ECONOMIC EFFECTS OF ARTIFICIAL INTELLIGENCE-DRIVEN DECISION-MAKING MODELS IN SUPPLY CHAINS

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Abstract: The integration of Artificial Intelligence (AI) within supply chains has become a key component of improving business operations and economic performance with the advancement of digital technology. The economic impact on AI-driven decision-making systems are investigated in this paper. Advanced Econometric methods are used, with an ARDL model with an associated ECM, to investigate the short-term and long-term implications of using these technologies. Our results show that the AI implementation in the supply chain industry will result in several advantages including cost savings in logistics operations as well as more accurate business decision making. There will be a substantial upfront capital investment together with current technology risks that will constrain the supply chain businesses in the short run.

Keywords: AI, supply chains, economic analysis, ARDL method, decision models, economic success

Introduction.

This rapid expansion of globalization, along with the rapid expansion of digital transformation has increased the complexity of how supply chains work. The current business environment includes significant uncertainty, volatile demand patterns, and frequent disruptions in terms of the logistics, all of which contribute to making it very difficult to use traditional decision-making processes effectively. In this environment, artificial intelligence (i.e.,machine learning) provides organizations with innovative solutions to many of these challenges and provides opportunities for organizations to develop a competitive advantage [1–3]. AI powered systems provide the ability for organizations to make informed decisions quickly due to AI's ability to provide real time analysis, predictive models, and optimize processes throughout all stages of supply chains. Organizations are able to reduce costs, reduce risk, and become more responsive to changing market conditions. The primary purpose for this research will be to assess the economic impacts associated with AI based decision-making through an econometric modelling approach.

Literature Review

Over the past several years, the amount of interest in artificial intelligence (AI) relating to economics has been on the rise. This has occurred in both the theoretical as well as applied research environments. Researchers have looked at the impact that artificial intelligence has on improving the efficiency with which an organization operates, the quality of decisions that are made and also the way that the organization competes within its respective market. Artificial Intelligence (AI) is becoming increasingly important for businesses specifically in the areas of manufacturing and logistics because of the role that AI is playing in optimizing processes, allocating resources effectively,and reducing costs [4–8].

According to Michael Porter, technological innovation continues to be the primary engine to drive competitive advantage, and the use of AI further improves the ability of companies to adjust their competitive positions in the marketplace.On the other hand, Klaus Schwab recognizes the presence of Artificial Intelligence as fundamental in the Fourth Industrial Revolution by the nature (i.e., unchanging) of AI's impact on economic systems and economic processes [9-13].

The accuracy of demand forecasting can be improved through the application of AI, which can also help improve inventory management systems and lower the associated costs of running and moving products. High initial investment, potential cyber-security risks, and reliance on technology can all create challenges for organizations looking to implement AI into their business processes. The literature concludes that, when used strategically, the implementation of artificial intelligence can produce significant improvements in the resilience and long-term competitiveness of our economic systems.

Methodology

The use of AI in evaluating decision-making models encompasses not only technology, but also measures of digital growth and sustainability in the environment. The model therefore incorporates three types of indices: ICT Development Indices, Green Economy Opportunity Indices, and Natural Capital Preservation Indicators. The model is one that represents a representation of an approach to evaluation that enables an evaluation of supply chains not only with regard to economic efficiency, but also with respect to their contributions to the global sustainable development structure. The model helps identify connections between efficient utilization of resources and greenhouse gas reduction, as well as optimizing logistics utilizing AI technologies [14,15].

In this study, economic-mathematical and econometric methods were used to measure the effects of AI decision-making models on supply chain performance. The research used annual samples of the performance of industrial enterprises in Azerbaijan from 2010 - 2024. The purpose of the research was to identify the functional relationships that exist between the level of adoption of AI technologies, digitalization, environmental sustainability and green potential in economic activity and supply chain efficiency. For the purposes of an empirical estimation, I used a multivariate log-linear regression model. The main reasons for selecting this particular model specification are; the ability of the model to provide elasticity-based interpretation of its results, capture proportional relationships between the various variables, and thus allow for transparent interpretation of the economic analysis performed. This regression model uses Supply Chain Economic Efficiency as the dependent variable (y), and the ICT Development Index (X1), Natural Capital Preservation Index (X2), Green Economic Opportunities Index (X3), and Level of AI Implementation (X4) as independent variables. The model can be written as follows:

$$\ln Y = C_0 + C_1 \ln X_1 + C_2 \ln X_2 + C_3 \ln X_3 + C_4 \ln X_4 + \varepsilon_t$$

The economic efficiency index of the supply chain is represented by the symbol Y, the information and communication technology (ICT) development index is represented by the symbol X_1, the natural capital preservation index is represented by the symbol X_2, the green economic opportunities index is represented by the symbol X_3, the artificial intelligence implementation index is represented by the symbol X_4, and the value of the stochastic error is represented by the symbol ε_t. The coefficients in the model function as elasticity parameters. That is, an increase of one percent in any explanatory variable will result in a percentage change in the value of the dependent variable, provided all other factors remain constant. Thus, this model is not just statistically robust but also very meaningful when it comes to interpreting information economically. The key hypotheses in this study are presented as follows: According to the null hypothesis, (H_0), four elements: preservation of natural capital, development of information and communication technologies (ICT), creation of green economies, implementation of artificial intelligence have no effect on the economic performance of the supply chain. In the alternative hypothesis, (H_1), at least one of the four elements has a statistically significant influence on the economic performance of the supply chain. [14,15].

The coefficients of variables X1, X2, and X4 are expected to have a positive effect based on economic reasoning. The effects of X3 have been considered to be much lower than the other three variables and possibly lagged.

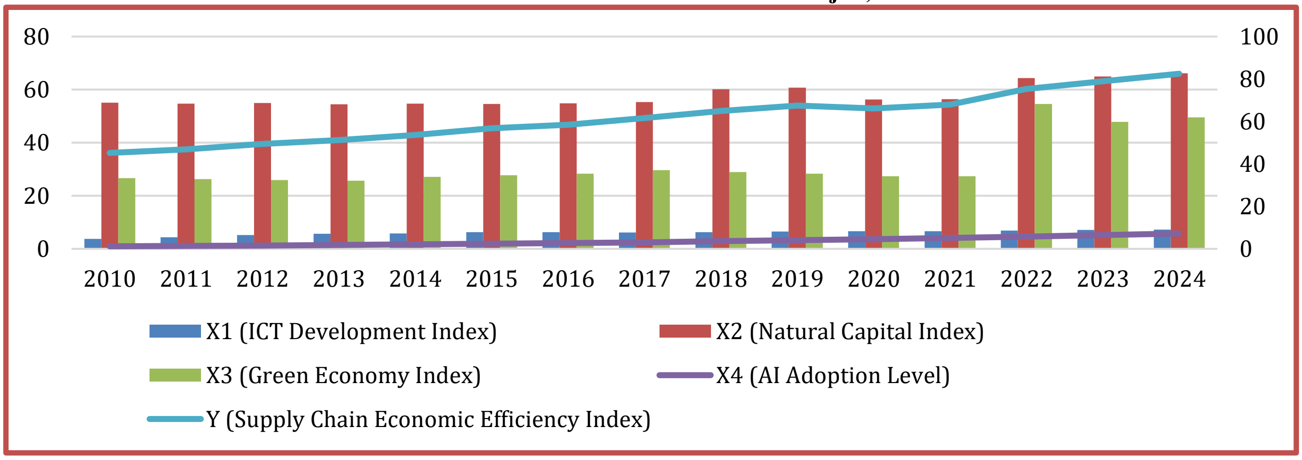
Therefore, our methodology is comprehensive in assessing the effect of artificial intelligence, digital development, and environment on supply chain economic efficiency. Our approach thus presents a suitable analytical framework for measuring the economic outcome of digital transformation processes in theory and in practice.

Main Section

A collection of macro-level and micro-level metrics are used to assess the effect of AI-based decision-making models on the supply chain's economic efficiency. Together, they offer an extensive overview of the digital development of the supply chain, the environmental sustainability of the supply chain, and the extent of use of innovative technology (AI) within the supply chain.In particular, the ICT development index reflects the degree of computer and internet connectivity and technology infrastructure available in a given area; the natural capital preservation index reflects the sustainable use of natural resources and conservation of our environment; and the green economic opportunities index reflects the amount of "green" (or sustainability-based) development opportunities available to a region's economy. The AI implementation index measures how much businesses implement innovative technology (AI) [16, 17]. The supply chain economic efficiency index represents the collective economic impacts of these factors and is analyzed as a combined index. Thus, this method of analysis permits the analysis to consider both the economic and technological and environmental components of the system.

The graph which is below shows the trends in the above mentioned indicators over the period of 2010-2024.

Figure 4.1. Trends in the utilization of Artificial Intelligence, Digital Advances, and Green Economy Measurements in the Industrial Sector of Azerbaijan, 2010–2024.



***Source**: compiled by the author based on the data from [18,19, 20, 21, 22, 23].*

The diagram demonstrates the positive trend, and ICT Technology has advanced and the AI Technology has become increasingly widespread over the duration of the study period. The favourable patterns of development of both of these technologies have been accompanied by improvements in the economic performance of the Supply Chain. In addition to the economic aspect, the green economic Capacity, and natural Capital Preservation indicators all impact the general economic Performance of the Supply Chain as well. Figure 4.1 shows that the ICT development index (X_1) continues on a consistent upward trajectory, moving from 3.78 in 2010 to 7.30 in 2024. This is due to consistent improvements in digital infrastructure and greater access to technology. The artificial intelligence index (x_4) is growing faster than the ICT development index, increasing from 1.2 to 7.2. This demonstrates the rapid introduction of advanced technologies into the manufacturing industry. Well, to be honest, the value of X_2 (i.e., natural capital preservation index) is highly variable; therefore, it cannot be said to be going up in general. However, the natural capital preservation index also shifts up and around a lot (starts to rise much quicker than before), especially since 2018. When you look closely at it, it is clear that there has been major progress (specifically in terms of improving environmental governance practices), and there has also been some progress in managing natural resources more effectively. On the other hand, the green economic opportunities index (X_3) is building since 2022, and this could be due to the intense investment in green technology and/or government's support for sustainable development.The supply chain efficiency index, Y, shows a steady increase overall from 45.2 to 82.5 over the study period. The increase in Y coincides with the improvement of ICT technology and the growth of AI technology, which confirms the relationship between digitalization and economic efficiency. A brief drop in Y in 2020 is likely due to external shocks in the global economy, such as the disruptions caused by the pandemic.From the evidence provided graphically, technological advances are not the only factor affecting the efficiency of the supply chain in the industry of Azerbaijan supply chains. The environmental sustainability and green growth are also equally important in influencing the efficiency of the supply chains; this calls for an integrated approach to development incorporating both digital and ecological aspects.Based on the trends displayed in Figure 4.1, the researcher performed correlation and regression analysis to establish the relationship between the variables of interest. The EViews-12 software package was used in this analysis. The following describes the results of the analysis.

Table 4.1 shows the results of a correlation and regression analysis examining the relationships between artificial intelligence, digital development and green economic indicators in industrial organizations of Azerbaijan.

Dependent Variable: LOG(Y)
Method: Least Squares
Date: 03/23/26 Time: 11:42
Sample: 2010 2024
Included observations: 15

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob**
C	1.818018	0.534305	3.402581	0.0067
LOG(X1)	0.124663	0.053465	2.331666	0.0419
LOG(X2)	0.424500	0.143350	2.961285	0.0143
LOG(X3)	0.022969	0.032278	0.711593	0.4930
LOG(X4)	0.237815	0.022286	10.67115	0.0000
R-squared	0.996258	Mean dependent var	4.107089	
Adjusted R-squared	0.994761	S.D. dependent var	0.187634	
S.E. of regression	0.013581	Akaike info criterion	-5.499119	
Sum squared resid	0.001844	Schwarz criterion	-5.263102	
Log likelihood	46.24339	Hannan-Quinn criter	-5.501633	
F-statistic	665.6006	Durbin-Watson stat	1.081521	
Prob(F-statistic	0.000000			

Source: *These results were obtained using the EViews-12 econometric software.*
The log-log (log linear) model stated in Table 4.1 was developed using Eviews-12 and look like below;
Estimation Equation:
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LOG(Y) = C(1) + C(2)*LOG(X1) + C(3)*LOG(X2) + C(4)*LOG(X3) + C(5)*LOG(X4)

Substituted Coefficients:
=========================

LOG(Y) = 1.81801775149 + 0.124663042831*LOG(X1) + 0.424499998535*LOG(X2) + 0.0229688695186*LOG(X3) + 0.237815384613*LOG(X4)

The estimation parameter for each variable represents elasticity. If any of the explanatory variables increases by 1%, the dependent variable would increase by acorresponding percent with all other variables frozen.

Empirical findings demonstrate that a one percent boost in ICT development index cud translates to nearly lu a 0.12percent increase in supply chain efficiency. The value of the coefficient, shows how the digital infrastructure has had a positive impact on the economic outcomes.

Of all the independent variables examined in the study, XN (natural capital preservation index) possesses the maximum elasticity (0.425). Therefore, the sustainability of the environment has a maximum impact on the model; an increase in the value of XN by one percent leads to an increase in the efficiency of the supply chain of approximately 0.42%. As such, ecological factors should be considered as a primary consideration affecting the operational and fiscal success.

The coefficient of green economic opportunities (X_3) was near zero (0.023) and was not statistically significant. Therefore, the green economic policies' impact may not yet be realized, and the impact will be seen for a long period.

X4,the variable that measures the use of artificial intelligence, has a significant and meaningful impact.The elastic value is about 0.238; P value of less than 1%, which indicates that a 1% increase in the use of artificial intelligence will increase the supply chain efficiency of the industrial sector of Azerbaijan by about 0.24%.

In summary, the econometrics shows that the supply chain performance is best influenced by the use of AI and the protection of the natural resource base. The very high statistical significance of the AI

variable provides evidence of how advanced technologies are basically determining economic efficiencies. Additionally, the elasticities of the environmental indicators are very high, indicating that sustainability is playing an ever-increasing role in the contemporary economy.

The economic variable is non-existent in terms of its statistical significance, presumably meaning that the effect will be slower rather than immediate. Conversely, another component of a technology variable, information and communication technology, while producing a positive effect which is significant statistically, is relatively insignificant in terms of magnitude.

The R^2 =0.996, as per Model Evaluation, shows that the model has very high explanatory power and the R^2 adjusted (0.995) provides further evidence that the model specification is stable and reliable. Besides, calculated F-statistic was found to be higher than the critical value and its probability value is almost zero and thus, Model is significant as a whole.

To check whether there is autocorrelation in the residuals. To do this, we use the Durbin–Watson statistic. Because the calculated Durbin–Watson value lies between the lower and upper critical bounds, it means that we cannot conclusively determine whether or not autocorrelation exists or does not exist.

Apart from checking autocorrelation, another important aspect is to ensure that the residuals have uniform (homoskedastic) variance. Therefore, constant variance (homoskedasticity) of residuals is very important to check the results of regression. The Breusch–Pagan–Godfrey test was used to examine the homoskedasticity of the residuals in the EViews environment and the test results are presented below.

Table 4.2 Results for the Breusch-Pagan-Godfrey Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.902310	Prob. F(4,10)	0.4982
Obs*R-squared	3.978078	Prob. Chi-Square(4)	0.4090
Scaled explained SS	1.647255	Prob. Chi-Square(4)	0.8003

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/29/26 Time: 12:16
Sample: 2010 2024
Included observations: 15

Variable	Coefficient	Std. Error	t-Statistic	Prob
C	0.010256	0.006933	1.479337	0.1698
LOG(X1)	0.000179	0.000694	0.257401	0.8021
LOG(X2)	-0.003046	0.001860	-1.637690	0.1325
LOG(X3)	0.000528	0.000419	1.259774	0.2364
LOG(X4)	8.05E-05	0.000289	0.278290	0.7865
R-squared	0.265205	Mean dependent var	0.000123	
Adjusted R-squared	-0.028713	S.D. dependent var	0.000174	
S.E. of regression	0.000176	Akaike info criterion	-14.18856	
Sum squared resid	3.11E-07	Schwarz criterion	-13.95254	
Log likelihood	111.4142	Hannan-Quinn criter.	-14.19107	
F-statistic	0.902310	Durbin-Watson stat	2.342075	
Prob(F-statistic)	0.498247			

Source: *Source: Calculations were performed using EViews-12 statistical software.*

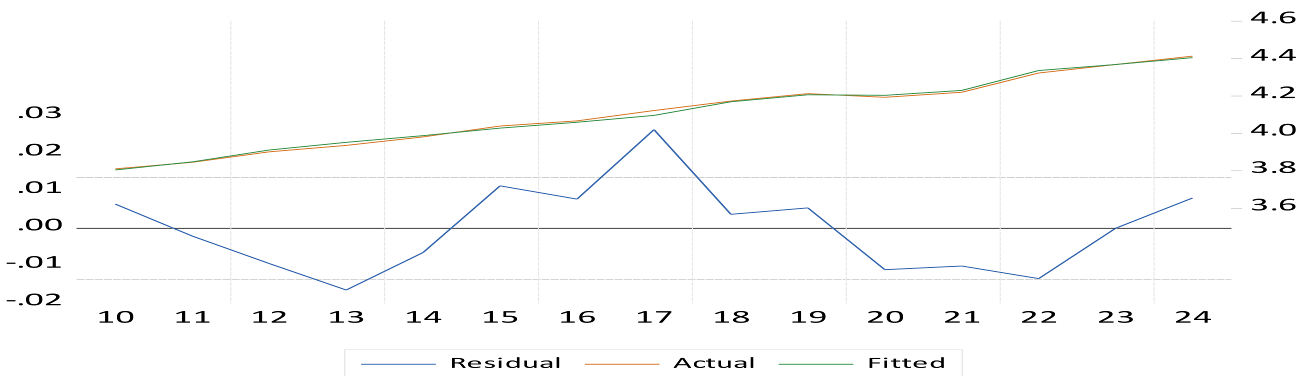
Table 4.2 shows the results of the heteroskedasticity test conducted through the Breusch–Pagan–Godfrey test, where the null hypothesis asserting uniform variance for the residuals could not be rejected. The probabilities associated with these three statistics (0.4982 for the F-statistic, 0.4090 for the Obs*R-squared statistic, and 0.8003 for the Scaled Explained Sum of Squares) were all above the traditional 5 percent significance level, which indicated no evidence of heteroskedasticity; therefore, the residuals have constant variance across all observations.

Therefore, the model satisfies an important assumption of the classical linear regression model-the constant error variance. The coefficient of the support regression does not have statistical significance, so there is no regular distribution of the residuals. Above result help to increase the confidence in consistency and efficiency of estimated parameters.

In general, testing showed that there were no issues with heteroskedasticity in the model we used to analyze our data. This allowed us to assume that the error variance was equally distributed [24-25].

The way in which the observed data points behave in relation to the model's calculated values (fit) and the residuals is also essential to analyze. The graph below will show both the actual and the predicted values of the model along with the associated residuals to the estimated specification.

Figure 4.2. Actual values, predicted values, and residual series for Azerbaijan's industrial organization from 2010 to 2024 is depicted in Figure 4.2



Source: *prepared using EViews-12 econometric program.*

The estimated (fitted) series and the real (actual) series displayed in this graph are closely aligned with each other in terms of the trajectory taken by them over a specified time period. The proximity of the two series contributes towards the explanatory power of the model and its capacity to represent the variation in the data.

When we look at the residual part, we can see that the deviations are evenly scattered around zero with no specific pattern. This kind of distribution of residuals indicates that the model is correctly specified, and the basic statistical

assumptions of the model are not being violated. The absence of a large magnitude of residuals indicates model stability and thus

predictive reliability. The agreement between the observed and predicted values along with the random dispersion of residuals demonstrate the

adequacy of the model.

Conclusions and Policy Recommendations.

The results of the empirical research show that supply chain performance, artificial intelligence, digital infrastructure, and environmental conditions have a significant effect on supply chain performance in the industrial sector in Azerbaijan. The log-linear estimation shows that one of the significant and important determinants of economic efficiency is the level of artificial intelligence implementation. Improvements in automatic decision-making, improved data processing, optimised logistics and optimised resource allocation are the reasons for this influence.

Meanwhile, the significant elasticity of the indicator of natural capital preservation makes it evident that environmental sustainability is now becoming more and more important in terms of its relation to economic sustainability. As such, ecological factors are not just related to social factors or regulations, but also directly related to economic results. The fact that the development of ICT has a positive impact indicates that the digital infrastructure supports the implementation of innovative technology in supply chains.

The Green Economic Opportunity variable has a comparatively lower statistical significance as compared to other variables, indicating that it will likely have a slow and subtle effect on the growth of the economy. The high degree of accuracy exhibited by the model as well as the high degree of statistical significance of all the variables and the lack of heteroskedasticity based on diagnostic tests indicate a high level of robustness of this model. The validity of the estimated model is confirmed by the similar predicted and actual data results.

There are practical implications to be discussed due to the above factors:

Broader application of AI-based decision support systems for industrial companies in areas like Demand Forecast, Inventory Control, Route Planning and Risk Mitigation.

Development and improvement of digital infrastructures and consolidated data systems in all organizations.

Incorporate sustainability through efficient use of natural resources as part of a larger economic efficiency objective, with a stronger focus on sustainable logistics.

Developing human resources through training programs specialized in artificial intelligence (AI) technologies and developing skills in analytical thinking and digital management.

The creation of integrated policy frameworks at the national level will bring together three different areas--digital transformation,green economy and industrial innovation.

The findings of the research demonstrate that artificially-intelligent (AI) decision-making systems represent more than just a technological breakthrough - they represent a strategic tool to improve the efficiency, resilience, and competitive nature of supply chains.

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TƏCHİZAT ZƏNCİRLƏRİNDƏ SÜNİ İNTELLEKTİYA İLƏ QƏRAR QƏBUL MODELLƏRİNİN İQTİSADİ TƏSİRLƏRİ

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Xülasə: Süni intellektin (Sİ) təchizat zəncirlərinə inteqrasiyası rəqəmsal texnologiyaların inkişafı ilə biznes əməliyyatlarının və iqtisadi göstəricilərin yaxşılaşdırılmasının əsas komponentinə çevrilmişdir. Bu məqalədə Sİ ilə idarə olunan qərar qəbuletmə sistemlərinə iqtisadi təsir araşdırılıb. Bu texnologiyaların istifadəsinin qısa və uzunmüddətli təsirlərini araşdırmaq üçün ARDL modeli ilə əlaqəli ECM ilə birlikdə qabaqcıl ekonometrik metodlardan istifadə olunur. Nəticələrimiz göstərir ki, təchizat zənciri sənayesində Sİ-nin tətbiqi logistika əməliyyatlarında xərclərə qənaət, eləcə də daha dəqiq biznes qərarlarının qəbul edilməsi daxil olmaqla bir sıra üstünlüklərlə nəticələnəcək. Qısamüddətli dövrdə təchizat zənciri müəssisələrinin fəaliyyətini məhdudlaşdıracaq irihəcmli ilkin kapital qoyuluşu və cari texnoloji risklər mövcud olacaqdır.
Açar sözlər: Süni intellekt, təchizat zəncirləri, iqtisadi təhlil, ARDL metodu, qərar modelləri, iqtisadi uğur

ЭКОНОМИЧЕСКИЕ ПОСЛЕДСТВИЯ ИСПОЛЬЗОВАНИЯ МОДЕЛЕЙ ПРИНЯТИЯ РЕШЕНИЙ НА ОСНОВЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В ЦЕПОЧКАХ ПОСТАВОК

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Резюме: Интеграция искусственного интеллекта (ИИ) в цепочки поставок стала ключевым компонентом улучшения бизнес-операций и экономических показателей благодаря развитию цифровых технологий. В данной статье исследуется экономическое влияние систем принятия решений на основе ИИ. Для изучения краткосрочных и долгосрочных последствий использования этих технологий применяются передовые эконометрические методы, в том числе модель ARDL с соответствующей моделью ECM. Наши результаты показывают, что внедрение ИИ в цепочку поставок приведет к ряду преимуществ, включая экономию затрат на логистические операции, а также более точное принятие бизнес-решений. В краткосрочной перспективе потребуются значительные первоначальные капиталовложения, а также сохранятся технологические риски, которые ограничат деятельность предприятий, работающих в сфере поставок.
Ключевые слова: ИИ, цепочки поставок, экономический анализ, метод ARDL, модели принятия решений, экономический успех