes the use of AI-based technologies in university French classes at the beginner level and assesses the feasibility of integrating these technologies into the structure of the educational process for adapted and personalized learning. The authors use the experimental method, including diagnostic tests, to determine whether it is appropriate to use AI-based tools at the beginning level of French teaching and learning. To determine the dynamics of learners' achievements while using AI-based tools in French learning, the authors applied the methods of quantitative counting and comparative analysis of data obtained at the pre- and post-testing. To gather feedback on students' using, evaluating, and perceiving AI-based tools in French learning, the authors used the questionnaire method. The results of this research demonstrate the advantages of using digital tools based on AI in French learning to develop linguistic competence, significantly improve learning outcomes, and make the language learning process more efficient. The originality of this research lies in the fact that it focuses on analyzing the use of AI-based technologies in French learning at the beginner level. The use of AI in education has become increasingly widespread. However, it is still relatively under-researched. Thus, this research contributes to developing the field of education and pedagogy by proposing an analysis of specific application scenarios and an assessment of the effectiveness of AI-based technologies in French learning.

Keywords Artificial intelligent · Education · French learning · Assessment · Effectiveness

JEL Classification A19 · C9 · I2 · I21 · I23 · M59 · O3

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1 Introduction

The dynamic digital transformation and constant development of all sectors of the economy, including education, are relevant trends in today's society. These trends can significantly change the technologies and methods of teaching and learning, expand access to knowledge, improve educational materials, and increase the effectiveness of the educational process. The potential impact of digital transformation on economic development is also undeniable. Learning aligned with the latest technologies and methodologies contributes to prepare high-level specialists who can work effectively in the conditions of the rapid growth of the digital economy. In turn, this can lead to increased labor productivity, innovative industry development, and the creation of new jobs.

One of the key points regarding the introduction of digital technologies in the educational process is the analysis of the effectiveness and results of using AI-based technologies for learning and teaching to improve the quality of education.

Leading higher schools, such as Stanford University, Massachusetts Institute of Technology, Tsinghua University, Nanyang Technological University, and others, are creating specialized research centers studying AI and offering various programs from bachelor's to doctoral degrees. Additionally, they create an advanced computing cluster to support advanced intellectual research based on an interdisciplinary approach, paying special attention to the practical application of AI technologies.

The analysis of the experience of introducing AI-based technologies in the Russian education system shows that higher educational institutions are trying to integrate AI-based technologies. For instance, the North-Caucasus Federal University uses the Proctoring system for formative and summative assessments. Moscow State Pedagogical University officially allowed students to use AI tools to prepare their graduation thesis. AI has been introduced in the educational process to generate and work out ideas at the National Research University ITMO. The active digital change of the economy requires the preparation of specialists capable of effectively implementing AI technologies in various fields, which leads to the creation of new educational programs in universities, including the following programs:

- “Digital transformation leader” (additional education);
- “Internet marketing” (additional education);
- “Neuromarketing” (additional education);
- “Website building” in the GAPM (Pastukhov Academy) (additional education);
- “Artificial intelligence, mathematical modeling and supercomputer technologies in the development of information systems” (master's program);
- “Applied artificial intelligence and machine learning” at the North-Caucasus Federal University;
- “Mathematical and software of artificial intelligence systems” (bachelor's and master's programs);
- “Artificial intelligence and data engineering” in the Volgograd State Technical University.

The implemented programs of different levels of training are focused on forming competencies in the field of AI and training qualified specialists and managers in the AI field.

Modernization of the educational system, including constant updating of curricula, enrichment of educational resources, development of online education, and increasing accessibility of education for all segments of the population contribute to developing the intellectual potential of society and economic progress in general.

This research aims to analyze the use of AI-based technologies in university French classes at the beginner level and assess the feasibility of integrating these technologies into the whole structure of the educational process for adapted and personalized learning.

2 Materials and Method

Features and prospects of digitalization of education and the use of AI in education are considered in the works of Bibauw et al. [1], Crompton and Burke [2], Divekar et al. [3], Fryer et al. [4], García-Martínez et al. [5], Godwin-Jones [6], Gorokhova [7], Goulet [8], Hamel et al. [9], Holmes and Tuomi [12], Holmes et al. [10, 11], Hwang et al. [13], Kwon [14], Leleka [15], Lelepary et al. [16], Luckin et al. [17], Mavropoulou [18, 19], Miras et al. [20], Mollick and Mollick [21], Moreno [22], Mucundanyi and Woodley [23], Ouyang and Jiao [24], Petrenko and Levina [25], Rangel-Corona et al. [26], Shefieva and Isaeva [27], Sysoyev [28, 29], Woo and Choi [30], Yang et al. [31], Zawacki-Richter et al. [32], and Zou et al. [33].

Research on the current state of AI integration in higher education indicates the formation of a new dynamic in educational technologies, manifesting itself in the redefinition of education through digital technologies [1, 24, 25, 32]. AI technologies provide participants in the process of teaching and learning a foreign language with the ability to solve several serious tasks, particularly to develop innovative methods of teaching and learning and adapt them in real time to the abilities, levels, and needs of learners to meet their diverse needs. The technical and pedagogical approaches used in teaching foreign languages, oriented towards using AI, are increasingly focusing on learning analysis [2, 3, 20, 23, 31] to better understand how students learn, what technological tools can be used to learn a foreign language, and personalize teaching, making it more successful.

A review of papers considering the use of AI-based technologies in education shows several categories for applying these technologies, including the following:

- Management of the educational process and administration;
- Performance and knowledge assessment;
- Empowerment of teachers and improving teaching;
- Continuous learning [10, 11].

Some authors overview existing AI systems in education and describe various ways of using AI, considering potential barriers and risks [12].

The researchers also focus on the concept of readiness to use AI technologies in education and professional training, considering the principles of their application in various industries [17, 32].

Research devoted to the integration of AI-based technologies into the process of learning foreign languages is presented in reviews of existing platforms and applications [3, 23, 30, 33] and demonstrates areas of work with AI that can increase the effectiveness of learning foreign languages [7, 23, 28, 29]. The ongoing case studies show the availability of digital resources for developing language tasks within the framework of hybrid learning and open context learning, presenting the developed technical and pedagogical recommendations for the optimal use of digital resources [9].

There are publications analyzing some of the advantages and disadvantages of AI using, which can be encountered by higher education institutions and students while learning foreign languages [8, 25, 27]. Numerous articles contain research on the analysis of the possibilities of integrating generative AI technology, particularly ChatGPT [6, 14–16, 18, 19, 26], noting its potential as a learners' partner to master a foreign language [4], as well as a teacher's assistant in planning classes and implementing optimal learning strategies [6, 21].

The feasibility of using AI tools in French teaching at the beginner level is revealed during an experiment that includes learners' pre- and post-testing. To determine the dynamics of learners' achievements while using AI-based tools in French learning, the authors applied the methods of quantitative counting and comparative analysis of data obtained at the pre- and post-testing. To gather feedback on students' use, evaluation, and perception of AI-based tools in French learning, the authors used a questionnaire.

Assessing the potential and relevance of AI technologies integrating into foreign language teaching and learning requires consideration of certain criteria [13], including the following:

- Effectiveness and possible improvement of the learning quality, which can be assessed by comparing the learning outcomes of students using AI with those who do not use it;
- Availability, ease of use, and compatibility of the used AI-based technology with various devices and operating systems;
- Absence of difficulties in its adaptation to the existing curriculum and integration into the educational process.

This should also be considered when choosing digital learning tools using AI. An important factor is also the cost of AI-based technology compared to traditional teaching methods.

Before the start of the experiment, to obtain data, the authors questioned potential participants on their experience in using AI-based tools while French learning and their attitudes and expectations from these tools.

The next stage was the preliminary selection and testing of resources intended for learning in terms of their adaptability or non-adaptability to the requirements of the curriculum, as well as their compliance with the provisions on personal data

protection. The authors also considered the motivational potential of the used technologies in presenting the material, its fascination, and interactivity as additional requirements.

Based on the data obtained from the questionnaire of potential participants and the analysis of available platforms and applications for learning a foreign language, in accordance with the above criteria, the authors selected three tools (Duolingo, Quizlet, and Memrise) for working with beginner-level students.

The choice of these tools for beginners to learn French is justified by the need for regular repetition of the studied material, which is presented in the form of simple exercises, allowing students to memorize and rephrase the material in accordance with their individual needs. Thus, the Duolingo platform uses AI technology for personalized and adaptive user learning based on their language skills and level of language proficiency. An additional option to create a virtual classroom allows the teacher to track the regularity of assignments and the level of progress in mastering the proposed material, which will be required to assess the feasibility of using this tool in the future.

The choice of the AI-based tool “Quizlet” is justified by the need to create a solid foundation of basic vocabulary and grammar. The tool allows its users to manage many memory cards distributed by categories. In addition to words and their meanings, there is an opportunity to supplement the cards with sounds, images, and diagrams. Using existing cards created by other users or creating a personal bank of cards is possible based on the studied material. Moreover, the teacher can create a virtual classroom and set up training tests in accordance with the curriculum and individual results of each student for additional material development.

The “Memrise” platform was chosen as a tool for learning French for entry-level students because, along with the technology of interval repetition using flashcards, the platform has various interactive learning tools, including games and videos recorded by native speakers, which makes the learning process less monotonous and more exciting. One of the main advantages is the opportunity to practice oral communication skills with an AI language partner, based on GPT-3, in the proposed communicative situations.

An important advantage of the selected platforms for use in French teaching outside the language environment is the ability to engage students, personalize the learning process, and provide access to materials that would otherwise be unavailable [23]. Thus, AI technologies make it possible to create a dynamic learning environment adapted to the students' needs, allowing them to receive feedback and personalized instructions in real time, which makes language learning more engaging and effective [5, 22].

3 Results

The experiment involved 32 first-year students who had been studying French as a foreign language for six months. Within the curriculum, students mastered the French reading rules, the basic rules of pronunciation of all sounds, verb conjugation, including the most commonly used irregular verbs, basic cases of determinants using (demonstrative, possessive adjectives, articles), adjectives agreement in gender and number, the syntax basics (simple affirmative and interrogative sentences), and a certain vocabulary necessary for self-presentation.

The results of the questionnaire on available experience and evaluation of the AI-based tools use for French learning showed that only 30% of all respondents regularly used free educational platforms, 15% studied irregularly, and 55% of respondents had heard but did not use these resources. Among the AI-based digital tools used were Duolingo, Babbel, Frantastique, Quizlet, and Reverso. In quantitative terms, the Duolingo platform turned out to be the most demanded, according to the number of mentions found in 78% of the total number of respondents who regularly and irregularly use AI-based tools for French learning.

The evaluation of the effectiveness of the tools used in the pre-experiment questionnaire was moderate. Only a quarter of all respondents expressed high satisfaction. The rest of the participants answered “rather satisfied” (43%) and “little satisfied” (32%). Among the satisfying criteria, participants noted availability (no payment required), the ability to study at any time, and the presence of an explanation block with rules and comments on errors made.

Among the answers to the question about the expectations of using AI-based digital tools in French learning, the most frequently mentioned opportunity was to master grammar and improve listening skills.

From the total number of participants, two groups with an equal number of participants were formed—experimental (EG) and control (CG). Control group participants were not controlled for criteria of constant work with platforms or in the application. Participants in the EG were registered and included in virtual classes on the Duolingo and Quizlet platforms. This was done so that the teacher could control the regularity of the tasks performed and record the results of the students’ work.

Both groups were offered diagnostic tests before and after the experiment. The tests included tasks evaluating students’ lexical knowledge, grammar, and listening skills.

The results of the pre-test showed the following. The average value of the test for the EG was 63.7%, which is slightly lower than the results of the CG participants (72.1%). The overall average includes the average value of the tasks to check lexical knowledge: 68.5% for EG and 70.3% for CG. The grammar test results were 56.2% in EG and 55.2% in CG. The average value of the results of the listening skills check was 54.8% in EG and 58.8% in CG. Thus, according to the results of the pre-test of lexical knowledge, grammar, and listening skills, we can talk about relatively equal opportunities for participants in both groups at the initial stage of the experiment.

However, the overall training of EG participants is almost 10% lower than that of the CG participants.

The experiment lasted five weeks. During this period, the EG participants regularly received and completed tasks to practice grammar and vocabulary on the Duolingo and Quizlet platforms and autonomously worked with videos for listening practice and interactive speaking tasks with the AI bot on the Memrise platform. At the end of this period, the final test was conducted.

According to the results of the post-test, the average score of the EG increased by 8.6% and amounted to 72.3%. The score of the CG participants decreased by 3.6% and amounted to 68.5%. Simultaneously, the percentage of lexical knowledge tests in the EG increased by 6.2%. In the CG, this indicator increased by 4% compared to the results of the initial testing. Thus, the final result amounted to 74.7% in EG and 74.3% in CG. The results of the grammar testing of the EG participants showed an increase of 7.4%, amounting to 63.6%. The results of the CG increased by 4.9%, amounting to 60.1%. The listening skills post-testing are presented with the following average values: 64.3% in EG and 61.9% in CG; that is, the EG participants showed significant progress: an increase in the indicator by 8.6%, while the results of the CG participants changed by 3.1% compared to the pre-test result.

The final testing results demonstrate the advantages of using AI-based digital tools in French learning to develop linguistic competence.

Thus, using AI tools as an additional source to the curriculum for knowledge mastery and skill improvement shows effectiveness. For instance, the EG participants managed to improve their pre-test results compared with the results of the CG participants, who improved less significantly.

At the end of the experiment, the EG participants were also questioned to assess the effectiveness of using the proposed tools and their correspondence to their expectations.

The absolute advantage of using AI-based tools, according to the participants of the experiment, is the possibility of regular processing of the material offered with consideration of the individual achievements of each student. The participants expressed absolute satisfaction with the results of using digital AI tools in French learning in accordance with the expectations expressed at the beginning of the experiment to master grammar and improve listening skills.

4 Conclusion

Thus, based on the analysis of the changes obtained during the experiment, we can conclude that the AI-based tools implemented into French learning at the beginner level are feasible. The main advantages include the possibility of regular practice of the studied material, a personalized approach focused on the progress of each learner, and maintaining motivation through the use of interactive exercises that simulate communicative situations and contribute to the development of language competence.

Since the problem of using AI-based tools in French teaching is very relevant in the context of constantly developing technologies, future research on this subject should be expanded to explore the possibilities of AI, particularly chatbots, and the prospects of its use for French teaching at the advanced level.

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Linguopragmatic Features of Communicative Practice “Human—Chatbot GPT”



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Abstract This research delves into the linguopragmatic characteristics of communicative practice between humans and chatbot GPT. The research explores the evolving dynamics of human–machine communication through a detailed analysis of dialogic interactions, semantic coherence, and pragmatic connectivity in German and Russian languages. Drawing on linguistic theories and computational models, the research highlights the structural and semantic cohesion of stimulating turns and reaction turns in dialogues, shedding light on the intricate nature of communication with chatbots. The research also examines the cognitive mechanisms involved in interpreting speech acts, such as implicature, presupposition, and entailment, within human–chatbot interactions. By investigating the functional roles performed by neural network chatbots, the authors aim to elucidate the specificity and correlation of communication practices in the realm of artificial intelligence. Furthermore, the analysis delves into the application of Gricean maxims in designing analytical conversational behavior for chatbots. The research underscores the relevance of further research to refine linguocognitive models for chatbots, enhancing the efficacy of communicative interactions.

Keywords Chatbot GPT · Human–machine communication · Linguopragmatic analysis · Dialogic interaction · Semantic coherence · Pragmatic connectivity

JEL Classification O33 · D83 · Z13 · L86

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1 Introduction

Digital communication was not so long ago limited to communication between people using various digital mediators such as texting, email, messages on WhatsApp, Viber or Telegram, and Zoom calls. Nowadays, we are witnessing a process of fundamental transformation in the field of communication mediated by advanced computer technologies.

Classical communication theories do not reflect the full range of possible ways of interaction. This has led to the emergence of a new field of “human–machine” research, which aims at a broader scope of scientific analysis of communication modes, the use of various research methods, and the assessment of the impact of digital communication processes on the individual and society as a whole.

The research aims to identify the linguopragmatic specificity of human interaction with the automated ChatGPT system. The paper analyzes the semantic and pragmatic connectivity of the communicative codes presented in the textual elements of the communicative situation “human—ChatGPT” in German and Russian languages and considers the correspondence of these speech samples to the postulates of H. P. Grice.

2 Materials and Method

The field of research on human–machine communication in contemporary scientific discourse encompasses a variety of automated communication systems: from robots with a physical appearance, where non-verbal means of interaction can be used, to virtual automated systems focused exclusively on verbal interaction, such as virtual assistants, language training programs, automated customer service systems, and chatbots. Chatbots are programs that enter into a dialogue and interact with users on certain topics using text, speech, or graphics.

Communication with a chatbot can be considered as a dialogue with an alternate handover of initiative. As noted by some researchers, the term chatbot has technological and communicative components. Recently, the communicative aspect of interaction with a chatbot has come to the fore [11].

There are different classifications of chatbots. Hussain et al. propose classifying chatbots based on four criteria: the way of interaction, the way of using a chatbot, the degree of application of artificial intelligence, and the sphere of use [10].

The material of this research is texts obtained by interacting with the ChatGPT chatbot. ChatGPT is an automated system trained on Large Language Models (LLM) that can generate answers to user questions using texts of different styles and functional focus. Nowadays, the terms describing mental states and mental activities of human beings (e.g., think, represent, recognize, prove, etc.) are applied to large neural network models and their computational results, realized on a huge set of data

[3, p. 12]. Researchers of consciousness, language, and AI argue that machines are reacquiring human traits in their verbal practice [4].

The scope of application of chatbots can be quite different. As the studies show, the possibilities of using chatbots in the educational process are positively evaluated by teachers of English as a foreign language [7]. The authors emphasize the linguo-didactic potential of chatbots and virtual assistants [1]. Additionally, chatbots can be used to provide therapy for patients suffering from depressive disorders [6].

The variety of spheres of use of chatbots makes it relevant to study the specifics of human interaction from the point of view of communication. Communicative failures and the degree of artificiality of the communication situation and textual result are subject to linguistic analysis [2].

One of the ways to study the effectiveness of communicative interaction is to refer to Grice's postulates. Grice's maxims can be used in developing chatbots and their training [15]. Particularly, to fully understand the context of a conversation, it is not enough to understand only the structure and semantics of an utterance. The consideration of the pragmatic features contributes to the greatest degree of user engagement in a conversation with a chatbot [12, p. 135].

This research provides a linguopragmatic analysis of the functional roles performed by neural network chatbots in the context of communication. To determine the specificity and correlation of human and ChatGPT communication with dialogic and monologic types of discourse, the semantic and pragmatic coherence of ChatGPT replicas and reactions to them are investigated.

3 Results

Contemporary automated systems are capable of simulating the dialogic form of communication. Despite the fact that the nature of replicas generated by AI is different from that of human utterances, they do not arise in the course of cognitive processes. They are determined by algorithms and data on which the system was trained. They do not reflect personal beliefs or opinions. From a formal point of view, interaction with advanced neural network chatbots is like a dialog between people: it has semantic and pragmatic coherence of communicative codes (i.e., it forms a dialogical unity). Semantic connectedness in dialogue implies semantic unity and the presence of logical consistency in the statements of interlocutors and their active interaction during the development of the dialogue topic.

In this research, the authors consider different types of pragmatic coherence in dialogue and their representation in communication with automated systems. Pragmatic cohesion is provided by the choice of linguistic means considering the motives and tasks of the addressee. It manifests itself in an adequate response to the stimulus contained in the initiating replica [13, p. 110].

The most common type of communication with automated systems is the agreement of replicas using the illocutionary function. The illocutionary function of an utterance implies the expression of one or another communicative intention of the

speaker (e.g., a request, an inducement, or various types of information request). By virtue of this type of connection, a question must be followed by an answer, an inducement, consent, or refusal. We observe this type of relation in the following example. The German query «*Hast du eine Idee, was ich meinem 12-jährigen Sohn zum Geburtstag schenken kann?*» [Do you have any ideas for what I can give my 12-year-old son for his birthday?] is followed by a full extended answer with the following introductory part: «*Natürlich! Hier sind einige Ideen für Geschenke für deinen 12-jährigen Sohn...*» [Of course! Here are some ideas for gifts for your 12-year-old son...] [8]. When we query a prompt in Russian, we observe a similar result. To the prompt «*Как ты думаешь, где я могу провести свой отпуск с ограниченным бюджетом?*» [Where do you think I can spend my holiday with a limited budget?], we get the following response, «*С ограниченным бюджетом отпуск можно провести разнообразно и интересно! Вот несколько идей...*» [With a limited budget, a holiday can be spent in a varied and interesting way! Here are some ideas...] [8].

The agreement of replicas by illocutionary function is the most common type of pragmatic cohesion. Along with agreement and inducement, the reaction to the stimulus in the initiating cue can be refusal. To the prompt in German «*Kannst du mir bis Freitag 500 Euro leihen?*» [Can you lend me 500 euros until Friday?], we get the following chat response, «*Es tut mir leid, aber ich kann dir kein Geld leihen*» [I am sorry, but I cannot lend you any money]. However, this response is redundant. In addition to the negative response, the chat offers a possible option for solving financial problems: «*Wenn du finanzielle Unterstützung benötigst, könnte es eine gute Idee sein, mit Freunden oder Familie zu sprechen, oder du könntest überlegen, einen Kredit bei einer Bank oder einer anderen Finanzinstitution aufzunehmen*» [If you need financial support, it might be a good idea to talk to friends or family, or you could consider taking out a loan from a bank or other financial institution] [8], although this information was not requested in the prompt.

The next type of pragmatic coherence is expressed by replicas addressed to the presumption of the preceding utterance. The presumption is an element of common knowledge of the speaker and the hearer, a belief shared by them [14, p. 98]. The example presented expresses disagreement with the addressee's presumption.

It does not consider the semantic component of the utterance, the addressee's judgment «*Alle Blonden haben schlechte Noten in der Schule*» [All blondes have bad grades at school], to be true. It writes, «*Die Annahme, dass alle Blondinen schlechte Noten in der Schule haben, ist ein Stereotyp und hat keine Grundlage in der Realität*» [The assumption that all blondes get bad grades at school is a stereotype and has no basis in reality] [8]. This example shows that a chatbot is capable of reacting critically to false claims and refuting or correcting them. However, unlike a human, this reaction of a chatbot is due to software code and algorithms, not the ability to think critically like a human.

The next type of communication can be seen in replicas based on discourse implicatures. An implicature is implicit information included in an utterance without being explicitly or verbally expressed [16, p. 30]. Knowledge of common forms of

implicature is socio-culturally conditioned (i.e., a person internalizes them as stable conventions of the community of native speakers) [5, p. 332].

The addressee in the example expresses his sadness and possible annoyance, not speaking about this feeling directly. The utterance is supported by an appropriate emotive signifier. In this example, the expression of sadness is an implicature. In its response, the chatbot shows a semblance of emotional responsiveness and empathy in response to comments about being at work too long, which is consistent with how a person, according to cultural expectations and norms, would normally respond to such situations.

The chatbot offers to consider possible solutions to the situation like a caring and empathetic interlocutor: «*Denk daran, auch Zeit für dich selbst und deine Erholung einzuplanen, um ein gesundes Gleichgewicht zwischen Arbeit und Privatleben aufrechtzuerhalten*» [Remember to also schedule time for yourself and your relaxation to maintain a healthy work-life balance].

The examples presented above show that the chatbot's response conforms to the key tenets of communication, namely George Lynch's principle of politeness and Paul Grice's principle of cooperation. According to Grice, effective communication is built on the principle of cooperation, in which four categories of maxims are subordinated. These are the maxims of quantity, quality, attitude, and manner [9].

However, ChatGPT does not always follow all of Grice's maxims in its responses. As a rule, its remarks are redundant. We can talk about the typical structure of a chatbot utterance according to the criterion of information distribution. That is, when constructing a reply, a chatbot usually repeats or reformulates a part of the query. Thus, it uses old information and then adjusts new information on it. Such construction contributes to the semantic and pragmatic coherence of the text.

4 Conclusion

In the narrow sense of the dialogic discourse, the communication “person—ChatGPT” is quite interactive. The analyzed construction of utterances in the responses to the prompts generally conforms to the principles of semantic and pragmatic coherence. On the other hand, some essential characteristics of interaction with automated systems do not allow us to consider interaction with chatbots as a dialogue in its classical interpretation. These characteristics include unidirectional communication and dialogue development according to one role scenario, limited understanding of the context, and communicative redundancy.

The question of the dominance of written dialogic or written micro monological discourse in the communicative interaction “human—ChatGPT” remains relevant and promising for further research. Systematization of data and more detailed analysis of chatbot communication will help create universal linguocognitive models for bots in the future, which will help avoid mistakes and make the communicative act as successful as possible.

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The Role of Audio Information Reconstruction Based on Brain Activity Analysis in Enhancing the Quality of Human–Machine Interaction



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Abstract The research aims to explore the potential of neural interfaces for enhancing human–computer interaction and identify new possibilities for their application in everyday life and medicine. The role of audio information reconstruction in developing brain–computer interfaces is also examined. Based on the analysis of existing research and achievements in the field of neural interface development, the authors highlight the main problems and trends in this area. The authors show that neural interfaces can improve the quality of life for people with disabilities by enabling them to interact with the surrounding world. It can be assumed that the number of such developments will increase, along with the number of areas in which they find application, including medicine, education, and entertainment. Currently, certain successes can be noted only in invasive neural interfaces. However, due to their significant limitations, attention should be paid to developing minimally invasive and non-invasive brain–computer interfaces (BCIs). The work also analyzes studies dedicated to reconstructing audio information based on brain activity data using machine learning methods and evaluates their role in developing neural interface technology. In conclusion, the authors emphasized the importance of integrating neural interfaces into various aspects of public and private life, which can contribute to creating a more inclusive society.

Keywords Human–computer interaction · Brain–computer interface · Neural interfaces · Artificial intelligence · Neural decoding

JEL Classification I39 · L82 · O31 · O35

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1 Introduction

With the increased digitalization of society, individuals constantly interact with various computer systems. Consequently, many studies focus on enhancing the efficiency of this interaction, a field known as Human–Computer Interaction (HCI). One of the primary objectives of HCI is the development of new methods for users to interact with external devices. Neural interface technology is advancing in this direction. Neural interfaces are traditionally understood as systems that read brain activity and transform it into commands for external devices using special algorithms. Thus, control occurs directly, without peripheral devices.

The journal *Nature* has included neural interfaces among the seven technologies to pay attention to in 2024 [4]. However, the research only cites examples of invasive brain–computer interfaces (BCI). These developments involve placing electrodes under the skull on the brain’s cortex (an example of an invasive method is electrocorticography). Although the data obtained by such methods are the most accurate [11], invasive BCIs are currently used only for clinical indications. A major drawback of such developments is that the implanted device is often rejected by the body, causing various complications. Another issue is that such operations require the involvement of highly qualified neurosurgeons.

Non-invasive neural interfaces are safer because they do not require surgical intervention. The electrodes for signal registration are placed on the scalp. The most commonly used non-invasive neuroimaging methods include the following:

- Electroencephalography (EEG);
- Functional Magnetic Resonance Imaging (fMRI);
- Magnetoencephalography (MEG).

In neural interfaces, EEG is most frequently used due to its safety and high temporal resolution, which ensures high sensitivity to rapid changes in the brain’s electrical activity [9]. However, the capabilities of such devices are more limited compared to invasive ones due to the low informativeness of the EEG signal.

On the other hand, there is a growing number of studies focused on reconstructing various types of information by analyzing brain activity. This work concentrates on decoding audio information. Speech is the most convenient channel of communication between people, making research in the field of audio information reconstruction extremely important to understand how humans perceive and process audio information and how this knowledge can help expand the capabilities of neural interfaces.

2 Materials and Method

To conduct a review and identify key publications in the field of neural interfaces and information reconstruction, the authors searched Google Scholar, the scientific database PubMed, the Frontiersin platform, and the archives of scientific journals Nature and PLOS Biology. Only peer-reviewed works were considered. The authors selected the most recent and frequently cited studies to access the most relevant information.

After selecting and reading the literature, the authors used a direct coding approach to determine the details of studies on audio information reconstruction, including the audio stimuli used, signal preprocessing methods, machine learning techniques, etc. The results of the analysis are presented in the next section of the research paper.

Recent developments in neural interfaces are presented in a Nature review [3]. This review focuses primarily on invasive BCIs aimed at assisting paralyzed individuals. Examples of non-invasive methods include tracking the attention of Chinese schoolchildren using EEG and monitoring employees' concentration levels by employers in various countries.

Audio information can include music, speech, and other forms of sound content. The combination of speech and music constitutes a song. The works of Bellier et al. [1], Daly [2], Hoefle et al. [5], Lawhatre et al. [6], and Stober [12] are dedicated to the reconstruction of musical pieces.

The analysis of existing technologies and the synthesis of information make it possible to determine the most effective approaches to audio information reconstruction, their shortcomings, and trends in the field of neural interfaces.

3 Results

3.1 *Overview of Contemporary Developments in Interface Technology*

The simplest and most common invasive interface is the auditory (cochlear) implant, which restores hearing. The most complex and promising are the Synchron neural chip [13] and Neuralink's development [8]. Notable non-invasive neural interfaces include OpenBCI equipment [10] and products from the Russian company Neiry [7].

In January 2024, Elon Musk's company Neuralink implanted its Telepathy chip into a human brain for the first time. The device is placed on the brain's cortex and registers signals using a ribbon composed of 64 threads, each several times thinner than a human hair. Each thread has 1024 flexible electrodes, a type of device that does not currently exist elsewhere. These electrodes are made from a material that helps avoid inflammation and rejection by the body. The precision required for implanting the threads led to the development of a proprietary surgical robot. Achievements include the ability to transmit data and wirelessly charge the interface wirelessly.

Synchron's product, The Stentrode, is an endovascular neural interface considered minimally invasive. The thin chip, made of a cylindrical mesh matrix with flexible electrodes about 3.8 cm long, is not implanted directly into the brain's gray matter but is directed through the forearm into the jugular vein and then guided to the brain's motor area via blood vessels. An implant is also placed in the forearm to transmit necessary information to external devices, with a wire connecting it to the brain chip. This product was first used in July 2022, providing developers with longer-term patient data compared to Neuralink. Research shows that the control capabilities of such minimally invasive interfaces are limited. They enable only simple commands like clicking a mouse button; most subjects had to use eye-tracking with an eye-tracker for cursor movement.

OpenBCI offers non-invasive interfaces applicable in various fields. Their EEG headset and Cyton/Daisy bioamplifier can, for example, use data to control a toy robot or a robotic arm. VR interfaces are used for patient rehabilitation or in gaming to maintain certain states in players. They can also control a mini quadcopter and provide a view of the surroundings, which is useful for people with paralyzed limbs.

Neiry's devices are more geared towards business, providing companies with various solutions using their products. Their equipment can monitor employee fatigue in critical production areas. When monitored parameters exceed acceptable limits, a signal is sent to the user and the dispatcher's console. They also developed a system allowing surgeons to control medical software without external assistance during operations. Control is achieved via flashing buttons on the screen that appear over any existing medical program. To select an action, the surgeon needs only to look at the desired button for one second.

3.2 Reconstruction of Audio Information from Brain Activity

In recent years, significant progress has been made in reconstructing audio information based on human brain activity analysis. Reconstruction can involve identifying the original stimulus from an existing set or recreating it based on key features. The success of these processes is largely due to advancements in AI.

Conducting an experiment on audio information reconstruction involves several key stages: creating or selecting audio stimuli, data collection, preprocessing, choosing machine learning methods, implementing the algorithm, testing, and analyzing results. When developing new approaches to solve the problem, the initial stages can be skipped if ready-made datasets shared by researchers in their work are used.

The summarized results of analyzing existing solutions for music reconstruction based on brain activity are presented in Tables 1 and 2. The most effective neuroimaging method for data collection is fMRI [5]. Using only EEG signal data does not provide sufficient quality. However, the correct combination of several neuroimaging methods, such as EEG data supported by fMRI, leads to better results. Key features must be extracted from the obtained data, for which preprocessing is

conducted. At this stage, independent component analysis is commonly used [2, 12]. Table 2 shows that classical machine learning methods and neural networks are used for recognition. Among classical methods, the k-nearest neighbors method shows the best results.

Among neural network models, the highest efficiency is demonstrated by the bidirectional recurrent neural network (RNN) with biLSTM [2] and the multilayer perceptron [1]. It should be noted that due to the use of different metrics for evaluating model quality, it is impossible to objectively determine which one is better.

The reconstruction of an imaginary musical fragment presented by scientists from the University of California, Berkeley, is available in the public domain on the Internet. One can listen to the reconstruction of the song “Another Brick in the Wall” and evaluate it themselves.

Table 1 Conditions of experiments on music reconstruction

No.	1	2	3	4	5
Title of the article	Classifying songs with EEG [6]	Neural decoding of music from the EEG [2]	Identifying musical pieces from fMRI data using encoding and decoding models [5]	Music can be reconstructed from human auditory cortex activity using nonlinear decoding models [1]	Toward studying music cognition with information retrieval techniques: lessons learned from the OpenMIIR initiative [12]
Number of subjects	20	20	6	29	10
Gender composition	16 men and 4 women	10 men and 10 women	5 women (music-related) and 1 man	15 women and 14 men	7 women and 3 men
Age	25.3 (mean)	20–30	30.8 ± 7.8 (mean \pm SD)	$16\text{--}60$ (33.4 ± 12.7)	19–36
Number of stimuli	12	36	40	1	12
Duration of one audio clip (s)	120	40	46	190.72	7–16
Condition	Healthy	Healthy	Healthy	Pharmacoresistant epilepsy	Healthy

Source Compiled by the authors

Table 2 Results of research on music reconstruction

No.	1	2	3	4	5
Title of the article	Classifying songs with EEG [6]	Neural decoding of music from the EEG [2]	Identifying musical pieces from fMRI data using encoding and decoding models [5]	Music can be reconstructed from human auditory cortex activity using nonlinear decoding models [1]	Toward studying music cognition with information retrieval techniques: lessons learned from the OpenMIIR initiative [12]
Data collection	EEG	EEG, fMRI	fMRI	ECoG, MRI, CT	EEG
Audio stimuli	–	Generated piano pieces	40 compositions from different genres	“Another Brick in the Wall”	OpenMIIR dataset
Preprocessing	Wavedec, DFA	AAS (Vision Analyser), ICA, SOBI	Savitzky–Golay filter, MIRtoolbox	Butterworth filter, Hilbert–Huang transform	ICA
Methods of machine learning	Classical training (k-NN)	Recurrent neural network (biLSTM)	Multiple linear regression	MLPRegressor	SVC
Results	Max classification accuracy (27.59%)	Mean decoding performances of 71.8 and 59.2%	Identification accuracy for all individuals: $76.8\% \pm 6.5\%$ (mean \pm SD)	Decoding accuracy (r-squared of 42.9%)	Classification accuracy (27.59%)
Years	2020	2023	2018	2023	2017

Source Compiled by the authors

4 Conclusion

In this research, the authors reviewed existing research and achievements in the field of neural interface development and audio information reconstruction, identifying current problems and directions for further research.

The development of an effective method for reconstructing audio information could lead to neural interfaces that enhance interaction with external devices and computers for people with disabilities and healthy individuals. Implementing a brain interface capable of sharing decoded information with mobile devices via Bluetooth or Wi-Fi technologies will primarily help people with disabilities. It could also enrich

the fields of education and entertainment. For example, an application could be developed that guesses the music in one's head or retrieves the original of an imagined song. In the future, communicating through imagined speech could become possible with voice assistants and each other.

However, current successes are limited to invasive neural interfaces, which are not applicable to a wide range of users. The capabilities of non-invasive and minimally invasive methods are severely limited. They are mainly applicable for assessing a person's condition and are hardly usable for control tasks. The main problem is the low informativeness of the EEG signal, which is used in most non-invasive neural interfaces. It is necessary to process redundant information from multiple electrodes to extract a useful signal. Applying new machine learning models for preprocessing and signal classification could help address this issue.

Another research direction involves developing little-known signal registration technologies, such as subcutaneous EEG, and creating compact and inexpensive magnetometers. Currently, magnetoencephalography (MEG) provides significantly more informative data than EEG but requires rather bulky equipment.

Another challenge lies in the need to customize the machine learning model for each specific task and each individual due to the unique physiological characteristics of the human body. To address this problem, it is possible to transfer learning techniques, which allow for the further training of a previously tuned neural model on new data for a similar task, rather than retraining the entire model from scratch.

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A Study of the Application Practices of Artificial Narrow Intelligence (ANI) and Neural Network Systems in the Management of Educational Entities



Angelina V. Petergova , Natalia E. Sokolova , and Nina E. Agopyan

Abstract Artificial intelligence (AI) is becoming an increasingly important tool in education. This research is relevant due to the necessity of bridging the gap between the interest in using AI in education and its actual implementation. The research aims to explore the practices of applying AI and neural network systems. In examining the practice of applying AI, the methodological foundation was based on practical experience and scientific research by Russian and international scholars in the field of AI in education. This research examines the main areas of AI application in the educational space and its impact on the educational process. The authors analyzed the use of AI technologies in Russia and abroad and provided recommendations regarding their future use. AI makes it possible to automate routine tasks, improves the quality of education, and adapts the educational process to the individual needs of each learner. Currently, the implementation of AI technologies is mostly experimental. However, most researchers consider this direction promising. The results of this scientific research can be useful for students, scientists, and specialists in AI.

Keywords Artificial intelligence · Neural networks · Information and communication technologies · Education · Learning · Technologies

JEL Classification A20 · B40 · B50 · D83 · D85 · D87 · H52 · I21 · I26 · M53 · O32 · Y10 · Y30

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1 Introduction

The twenty-first century has been named the century of digital technologies. Since the mid-twentieth century, humanity has made numerous technical and technological breakthroughs, particularly in computer science. Computing machines, digital data storage, and the global Internet have fundamentally transformed the world in less than a century. However, the world continues to evolve with the creation of new materials, devices, and digital technologies, becoming ever more integrated into daily life. Consequently, individuals must adapt to these new conditions, necessitating quality education. One of the most promising directions in the development of the education system is the integration of artificial intelligence (AI).

The application of AI in education promises great potential by leveraging AI's ability to analyze and establish connections between various data sources. Through its technical capabilities, education becomes more accessible, promoting the democratization of learning and helping each student maximize their potential, even if they cannot attend educational institutions.

Particular attention should be given to personalized learning and adapting educational programs to meet the individual needs of students. Additionally, automation in assessment, using AI to automatically check tests and homework, should be emphasized.

2 Methodology

The value of AI on the global market is \$136 billion. It is projected that the AI industry will grow 13 times over the next seven years. Notably, 83% of companies recognize AI as a key priority for their business; 97% of business owners believe that GPT-based chatbots can assist them in their work.

Research by Analytics Insight has shown that AI is used for a limited number of tasks. Only 25% of companies integrated AI into their business processes. Another 21% have found these technologies effective and plan to expand their use. Currently, 7% of companies are considering the implementation of AI in the future. A survey conducted by Anketolog revealed that 28% of users fully trust AI, and 42% generally approve of its use. More than 60% of users are willing to share their data with neural networks [2].

According to an Anketolog survey, only 13% of Russians are well-acquainted with GPT-based chatbots, while 37% find no interest in this neural network. However, 63% of users use chatbots to find answers to questions, 41% use them to translate texts, and 34% delegate routine tasks to AI. Additionally, services like Midjourney, Kandinsky 2.1, and Shedevrum are popular in Russia [20].

Among marketers, the most popular tools are chatbots, text generation, and visual and audio tools.

A HubSpot survey indicated that using AI helps marketers save up to 3 h of work time. Twenty percent of marketers use AI technologies to write texts, 20% to create images, and 18% to plan content [15].

Most marketing department employees report the undeniable benefits of AI. It significantly simplifies the content creation process and greatly increases its volume. AI technologies also facilitate content localization and personalization. Thus, 21% of marketers use AI to generate quotes from texts, and 37% use neural networks to analyze content and find useful information.

Neural networks are widely used for working with texts (68% of respondents). The most popular functions include information retrieval (48%), new text generation (42%), error correction and text translation (24%), data analysis (20%), decision-making (14%), and coding (14%).

The second most popular is neural networks for image processing (48% of respondents). These networks are used to generate new images (43%), enhance quality (22%), or recognize objects (15%).

More than 1500 respondents aged 18–55 participated in the survey, providing insight into the growing use of neural networks in Russia.

3 Results

Generative neural networks have become an integral part of today's life, assisting in creating texts or images and solving various tasks. According to the search engine Yandex, interest in neural networks multiplied in the early months of 2022. The term "neural network" appears in search queries as frequently as "fitness," "psychologist," or "beer." Yandex also compiled statistics on how many people know about generative neural networks and use them daily.

AI in education is undergoing active development and has attracted significant attention in recent years. In the 2018 Horizon report [10], AI and adaptive learning technologies were highlighted as important areas in educational technology. The 2019 Horizon report [1] forecasted a more than 40% increase in the use of AI in education [6, p. 5] due to substantial investments from various companies, such as Google's \$400 million acquisition of the startup DeepMind [18].

AI has been a research focus in education for over three decades. The International Society for Artificial Intelligence in Education has existed since 1997 and publishes an international journal on the subject.

Despite its enormous potential and numerous advantages, the use of AI also has potential negative consequences: data breaches, the exclusion of teachers from the education system, intellectual property rights issues, etc. To address these concerns, institutes are being established to develop ethical standards and regulations for AI use in education, such as the Institute of Ethical AI in Education in the UK.

Currently, we can identify several key areas of AI application in education. The first area is the assessment of students' knowledge and performance. Contemporary AI technologies (image recognition, neural networks, prediction systems, and

computer vision) significantly enhance the learning process. Assessing students' knowledge is an integral part of the educational process. However, traditional assessment methods are time-consuming and mentally taxing for teachers. With AI, the assessment process becomes more varied, scientific, and precise [19], allowing for the automatic correction of assignments and tests [17]. Grading homework and exams is a routine task for teachers. Prolonged grading can lead to fatigue; correcting errors takes considerable time. AI technology is used to evaluate exams and detect suspiciously similar works, saving teachers' time.

Chinese companies IFLYTEK and New Oriental developed RealSkill, a platform that allows learners to study English through error correction, behavior analysis, and intensive essay-writing lectures. The project aims to improve the quality of IELTS and TOEFL preparation through intelligent correction and oral practice. The International English Language Testing System (IELTS) is a global assessment system for English proficiency, determining the level and skills of non-native English speakers. When students study for IELTS and TOEFL using RealSkill, the system evaluates their work, corrects errors, analyzes behavior, offers intensive essay lectures, and records the learning process to help students better prepare for the tests [8]. More details can be found in Deloitte's research [9].

The Educational Testing Service (ETS) in the USA has developed an innovative system called E-rater, designed for the automatic evaluation of student essays. This system promotes more accurate assessment and helps develop students' writing and speaking skills. A study on the effectiveness of this system was conducted in 2016 [4]. The results showed that AI-based methods accurately evaluate student essays, final scores, and sentence structure, enabling students to identify gaps in their knowledge. ETS also developed SpeechRater to help students improve their spoken English [5].

In addition to acquiring knowledge, AI provides new opportunities for assessing students' physical education activities. Autonomous learning systems for university students and sports skills assessment systems have been developed. These technologies help students conduct self-assessment tests, receive feedback, and improve their physical fitness, reducing the burden on instructors. In 2018, an innovative AI-based system for autonomous university student learning was created [12]. This system operates within a browser/server architecture, integrated with Visual Studio and SQL Server databases, under the Windows operating system. Yong [25] developed a sports intelligence assessment system based on an AI decision-making expert system. This system is used in sports training evaluation. Studies confirm that the AI-based physical education assessment system offers new strategies for developing and applying advanced sports technologies. Additionally, it provides theoretical support and guidance for the further development of scientific technology in education.

In Russian schools, it is planned to automate the grading of homework by 2030, entrusting this task to AI. This is outlined in the Order of the Government of the Russian Federation (October 18, 2023 No. 2894-r) [14].

Bauman Moscow State Technical University and the Moscow Institute of Physics and Technology created a virtual computer science teacher—a service for learning programming through practice using AI.

In 2023, the Moscow City Pedagogical University (MCPU) officially permitted students to use AI technologies to write their graduation theses. This decision was made at a meeting of the academic council. It marks the first step in legalizing the use of AI for thesis projects in Moscow universities.

Neural networks are one of the technologies within AI. They are a network of artificial neurons capable of learning from received data. Neural networks solve various tasks, such as image classification, speech recognition, time series prediction, etc. This technology is one of the most promising yet one of the most expensive and technically complex. Currently, Russia has no research on implementing these technologies in education.

The second aspect is adaptive learning. The key task of adaptive learning is to integrate all stages of the educational process (from testing to practice) into a unique system that promotes more effective knowledge acquisition by students [22]. An important advantage of this system is the ability to obtain data about the learning process without interruption or interference [7]. This allows for the development of optimal learning plans based on the analysis of students' abilities and the completion of the educational cycle by offering online video lessons. Applying advanced technologies and AI opens up new opportunities for interaction between teachers and students in online education. Thanks to human-computer interaction technologies, teachers can always be in touch with students without limitations on time or availability. This significantly expands their capabilities and the effectiveness of teaching. Such innovations greatly simplify and automate the communication and interaction process between teachers and students. They create unique opportunities for individualized learning and provide quick and accurate responses to each student's questions. This approach to education gives teachers more free time and resources to develop new teaching methods and approaches. Moreover, it allows students to receive accurate and comprehensive answers to their questions [13].

Learning systems such as DreamBox Learning, Byju's, and IBM Watson Education are widely implemented in educational institutions worldwide. These systems rely on intelligent educational platforms and analytical tools to create optimal learning conditions for each student. They make it possible to collect data on student behavior, analyze their learning needs, and offer personalized learning plans.

One example of such a system is Assessment and Learning in Knowledge Spaces (ALEKS), which is widely used in the USA. Research shows that using ALEKS leads to significant improvements in students' performance in mathematics [24]. However, despite its advantages, this system does not demonstrate a significant superiority over traditional teaching methods [11]. Another popular application that uses AI for education is Byju's. It integrates online lectures, exercises, and animations to explain complex concepts to students more clearly. Byju's also employs a gamified interface, making the learning process engaging and enjoyable. Additionally, the Byju's system can recommend courses based on the individual abilities of each student [16]. Studies showed that using Byju's is transforming the educational environment in India and contributing to a deeper understanding of the study material [21].

The third aspect is student behavior and emotional state. Research conducted in 2016 [3] indicates the potential of using AI and multimodal social computing to

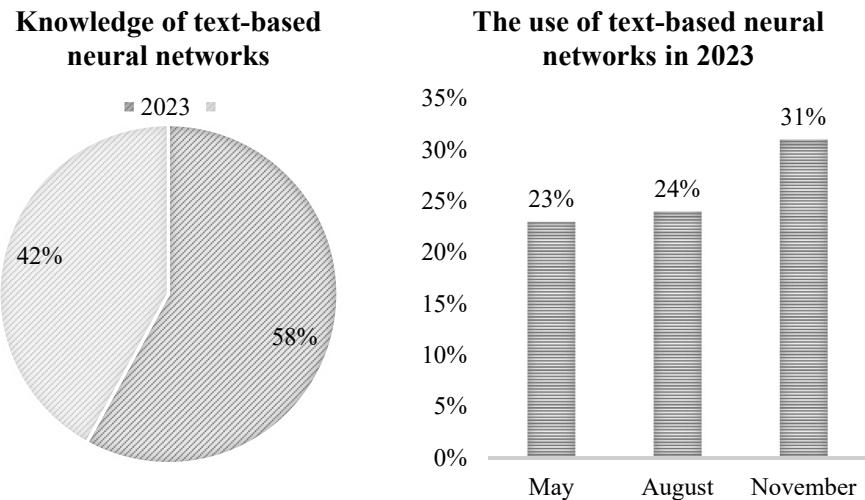


Fig. 1 Text neural networks. *Source* Developed by the authors based on [23]

develop cognitive, social, and emotional skills. Data analysis and machine learning methods make it possible to develop the social and emotional skills necessary for successful learning. Educators can adapt the learning process and assess the level of development and mastery of cognitive, social, and emotional skills in students.

By the end of 2023, 58% of Russians aged 18–45 were aware of neural networks (Fig. 1).

The use of text-based neural networks has already become popular with 31% of respondents (Fig. 1). In the six months from May 2023, the number of users has grown significantly, exceeding a third of the original number.

4 Conclusion

The process of creating images and videos from text prompts using neural networks for image generation has become a reality. Users describe what they want to obtain, and the neural network, utilizing its capabilities, can generate the corresponding image. Such neural networks are often referred to as image or art neural networks.

According to data from November 2023, 75% of Russians aged 18–45 have already heard of image neural networks. Over the three months from August of last year, there was a significant increase in the proportion of users interacting with neural networks. According to the data, the share of users increased from 26 to 31% (Fig. 2).

It is noted that users interact with neural networks through the use of prompts. These prompts are text-based tasks or instructions that users can give to the neural network.

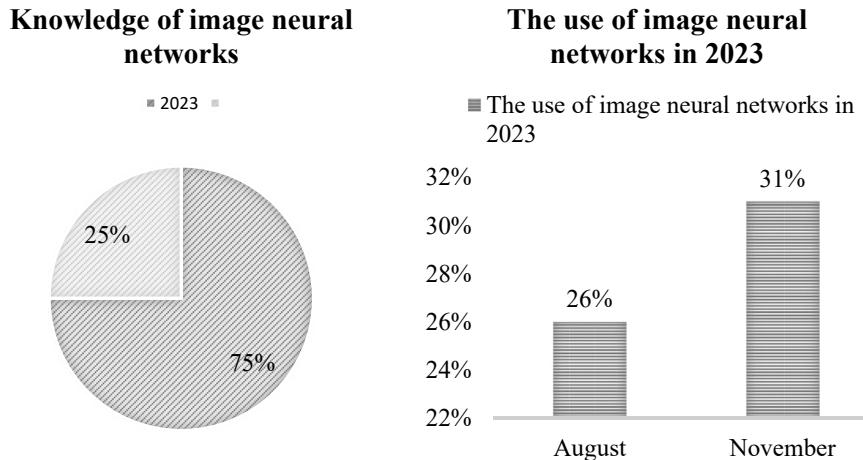


Fig. 2 Image neural networks. *Source* Developed by the authors based on [23]

Interestingly, the concept of prompts is not yet widely known. Among those already familiar with text-based neural networks, only 13% are familiar with this term. Among those actively using neural networks, only 18% have heard of prompts. Neurostat assures that the data will be updated.

AI plays a significant role in shaping the world in the coming years. Although the implementation of AI technologies is currently more experimental, most researchers and leading countries consider this direction strategically important and highly promising. In the field of education, there is already enough data to speak of the fundamental changes that AI brings. The optimization and individualization of the learning process, as well as its increased efficiency, have a significant impact on the quality of education. However, despite all advantages, AI must be balanced because it is associated with potential problems.

Overall, the impact of AI on our lives represents a complex and multifaceted process that requires a balance between innovation and ensuring the sustainable and ethical development of society.

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The Application of Neural Network Systems for Data Mining in Assessing Demanded Competencies for the Development of New Educational Programs



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Abstract Based on the existing forms of interaction between expert systems in evaluating labor market competencies, this research aims to conceptually describe the functioning of a neural network system for assessing new competencies (using a multilayer network with Adaline neurons) in the labor market through a graphical model. The system's functioning is shown as a process using the BPMN 2.0 process modeling language. The proposed scheme highlights the interaction between labor market actors (employers) and educational organizations in Russia. The research also proposes a fundamental scheme for integrating expert councils of educational organizations into data mining processes, labor market competency assessment, and enhancing the accuracy of the proposed neural network system. The functioning of the neural network system is described within three modules: data mining, communication-driven, and document-driven modules. The model identifies three top-level processes and nine subprocesses. Each subprocess is provided with documentary and informational support. The role of decision-making components (university expert councils) is described as a link in the neural human-machine assessment system. The process of developing relevant educational programs based on the evaluation of data collected through data mining is outlined. This research formulates a fundamental scheme for the interaction between employers (labor market actors), university expert councils, and federal authorities within a unified information space. The authors propose a concept for developing educational programs using neural network IT. A business process for forming educational programs is developed as a graphical model, displaying actors, support, top and lower-level processes, and connections.

Keywords Measurements · Machine learning · Workforce · Big data · Data science · Data mining · Skilled labor shortage · Employer requirements · Labor

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economics · Modeling · Neural networks · Expert systems · Educational organizations

JEL Classification C81 · C12 · C13 · C44 · C45 · C87 · D02 · D82 · D83 · D85 · J21 · J23 · J24 · M15

1 Introduction

Currently, there is an observed increase in the use of artificial intelligence (AI) tools for processing big data from various secondary information sources. This rise in the popularity of AI tools is characterized by the increasing complexity of macro-regional processes in large territorial entities, such as the labor market of the Russian Federation. As a global system, the labor market is a conglomerate consisting of numerous subsystems.

The existing information sources highlight the following problems in the functioning of this complex [8]:

- Results from scientific and technological foresight indicate a transition to Industry 4.0, leading to the obsolescence of certain professions;
- The average time to develop an educational program at a higher education institution is 1.5 years, which is insufficient to promptly meet the needs of employers for new specialists [8];
- Labor market actors, including employers and educational organizations, operate within different standards and accounting systems, complicating the data collection process on labor market needs and necessitating searches in a poorly determined environment;
- There are no unified information tools (ecosystem) for the interaction between employers and educational organizations in Russia.

2 Materials and Method

James et al. discussed the application of neural network technologies for labor market assessment in their article “Using neural networks to predict wages based on worker skills” [5].

The use of AI technologies to forecast global changes in the labor market is examined in the work “A rank-order test on the statistical performance of neural network models for regional labor market forecasts” by Patuelli et al. [9].

Aspects of comparison and differentiated selection of systems using artificial neurons are discussed in the work “Multicriteria analysis of neural network forecasting models: An application to German regional labour markets” by Patuelli et al. [10].

Basic algorithms for market-oriented job skill valuation using neural networks are examined by Sun et al. [11].

Dawson et al. considered using machine learning to predict future skill shortages in the research paper “Predicting skill shortages in labor markets: A machine learning approach” [4].

The application of AI technologies to assess labor market requirements in regional territorial systems is described in the work “Mining labor market requirements using distributional semantic models and deep learning” by Botov et al. [3].

Models for applying neural network expert systems for data mining are provided in the scientific article “Models and guidelines for integrating expert systems and neural networks” by Medsker and Bailey [7].

In their article “The method of interaction modeling on basis of deep learning neural networks in complex IT-projects,” Morozov et al. characterized subject-object interaction in expert systems performing data mining [8].

The concept of subject-object integration in expert systems was discussed in the article “Neural network interaction of expert councils in the interests of strategic decision-making” by Vasin et al. [12].

The issue of human–machine interaction is examined by Bolotnikov and Vasin. A categorization of the main elements is provided, and a description methodology is proposed [2].

The development of specific postulates for coordinating educational institutions and labor market entities is discussed in the article “The mechanism of neural network change management in the process of vocational education” by Mazur and Senderov [6].

The justification for using advanced tools to manage the coordination process of diverse economic entities is proposed in the article by Alenina et al. [1].

This research hypothesizes that the interaction between labor market actors, universities, and expert councils within a unified information ecosystem can be sufficiently described using the BPMN 2.0 business process modeling method.

The research aims to conceptually describe the functioning of a neural network system for assessing new competencies (based on a multilayer network with Adaline neurons) in the labor market through a BPMN 2.0 graphical model.

The research tasks are as follows:

1. To describe the main elements of the proposed neural network model;
2. To build the structure of lower-level processes in the BPMN 2.0 notation for the data mining, communication-driven, and document-driven modules;
3. To describe the mechanism (functional role) of the key elements of the neural network system (university expert councils) and propose a mechanism for evaluating information in the system’s database.

The functioning of the system is depicted as a process using the BPMN 2.0 process modeling language.

3 Results

The architecture of the proposed information system for data mining includes three key modules operating within a unified information ecosystem, connected through bidirectional communication via authorized access to an internet resource:

- Module 1 (Data mining). Basic functionality—collection, processing, and structuring of labor market data, identification of key elements by artificial neurons based on the quantitative frequency method.
- Module 2 (Communication-driven). Basic functionality—evaluation of data on promising types of activities by the system's decision-making elements (university expert councils), and formation of recommendations for developing educational programs (EP).
- Module 3 (Document-driven). Basic functionality—development of educational programs for new types of activities. A neural network algorithm can be used here to organize feedback from employers in the Russian labor market.

Each module of the system is detailed by subprocesses.

Module 1 (Data mining). “Collection and processing of labor market data, identification of key elements by artificial neurons based on the quantitative frequency method” (Fig. 1).

Constituent subprocesses include the following:

1. Information collection: The process begins with forming a dataset from various secondary sources, the list of which is uploaded to the system's knowledge base. The data is collected dynamically over multiple cycles.

The information support for the process is as follows:

- Scientific sources: research articles, dissertations, and monographs;
 - Open sources: documents from social networks, messengers, blogs, and forums;
 - Professional sources: job vacancies from aggregator websites.
2. Dataset evaluation: Documents in the dataset undergo an evaluation procedure by a recurrent neural network based on Adaline artificial neurons. The process uses content analysis technology, with the unit of account being a phrase and the evaluation vector. The identified semantic units form the input signal for the artificial neurons.
 3. Selection of promising activities: The basis for selection is the passage of signals through the artificial neural network. The selection criterion is the signal weight (a numerical value assigned based on the frequency of occurrence of each document in the dataset). The neuron's summator passes signals with weights above a set threshold. The selected signals form the output of the neural network and are sent for evaluation by the decision-making elements.

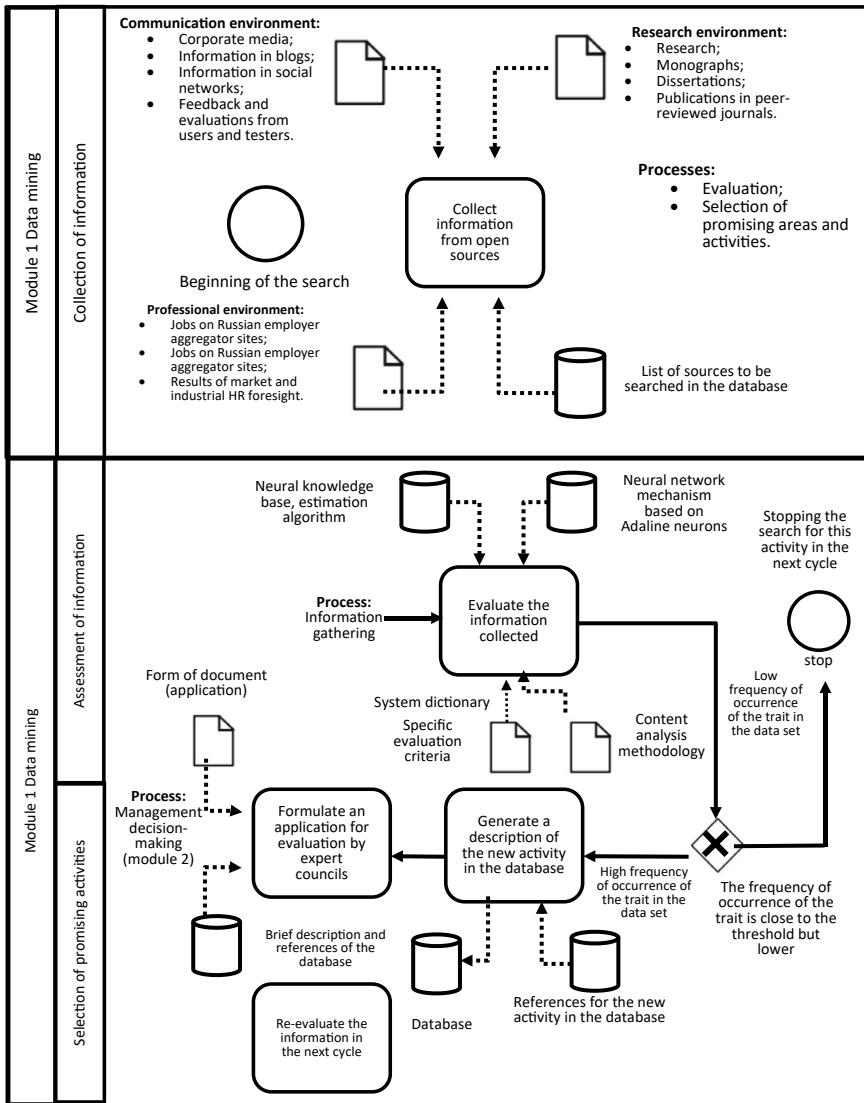


Fig. 1 Business process description: Module 1 Data mining, information gathering, evaluation of prospective activities selection. *Source* Developed by the authors

Module 2 (Communication-driven). Evaluation of data on promising activities by the system's decision-making elements (university expert councils), forming recommendations for the development of educational programs (Fig. 2). It includes the following subprocesses:

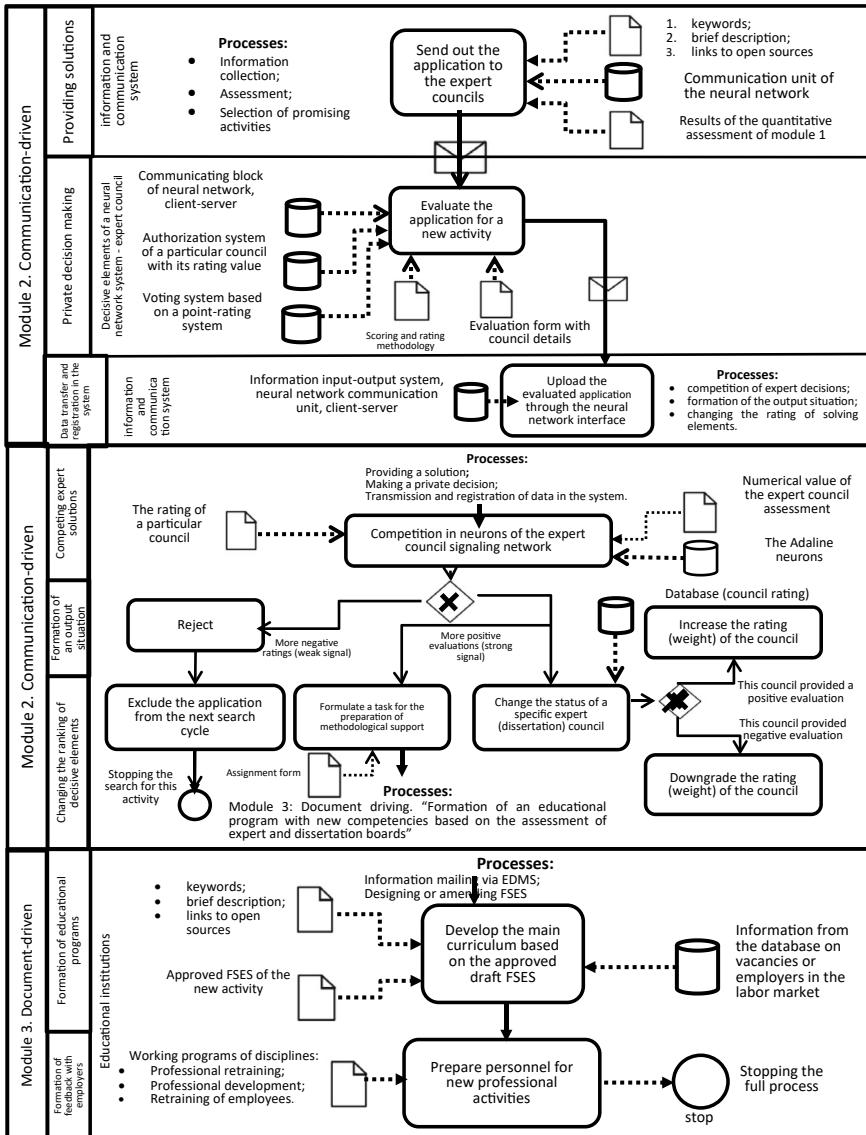


Fig. 2 Description of a business process: Module 2 Communication-driven, Module 3 Document-driven. *Source* Developed by the authors

1. Decision support: Applications for new activities (keywords, brief description, and links to sources) that have passed through the neural network are communicated to the expert (dissertation) councils registered in the system as decision-making elements. The status of a specific council is determined by its previous activities [12].
2. Individual decision making: The decision-making elements of the network (expert councils) rate specific applications using a selected point-rating scale. The evaluation is conducted remotely through the neural system's information resources. The output result of this phase is a signal in the form of evaluating specific councils on individual applications.
3. Data transmission and registration in the system: Members of the expert councils use the system interface (client-server accessible from a mobile device) to conduct evaluations. Statistical processing and aggregation of evaluations are carried out. The Delphi method may be used. The subprocess output is an aggregated evaluation of the application by each expert council, adjusted for the weight (rating) of the evaluating element. If a program is developed based on the application, the rating of the councils that gave high evaluations changes [2].
4. Competition of expert decisions: A quantitative accounting of expert evaluations loaded into the system is conducted. Signals with parametric characteristics enter the artificial neurons of the network: frequency of occurrence in the dataset (recorded at the data mining stage) and weight value based on the average evaluation by the expert councils [12].
5. Formation of the output situation: Signals with high frequency and high average evaluation by the rating councils (above the set threshold) pass through the layers of artificial neurons. Signals that pass through the neuron's summator are formed into an application for the design of an educational program, including the name, brief description of the activity, brief justification, and the average rating by the expert councils. Applications with evaluations below the entry threshold are filtered out and entered into the database for a new data mining cycle.
6. Changing the rating of expert and dissertation councils: For councils that positively evaluated the applications accepted for further development, their individual rating is increased and recorded in the database. Councils whose evaluations significantly differed from the average value within the cycle are downgraded. Councils with ratings below the threshold level are excluded from the system. Councils with high ratings are tied to specific thematic sections (areas of activity) within which they give high evaluations [12].

Module 3 (Document-driven). Development of educational programs for new activities highly rated in previous stages (Fig. 2). It includes the following subprocesses:

1. Information distribution through EDS. Actors responsible for the formation of educational standards and the educational and methodological support of educational programs (research universities, federal universities, and universities from the list of the President of the Russian Federation) receive requests for designing an educational program. The request includes details such as the field of activity,

- possible name of the educational program, a brief description, a score rating with the ranking of expert councils, and links to information sources where the highest numerical manifestation of the feature was recorded during the data mining cycle [12].
2. Design of the Federal State Education Standards (FSES) for a new direction or improvement of the existing FSES. Actors responsible for forming educational standards, guided by the expertise data from the communication-driven stage, create a FSES project reflecting promising activities or adjust the existing FSES of the relevant professional field. Information about the new activity obtained from the neural network database is attached to the FSES project (amendment package). The Ministry of Science of the Russian Federation accepts or rejects the proposed changes. Operations depend on the decision outcome. If the project is rejected, the request is sent to Module 2 for re-examination by the expert council. If approved, this type of activity is excluded from subsequent data mining cycles of Module 1 [12].
 3. Formation of the main curriculum. Based on the positive evaluation from the Ministry of Science of the Russian Federation, educational institutions develop the main curriculum for higher education. The design support for the main curriculum is based on information from the database through individual authorization of educational institutions as participants in the system [2, 12].
 4. Feedback formation with employers. Within the framework of the specialization of the developed educational programs, educational institutions can use information about the new activity in the neural network database for communication with employers, establishing contacts with target audiences of the programs, career guidance, advanced training, and the formation of additional professional education [2, 12].

4 Conclusion

1. A description of the interaction process of labor market actors in the Russian Federation has been developed based on the BPMN 2.0 business process modeling notation, considering top-level processes and subprocesses;
2. The main elements of the neural network system are depicted as three interacting modules, each decomposed into individual elements;
3. The characteristics of the main entities of the proposed neural network system are provided (using the tools “pool” and “swimlane”; Figs. 1 and 2), and a schematic diagram of their interactions within the system is developed (using the tools “flow” and “messages flows”; Figs. 1 and 2);
4. Based on BPMN 2.0 notation, a scheme for integrating expert councils into the neural network system is reflected by forming a local business process in the communication-driven module;

5. An ecosystem conceptually defined to unite potential employers and educational organizations in the Russian Federation by forming an end-to-end multiprocess with feedback.

The impact of implementing the neural network system for data mining and assessment of in-demand competencies in the Russian labor market when developing new educational programs:

1. The cyclical accumulation of information about new activities in the neural network system will form a data array characterizing the development of the Russian labor market;
2. This array can be used by economic entities for business analysis, strategic analysis, workforce planning, market and technological foresight, and business modeling;
3. Reduction in the time between the emergence of employer needs and the response of educational organizations;
4. Reduction in the duration of the strategic decision-making process based on business analysis by economic entities;
5. Increased informational support for promising activities (startups and innovations) through globalization and the formation of a unified information ecosystem;
6. Improved efficiency in forming horizontal management structures and coordinating the activities of project teams through the internal communications of the neural network system;
7. The ability to assess the quality of specific expert councils through a rating mechanism based on their decisions.

The practical significance of this research lies in the fact that the proposed mechanism for using expert councils in assessment can be used to improve the accuracy of data mining in neural network systems when processing information from multiple secondary information sources about market needs related to the Russian labor market.

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Eye-Tracking as a Neuromethod in Educational Discourse



Marina R. Zheltukhina , Gennady G. Slyshkin , and Olga V. Sergeeva

Abstract The research aims to analyze the possibilities of contemporary neuromethods in educational discourse. The distribution of attention, its stability, and volume are significant factors in mastering educational programs. The research considers attention as one of the most important conditions for the effectiveness of any activity (face-to-face or online, independent or collective, research, project, etc.). The task of the neuromethodological approach is to minimize and increase the effectiveness of a person's bioenergy costs to perform any actions of a professional or educational nature, as well as to concentrate on the accuracy of their implementation. During the research, the authors identified the possibilities of eye-tracking and some other technologies in preparing students. At the entrance stage, the results of the subjects do not differ much from each other. The thesaurus was 25–27 words. By the end of the study, the students' results had changed significantly. On average, the students' results increased to 145–148 words. These data show that implementing neuroeducation in the framework of vocational training using eye-tracking technology makes it possible to form a clear idea of how a person remembers information best and how to present materials so that students remember it most quickly. When neurotechnologies are applied in educational settings, students learn to recognize patterns in eye movements across visual materials. By understanding these patterns, they can more effectively develop and tailor course content to enhance their mastery of the taught subjects.

Keywords Educational discourse · Educational content · Neuroeducation · Neuromethod · Landscape attention · Eye tracking

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1 Introduction

The main factors in implementing the educational process are stability, volume, and distribution of attention.

Perception and visual memory affect many aspects of the interaction of students with the world in full-time and remote formats [19].

With limited attention resources, students need to navigate a complex, ambiguous, and dynamically changing world. The selection of technologies and methods for studying attention contributes to the most effective construction of the educational process. There is an intention to consider and select technologies that will be adequate to students' demands [1].

Neuroeducation is one of the most promising areas in science. This direction makes it possible to solve the problem of forming the students' attention.

In this case, attention is understood as one of the main conditions for the effectiveness of any activity implemented in any convenient format (online and offline, research and project activities, etc.) [6].

The primary task of vocational education is implementing the existing capabilities of contemporary tools to study the landscape of attention to the training of future specialists [12].

The main objective of the neuro-methodological approach is to minimize and increase the effectiveness of the bioenergetic costs of the individual to perform specific actions in the professional or educational field, focusing on the accuracy of their implementation.

The study and development of student attention will increase the effectiveness of teaching. The clearer the patterns of information memorization are, the easier it becomes to choose the right tools and develop educational content [7]. The educational interest in the potential of neurotechnologies stems from their ability to address the requirements of contemporary educational trends, particularly the customization of learning experiences [11].

New neurotechnologies are designed to identify and adapt to the unique characteristics of individuals participating in educational endeavors, particularly catering to inclusive education for children with attention deficit or hyperreactivity disorders. Moreover, the adaptability of neurotechnologies allows for customization based on the goals and interests of students, proving especially beneficial in working with exceptionally talented individuals.

Neuroeducation represents a novel approach that diverges significantly from traditional cognitive, constructivist, or behaviorist perspectives on learning by delving into educational challenges at a neurological level, leveraging sophisticated visualization techniques in research.

Functioning as a bridge between neuroscience and education, neuroeducation aids in comprehending and elucidating the learning process, shaping a repertoire of

instrumental and pedagogical research methodologies that align with brain functions. Neurotechnologies allow the current education system to cope with the volumes of information that a specialist needs.

To understand the process of memorizing information, students are invited to measure the parameters of eye movement and the possibilities of various tools in studying the process of focusing human attention. Eye-tracking is the most used neurotechnology. The eye-tracker is involved during the work.

2 Materials and Methods

The research aims to analyze the possibilities of contemporary neuromethods in vocational education. To achieve this goal, it is necessary to collect objective data about the students' attention and determine the coordinates of a person's gaze. As part of the research, future teachers are invited to develop the content of the discipline by the patterns of eye movement in the image.

Neuroformation is a subject for global study. Russian and international researchers agree on the effectiveness of neuromethods.

The research was conducted among future vocational training teachers. It aims to identify the experience of determining landscapes of attention and heat maps for each presented image. The data obtained were entered into a table showing the stimulus, stimulus valence, and the number of fixations [4].

During the research, the subjects were asked to look at three pictures. Each image had a specific emotional valence: positive, neutral, and descriptive.

The study was conducted in the 2022–2023 academic year for six months based on Volgograd State Socio-Pedagogical University (Volgograd, Russia).

After the students developed the ability to determine the patterns of focusing attention, they were asked to formulate the discipline's content based on the knowledge they gained. Under the guidance of teachers, students carried out design work, which they applied to other student volunteers.

The study involved indicators for conducting a qualitative analysis: the number of fixations, pupil diameter along the X-axis, and pupil diameter along the Y-axis. Saccade amplitude and fixation length were measured.

The knowledge of patterns for focusing students' attention was assessed by evaluating the development of the conceptual framework among future vocational training teachers.

The study of the human gaze and the structure of the eye has been going on for many decades.

During this time, data was collected to get an idea of the process and characteristics of human attention [17, 25].

The technological initiative of the country serves as an impetus for the rapid development of scientific research in the field of neuropedagogy. With the advent of a neurocomputer interface for exchanging information between the brain and

computers (an electronic instrument), the study of the patterns of human attention has become more intense [3, 24].

Attention involves an increase in the sensory, intellectual, and motor activity of a person due to the direction and concentration of consciousness [5, 13].

The importance of attention is explored in various ways. For example, Hvelplund [8] considers eye-tracking to implement a vision for making translations. The analysis and interpretation of data obtained from eye movement studies provide insights into the quality of cognitive processes during text translation.

The study of cognitive load in the interpretation of dialogues, the study of gaze patterns depending on the action, and the language used is reflected in the work of Tiselius and Sneed [16].

Eye-tracking technology is being used to investigate the utilization of Internet technologies and the application of online information retrieval principles because these elements are crucial to the educational domain. For example, Merlotti designates the features of building the interface of a well-known search engine depending on the movement of the user's eye [12].

In this context, Berger's research into adjusting cognitive load for distinct student groups introduces various variables for eye movement analysis, including fixation duration, exposure time, and reading depth [3].

Using eye-tracking, Jiang et al. [10] studied the reliability of the behavioral significance of social preference models.

Nowadays, in building the educational process, collaborative methods are used that combine classical and innovative elements of concentration and checking the student's attention [16, 18].

The eye-tracking method provides an opportunity to identify the reasons why the subjects look at certain points. The task of the method is to determine the coordinates of a person's gaze. The eye tracker tool makes it possible to identify pupil positions [2, 10, 14].

The device is used in a stationary form and in the form of glasses. One of the main advantages of the method is the exclusion of subjective opinion because the attitude of the subject to the object of study is reduced to a minimum, or rather to zero. Therefore, the study's accuracy does not depend on the respondent's motivation [9, 25].

Rapid, spasmodic movements of the pupil are called saccades. Focusing on an object when the eye remains stationary is known as fixation. During fixation, information is stored. The combination of saccades and fixations, along with their distribution over an image, is called the landscape of attention [21, 23]. While the eye continuously moves over the image, the person remembers fragments of information about it [10]. Among the methods for registering eye movement, one should pay attention to electrooculography (EOG), Eye-Tracking, SMI (SensoMotoric Instruments) High Speed, and others.

With EOG, direct contact of the device with the eye is assumed. The data enters the device and is recorded. The device registers data on the direction of a person's gaze [11]. The Eye-Tracking method allows one to follow the direction of eye movement using a video camera and record the process.

It is worth highlighting two technologies. In the first case, oculomotor activity is associated with the use of mechanical contact with the eyeball. Since these measurements are highly sensitive, the dynamics and hidden physiology of the eye can be easily revealed [20]. The most common option is non-contact technology, which uses infrared radiation and a camera that is especially sensitive to the light reflected from the eye.

The main advantages of the system are as follows:

- Stability of eye movement recording;
- Registration accuracy;
- Sensitive recording ability;
- Shooting speed;
- The level and constancy of the delay of the system in the process of data recording;
- Registration angle. In the SMI High Speed system, the displacement vector between the positions of the center of the pupil and the corneal glare is determined (Pupil-CR method).

3 Results

To select the discipline's content and build the teaching process, students studied the patterns of human attention. They did lab work that helped them capture eye movement in an image [5, 6, 8].

The number of fixations was estimated using the BeGaze module. Table 1 shows the number of fixations. Students were able to take part in the work on their own.

Students were also asked to calculate the average values for all parameters for each image. The results are included in Tables 2 and 3.

Table 1 Results of quantitative analysis of fixations

Stimulus	Stimulus valence	Number of commits
Image 01	Positive	4
Image 02	Neutral	12
Image 03	Negative	3

Source Compiled by the authors

Table 2 Results of quantitative analysis of fixations

	Event duration (mc)	Pupil diameter X (mm)	Y pupil diameter (mm)	Saccade amplitude (°)
Image 01	300.44	35.30	35.27	5.41
Image 02	288.32	32.50	33.01	4.90
Image 03	235.27	36.24	38.77	4.70

Source Compiled by the authors

Table 3 Results of qualitative analysis of fixations

Stimulus	Stimulus valence	Number of commits
Image 01	Positive	5
Image 02	Neutral	8
Image 03	Negative	7

Source Compiled by the authors

As practice shows, the pupil's diameter directly depends on emotional arousal, which is one of the main elements in the reaction to a stimulus.

Laboratory work on the study of eye fixations among students was carried out for six months. During this time, students completed projects in which other students participated. Future teachers of vocational training developed the discipline's content by the patterns of eye movement in the image [21, 24].

The study documented the participants' outcomes as the onset and conclusion of the research, with the initial findings presented in Fig. 1. There are four groups of students in total. The authors took 150 terms as a basis.

At the input stage, the results of the subjects do not differ much from each other. The thesaurus was 25–27 words. By the end of the study, the results of the students had changed significantly (Fig. 2).

On average, the results of students increased to 145–148 words. These data show that the implemented neuroeducation as part of professional training using eye-tracking technology makes it possible to form a clear idea of how a person best

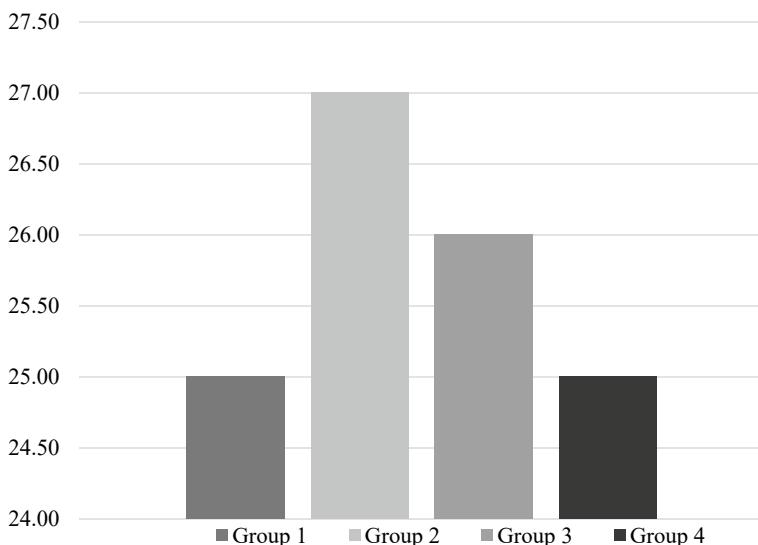


Fig. 1 Initial findings. *Source* Compiled by the authors

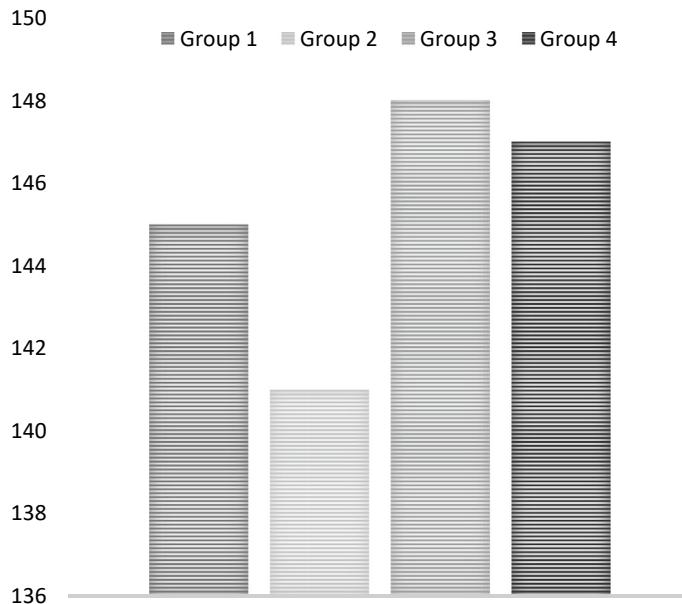


Fig. 2 Conclusive findings. *Source* Compiled by the authors

remembers information and how to present materials so that students remember it most quickly.

4 Discussion

The results obtained confirm the point of view of Lyzhin et al. [11] that eye-tracking allows one to effectively monitor the cognitive intricacy of texts, pinpoint distractors in visual content, monitor the viewing of elements crucial for the learning process, and assess the usability of educational materials. Consequently, eye-tracking facilitates a comprehensive assessment of digital educational content across various pertinent learning parameters such as complexity, distraction, attention, and content ergonomics, making it possible to formulate recommendations for enhancing content optimization. The integration of neurotechnologies makes it possible to develop systems for crafting and expertly evaluating educational content, considering the age, physiological attributes, and neuropsychological characteristics of students [15].

Alexandrova et al. [2] express similar views. According to the authors, eye-tracking determines the orientation of the optical axis of the eyeball within the eye movement space to gauge the duration of gaze fixation while reading or viewing visual materials. It offers a detailed quantitative and qualitative examination of the

observer's gaze, capturing pertinent data related to individual interests, attention levels, and visual engagement during learning processes [22].

In academic studies, eye-tracking is frequently employed to assess cognitive workload, such as measuring the time spent on viewing specific segments of video lectures. Gaze-tracking technology aids in evaluating the distribution of students' attention in virtual environments.

5 Conclusion

The study of a person's attention through the study of the reactions of their visual apparatus is a significant process in the construction of the educational process. Eye-tracking contributes to a better understanding of the patterns of focusing attention on certain elements of the image.

The conducted research shows that microlearning contributes to the expansion of training opportunities for students. By analyzing eye movement patterns and refining skills during laboratory activities, prospective training teachers can curate discipline-specific content. This research increases the level of knowledge of the terminological apparatus. The result was the qualitative formation of a thesaurus on professional pedagogy. Specially selected content made it possible to memorize words with greater speed.

The use of neuromethods in professional training makes it possible to deeper study the processes of eye movement in theory and practice. Students are more actively involved in the educational process. The effectiveness of training becomes higher. Neurotechnologies open new opportunities for the transformation of education because they assume the ability to diagnose the level of attention and memory and train these processes. The introduction of eye tracking allows one to personalize the learning process. An individual educational trajectory can be created for each student, corresponding to their personal and professional characteristics. This is important because people nowadays strive to improve their competence and adapt to the technological sphere.

In the future, it is advisable to conduct research related to using eye-tracking capabilities for students with disabilities. For example, it can be the development of so-called "non-glare interfaces," when all actions to control the software are performed using the eyes.

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Integrating AI in CLIL: The Case of Language Teaching in Higher Education



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Abstract The Rapid development of digital technologies and the transformation of learning standards caused significant changes in higher education. Such factors as shortage of personnel with the knowledge of foreign languages, unsuitability of curricula to the requirements of the Fourth Industrial Revolution, and rapid development of the gig economy, which requires the transformation of industries, demand new approaches to teaching foreign languages. An integrated approach to content language learning can help address these challenges. It has proved to be highly effective in language and subject teaching because it contributes to the formation and development of students' foreign language communication skills and their personal development and prepares them for professional activity in a multilingual and multicultural world space. Besides, implementing content language integrated learning (CLIL) helps bring language learning closer to the real interests of students, which contributes to their personal growth and the development of professional competencies. However, to meet the demands of contemporary education, CLIL needs revision as far as new technologies are concerned. Artificial intelligence (AI) has great teaching potential, which can be used to make language teaching more effective. Besides, it opens up new possibilities for developing professional knowledge, providing access to current subject-relevant information. Integrating AI potential with CLIL methodological principles will benefit language teaching in a contemporary educational environment.

Keywords Artificial intelligence · Content language integrated learning · Language teaching · Higher education

JEL Classification I12 · O3 · Y8

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1 Introduction

In today's world, the use of digital technologies in education, regardless of the level of education and methodological framework, is becoming more popular, which can be easily explained by several factors. One of the most relevant technologies is artificial intelligence (AI), which can be successfully and effectively used to integrate various study approaches, serving as a learning and teaching tool. The presented research is focused on the teaching potential of AI in the case of its integration with one of the most popular study approaches—Content Language Integrated Learning (CLIL), as far as language teaching is concerned. The authors are convinced that such integration of AI and CLIL is of much methodological value and may inspire teachers to try new methods of instruction in their search for the most effective techniques.

CLIL is a teaching method that has proven its efficiency throughout years of active use in many European countries. It is widely praised for the following reasons:

- It improves the level of foreign language proficiency;
- It shapes students' professional language personality;
- It develops mental connections between native and foreign languages and the language content of students' future professional activities;
- It develops meta-linguistic skills and the ability to perform professional tasks in two languages;
- It contributes to the transformation of educational systems and adaptation to contemporary requirements.

Students who are taught within the CLIL methodology show such results in their language knowledge and the knowledge of the profession that distinguish them from their peers. They include the following:

- A high level of English language proficiency, which contributes to successful communication in an international environment and increases competitiveness;
- Developed professional linguistic personality based on a professional linguistic picture of the world [11, p. 25];
- Enhanced metalinguistic skills;
- Good knowledge of English and a professional discipline.

2 Materials and Methods

The research is focused on determining the possibility of using AI within the CLIL methodological approach in the case of language teaching at higher education institutions. For this purpose, the authors find it necessary to conduct a theoretical study into AI potential in language teaching and CLIL methodology at the level of higher education applied to language teaching.

Following the theoretical research, the authors will develop a series of exercises using an AI tool that can be used in a CLIL classroom.

The research is based on the experience of teaching English at Pyatigorsk State University using course materials developed by the authors. Three textbooks [1, 4, 9] are involved in developing sample study plans following CLIL methodological principles and employing the services provided by AI.

3 Results

The review of scientific and methodological literature on the considered topic has shown that the excitement around the use of AI for education purposes is explained by the successful experience of AI application in other sectors, including finance, marketing, and medical research. Based on the specifics of these activities, automation can be considered an effective way to reduce costs. However, it is hardly feasible in education because the main part of costs is the labor remuneration of teachers. Therefore, the goal of implementing neural networks in education is to increase the efficiency of teaching and learning and, consequently, increase the results in the economic sense: higher learning results will give more benefits at the same or higher costs.

Researchers note that AI-based learning systems can be used to accomplish the following functions:

- Providing learners with learning content and simultaneous support by offering adaptive feedback and advice on how to solve content-related issues, as well as identifying learners; difficulties or errors with content or exercises;
- Organizing learning material according to learners' needs (e.g., providing specific guidance on the selection of reading material and exercises) and developing individualized action plans;
- Facilitating learner collaboration (e.g., by providing automated feedback, generating automated discussion questions, and analyzing the process).

3.1 *AI as a Language Teaching Tool*

One of the most significant benefits of applying AI to language teaching is that it has a diversity of didactic tools. It means that AI can generate materials for study courses, generate and process texts of various genres and styles, transform texts into speech, generate images, or provide dubbing. Since its appearance, AI tools have been viewed as powerful tools offering interactive and personalized learning experiences to both parties of the educational process. We will highlight some features offered to educators that may be relevant to the CLIL approach (Fig. 1).

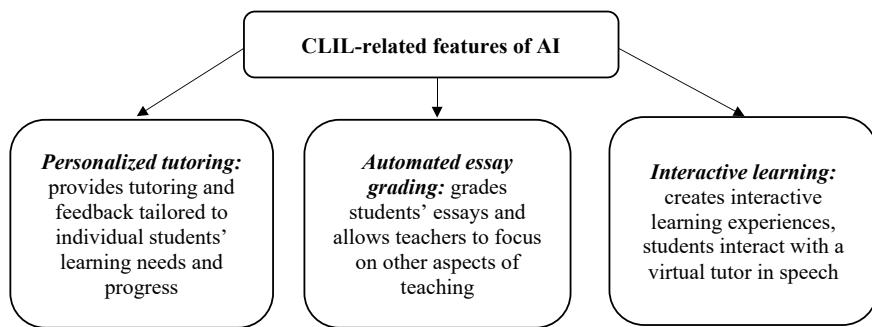


Fig. 1 Features of AI corresponding with CLIL principles. *Source* Compiled by the authors based on [2, 10]

3.2 CLIL for Language Teaching

Though CLIL is not primarily a language-teaching methodology, as language is used to gain subject-oriented knowledge, we consider it to be very effective in language teaching for several reasons. First, language is used as a study tool. In such a way, students develop not only the knowledge of a certain subject but also acquire new vocabulary and practice it while preparing tasks or doing research. Second, language is used as a communication tool. This allows students to practice professional vocabulary, effectively combining the study of a foreign language with the study of professional knowledge, which is highly demanded by today's education. Third, language serves as a personal professional development tool, shaping the development of foreign language communication skills among students, directing their personal development, and preparing them for professional activity in a multilingual and multicultural world.

CLIL provides the following benefits:

- Improves the level of foreign language proficiency;
- Shapes professional language personality of students;
- Develops metalinguistic skills, which consist of performing professional tasks in two languages;
- Develops mental links between a mother tongue and a foreign language;
- Expands the content of professional knowledge [5–8, 12].

The essence of the CLIL is the idea that a foreign language is used to teach a foreign language and master professional knowledge in a certain field. This method of teaching involves integrating educational material on the subject (content) and language material (language) to achieve a common learning goal.

The basic principles of the CLIL methodology are as follows [5, 13]:

- The priority in teaching is given to communication in a foreign language: the emphasis is placed on using a foreign language for understanding and communication, not just on the accuracy of language structures;

- The widespread use of active listening and communication technology: students' creative activity is stimulated through a variety of tasks that match their interests and learning styles;
- The inclusion of motor activity in the learning process: some specific and realistic educational tasks aimed at developing the understanding and use of language in the context of a specific field of knowledge may require organizing various activities during the lesson.

CLIL promotes foreign language learning, the development of professional skills and metalinguistic abilities, and the increase in students' motivation to learn a foreign language at a higher level.

To develop a lesson plan based on the CLIL methodology, it is necessary to follow certain steps:

1. Define lesson goals: identify the main objectives of the lesson in the subject and language that must be achieved; consider what specific subject knowledge and language skills students should acquire.
2. Choose a lesson topic: choose a topic that will integrate the content of the subject and the language material; the topic should be interesting for students and correspond to their level of knowledge.
3. Plan the lesson: divide the lesson into parts, including the introduction, the main part and the conclusion; determine the sequence of actions and tasks that will help students achieve their goals.
4. Use a variety of teaching methods: include a variety of learning methods in the lesson, such as group work, discussion, games, projects, etc.; ensure the active participation of students in the lesson and stimulate their communication in a foreign language.
5. Integrate language material: ensure the integration of language material into the teaching material on the subject; support the use of a foreign language by students during the lesson to communicate and understand the material.
6. Evaluate and provide feedback: provide methods for assessing students' knowledge in both the subject and the language; provide feedback to students to evaluate the effectiveness of the lesson and identify areas for improvement.

Lesson preparation and delivery are conducted considering the steps described above. Integration of AI and CLIL is possible in all four stages of a CLIL educational model (Fig. 2).

3.3 Integration of AI and CLIL

To show how to integrate AI in CLIL teaching, we have chosen an AI application Twee [10]. In the authors' view, this application offers a very impressive list of tools that correspond both to language teaching and CLIL approach.

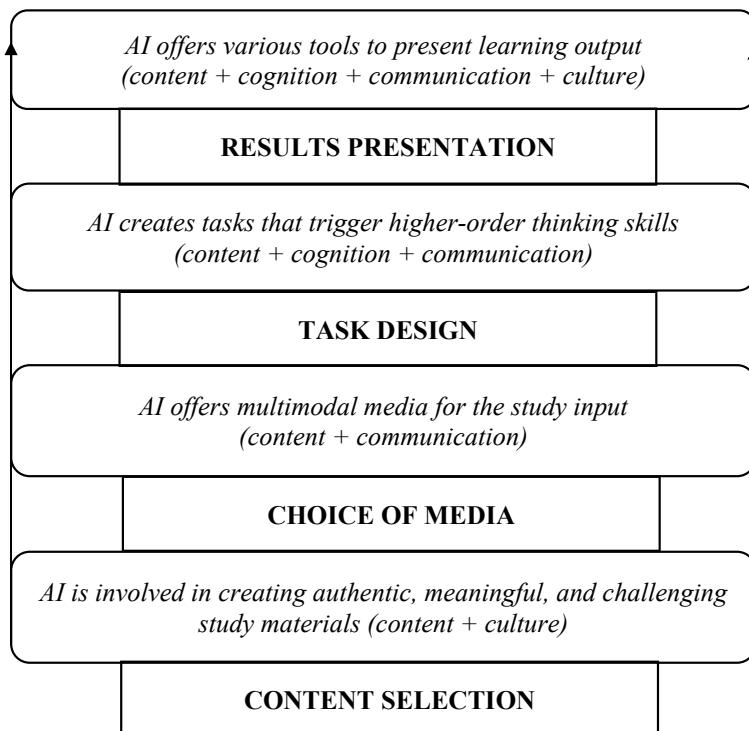


Fig. 2 Integration of AI in CLIL. *Source* Developed by the authors

What can Twee do? One can choose any topic and ask the AI to generate a text or just upload the existing text. Once we have a text, we can work with it and develop numerous exercises virtually with one click (Table 1).

Below is the demonstration of correspondence of CLIL-type tasks and Twee features in listening and speaking activities. In listening activities, listening is the first stage of the task, where receptive skills are developed. In speaking activities, speaking is a final stage aimed at developing production skills (Table 2).

The authors chose three thematically diverse topics from the textbooks they developed, which are studied at three different departments of Pyatigorsk State University. Let us now show how to use Twee for creating CLIL-type tasks to develop listening and speaking skills.

Topic 1. Life insurance—learning to use new vocabulary based on the text in different communicative situations

The topic is taught in professionally-oriented English at the Higher School of Administration using a textbook “Introduction to English for Insurance Professionals.”

Table 1 Task options provided by Twee

<i>Read and understand a text</i>				
Create open questions about the text	Create ABCD questions for a text with only one answer		Create true/false statements based on your text	Create a dialogue on any topic
Lead-in activities for a text	Create three titles for a text		Reading bits and pieces	Simplify or upgrade the text
<i>Watch and listen</i>				
Convert audio and video to text	Audio and video question creator	Choose the right summary	Warm-up discussion questions before listening	Audio and video summary gap-fill
<i>Learn and practice new words</i>				
Fill in the gap	Create a matching exercise word-definition		Create a list of sentences with your vocabulary	Essential vocabulary on the topic
Create a word formation exercise	Create communicative situations with vocabulary	Extract collocations from the text	Word-translation matching	Rephrase using the word given
<i>Drill some grammar</i>				
Scramble the words in sentences		Create an exercise matching halves		
<i>Make your students speak</i>				
Find discussion questions		Find interesting facts about a given topic		Create a list of advantages and disadvantages on the given topic
Find quotes by famous people on the topic		Four opinions		Link words into sentences
<i>Ideas for homework</i>				
Create a list of essay topics on a given subject			Creative writing with target vocabulary	

Source Compiled by the authors based on [14]

To create a text, it is necessary to input a topic and vocabulary (up to 20 words), choose the genre (text, fictional story, descriptive article, newspaper article, argumentative article, blog post, review, report, formal letter, or informal letter), and set the length range (50–100, 100–250, 250–350, or 500–750 words) and the level (A1, A2, B1, B2, C1, or C2).

Settings for the task were as follows: topic—Life insurance in the UK, genre—descriptive article, length—250–350 words, and the level—A1–A2.

To master new vocabulary, the authors propose using the whole range of skills-based tasks from different Twee sections in the following order: open questions (to check text understanding)—essential vocabulary (to focus on specific terminology)—word definition matching (to practice new vocabulary)—rephrase using

Table 2 Correlation of CLIL tasks and Twee features

CLIL-type task	Twee features
<i>Based on listening ...</i>	
Label a graphic object	Warm-up discussion questions
Reorder the information	Reading bits and pieces
Make notes on information	Three summaries
Fill in a table	Audio and video summary gap-fill
Fill in the gaps in the text	Audio and video summary gap-fill
Identify ... (speakers, location)	True/false statements based on listening
Mark stages of ... (instructions, process)	Link sentences into paragraphs
<i>Based on some information (text, series of tasks), prepare to speak ...</i>	
From a visual supported by verbal handout	Create a list of advantages and disadvantages on the given topic
Answer questions	Find discussion questions
Matching tasks (words and definitions, questions and answers, sentence halves)	1. Create a matching exercise word-definition 2. Create an exercise with matching halves
Information gap tasks	Fill in the gap
Word guessing tasks	1. Essential vocabulary on the topic 2. Rephrase using the word given
Trivia search—things you know, things you want to know	Find interesting facts of a given topic

Source Compiled by the authors based on [3, 10]

the word given (to practice new vocabulary in context)—communicative situations (to learn how to use new vocabulary in everyday speech). The authors believe that, being guided by CLIL principles described above, this succession of tasks will be most useful for mastering new vocabulary.

Topic 2. Stressful life—practicing grammar material through listening based on the text: Gerund and Infinitive

The topic is taught in the practical course of the second foreign language (English) at the Institute of Roman-Germanic Languages, for the specialty “Information and Humanitarian Technologies” using a textbook “Strategic Issues: Globalization.”

We can use the video provided in the textbook “Stress Management Strategies: Ways to Unwind.” Based on the video, Twee develops the following series of tasks: three summaries—summary gap-fill—conversion of a video to a text—fill in the gap—matching halves.

Topic 3. Civil society and legal state—developing speaking skills based on a visual object

The topic is taught in the course of English for professional communication at the Law School using a textbook “Theory of State and Law in Schemes and Definitions.”

The tasks developed by Twee are based on two schemes from the textbook—features of the legal state and functions of the legal state. Using the information and key vocabulary from the schemes, Twee creates the following tasks: discussion questions (warm-up)—dialogue based on the topic (to practice key vocabulary through discussion)—famous quotes (to discuss the professional topic from different angles and proposing various arguments)—find facts (to check understanding of the topic through a quiz).

4 Conclusion

As the research shows, CLIL can be successfully integrated with advanced technologies, namely AI, to provide certain advantages for language learning to meet the requirements of the contemporary educational environment.

AI can be implemented at all stages of lesson preparation and delivery, including content selection, choosing the media for content presentation, task design, and presentation of results. It can also actualize all four basic principles of CLIL, such as content, culture, communication, and cognition.

Applying AI-based technologies will increase students' motivation, providing an interesting and original way of learning. Besides, such a symbiosis of AI and CLIL will make it possible to adapt the learning process to students' personal needs, developing individual learning trajectories that correspond with contemporary educational standards.

The authors are strongly convinced that integrating the latest technologies into the educational process through easy adaptation of the CLIL methodology to the use of AI will make learning more effective and interactive.

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Methods of Data Preparation for Multilingual Sentiment Analysis Using Neural Networks



Roman D. Golovin

Abstract The research aims to compare various techniques and methods for text data preparation in terms of improving the quality of the classifier. As the preparation of this type of data involves several stages, the author tested various methods for implementing them in each stage. The research objects are reviews, tweets, and statements from 12 datasets. The author determined that different stages of data preparation have different impacts on the algorithm's quality. For instance, the order in which the tokenization and translation stages occur is unimportant. Similarly, choosing a translation service does not play a big role. On the contrary, selecting embedding and lemmatization methods significantly impacts the outcome. More specifically, using the correct lemmatization method increases classification quality from 1 to 10% and provides the correct embedding models. Based on the comparison of classification quality results from a series of experiments, the author found that selecting the most suitable data preprocessing techniques affects the quality of the outcomes. This implies that incorrectly chosen methods for implementing this phase of constructing a machine learning model can significantly and negatively impact the final classification results.

Keywords Machine learning · Natural language processing · Sentiment analysis · Data preparation · Neural networks

JEL Classification C45 · C83 · C88 · C81

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1 Introduction

Emotions play a significant role in human lives, simplifying our interactions and existence in society. They aid in illustrating our attitude towards a particular phenomenon. Many emotions are similar to one another. If grouped, they can determine the overall emotional orientation towards the phenomenon or the tonal quality.

Since emotions reflect the attitudes of individuals towards something, they can be analyzed to determine public attitudes on various matters. It is often sufficient to analyze the tonal quality, that is, to simply identify whether a positive, negative, or neutral attitude towards the entity in question prevails in society.

A similar approach, emotion or tonality analysis, is widely used in various industries where feedback and public opinion are important and where manual processing of information is not feasible due to the vast amount of data involved. Thus, a simple example of sentiment analysis would be the rating system for reviews on a 1–5 point scale, which is used by most marketplaces to assess product or seller quality. While this is useful for some purposes, it may be insufficient for other tasks.

Marketplaces are known to have a problem with biased reviews. Thus, if a business wishes to obtain a more objective opinion on its products or services, it would be more prudent to seek out opinions from social media. This implies that one will likely need to work with textual data. According to W3Techs, a leading Internet research organization, more than 50% of the content published on the Internet in 2019 was in English. This statistic, along with several other factors (e.g., the origin of many large IT companies in English-speaking countries), results in the availability of many pre-existing datasets suitable for training sentiment analysis models in English. Additionally, many sentiment analysis algorithms have been developed for the English language.

While the Russian Internet segment is the second largest in terms of published content, there are relatively few pre-trained models and algorithms available for the Russian language compared to English. Two potential solutions to this issue are the development of multilingual models and the adaptation of English-language models to the Russian language context.

The research aims to examine various data preprocessing techniques in the context of multilingual sentiment analysis and assess their impact on classification accuracy.

2 Methodology

This paper discusses the issue of multilingual text classification. Several approaches to dealing with different languages in this task have been explored, with the most common being the use of machine translation and multilingual language models. Methods with machine translation are studied in the works of Abdullah and Rusli [1], Dashtipour et al. [4], and Lin et al. [6]. The use of multilingual models is studied

in the works of Barbieri et al. [2], Can et al. [3], Khan et al. [5], and Mabokela et al. [7].

Based on the analysis of the cited literature, it has been determined that using machine translation is the preferred approach due to its greater flexibility, faster processing speed, and lower hardware requirements, particularly in terms of video memory capacity on a personal computer. To use machine learning, there are four main stages. The first stage is tokenization, during which the text is split into tokens—individual units of text that can be sentences, words, or parts of words. Most often, words serve as tokens. Additionally, at this stage, the so-called “stop words” are removed, which are common words that do not contribute to the meaning of the text and simply increase its length.

The next stage is lemmatization, which is essential for the classification algorithm to treat different forms of the same word as the same entity. Lemmatization directly converts words to their base form, while stemming removes the endings from words, resulting in different forms being treated as the same.

After lemmatization and stemming, machine translation occurs, converting the corpus of multilingual texts into a monolingual format. Since most models are primarily designed to work with English and most datasets are in English, the translation will be done into English. The final stage is the creation of embeddings, which are vector representations of words that convert a word into a numerical vector in a specific way. This is necessary because classification algorithms only work with numerical data, not text data.

Let us list the methods used in this project. Two options were considered for implementing tokenization: one with tokenization before machine translation and the other after. Lemmatization and stemming were selected among lemmatization techniques. Google Translate and Yandex Translate were chosen for machine translation; Word2Vec [8] and FastText [9] were selected for embeddings.

With regard to the data, a total of 12 distinct datasets were employed across three different domains: tweets, statements, and reviews. These datasets collectively constitute a corpus of 600,000 texts, with approximately 200,000 being written in Russian and English and the remaining 200,000 in 40 additional languages.

There are 42 languages in the corpus. However, the number of texts representing each of them is not equal. It is reasonable to distinguish the following categories:

- Very large languages: languages represented in the corpus by more than 10 thousand texts: Russian (277,300), English (159,890), Finnish (18,285), and Brazilian Portuguese (10,378);
- Major languages: languages represented in the corpus by more than 5 thousand texts: Spanish (9399), Romanian (7548), Turkish (7505), Greek (6890), Arabic (6454), French (6238), Bulgarian (6133), Polish (5979), Serbian (5859), Italian (5556), Czech (5511), and Hungarian (5050);
- Small languages: languages represented in the corpus by more than 1 thousand texts. This group is represented by 12 languages, which include, for example, German and Hebrew;

- Extremely small languages: languages represented in the corpus by more than 1 thousand texts. This group includes the remaining 14 languages, including Chinese and Indonesian.

It is worth adding that the concepts of “large” and “small” in this context do not mean the number of native speakers worldwide. It is rather about the representation in the building.

Each dataset is separately described below:

- Amazon Clothing. This dataset contains about 55,000 reviews written in English. These reviews relate to various topics, which provides greater versatility of the dataset;
- Dusha Crowd. This dataset was compiled by Sberbank. It is dedicated to the issue of emotion recognition in speech. However, it also contains speech transcription and tonality labels, which allows it to be used for the purposes of this work. Unfortunately, of the entire dataset, such data is available only for two thousand texts;
- Fake News Prediction. The dataset also contains English-language tweets and their tonality. It will be problematic to use it due to the lack of a category of neutral tweets. On the other hand, when using the Rubtsova dataset (RuTweetCorp), which also lacks neutral tweets, it is possible to use this dataset to better match the English-speaking model of the Russian-speaking one;
- Large Movie Review Dataset. The dataset contains 75,000 English-language reviews of films (no more than 30 reviews of the same film; the dataset contains reviews of at least 1600 films), distinguishing it from previous datasets containing tweets. The reviews are divided by tone based on the final score (0–4 points for negative, 5–6 for neutral, and 7–10 points for positive ones);
- Multi-Domain Sentiment Dataset. This dataset contains 280,000 reviews of various products (the product category is also marked) on Amazon and their rating from 1 to 5, which can be used as a five-point scale of tonality;
- RuTweetCorp. This is one of the first and largest datasets with texts in Russian, designed for tonality analysis. This dataset contains 226,000 tweets in Russian. It has significant drawbacks, primarily the lack of neutral tweets, which makes it difficult to use. Additionally, when the dataset was created, the tags were generated automatically, which reduced the algorithm’s quality. It also contains some garbage data;
- Sanders. This dataset contains 5513 tweets divided into four classes: positive, negative, neutral, and irrelevant. It contains tweets in various languages. However, it does not mark what language is used in a particular tweet, which can create problems;
- SemEval2016. This dataset contains English-language tweets about five different topics (atheism, climate change, feminism, Hillary Clinton, and the legalization of abortion) with an assessment of the user’s opinions on them. In total, the dataset contains 4163 texts. There are the following target variables in the dataset: the tweet’s topic, the position of the topic, and the tonality on a three-point scale;

- STS-Gold. The dataset contains 2026 tweets on various topics and their tonality on a five-point scale. It is based on the STS dataset (1.6 million tweets, the tones of which were determined automatically based on the emojis used in the tweet), from which 2026 tweets were randomly taken, and their tonality was manually determined;
- SemEval2017. The dataset is similar to SemEval2016. However, it has been slightly modified. For example, it includes tweets in Arabic (8–10 thousand) and some information about the tweet's authors and their age and location;
- Twitter US Airline Sentiment. This dataset contains 14,000 tweets concerning the work of airlines. In addition to the tweet's tone, there is also a reason for dissatisfaction. The majority of tweets (63%) are negative, which differs from ordinary speech, where neutral statements prevail;
- XED. The main part of the data in the dataset is presented by subtitles for films in English and Finnish. Other languages are also present, including Russian. The main drawback of this dataset, when used in this study, is that it represents not tonality but emotions according to the Cheat. Therefore, if it is used, it will be necessary to translate the scale of emotions into the scale of tonality.

To ensure the accuracy of the comparison, the same classification algorithm was employed, specifically a recurrent neural network based on Gated Recurrent Units (GRU) with six layers. Additionally, the Leaky ReLU activation function and batch normalization were utilized.

Concerning additional parameters for the experiments, the author used the NLLLoss loss function; the values of the learning rate and batch size are 0.0002 and 512, respectively. Metrics of quality are accuracy and F1-score. Additionally, the author employed cross-validation to ensure more reliable results, with the average results from this process being used in the comparisons below.

Creating a training and validation dataset also should be described. A 25% portion of each dataset will be designated as part of the overall validation set. The remaining 75% will form the training set. Algorithms will be trained using all training data. The metrics of the classification will be assessed for each validation dataset individually.

3 Results

As described above, four different parameters are used. First, it is worth studying the dependence of the classification quality on the position of tokenization (before or after machine translation) and the choice of translator (Google Translator or Yandex Translator). The average values of quality metrics for these parameter values will be used as quality values (Table 1).

Thus, the classification quality does not depend in any way on the position of the tokenizer or on the choice of the translator.

Table 1 Quality metrics by the position of tokenization and the choice of translator

Dataset name	Metric	Before		After	
		Google	Yandex	Google	Yandex
Amazon clothing	Accuracy	0.621	0.630	0.621	0.619
	F1-score	0.649	0.649	0.655	0.657
Dusha crowd	Accuracy	0.389	0.386	0.394	0.401
	F1-score	0.476	0.469	0.468	0.473
Kaggle fake news prediction	Accuracy	0.462	0.454	0.455	0.449
	F1-score	0.478	0.474	0.480	0.477
Large movie review dataset	Accuracy	0.370	0.373	0.369	0.371
	F1-score	0.376	0.373	0.369	0.366
Multi-domain	Accuracy	0.641	0.632	0.631	0.634
	F1-score	0.703	0.704	0.696	0.690
RuTweetCorp	Accuracy	0.552	0.557	0.565	0.572
	F1-score	0.604	0.594	0.588	0.584
Sanders	Accuracy	0.355	0.347	0.357	0.353
	F1-score	0.351	0.344	0.353	0.348
SemEval2016	Accuracy	0.559	0.553	0.543	0.552
	F1-score	0.588	0.590	0.598	0.595
SemEval2017	Accuracy	0.492	0.486	0.486	0.482
	F1-score	0.478	0.479	0.473	0.478
STS-Gold	Accuracy	0.414	0.414	0.417	0.411
	F1-score	0.463	0.464	0.462	0.470
US	Accuracy	0.492	0.494	0.493	0.491
	F1-score	0.522	0.521	0.516	0.524
XED	Accuracy	0.469	0.467	0.466	0.456
	F1-score	0.475	0.482	0.481	0.489

Source Compiled by the author

As determined, two of the four parameters have no significant impact on quality. Thus, the author will focus on the remaining two parameters. It is advisable to study the learning outcomes for each dataset individually (Table 2).

Lemmatization wins over stemming in almost every case. With the comparison of the two embedding models, the situation is more complicated. They show themselves differently depending on the specific data.

As can be seen, classification quality varies significantly for different datasets. This is due to several factors. The most significant one is that the datasets differ in size. Therefore, the model pays more attention to data from certain datasets. Another important factor is that the datasets vary in the type of text, as described above.

Table 2 Metrics by parameters and datasets

Dataset name	Metric	FastText		Word2Vec	
		Lemmatizing	Stemming	Lemmatizing	Stemming
Amazon clothing	Accuracy	0.809	0.544	0.528	0.604
	F1-score	0.743	0.602	0.613	0.637
Dusha crowd	Accuracy	0.407	0.374	0.417	0.358
	F1-score	0.486	0.476	0.485	0.458
Kaggle fake news prediction	Accuracy	0.415	0.472	0.507	0.453
	F1-score	0.459	0.482	0.513	0.459
Large movie review dataset	Accuracy	0.374	0.37	0.373	0.361
	F1-score	0.38	0.381	0.375	0.366
Multi-domain	Accuracy	0.641	0.637	0.658	0.627
	F1-score	0.705	0.697	0.72	0.689
RuTweetCorp	Accuracy	0.555	0.542	0.558	0.551
	F1-score	0.604	0.597	0.611	0.604
Sanders	Accuracy	0.363	0.332	0.372	0.353
	F1-score	0.358	0.33	0.364	0.35
SemEval2016	Accuracy	0.556	0.537	0.585	0.559
	F1-score	0.584	0.571	0.612	0.586
SemEval2017	Accuracy	0.492	0.471	0.498	0.505
	F1-score	0.478	0.456	0.484	0.492
STS-Gold	Accuracy	0.419	0.417	0.414	0.406
	F1-score	0.467	0.467	0.466	0.452
US	Accuracy	0.493	0.48	0.504	0.492
	F1-score	0.521	0.513	0.53	0.525
XED	Accuracy	0.471	0.454	0.481	0.471
	F1-score	0.478	0.459	0.485	0.479

Source Compiled by the author

To clearly visualize the differences in classification quality for different parameters, the author grouped the results according to all validation data:

- Lemmatizing and FastText: accuracy is 0.499, and F1-score is 0.583;
- Lemmatizing and Word2Vec: accuracy is 0.509, and F1-score is 0.511;
- Stemming and FastText: accuracy is 0.484, and F1-score is 0.498;
- Stemming and Word2Vec: accuracy is 0.501, and F1-score is 0.504.

Thus, stemming significantly loses to lemmatization on both metrics. As for embedding, Word2Vec is inferior to FastText in F1-score but superior in accuracy.

4 Conclusion

Thus, the author tested the influence of specific techniques of the four stages of data preprocessing for the task of multilingual tonality analysis. It was revealed that the position of tokenization in relation to translation and the choice of translator have little effect on the final quality, which can be explained by the high quality of advanced automatic translation methods. In turn, the choice of the method of lemmatization and the creation of embeddings significantly affects the quality of classification.

However, this has only been tested for the case of recurrent neural networks in a specific task. Other cases require a future study because there may be different results.

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Macrostructure of the Concept of “Equality” in the English-Language Discourse of the Sphere of Sustainable Development



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Abstract The research aims to identify the characteristics of the concept of “equality” in the context of discursive sustainable development practices. The research considers discursive practices as speech ways of generating, perceiving, and interpreting texts related to one or another social sphere and aimed at reflecting the knowledge and experience of individuals and social institutions whose activities are directed at transforming one or another area of society. The concept of “equality” is analyzed through a linguo-cognitive description of its macrostructure in discursive sustainable development practices. The analysis of the contexts, including the key nominative units “equality” and “sustainable development,” allows the authors to identify what macrocomponents of the considered concept are most clearly represented and reflect the specificity of its content and structure as a mental unit of people’s linguistic consciousness. The statistical results of the concept verbalization study allowed the authors to identify the most pronounced signs of its macrocomponents, namely the informational, interpretive, and figurative content of the considered concept.

Keywords Linguo-cognitive approach · Concept · Discourse · Discursive practices · Macrostructure · Cognitive metaphor

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1 Introduction

In the mid-twentieth century, humanity came to recognize that rapid economic growth is not only beneficial but also a destructive force that can deplete the resources of nature before they can recover. In turn, this can lead to a global crisis in all areas of human life: economics, politics, social life, and ecology. This has contributed to the formation of the concept of sustainable development, which represents a novel civilizational model of human evolution. The implementation of this model can prevent the growing global crisis.

Adopted by the United Nations General Assembly in the “Millennium Declaration” [5], the SDGs serve as a “guideline for action” for the 193 UN member countries. They form the basis of what is commonly known as the “triune concept,” which encompasses the interrelated dimensions of human development, including economic, environmental, and sociological considerations.

The fundamental premise of the considered concept is the equal and balanced development of these components, with due consideration to their interdependence and interrelatedness. This is aimed at satisfying the needs and requirements of people while preserving the planet in a form suitable for the life of future generations.

One of the most crucial elements of a sustainable development strategy is the provision of equal opportunities in gender, social, labor, economic, legal, and political relations. Without such equality, it is impossible to achieve the progressive development of the economic, social, and environmental components of this concept. In this context, the concept of equality is the subject of investigation in a range of academic disciplines, including law, economics, politics, sociology, psychology, pedagogy, and part of humanitarian knowledge, including linguistics.

The research object is the concept of “equality,” as it is presented in the English-language discourse on sustainable development. The concept is analyzed on the materials posted on the Internet and selected according to the principle of coincidence with the key nominative units “equality” and “sustainable development.”

2 Methodology

The research considers discursive practices as speech ways of generating, perceiving, and interpreting texts related to one or another social sphere and aimed at reflecting the knowledge and experience of both individuals and public institutions. These institutions engage in activities aimed at transforming one or another area of society [6]. The term “discourse” is defined as a set of texts that are interdisciplinary in nature and are connected by the overarching topic of sustainable development. These texts illustrate the various transformations necessary to achieve sustainable development in the

economic, social, and environmental areas. The theoretical basis of the research is the semantic-cognitive approach [7]. The concept of “equality” is analyzed through a linguo-cognitive description of its macrostructure in the framework of discursive practices in the sphere of sustainable development. This analysis is based on the analysis of contexts that include key nominative units, such as “equality” and “sustainable development.” This approach makes it possible to identify the macrocomponents of the considered concept, those with the greatest brightness and density. Moreover, the approach allows us to reveal the specificity of the content and structure of the concept as a mental unit of the linguistic consciousness of the people. The results of concept verbalization were obtained through the statistical method during the course of the study. This method revealed the most pronounced signs of the macrocomponents of the concept, including information content and interpretive and figurative fields.

3 Results

The research analyzed the following components of the macrostructure of the concept “equality” in a sample of texts unified by a common force field of the theme of sustainable development to identify the most stable features. To identify each feature, a minimum of one verbalization was considered. The total number of features is provided in parentheses.

- I. Information content (62). Discursive practices of the sphere of sustainable development show that eight features represent the information content of the concept “equality”:
 1. Equality means ensuring equal social, economic, and political rights and opportunities for people:
 - Of different gender (8);
 - Of different age (6);
 - Healthy and physically disabled (8).
 2. Equality refers to ensuring equal access to:
 - Decent work and equal pay for work of equal value (7);
 - Economic and natural resources (clean water, clean air, energy) (5);
 - Social institutions (education, health, justice) (6).
 3. Equity refers to ensuring that smallholder households and large enterprises have equal access to natural and financial resources (land, sea, and air) to achieve the goals of sustainable development [4];
 4. Equality is understood as the guaranteed participation of all sectors of society in responsible decision-making (2);
 5. Equality implies openness and accountability of institutions at all levels (6);
 6. Equity refers to ensuring equal opportunities for developed and developing countries to achieve the SDGs (3);

7. Equality means ensuring the equal rights of present and future generations to maintain a livable environment (4);
8. Equality means that people are equal before moral laws (2).

II. Interpretative field (268).

1. Regulatory zone (107). The greatest degree of brightness and density of the cognitive features of the concept of “equality” was revealed in the regulatory zone. It included constructions containing such linguistic means for expressing the modality of obligations as “must,” “should,” “required,” or “needed.” With their help, the following eleven features of this concept zone were revealed:
 - (1) Child abuse and gender-based violence *must* be addressed (12);
 - (2) All forms of discrimination *should* be eliminated (9);
 - (3) All forms of age- and gender-based discrimination *must* be eliminated (11);
 - (4) Equal access to education at all levels is *required* for different genders and persons with disabilities (11);
 - (5) Equitable access to natural resources such as water and reliable sources of energy *must* be ensured (10);
 - (6) People *should* have equal access to economic resources, equal rights to own and dispose of land, inheritance, and financial services (12);
 - (7) Equitable access to essential health services and quality, affordable essential medicines and vaccines is *needed* (9);
 - (8) Fundamental civil, cultural, economic, political, and social rights *should* be enshrined in national laws for all segments of the population (7);
 - (9) Equitable access of small, medium, and large economic actors to basic natural resources (terrestrial and marine ecosystems), financial services *should* be ensured (7);
 - (10) Less developed countries *should* be provided with comprehensive economic, social, and environmental assistance to enable them to achieve sustainable development on a level playing field with developed countries (6);
 - (11) Comprehensive measures *must* be taken to conserve natural resources and biodiversity and to combat climate change in order to create equitable livelihood opportunities for present and future generations (13).
2. Utilitarian zone (68). The second position by the degree of brightness and density of cognitive features of the concept “equality” in the English-language discourse of the sphere of sustainable development was occupied by the utilitarian zone. It is a verbalization of the function that the denotation of the concept of “equality” performs for the practical achievement of sustainable development goals and objectives. The following thirteen features were identified in total:

- (1) Achieving socio-economic equality will eradicate poverty, hunger, and malnutrition (5);
 - (2) Achieving social equity will facilitate the participation of all segments of society in responsible decision-making to implement the SDGs (4);
 - (3) Achieving social equality will significantly reduce deaths due to hunger, inability to access basic life resources (housing, drinking water, food, reliable and affordable energy sources), and social protection institutions (health care) (7);
 - (4) Achieving social equality will ensure the right to all levels of education for people from different social backgrounds, as well as for people with disabilities (5);
 - (5) Achieving equality in labor rights will help reduce unemployment and improve the well-being of citizens (5);
 - (6) Achieving equality of rights among different gender groups will eliminate gender discrimination in the political, social (right to education, health care), and labor spheres, as well as gender-based violence (8);
 - (7) The realization of the principle of sovereign equality of States will enable less developed countries to participate more fully and actively in the achievement of the SDGs (6);
 - (8) Comprehensive financial, economic, political, social, cultural, technological, scientific, and environmental assistance from developed countries to developing countries will reduce inequalities and gaps in the successful achievement of SDGs (4);
 - (9) The realization of the moral equality of all people on the planet will enable all nations to unite in addressing the global problems facing humanity as a whole (3);
 - (10) Educating people about the equality, interconnectedness, and unity of human beings and nature will strengthen the fight against climate change and the conservation of the Earth’s natural resources and biodiversity (8);
 - (11) Recognition of the equal rights of present and future generations to use the planet’s natural resources suitable for survival will lead to greater responsibility on the part of all people for the ability of humankind to continue its full existence into the distant future (6);
 - (12) The establishment of equal rights for human beings in the economic, social, political, and cultural spheres and the elimination of discrimination on any grounds (gender, age, etc.) will contribute to the positive dynamics of economic growth, together with the efficient use of natural resources, as well as to the achievement of peace and respect among States (3);
 - (13) Unless gender and social inequality were eliminated, it would not be possible to build a just and sustainable world (4).
3. Encyclopedic zone (49). The encyclopedic zone occupies the third position by the degree of manifestation of brightness and density of cognitive features of the concept of “equality” in the English-language discourse of the sphere

of sustainable development. Seven cognitive features of the concept under consideration were identified:

- (1) Social equality is a situation in a community of human beings in which all individuals have the same rights, freedoms, and status, which means equality of persons in civil rights, freedom of expression, and the right to autonomy, as well as equal access to basic public goods and social services [8] (7);
 - (2) Gender equality is the equal legal status of men and women, the concept of equal opportunities for individuals of different gender groups to participate in all spheres of society (economy, politics, culture, work, public life) [9] (9);
 - (3) Moral equality is based on the concept that the laws of morality apply to human beings regardless of their social or material status [4] (5);
 - (4) The equality of people and nature implies the application of the principle of “do no harm” in relation to both parties, considering their interconnectedness and interdependence. This concept is also manifested in the fact that a human being is able to harm the health of another person (people, future generations) through the negative impact of his/her activities on nature (pollution of water, land, air, climate change, etc.) (5);
 - (5) The principle of sovereign equality of States signifies the legal equality of all parties to the international legal order, which is enshrined in paragraph 1 of Article 2 of the UN Charter [10] (6);
 - (6) Economic equality is the concept of fair distribution of economic benefits within a society, particularly in the context of taxation and social protection of citizens. It entails the provision of equal economic opportunities for all members of society, as well as the guarantee of an equal basic minimum in terms of income, goods, and services [3] (9);
 - (7) The principle of equality is the foundation of labor law, which guarantees equal rights for all citizens, regardless of gender, age, race, or nationality. This principle is reflected in the equal rights to choose a type of professional activity, the prohibition of forced labor and discrimination in this sphere, the provision of assistance to society in employment, the establishment of fair working conditions, the right to rest, and the guarantee of equal pay for equal work [11] (8).
4. Assessment zone (44). The final position was occupied by the assessment zone of the concept of “equality.” This concept is represented by the following eight cognitive features, which collectively reveal its importance for achieving the SDGs. These features also demonstrate the complexity and degree of realization of this task:
- (1) Gender and social equality are fundamental aspects of sustainable development (8);
 - (2) The achievement of gender and social equality will result in the elimination of violence, labor, and economic inequalities (7);

- (3) A movement towards greater equality of rights for the poorest countries compared to developed countries will contribute to the establishment of equitable and sustainable development for all people on the planet (3);
- (4) The greatest challenge facing human civilization is establishing gender and social equality among people in all countries (5);
- (5) The elimination of the threat of extinction of the planet’s biological species, as well as humans themselves, is difficult because it involves implementing measures related to reducing global inequality and exorbitant consumption, and only in combination does it lead to the achievement of the SDGs (6);
- (6) The problem of social, economic, and gender inequality represents a significant global problem that affects all members of the human race (4);
- (7) The problem of social, gender, and labor inequality persists and even increases in some zones, which hinders the solution of problems such as poverty eradication, reduction of social tensions, growth of socio-economic development, and improvement of the environment (6);
- (8) The advancement of gender equality has a positive impact on the majority of the SDGs (5).

III. Figurative content (8).

The cognitive features of the concept of “equality” are represented by isolated cases of verbalization in the discourse of the sphere of sustainable development. Due to the high degree of abstraction inherent to the concept in question, the authors identified hidden images (gestalts) [2], which can be discerned from the combination of the explicitly expressed main subject of the metaphor and the verb in its direct meaning. These hidden images (gestalts) constitute the main part of the figurative component of the concept of “equality” in the considered type of discourse. This is represented by the following types of cognitive metaphors, according to the classification of Chudinov [1]:

1. Anthropomorphic metaphors represent the concept of “equality” in the following forms:
 - (1) A partner: *Achieving equity contributes to the Sustainable Development Goals* (1);
 - (2) A friend: *Economic and gender equality go hand in hand with social equality* (1);
 - (3) A person: *We should not belittle the equality of opportunities for people, both within and outside the state, to achieve sustainable development* (1);
 - (4) A way: *Moving towards social and gender equality is a prerequisite for realizing the idea of sustainable development* (2).
2. Naturemorphic metaphors that represent equality as a living organism, rooted and requiring some nourishment in order to achieve the SDGs:

- (1) *The concept of social equality is deeply rooted in the religious belief that all humans are equal before God* (1);
- (2) *Human equality is born out of equal opportunities to meet basic socio-economic needs* (1).
3. Artifact metaphors represent equality as a mechanism: *Equal rights are a tuning fork to the sustainable development of relations between citizens of the state* (1).

4 Conclusion

The research conducted on the macrostructure of the concept “equality” in the English-language discourse of the sphere of sustainable development allowed us to identify its main cognitive features and to establish by statistical method the degree of their density and brightness. The greatest degree of brightness and density was demonstrated by such a component of the macrostructure of the studied concept as the “Interpretive field,” which accounted for 79.3% of the totality of cognitive features. The second most important factor was the “Information content,” which accounted for 18.3% of the total. The “Figurative content” of the concept was the third most significant factor, accounting for 2.4% of the total.

The macrocomponent “Information field” elucidates the vocabulary content of the concept “equality” in the discourse of the sphere of sustainable development. The elements of this macrocomponent reveal the meaning of the concept in various areas. These areas include the relationship between genders, people of different age categories, legal, social, and economic status, equality of human beings and nature, the relationship between various institutions, agencies, and states, and the moral aspect of equality. The structure of this macrocomponent demonstrates the fundamental principle of equal opportunities for both individuals and states on the path to achieving the SDGs. At the same time, it illustrates the multidimensionality of the concept of “equality” in the discursive practices associated with the topic under study.

The most pronounced cognitive features of the concept are manifested in the regulatory zone (39.9%) of the macrocomponent “Interpretative content,” followed by the “Utilitarian zone” (25.4%), the “Encyclopedic zone” (18.3%), and the “Assessment zone” (16.4%). The cognitive features of the studied concept, as a part of this macrocomponent, serve to expand and supplement its information content, as well as to assess the high degree of its importance in terms of achieving the SDGs.

The macrocomponent “Figurative content” demonstrates the lowest degree of brightness of cognitive features, which is associated with a high degree of abstraction of the concept under study in the discourse of the sphere of sustainable development. The primary type of cognitive metaphor of the concept of “equality” is the hidden images (gestalts) that permit the conceptualization of this concept through anthropomorphic, naturemorphic, and artifact metaphors.

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Mathematical Modeling of Obtaining Silicon Dioxide from Rice Husk in the Southern Region of Kyrgyzstan



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Abstract The authors analyze the production of rice husks around the world and the production of silicon dioxide from rice husks. The research aims to analyze and forecast the production of rice husk and create a mathematical model to obtain silicon dioxide from it. The authors examine the problem of processing rice husk and obtaining silicon dioxide from it through mathematical modeling. The results of solving the Kolmogorov equation to obtain silicon dioxide from rice husk have shown that rice husk in the gross yield of rice in the Batken Region of Kyrgyzstan amounts to 36%, and silicon dioxide (SiO_2) from this husk amounts to 64%. The percentage of rice husk from the southern region of the Kyrgyz Republic obtained using the Markov chain is compared with the percentage composition of rice husk from the same place obtained experimentally. The authors also established that low-temperature chlorine treatment of rice husk makes it possible to enrich silicon dioxide (SiO_2) to 100% (i.e., to the maximum). The research materials are of practical value for obtaining technical silicon from the rice husk.

Keywords Rice · Ash · Rice husk · Gross yield · Silicon dioxide

JEL Classification Q01 · Q16

1 Introduction

In recent years, interest has grown in agricultural wastes as an essential raw material resource to obtain (e.g., silicon-based materials and compounds). Many tons of rice husk (hull) waste are created while processing rice grains. The yield of rice husk when processing the overall mass of plants depends on a plant variety and amounts

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to 20–30%. These wastes usually remain in the fields or are burnt. That is, plenty of raw plant material waste in Kyrgyzstan is used inefficiently annually. Hence, the present work examines the potential for employing rice husk (rice production waste) from the southern region of the Kyrgyz Republic as a raw material to obtain silicon oxide.

Rice husk is one of the two residues of agricultural crops with a maximum volume. It constitutes a worldwide annual product that amounts to about 100 million tons, which is 123,108 million tons annually [20, 24].

Abundant by-products are environmentally hazardous. Therefore, the way of using these wastes is non-compliant with the global paradigm shift towards sustainable development. However, rice husk currently finds limited use to manufacture products with a low value-added tax (e.g., fertilizer additives, cattle mats, fuel, and materials for filling or pavement) [9, 18].

Rice husk is a component of rice chaff. There is no competition between rice husks and food resources for land use. Abrasive structure and low nutritional value make rice husk inedible and typically discarded [4, 7, 17].

About 44.5 thousand tons of rice per year are cultivated in the three regions (Batken, Osh, and Jalal-Abad) of Kyrgyzstan. The volume of rice husk when polishing is 20–28% of the grain weight and depends on rice varieties. Thus, abundant rice waste is accumulated annually [6, 14, 22].

Processing such an amount of rice grains annually generates about 12.5 thousand tons of waste as rice husk. It is rather complicated to utilize it. Burning this waste is very expensive. Additionally, the creation of dumps and husk burning in the open terrain causes severe environmental damage. Using rice waste poses a complex problem because it has a high ash content and is combustion-prone when stored in the air for a long time.

Mineral materials, namely quartz sands, kaolin clays, and rocks [11, 12, 19], serve as traditional raw materials to obtain amorphous silicon dioxide. However, the methods to do it are rather expensive and energy-intensive. Such silicophilous plants as rice husk and chaff, horsetails, needle grass, oat, etc. can be employed as an alternative type of raw material. When using plant raw materials, plenty of inflammable wastes of agricultural production are utilized. The methods of processing are rather simple and require no huge financial expenses [1, 2].

2 Materials and Methods

It had long been found [10, 16] that rice husk (RH) is a viable source of considerable levels of high-quality opaline silica. Silica from rice husk found wide use in several areas, for example, as a good pozzolan in cement industry [13, 26], aerogels [3], SiC [8], solar-grade silicon [22], and cordierite [5].

2.1 Analysis and Forecasts of Rice Husk Productions

To analyze and forecast rice husk productions, the authors employed a least-square method (LSM) (i.e., a statistical procedure for a relatively accurate forecast of the behavior of dependent variables). The LSM aims to find the best approximation to reality out of all linear functions. It can be done by searching for a minimum deviation function (to be more precise, in terms of the LSM process: a search for a minimum sum of squared deviations of Y values (the letter “y”) from the obtained regression equation).

The method has numerous applications because it allows for making an approximate representation of a specified function through other simpler functions. The LSM can be most helpful in processing observation values. It has been actively employed to evaluate one value based on the results of others, which contain random errors.

2.2 Statement of the Problem to Determine an Average Volume of Rice Husk Production

Assume that there are two indicators x and y ; y depends on x because they are of interest in terms of regression analysis in the least-square method. Thus, let x be years when rice husk was produced, y —rice husk productions. It is required to forecast what production y will take place during several years. Function $y = f(x)$ is increasing because the production rate rises annually.

2.2.1 Principle of the Method

Table 1 shows the data on rice production for 2016–2020.

The table data can be depicted in the Cartesian coordinate system as points $M_1(x_1, y_1), \dots, M_n(x_n, y_n)$. The solution to the problem will be reduced to selecting

Table 1 Rice crop production area in the Kyrgyz Republic (in tons)

	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	Total value
Gross yield of rice	34,846.7	38,179.6	40,738.0	41,219.1	44,473.6	199,457
Husk (tons) (y_i)	9757.076	10,690.288	11,406.64	11,541.348	12,452	55,847.35
x_i	1	2	3	4	5	15
x_i^2	1	4	9	16	25	55
$x_i y_i$	9757.076	21,380.576	34,219.92	46,165.392	62,260	173,783

Source Calculated and built by the authors

approximating function $y = f(x)$, which has a graph, passing as close to points M_1, M_2, \dots, M_n as possible.

Certainly, a high-order polynomial can be used. However, such an option is difficult to implement and is incorrect because it will not reflect the main tendency to be identified. The most reasonable solution is to search for a line $y = ax + b$, which best approximates experimental data or, to be more precise, coefficients a and b .

To determine an average volume of rice husk production, let us use a least-square method and construct a linear dependence:

$$y_n = f(ax_n + b) \quad (1)$$

That is, we find the values of the coefficients and at which the errors a and b are minimum:

$$e(a, b) = \sum_{n=1}^N (y_n - (ax_n + b))^2 \quad (2)$$

To define average values of computing \bar{x} , \bar{y} , $\bar{x^2}$, and \bar{xy} , let us use formula (2) in the following form:

$$\begin{cases} a\bar{x^2} + b\bar{x} = \bar{xy} \\ a\bar{x} + b = \bar{y} \end{cases} \quad (3)$$

If some physical value depends on another value, this dependence can be examined by measuring y at various values of x . The measurements provide several values:

$$\begin{aligned} &x_1, x_2, \dots, x_i, \dots, x_n; \\ &y_1, y_2, \dots, y_i, \dots, y_n. \end{aligned}$$

In this case, to accomplish this, the researchers used the statistical data about producing rice in the Kyrgyz Republic over five years, shown in Table 1.

Based on the data presented in Table 1 and using Eq. (3), we obtain the following:

$$\begin{cases} 55a + 15b = 173,783 \\ 15a + 15b = 55,847.35 \end{cases}$$

To solve these equations, Kramer's rule was used and the following equation was obtained

$$y = 624.095x + 9297.185 \quad (4)$$

Rice husk is combustible in the air with the formation of rice husk ash. Organic matter disintegrates during this process; the main residue is silica. Surprisingly, the

silica thus obtained is relatively pure and amounts to about 20% of the dry weight of rice husk.

The literature sources say that silicon dioxide, namely, the substance in demand in many industry sectors, can be obtained from rice husks. The mineral part of rice husk contains plenty of silicon dioxide, the nature of which has been thoroughly studied in some works [23]. Silicon dioxide is employed as an ingredient of construction materials. In amorphous form, it is used as a desiccant, adsorbent, catalyst, etc. In amorphous vitreous-like form, it finds applications when manufacturing optic components and glass wires, it also serves as the main material in glass, ceramic, and refractory industries [27].

2.3 Using the Markov Process to Determine Percentage Composition of Silicon Dioxide

Several random processes are known, one of which is Markov chains. This greatly simplifies the study of a random process [15, 21]. The authors employ a mathematical description of the Markov process with discrete states to determine the percentage composition of silicon dioxide. Suppose that all transitions of the system from the state P_i to P_j occur in the simplest streams of events with intensities I_{ij} ($i, j = 0, 1, 2, 3$). Thus, the system's transition from state P_0 to P_1 will take place as affected by the flow of failures of the first node; the reverse transition from state P_1 to P_0 happens when affected by the flow of terminations of processing rice plants.

3 Results

Let us consider the system at the moment t and, by specifying a very short time Δt , find the probability $P_0(t + \Delta t)$ of the fact that the system will be in state P_0 at the moment $t + \Delta t$. Thus, the main stages of the analysis performed in this research are as follows:

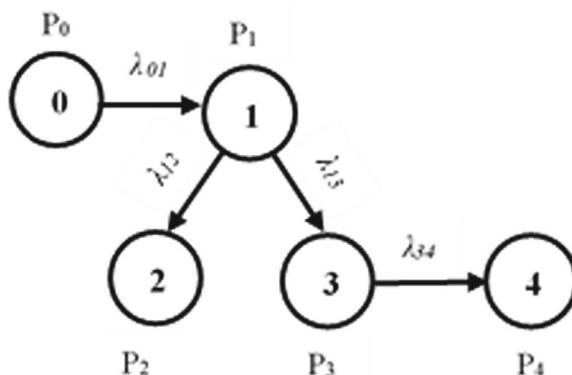
- Modeling the system states employing the Markov process (i.e., considering constant indices of failures and overhauls for each individual person). The model shall be updated, viewing all fault states as absorbing states (i.e., once getting into the state, there is no way of getting out of this state);
- Mathematical modeling is performed using the Markov process.

To analyze the technology of obtaining silicon dioxide from rice husk, it is necessary to analyze the treatment process using the Markov chain; the analysis will require the creation of the graph of the rice husk treatment process and writing Kolmogorov equations based on the treatment process graph.

The rice husk treatment process was modeled as exemplified by the Batken Region of the Kyrgyz Republic (Fig. 1). Following such reasoning for all states of the system P, we obtain a system of Kolmogorov differential equations for the probabilities of states:

$$\left\{ \begin{array}{l} \frac{dP_0}{dt} = -\lambda_{01}P_0 \\ \frac{dP_1}{dt} = \lambda_{01}P_0 - \lambda_{12}P_1 - \lambda_{13}P_1 \\ \frac{dP_2}{dt} = \lambda_{12}P_1 \\ \frac{dP_3}{dt} = \lambda_{13}P_1 + \lambda_{34}P_3 \\ \frac{dP_4}{dt} = \lambda_{34}P_3 \end{array} \right.$$

where, λ_{01} is the coefficient of transition from harvest to gross rice harvest in the Batken Region of the Kyrgyz Republic and is equal to 3322×10^4 ; λ_{12} is the coefficient of transition from gross harvest to rice grain and is equal to 1165.93×10^4 ; λ_{13} is the coefficient of transition from rice grain to rice husk and is equal to 347.44×10^4 ; λ_{34} is the coefficient of transition from rice husk to silicon dioxide and is equal to 92; P_1 is the probability of transition from harvest to gross rice harvest; P_2 is the probability of transition from gross harvest to rice grain; P_3 is the probability of transition from rice grain to rice husk; P_4 is the probability of transition from rice husk to silicon dioxide.



0-crop, 1-gross yield of rice, 2-rice, 3-rice husk, 4-SiO₂.

Fig. 1 Graph of obtaining SiO₂ from rice husk of the Batken Region of the Kyrgyz Republic.
Source Calculated and built by the authors

Solving this system of equations, using these data, the transition probabilities will be found:

$$P_0 = 0, P_1 = 0.0376, P_2 = 0, P_3 = 0.36, P_4 = 0.64.$$

4 Discussion

According to the obtained results, in the limiting standard mode, rice husk amounts to 36% of the gross rice yield in the Batken Region of the Kyrgyz Republic; there are 64% of SiO_2 as a component of rice husk.

Silicon dioxide from rice husk ash, containing 61% pts. Wt. of SiO_2 and 36% pts. Wt. of carbon, is obtained by processing 1 M ash with sodium hydroxide solution [25].

It should be noted that low-temperature treatment of rice husk with chlorine makes it possible to enrich SiO_2 up to 100%. It is possible to enrich SiO_2 up to 100% by low-temperature chlorine treatment of rice husks. For this research, we used data on the dependence of the chlorination of rice husks, composed of a mixture of the studied oxide and carbon, on temperature, feed rate, and partial pressure of chlorine, the particle size of the chlorinated material, and the composition of the gas phase formed during treatment with chlorine. Chlorination was performed in a tubular furnace at a 20–550 °C temperature range.

5 Conclusion

The study showed that the yield of rice husk when processing the total mass of plants depends on the plant variety and is 20–30%. To determine the volume of waste, the authors used a least-square method, analyzed rice production, and made their forecasts. The authors demonstrated that the processing of rice grains in the Kyrgyz Republic annually generates about 12.5 thousand tons of waste as rice husk.

Solving the system of Kolmogorov equations made it possible to find that rice husk amounts to 36%, and silicon dioxide (SiO_2)—64% in the gross yield of rice in the Batken Region of Kyrgyzstan. The results demonstrate that low-temperature chlorine treatment of rice husk allows for enriching silicon dioxide (SiO_2) to 100% (i.e., to the maximum value).

Based on these data, the following conclusions can be drawn:

1. While the rice-sown area remains unchanged, more than 12,500 tons of rice husks are annually accumulated in three regions of southern Kyrgyzstan. Hence, there is a need to process these raw materials.

2. The theory of graphs and the Markov chains (Kolmogorov equations) are used in the work to analyze the processing of rice production waste in the Kyrgyz Republic to obtain silicon dioxide.
3. The share of rice husks in the total rice harvest of the Batken Region of the Kyrgyz Republic is 36%; SiO₂ is 64%.
4. The authors found that low-temperature chlorine treatment of rice husk makes it possible to enrich silicon dioxide (SiO₂) to 100%.
5. The authors revealed that the maximum time for chlorine treatment is about 120 min to obtain 99.9% of pure silicon dioxide.

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Big Data and Artificial Intelligence on the Horizon of Industry 5.0: The Future of Decision-Making in the Smart Economy (Conclusion)

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Big data and AI are among the most promising technologies, shaping the future of the smart economy on the horizon of Industry 5.0. This book provides solid evidence showing that big data and AI can transform decision-making systems into cyber-physical entities. However, this introduces a new question about whether these decision-making systems will evolve into cyber-social systems.

The Fifth Industrial Revolution is becoming increasingly apparent in various economic sectors. The transition to Industry 5.0 is most apparent in marketing and sales, where the socialization of big data and AI is underway: human-machine communications are becoming more common and increasingly sophisticated. However, it remains uncertain how productive the socialization of big data and AI will be in managing the smart economy.

One possible future scenario for decision-making in the smart economy on the horizon of Industry 5.0 involves a shift to fully automated management. In this case, big data and AI would assume all managerial functions within the economic entities of the smart economy, eliminating the role of managers. Combined with automated production, this would mean the absence of a social component and a shift to exclusively machine-based communications. Under this scenario, economic systems would not become cyber-social but would remain cyber-physical, advancing to a higher level of automation.

An alternative scenario envisions maintaining “manual” management in social systems that, despite the Fourth and Fifth Industrial Revolutions, do not become cybernetic. This future is most likely in areas of economic activity where collecting big data is challenging due to technical and ethical reasons and where AI may fail.

A third possible scenario for decision-making in the smart economy on the horizon of Industry 5.0 envisions a new impetus for developing decision-support technologies. This scenario would result in the formation of cyber-social systems where human-machine communications are practiced. The advantage of this scenario is

the continued involvement of humans in value creation and relative labor market stability.

Overall, the practical implications of this scenario are uncertain because its boundaries are blurred. To better understand the potential of decision-making scenarios in cyber-social systems within the smart economy on the horizon of Industry 5.0, it is essential to define the roles of humans and AI and how big data collection and analytics will be organized.

Whose opinion will be paramount? Whose voice will be decisive: that of humans or AI? Will big data gain an independent analytical component or remain a complement to AI? Will AI and big data remain labor tools, or will they transition to being subjects of labor, including managerial tasks? Future research, building on this book, should aim to find answers to these questions.