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IMPACT AND ECONOMIC CONSEQUENCES OF ARTIFICIAL INTELLIGENCE ON SUPPLY CHAIN MANAGEMENT IN THE DIGITAL ECONOMY

Abstract

The article comprehensively studies the impact of artificial intelligence (AI) technologies on supply chain management in the digital economy and its economic consequences. The research analyzes the impact of AI-based optimization models on logistics costs, inventory management, operational efficiency, and financial indicators of enterprises. The main objective of the study is to assess the impact of artificial intelligence on supply chain management in the digital economy and how this is reflected in the economic results of the enterprise. The object of the study was the time series data on the oil and gas sector of Azerbaijan, including a large integrated energy and logistics enterprise such as SOCAR. Since the oil and gas sector is distinguished by its high capital intensity, complex supply and logistics chain, and sensitivity to external shocks, the economic impact of artificial intelligence-based management tools can be observed more clearly here. The methodological framework includes econometric modeling, systems approach, and comparative analysis methods. The results show that the application of artificial intelligence makes a significant contribution to reducing uncertainty in the supply chain, optimizing decision-making processes, and increasing overall economic efficiency.

Keywords: *artificial intelligence, supply chain, digital economy, logistics, optimization, econometric model.*

1.INTRODUCTİON

The formation of the digital economy in the globalized world economic system has led to fundamental changes in the activities of modern enterprises, and has led to the emergence of a new management mechanism in the field of supply chain management, as well as in all areas of economic activity, through the application of information technologies and artificial intelligence. Globalization, the uncertainty of market relations formed on the basis of supply and demand, and the hardening of the competitive environment require enterprises to apply more agile and efficient decision-making mechanisms.

Artificial intelligence technologies play a significant role in supply chain management, mainly due to the ability to collect, process, predict and optimize large volumes of data. Through the application of these technologies, enterprises mainly achieve the refinement of demand forecasts, optimization of enterprise inventory levels, reduction of transport and logistics costs and more effective management of risks that may arise in the enterprise. Since all this is aimed at improving the economic results of supply chains through the application of artificial intelligence technologies, it determines the relevance of systematically analyzing and evaluating the economic results of the impact of the application of AI technologies on the supply chain.

2. LİTERATURE REVİEW

In recent years, extensive research has been conducted in the field of artificial intelligence and supply chain management, and the authors have shown the importance of applying AI technologies in logistics and production processes. Christopher M. (2016) notes in his work that supply chain flexibility creates a competitive advantage [4]. Ivanov and Dolgui (2020) emphasize the role of artificial intelligence in risk management and extensively explain the importance of the economic benefits it creates [7, 11].

Research shows that in modern research on the economic consequences of the impact of artificial intelligence on supply chain management in the digital economy, the following areas are of primary importance: AI-based demand forecasting models, inventory management through machine learning, blockchain and AI integration, and real-time logistics optimization. Based on these areas, the issues of demand forecasting, inventory optimization, logistics route management, strengthening risk and resilience, as well as improving financial and productivity results in enterprises are reflected. At the same time, recent studies show that economic results depend not only on the technology itself, but also on the quality of information, organizational readiness, digital infrastructure, and management integration.

Giovanna Culot, Matteo Podrecca, and Guido Nassimbeni's approach to issues related to the impact of artificial intelligence on supply chain management in the digital economy is reflected in their systematic research conducted in 2024 [3,4,5]. These authors try to separate the application of AI in the supply chain from the “hype” and, based on empirical work, divide it into four main blocks: information and system requirements, technology implementation process, inter-organizational integration and performance outcomes. The strength of these authors’ approach is that, in addition to technological optimization, they also accept organizational alignment and integration as a condition for economic outcomes. The weakness is explained by the fact that in this approach, AI classifies the application conditions rather than measuring economic indicators such as profitability, ROI, ROA or cost elasticity, i.e., although it is strong from a management perspective, it is relatively weak from an econometric perspective.

It should be noted that in terms of institutional and macroeconomic approaches, the approaches of organizations such as the OECD and the World Economic Forum are of great importance. These approaches mainly focus on the impact of artificial intelligence on supply chain management in the digital economy, not only on internal efficiency, but also on broader institutional factors such as digital infrastructure, data, cloud computing, computing power, knowledge, and the competitive environment. OECD 2024 documents show that the AI value chain itself is a complex economic system consisting of information, finance, computing power and deployment stages; therefore, the result of AI implementation at the enterprise level cannot be assessed separately from the country's digital ecosystem [17, 20]. The WEF 2025 approach presents AI as a tool for building a more resilient and sustainable supply chain against future shocks. The strength of these approaches is their systematic nature, and their weakness is that they do not directly measure the real financial indicators of firms at the micro level.

It should be noted that the strategic importance of the supply chain in terms of competitive advantage, agility, and sustainability is widely substantiated in modern literature, and recent studies show that artificial intelligence in this area improves economic outcomes through forecasting, risk management, decision support, generative analytics, and operational optimization [1–13].

Research shows that the economic outcomes of AI should be determined primarily by operational efficiency, risk reduction, and institutional readiness.

3. METHODOLOGY AND RESEARCH

In the research work, the ROA indicator, which shows the profitability of the enterprise's assets, is adopted as a result indicator. ROA shows how efficiently the enterprise uses its assets and is the main indicator for measuring the economic results of artificial intelligence. The variable that expresses the explanatory indicators included in the model (factor X1) is the artificial intelligence intensity indicator. This indicator is defined as a conditional index as the ratio of the enterprise's expenses directed at digital technologies, automated planning systems, ERP, IoT, analytical platforms and AI-based decision support systems to capital investment. The second explanatory indicator included in the model (factor X2 INV) is capital investment. This factor indicates investments directed at production, logistics, warehouse, transport, pipeline, terminals, digital infrastructure and technological innovation. The third explanatory indicator included in the model (factor X3- COST) expresses logistics costs. These costs mainly indicate transportation, storage, terminal, supply, distribution and related operating costs. The 4th explanatory variable is the (X4-RISK) risk index. This indicator is formulated as a conditional composite index combining geopolitical, market, operational, supply, currency, and supply disruption risks.

The methodological basis of the study consists of several stages. In the first stage, descriptive statistical analysis is performed on the indicators, the average value, minimum and maximum limits, variation and trends of the variables over time are estimated. In the second stage, the time series approach is applied and the stationarity of the variables is checked using the ADF and Phillips–Perron tests. If the variables have mixed integration levels I(0) and I(1), then the ARDL approach is considered more appropriate. This method has practical advantages in small samples and mixed integration levels [14, 15]. The basic model for the study can be constructed as follows:

$$Y_t = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \varepsilon_t$$

Here are the expected signs:

$\beta_1 > 0$, because as the intensity of artificial intelligence increases, the quality of forecasting, inventory management and operational agility increase;

$\beta_2 > 0$, because capital investment expands technological modernization and production-logistics capabilities;

$\beta_3 < 0$, because increasing logistics costs reduce profitability;

$\beta_4 < 0$, because increased risk leads to disruptions in the supply chain, additional insurance and operational costs.

If the long-term relationship is confirmed, an error correction form of the model can also be constructed:

$$\Delta Y_t = \alpha_0 + \sum \alpha_i \Delta X_{t-i} + \lambda ECM_{t-1} + u_t$$

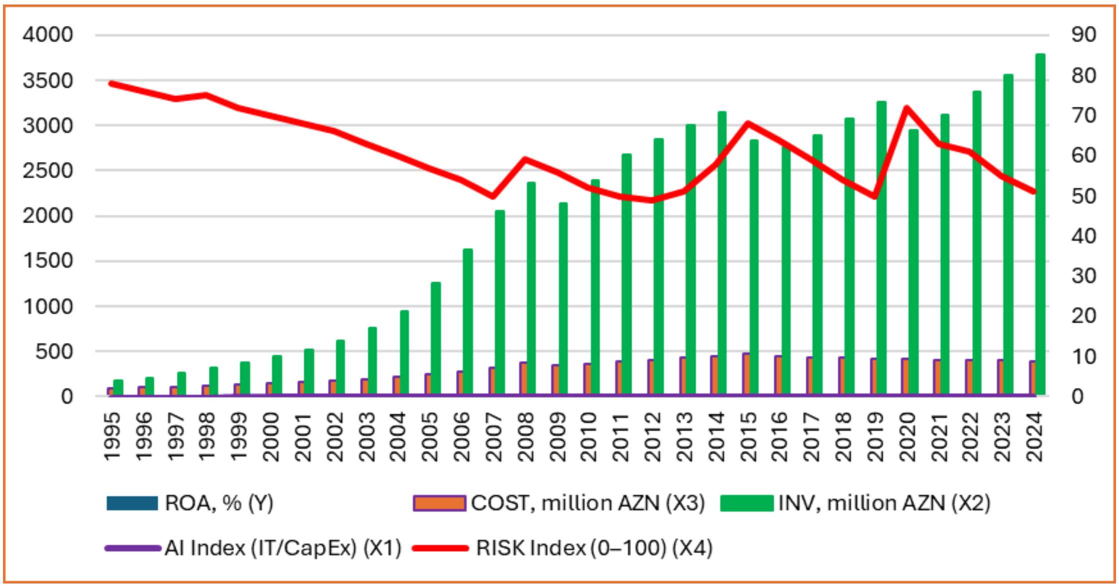
Here, ECM_{t-1} it shows how quickly short-term deviations return to long-term equilibrium. λThe negative and statistically significant coefficient indicates that the model is economically logical. The advantage of this research approach is that the impact of artificial intelligence is assessed not only as a technological variable, but also in interaction with capital investment, logistics costs and the risk environment. Thus, the process of digital transformation affecting the economic results of the enterprise is explained systematically [17,18,19].

It should be noted that this approach can be applied to both the oil and gas sector of Azerbaijan and adapted to other large industrial and logistics enterprises.

4. Analysis and assessment of the impact of artificial intelligence on supply chain management at SOCAR's Oil and Gas Construction Enterprise

The theoretical and methodological analysis conducted above shows that in the conditions of the digital economy, the integration of artificial intelligence technologies into supply chain management has a multifaceted impact on the formation of economic results of enterprises. This impact is manifested not only in the automation of operational processes, but also in the refinement of demand forecasting, optimal management of inventory, reduction of logistics costs, preventive assessment of risks and improvement of decision-making mechanisms. The oil and gas sector, which is characterized by high capital intensity, complex production-logistics relations and sensitivity to external shocks, is of particular importance in this regard. Large production and logistics structures operating in the oil and gas industry of Azerbaijan, including SOCAR's Oil and Gas Construction Enterprise, are of great importance as a convenient research object for assessing the economic efficiency of digital technologies and artificial intelligence-based solutions in supply chain management. The volume of investments in this enterprise, the scale of logistics operations, the variability of the risk environment and the impact of operational results on financial indicators allow us to more clearly observe the real economic results of the application of artificial intelligence.

The graph below shows this information for SOCAR's Oil and Gas Construction Enterprise for the period 1995-2024, based on the enterprise's data and the author's calculations.



4.1. Graph: Dynamics of ROA, AI intensity, capital investment, logistics costs and risk index in the oil and gas sector for 1995–2024

Source: *Author's calculations based on SOCAR data. (21)*

As can be seen from the graph reflecting the dynamics of the return on assets (ROA) of SOCAR's Oil and Gas Construction Enterprise operating in the oil and gas sector during 1995–2024 and the main factors determining it, in 1995–2004 the AI indicator was kept close to zero in SOCAR's Oil and Gas Construction Enterprise. This is explained by the fact that at that time the enterprises did not have AI, but mainly traditional automation and initial digitalization. After 2005, the intensity of AI began to gradually increase due to the spread of digital technologies, especially ERP, data analytics and optimization programs, and this growth accelerated after 2015. In 2020-2024, it was observed that the indicator increased further due to real-time analytics, forecasting models and smart logistics systems. According to the graph, the dynamics of the ROA indicator is aligned with the investment and risk environment. In 2005–2007, profitability increased due to high investment and relatively low risk, while in 2008–2009, a decrease in ROA was observed due to the global financial shock, the sharp drop in oil prices on the world market in 2015, and the pandemic shock in 2020. In subsequent years, ROA recovered and increased as a result of increased AI intensity, more efficient management of logistics costs, and optimization of operating costs.

As can be seen from the graph, although the COST indicator has been increasing in nominal terms for a long time, it has become more stable and relatively manageable after 2018. This situation is explained by improvements in digital planning, route optimization, inventory management and supply coordination. The RISK index, on the other hand, has been observed to increase in high shock years and decrease in more stable years.

It should be noted that based on the statistical data generated for SOCAR's Oil and Gas Construction enterprise, the dynamics of key indicators such as asset profitability, artificial intelligence intensity, capital investment, logistics costs and risk index will be analyzed. The econometric model built on the basis of these indicators will allow for a more concrete and substantiated assessment of the impact of artificial intelligence on supply chain management and how it manifests itself in the economic results of the enterprise.

Based on the above graphical data, it is possible to assess the impact of artificial intelligence on supply chain management in the digital economy by building an autoregression model in the EVIEWS program.

Table 4.1.

Results of the ARDL(1,2,1,0,1) model

Dependent Variable: Y
Method: ARDL
Date: 03/19/26 Time: 11:05
Sample (adjusted): 1997 2024
Included observations: 28 after adjustments
Maximum dependent lags: 2 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (2 lags, automatic): X1 X2 X3 X4
Fixed regressors: C
Number of models evalulated: 162
Selected Model: ARDL(1, 2, 1, 0, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Y(-1)	0.777666	0.069667	11.16264	0.0000
X1	-0.009023	0.004238	-2.129014	0.0473
X1(-1)	0.022867	0.005299	4.315487	0.0004
X1(-2)	-0.006331	0.002582	-2.452060	0.0246
X2	0.002213	0.000448	4.937362	0.0001
X2(-1)	-0.003560	0.000431	-8.253313	0.0000
X3	25.29719	5.965165	4.240820	0.0005
X4	-0.072351	0.010559	-6.851787	0.0000
X4(-1)	0.022238	0.012455	1.785509	0.0910
C	3.885713	1.182806	3.285164	0.0041

R-squared	0.994462	Mean dependent var	5.417857
Adjusted R-squared	0.991693	S.D. dependent var	1.557076
S.E. of regression	0.141920	Akaike info criterion	-0.794650
Sum squared resid	0.362545	Schwarz criterion	-0.318862
Log likelihood	21.12510	Hannan-Quinn criter.	-0.649197
F-statistic	359.1202	Durbin-Watson stat	2.410878
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model **selection.**

Source: *EVIEWS program.*

If we construct the ARDL-EKM model for the short and long run based on Table 1, which shows the results of the ARDL(1,2,1,0,1) model using the EVIEWS software package, we will obtain the following result.

Estimation Command:
=========================
ARDL(DEPLAGS=2, REGLAGS=2) Y X1 X2 X3 X4 @
Estimation Equation:

=========================

Y = C(1)*Y(-1) + C(2)*X1 + C(3)*X1(-1) + C(4)*X1(-2) + C(5)*X2 + C(6)*X2(-1) + C(7)*X3 + C(8)*X4 + C(9)*X4(-1) + C(10)

Substituted Coefficients:

=========================

Y = 0.777666358335*Y(-1) - 0.00902305253114*X1 + 0.0228671956214*X1(-1) - 0.00633117970896*X1(-2) + 0.00221275039913*X2 - 0.00355958459485*X2(-1) + 25.2971910632*X3 - 0.072350745266*X4 + 0.0222381039839*X4(-1) + 3.88571339757

Cointegrating Equation:

D(Y) = -0.222333641665*(Y(-1) - (0.03379139*X1(-1) -0.00605772*X2(-1) + 113.78031176*X3 -0.22539388*X4(-1) + 17.47694757))

The results of the conducted ARDL model show that the model has a high explanatory power in general. Thus, $R^2 = 0.994$ and Adjusted $R^2 = 0.992$ indicate that the model almost completely explains the variation of the dependent variable. The F-statistic (359.12; $p < 0.01$) confirms the overall statistical significance of the model. Durbin–Watson = 2.41 indicates that autocorrelation is not a serious problem. The lagged value of the dependent variable Y(-1) = 0.777 ($p<0.01$) is positive and high. This indicates that the ROA indicator has high persistence and the effect of the past period is significantly transferred to the current period. As can be seen, the AI variable has a mixed effect, its short-term effect is negative (X1 = -0.009, $p<0.05$), but the lagged effects are positive and statistically significant (X1(-1) > 0, $p<0.01$). This result shows that although the initial implementation of AI creates costs, over time it creates a positive economic effect through increased productivity and efficiency.

The current effect of the capital investment (X2) indicator is positive and statistically significant (0.0022, $p<0.01$). However, the lagged effect is negative (-0.0035, $p<0.01$). This indicates that investments provide short-term benefits but may put pressure on long-term profitability due to ineffective or delayed returns [9].

The variable X3, which represents logistics costs, is considered positive and significant (25.29, $p<0.01$). This indicates that the increase in logistics costs is associated with a larger scale of activity and turnover, leading to an increase in revenues. The current effect of the factor X4, which represents the risk index, is negative and highly significant (-0.072, $p<0.01$), while the lagged effect is weak and statistically unstable ($p \approx 0.09$) [9]. This indicates that the increase in risk reduces ROA, but the impact of risks is mainly short-term.

Long-run relationship As can be seen from the ECM model expressing the cointegration relationship, the error correction coefficient is ECM= - 0.222 and $p<0.01$. This result shows that there is a long-run equilibrium relationship in the model. That is, there is cointegration. Approximately 22% of the discrepancies arising in the system are eliminated in each period. This confirms that the model is stable and economically logical.

In order to more accurately assess the reliability and adequacy of the results of the econometric model, the distribution of residuals in the model was analyzed. In this regard, the following graph presents a histogram of residuals and their statistical characteristics for the years 1997–2024.

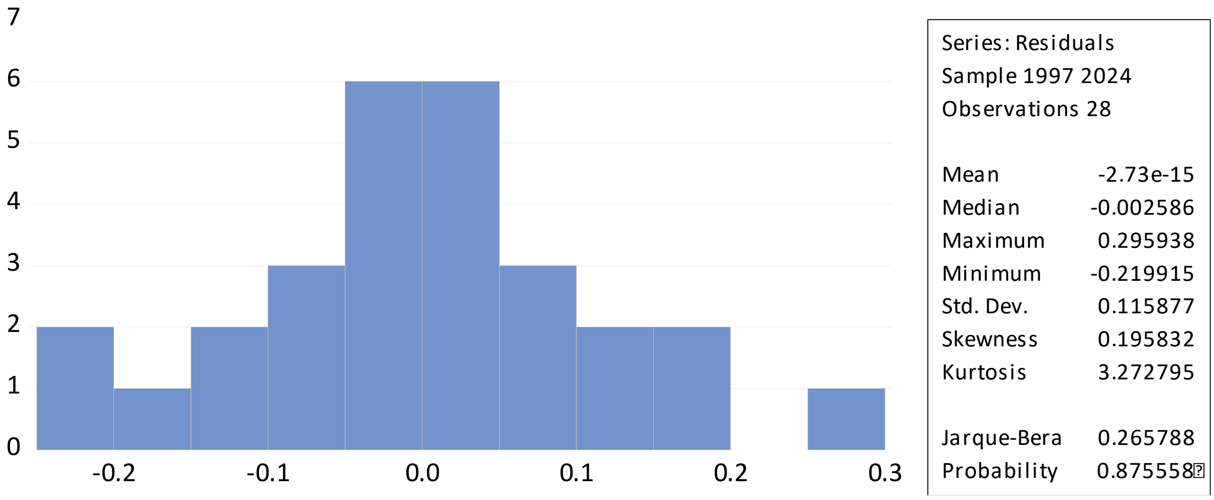


Figure 4.2.: Histogram of the distribution of residuals for the model and results of the Jarque–Bera test

Source: *EVIEWS program.*

As can be seen from the graph, the residuals are mostly concentrated around zero and have a shape close to a symmetrical distribution. The fact that the mean value is almost equal to zero (Mean = -2.73e-15 ≈ 0) indicates that there is no systematic error in the model. At the same time, the fact that the median is close to zero confirms that the residuals are distributed in a balanced manner. The relatively small standard error (Std. Dev = 0.115877) indicates that the model's predictions are close to real observations. The skewness index of 0.196 indicates that the distribution is slightly right-skewed, but this bias is not statistically significant. The kurtosis index of 3.273 confirms that the distribution is close to a normal distribution [9,10].

According to the results of the Jarque–Bera test used to test for normal distribution, JB = 0.266 and p-value = 0.876 indicate that the null hypothesis is accepted at the 0.05 significance level. This means that the residuals of the model do not violate the assumption of normal distribution and the residuals are normally distributed [9,10].

Overall, the graphical and statistical indicators show that the residuals of the constructed ARDL model are random, close to normal distribution, and the model specification is adequate. This confirms that the obtained econometric results are reliable and statistically justified.

RESULT

The results of the study show that in the digital economy, the integration of artificial intelligence technologies into supply chain management leads to structural and qualitative changes in the economic activities of enterprises. The results obtained on the basis of econometric modeling prove that the impact of artificial intelligence has a different nature in the short and long term. At the initial stage, the implementation of AI can have a certain negative impact on profitability, since it is accompanied by additional investment and technological adaptation costs. However, over time, the analytical capabilities, optimized decision-making mechanisms and operational efficiency created by these technologies have a positive impact on the overall financial results of the enterprise. According to the results of the study, capital investments and expansion of logistics activities make a significant contribution to the increase in the ROA indicator, but this effect depends on the effective management of investments and their payback period. The increase in logistics costs should be assessed not as a direct negative factor, but rather as a complex economic effect associated with the expansion of the scale of activities and the increase in turnover. On the other hand, a high risk index negatively affects the financial stability and profitability of the enterprise, weakening the stability of the supply chain. Overall, the results show that the impact of artificial intelligence on supply chain management should be viewed not only as a technological innovation, but as a complex economic system interacting with investment, logistics, and risk factors. This approach allows enterprises to build digital transformation strategies in a more informed manner, use resources more efficiently, and ensure sustainable development in uncertain conditions. Thus, the application of artificial intelligence technologies acts as an important strategic tool in terms of optimizing the supply chain and increasing the competitiveness of enterprises in the long term.

References:

1. Baryannis, G., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. International Journal of Production Research, 57(7), pp. 2179–2202.

2. Brynjolfsson, E., & McAfee, A. (2017). The Business of Artificial Intelligence: What it can – and cannot – do for your organization. Harvard Business Review Press, Boston, pp. 1–24.

3. Choi, TM, Wallace, SW, & Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, 27(10), pp. 1868–1883.

4. Christopher, M. (2016). Logistics and Supply Chain Management (5th ed.). Pearson Education Limited, Harlow, pp. 3–312.

5. Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review. International Journal of Production Economics, 272, 108–125.

6. Dubey, R., Gunasekaran, A., Childe, SJ, Blome, C., & Papadopoulos, T. (2020).
Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. Technological Forecasting and Social Change, 144, pp. 341–351.

7. Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: A conceptual and formal generalization of four major adaptation strategies. International Journal of Culot, G., Podrecca, M., & Nassimbeni, G. (2020). Artificial intelligence in supply chain management: A systematic literature review. International Journal of Production *Research* , 58(15), 4666–4683.

8. Culot, G., Podrecca, M., & Nassimbeni, G. (2021). The role of artificial intelligence in supply chain management: A structured literature review and research agenda. Technological Forecasting and Social Change , *168, 120784, pp. 1–12.*

9. Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence and supply chain management: Beyond the hype—An empirical and conceptual assessment. International Journal of Operations & Production Management , *44(2), 215–238.*

10. Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Data, technology and integration requirements for AI adoption in supply chains. Journal of Business Research , 172, 114431, pp. 1–14.

11. Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Production Planning & Control, 31(10), pp. 1–14.

12. Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. International Journal of Operations & Production Management, 37(1), pp. 10–36.

13. Lee, HL (2004). The triple-A supply chain. Harvard Business Review, 82(10), pp. 102–112.

14. Yadigarov TA, Ramazanov MK, Alirzayev EV Assessment of the formation of investments in the oil and gas sector under conditions of uncertainty. SOCAR Proceedings No. 4 (2025) pp. 196-204

15. Yadigarov TA, (2019) Operations research and solution of econometric problems in MS Excel and EViews software packages: Theory and practice - Baku: Europe Publishing House, 2019 p. 352.

16. Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. International Journal of Logistics Research and Applications, 13(1), pp. 13–39.

17. OECD (2024). Artificial Intelligence in the Digital Economy: Policy Perspectives. OECD Publishing, Paris, pp. 15–120.

18. Tang, CS (2006). Perspectives in supply chain risk management. International Journal of Production Economics, 103(2), pp. 451–488.

19. Wamba, SF, Gunasekaran, A., Akter, S., Ren, SJF, Dubey, R., & Childe, SJ (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, pp. 356–365.

20. World Economic Forum (2025). The Future of Supply Chains: Resilience through AI and Digital Transformation. WEF, Geneva, pp. 5–60.

21. Data from SOCAR's Oil and Gas Production Enterprise for 1995-2024.

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Süni intellektin rəqəmsal iqtisadiyyatda təchizat zəncirinin idarə edilməsinə təsiri və iqtisadi nəticələri

Xülasə

Məqalədə süni intellekt (Sİ) texnologiyalarının rəqəmsal iqtisadiyyatda təchizat zəncirinin idarə edilməsinə təsiri və onun iqtisadi nəticələri ətraflı şəkildə araşdırılır. Tədqiqatda Sİ əsaslı optimallaşdırma modellərinin logistika xərclərinə, inventar idarəetməsinə, əməliyyat səmərəliliyinə və müəssisələrin maliyyə göstəricilərinə təsiri təhlil edilir. Tədqiqatın əsas məqsədi süni intellektin rəqəmsal iqtisadiyyatda təchizat zəncirinin idarə edilməsinə təsirini və bunun müəssisənin iqtisadi nəticələrində necə əks olunduğunu qiymətləndirməkdir. Tədqiqatın obyekti SOCAR kimi böyük inteqrasiya olunmuş enerji və logistika müəssisəsi də daxil olmaqla, Azərbaycanın neft və qaz sektoru üzrə zaman seriyası məlumatları idi. Neft və qaz sektoru yüksək kapital intensivliyi, mürəkkəb təchizat və logistika zənciri və xarici şoklara həssaslığı ilə seçildiyindən, süni intellektə əsaslanan idarəetmə vasitələrinin iqtisadi təsiri burada daha aydın şəkildə müşahidə edilə bilər. Metodoloji çərçivəyə ekonometrik modelləşdirmə, sistem yanaşması və müqayisəli təhlil metodları daxildir. Nəticələr göstərir ki, süni intellektin tətbiqi təchizat zəncirində qeyri-müəyyənliyin azaldılmasına, qərar qəbuletmə proseslərinin optimallaşdırılmasına və ümumi iqtisadi səmərəliliyin artırılmasına əhəmiyyətli töhfə verir.

Açar sözlər: *süni intellekt, təchizat zənciri, rəqəmsal iqtisadiyyat, logistika, optimallaşdırma, ekonometrik model.*