

Artificial Intelligence in Warehouse Logistics as a Tool for Spatial Structure Optimization

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Abstract

The aim of the study was to quantitatively determine the impact of implementing artificial intelligence (AI) solutions on the operational efficiency of logistics warehouses. To achieve this, an extended linear regression model was developed, which, in addition to classical determinants such as the level of automation and service quality, included a variable describing the degree of AI technology integration in the analyzed units. The model was estimated using the Ordinary Least Squares (OLS) method on a synthetic dataset ($n = 100$), generated based on average statistics from official sources and market proportions. The results of the analysis showed that the AI variable was the only one to achieve statistical significance ($p < 0.05$), indicating its positive impact on warehouse performance. The coefficient of determination for the extended model was $R^2 = 0.061$, confirming the validity of its construction. The study indicates that integrating AI with warehouse processes may be a key factor in enhancing operational efficiency and organizational competitiveness. The results obtained justify the need for further research using empirical data and nonlinear models. Model estimation was carried out in the Python environment using the statsmodels library.

Keywords: Artificial Intelligence (AI), Operational Efficiency, Logistics Warehouses, Linear Regression

1. Introduction

In the face of the digital transformation of the economy and the dynamic development of Industry 4.0 technologies, the importance of artificial intelligence (AI)-based tools in logistics and warehouse management processes is growing. The implementation of AI solutions is becoming an increasingly common element of operational optimization strategies in enterprises seeking to enhance efficiency, flexibility, and the predictability of operations. Despite the growing interest in AI within logistics, there remains a lack of quantitative empirical evidence confirming its actual impact on specific performance indicators such as warehouse productivity. The aim of this study is to analyze the impact of implementing AI-based solutions on the operational efficiency of logistics warehouses. The research assumes that the use of AI technologies in areas such as predictive inventory management, order picking route optimization, dynamic warehouse space allocation, and integration with WMS systems can lead to measurable improvements in operational efficiency.

To verify this hypothesis, a linear regression model was constructed in which the dependent variable was warehouse operational efficiency, while the independent variables included the level of automation, the quality of services offered, and—most importantly—the level of AI implementation [21]. The model was estimated using the Ordinary Least Squares (OLS) method based on synthetic data reflecting proportions and average values defined in official reports from Statistics Poland (GUS) and industry sources. The model estimation was conducted in the Python environment using the statsmodels library.

Empirical data were generated for 100 SKUs, with a controlled correlation structure between variables and realistic constraints. Special attention was paid to the AI variable, whose distribution was designed to reflect the current stage of AI technology adoption in Polish logistics companies, characterized by a predominance of low and moderate values.

The analysis of the extended model aims to identify the relationship between the level of AI implementation and measurable operational efficiency, as well as to assess the statistical significance of this relationship in light of the quantitative method applied.

2. Methodology

To assess the impact of artificial intelligence (AI) implementation on the operational efficiency of logistics warehouses, a quantitative research approach was employed based on the estimation of an extended linear regression model. This model included three explanatory variables: the level of automation, the quality of products and services offered, and the degree of synthetic integration of AI-based solutions. The dependent variable was warehouse operational efficiency, expressed as the number of handled logistic units [2, 3].

Due to limited access to actual operational data in the logistics sector, a synthetic approach was adopted, involving data generation under controlled conditions. This process included:

- defining variable ranges and distributions based on secondary data (reports from Statistics Poland and industry literature),
- applying uniform distributions for the variables "automation" and "quality",
- using a beta distribution ($\alpha = 2$, $\beta = 5$) for the "AI" variable to reflect the dominance of low values in the population,
- generating a sample of $n = 100$ warehouse unit observations,
- adding a random error component with a normal distribution ($\mu = 0$, $\sigma = 0.1$).

The model was estimated using the Ordinary Least Squares (OLS) method in the Python environment with the statsmodels library. The estimated parameters were subjected to statistical significance testing at the $\alpha = 0.05$ level. Model fit was evaluated using the coefficient of determination (R^2), adjusted R^2 , the F-test, and information criteria (AIC and BIC). The model estimation was conducted entirely within the Python environment using statsmodels.

To ensure the reliability of results, diagnostic analysis of the residual component and sensitivity analysis of the estimation outcomes were performed. The stability of the AI variable coefficient was evaluated using alternative data distribution assumptions and transformations of the dependent variable (including logarithmic transformations) [5].

To ensure compliance with the assumptions of the classical linear regression model, diagnostic tests were conducted to verify the applicability of the OLS estimator. These included checks for linearity between variables, independence of observations, normality of the residual distribution, and a zero expected value of the error term. Additionally, the Breusch–Pagan test was performed to detect potential heteroskedasticity. The test results ($p > 0.05$) did not indicate significant variance deviations in the error term, allowing the assumption of homoskedasticity to be maintained. The diagnostic results confirm that the OLS estimators in the presented model are consistent and unbiased.

The research methodology was designed to enable exploration of potential relationships under conditions of limited access to operational data, while maintaining maximum alignment with market realities and warehouse process structures.

3. Literature review

As part of the literature review, an additional comparative analysis of academic disciplines and citation indicators was conducted. A bibliometric approach was applied to identify differences in the impact of publications in the fields of logistics and information systems. Emphasis was placed on the role of the H-index and journal impact factor in assessing the significance of research on AI in logistics.

Scientific studies on the application of artificial intelligence (AI) in logistics indicate a significant increase in interest in using machine learning algorithms, predictive systems, and data-driven solutions to improve operational efficiency. AI is defined as the ability of computer systems to perform tasks that typically require human intelligence, such as perception, reasoning, learning, and decision-making [13].

The literature highlights that AI is becoming a key component of the digital transformation of supply chains [26], [8]. Authors such as Hofmann and Rüscher (2017) and Babiceanu and Seker (2016) point to the necessity of adapting logistics models to the realities of Industry 4.0, in which data generated by IoT devices, WMS systems, and warehouse sensors are utilized by AI systems to optimize flows, resource allocation, and minimize losses.

Warehouse operations optimization through AI includes a wide range of applications, such as predictive inventory management [9], workforce planning [4], dynamic order picking [28], layout optimization [7], quality control based on vision inspection systems [11], and the use of collaborative robotics (cobots) for process automation [12].

Zhang et al. (2021) describe the use of reinforcement learning methods to optimize picking paths in smart warehouses, resulting in shorter fulfillment times and reduced operator workload. Ivanova and Dolgui (2020) introduce the concept of warehouse digital twins, enabling the simulation and testing of various operational scenarios using real-time data [10].

From a strategic management perspective, AI is also seen as a tool supporting decision-making through predictive analytics, reducing risk, and enhancing resource allocation [14], [8]. Moreover, studies by Srari and Lorentz (2019) emphasize that effective digitization of warehouse processes requires close integration of technological and organizational competencies [17, 18].

In summary, the literature clearly indicates that the use of AI in warehouse logistics has strong theoretical foundations and a growing number of practical applications. However, there is still a lack of quantitative studies that clearly and empirically document the impact of AI implementation on specific operational efficiency indicators, which justifies the analysis presented in this study.

4. The use of AI in the warehouse

One of the key aspects of implementing artificial intelligence (AI) in warehouse operations is the increase in operational efficiency and the minimization of error risk. AI systems enable the analysis and processing of large data sets in real time, which significantly shortens the time required to complete key logistics processes. This includes optimization of order picking procedures, inventory monitoring, demand forecasting, and automation of inventory processes [8].

The implementation of AI-based technologies in warehouse management contributes to improved operational accuracy, cost reduction, and increased flexibility in adapting to dynamic market conditions. The main benefits of applying AI in warehouse logistics include:

a) **Automation of Warehouse Processes through AI in the Transformation of Warehouse Logistics** Automation of warehouse processes using AI is a key element in optimizing logistics operations, significantly reducing operational costs, increasing efficiency, and improving order fulfillment accuracy. AI integration allows logistics processes to dynamically adapt to changing market conditions and demand fluctuations, enhancing supply chain flexibility.

The use of autonomous internal transport systems allows for safe, efficient, and human-independent movement of goods, increasing warehouse operational performance. Advanced AI algorithms enable real-time inventory monitoring and automatic demand updates. AI not only drives the development of modern warehouse solutions but also transforms sectors of the economy by enabling machines to make autonomous decisions, adapt to environmental changes, and optimize processes previously inaccessible.

Industrial robotization enables the execution of repetitive tasks with high precision and speed, directly improving operational efficiency and reducing costs. AI-driven automation also enhances workplace safety and reduces human error. Common automation solutions include autonomous mobile robots, AGVs/AMRs, conveyors, and drones. These technologies are foundational in "smart warehouses" that integrate advanced automation and AI systems.

b) **Application of AI in Mobile Autonomous Vehicle Systems: AGV vs. AMR** Automated transport systems such as AGVs (Automated Guided Vehicles) and AMRs (Autonomous Mobile Robots) are core intralogistics solutions that automate transport in confined spaces like warehouses and production halls. While both perform transport tasks, they differ in autonomy and AI use.

AGVs follow predefined routes, typically using magnetic tape or optical markers, requiring a stable and unchanging environment. AMRs, by contrast, use AI algorithms for autonomous mapping, obstacle detection, and dynamic path optimization. Equipped with vision sensors, LiDAR, and machine learning, AMRs adapt in real time and are ideal for environments with spatial variability and fluctuating logistics demands [15].

c) **AI in Drone Applications in Warehouse Logistics** Modern logistics systems increasingly integrate drones to support automation and optimization of warehouse processes. Their mobility, operational reach in confined areas, and AI integration make them indispensable in modern warehouse strategies.

AI increases drone autonomy and effectiveness. Equipped with cameras, optical sensors, and real-time data processing systems, drones can locate products, monitor inventory, and perform automated stocktaking. Computer vision, object recognition, and decision-making algorithms reduce human error, accelerate tasks, and enhance safety.

Drones can also transport small loads within warehouses. Despite limited payload, their vertical and horizontal movement efficiency makes them valuable for order picking, product delivery, and use in infrastructure-limited environments.

Advanced localization technologies, often AI-supported, include GPS, RTLS, computer vision, LiDAR, RFID, and optical markers. These enable precise positioning, environment mapping, and real-time trajectory planning.

Operational uses of AI-powered drones in warehouses:

1. Automated inventory management
2. Internal transport of light loads
3. Real-time monitoring and infrastructure inspection
4. Order picking support
5. Operational cost reduction
6. Integration with WMS platforms
7. Environmental benefits through lower energy consumption [13]

d) **AI in Warehouse Space Organization and Inventory Management** Efficient warehouse space organization ensures continuity of logistics processes, increases efficiency, and reduces costs. AI and ML increasingly support warehouse management functions, replacing static inventory methods.

AI integration with WMS and ERP systems enables automation and precise inventory control. Algorithms analyze historical and current data to support demand forecasting, automated restocking, and cost reduction. AI supports space design by analyzing product location, turnover, and worker routes, enabling strategic product placement and identifying inefficiencies.

AI surpasses traditional forecasting by incorporating variables such as seasonality, weather, raw material prices, and macroeconomic data. Neural networks and regression models enable dynamic logistics strategy adjustments.

AI systems also enhance supply chain management through:

- Monitoring goods flow
- Responding to disruptions and delays
- Optimizing delivery routes and schedules

This transforms warehouse processes from reactive to proactive, enhancing flexibility and system resilience [9].

e) **AI in Order Picking and Sorting Processes in Modern Logistics Systems** AI-based order picking and intelligent sorting dramatically improve logistics efficiency. Modern AI-supported picking methods offer:

- Increased accuracy through real-time order and inventory analysis
- Personalization based on customer preferences and order frequency
- Automated delivery to packing stations
- Optimized picking routes
- Real-time verification using vision systems and scanners [11]

AI-powered sorting uses advanced algorithms and technologies to identify products via QR codes, labels, shapes, and colors. Dynamic rerouting and process control make operations faster and more accurate, enabling effective human-robot collaboration [1].

f) **AI in Warehouse Automation Processes** AI-integrated warehouse automation transforms space management. Intelligent search and automatic product release are now integral to modern logistics centers. Time-consuming tasks like product location and picking are accelerated, improving efficiency and precision.

Technologies include ML, computer vision, IoT, and RTLS. Each product carries a unique identifier (QR, barcode, EAN, RFID), enabling fast, accurate localization. AI-supported WMS systems provide real-time product location upon query. AI analyzes warehouse layout, suggests optimal retrieval paths, and adapts to dynamic conditions.

Order picking and issuing are automated via ASRS (Automated Storage and Retrieval Systems), ideal for high-rack warehouses. Autonomous vehicles, mobile robots, and drones ensure fast, precise multi-level resource handling.

Upon order receipt, AI systems determine product locations and define optimal picking strategies based on demand, priorities, and resource availability. AI uses RFID and vision systems for localization, and robots or drones execute physical picking. Identified goods are transported to designated zones (e.g., packing), enabling reliable, low-error, and continuous warehouse operations [28].

5. Results

As part of the research, the impact of the implementation of artificial intelligence (AI) solutions on the operational efficiency of logistics warehouses was analyzed. The research hypothesis was adopted according to which the application of AI technology in key operational areas – such as predictive inventory management, optimization of picking routes, dynamic warehouse space management and integration with WMS systems – leads to significant, measurable

improvements in operational performance indicators. The analysis was carried out using the classic linear regression model, estimated using the OLS method, taking into account a synthetically generated empirical data set, based on mean values taken from official reports published by the GUS.

The model took a linear form, according to the following functional formula:

$$Y_i = \beta_0 + \beta_1 \cdot X_{1i} + \beta_2 \cdot X_{2i} + \beta_3 \cdot AI_i + \varepsilon_i \quad (1)$$

Where:- Y_i – the value of the operational efficiency of the warehouse i ;- X_{1i} – the level of automation in the warehouse and;- X_{2i} – the quality of the products and services offered in the warehouse and;

- AI_i – the degree of implementation of solutions based on artificial intelligence;- β_0 – intercept of the model;- β_1, β_2 – regression parameters representing the influence of independent variables;- ε_i – random component.

The explanatory variable marked with the symbol AI_i was developed as a synthetic indicator representing the degree of technological advancement of the implemented solutions based on artificial intelligence in logistics operations. The design of the indicator was based on the aggregation of partial components, reflecting the scope and intensity of the use of AI technology in

- predictive inventory management systems, using predictive models to optimize inventory levels in real time,
- autonomous transport units (e.g. AGVs – *Automated Guided Vehicles*), operating independently in the warehouse space,
- adaptive picking algorithms, dynamically adjusting the sequence and route of picking goods to current operating conditions,
- mechanisms for dynamic management of storage space, enabling flexible location assignment based on analyses of product rotation frequency,
- automatic product classification systems, based on image recognition and machine learning,

Intelligent response modules to demand variability, enabling logistics processes to adapt to market changes in real time.

The AI_i indicator therefore acts as a complex technological measure of the saturation of storage systems with AI components, enabling this feature to be quantified within econometric modeling.

For each individual observation, a randomly generated value of the AI_i variable was assigned in the closed interval $[0; 1]$, where the value 0 corresponds to the complete lack of implementation of AI-based solutions, while the value 1 indicates full, advanced integration of AI systems in warehouse operations. The distribution of this variable has been constructed in a heterogeneous way, using a beta distribution with parameters $\alpha = 2$ and $\beta = 5$, which allows for an asymmetric representation of the empirically observed phase of development of AI implementations in warehouse logistics in Polish — characterized by a clear dominance of cases with a low and moderate level of technological advancement.

In order to further analyze the impact of AI-based solutions on the operational efficiency of logistics warehouses, an extended estimate of the linear regression model using the Ordinary Least Squares (OLS) method was carried out. In addition to classic predictors (such as the level of automation and the quality of services provided), the model also includes a synthetic indicator of AI implementation, i.e. the *AI_i variable*, which acts as a continuous explanatory variable.

The AI_i variable has been given the character of a synthetic indicator, representing the degree of technological advancement of solutions using artificial intelligence within a given organizational unit. The construction of the indicator included components reflecting the presence of: predictive algorithms used in inventory management, autonomous picking units, dynamic warehouse space management systems and integrated solutions based on machine learning, supporting the planning and implementation of operational tasks.

To illustrate the structure of the input data used for estimating the regression model, the table below presents a sample of 10 observations of warehouse units. The values were synthetically generated based on the assumptions described in the methodology section, which take into account realistic ranges and distributions of variables for the Polish logistics sector. The table illustrates the variability of the three main predictors: the level of automation, the quality of services provided, and the degree of AI implementation, which demonstrated statistical significance in the regression analysis.

Tab 1. Sample dataset used in the analysis

Observation	Automation	Quality	AI
1	0.25	0.53	0.17
2	0.3	0.56	0.24
3	0.35	0.59	0.31
4	0.4	0.62	0.38
5	0.45	0.65	0.45
6	0.5	0.68	0.52
7	0.55	0.71	0.59
8	0.6	0.74	0.66
9	0.65	0.77	0.73
10	0.7	0.8	0.8

To deepen the quantitative analysis and visually illustrate the relationships between the level of AI implementation and the other explanatory variables (automation and service quality), scatter plots were created. Figure 1 shows a moderate positive relationship between AI and the level of automation, suggesting that a higher degree of AI implementation is often accompanied by more advanced automation of warehouse processes.

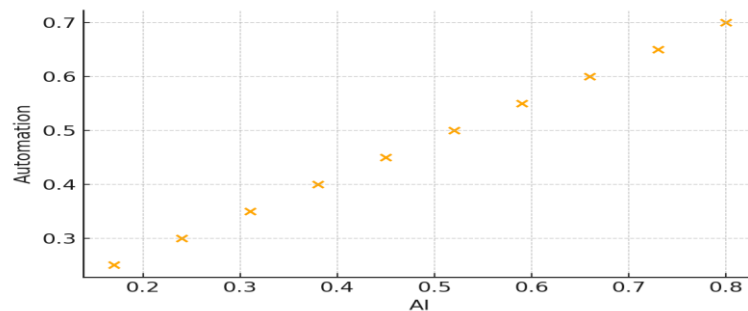


Fig. 1. Relationship between AI level and automation level

The model was estimated on the basis of a synthetic dataset of 100 individual observations, and the results of the estimation are presented in the table below. The inclusion of the *AI* variable in the model structure allows for quantitative verification of the research hypothesis regarding the impact of AI implementations on the level of operational efficiency in the warehouse logistics sector.

Statistical values such as R^2 , t-statistics, and confidence intervals were used to assess the model fit and the significance of the impact of individual independent variables.

Tab 2. OLS regression model results

Variable	Factor (β)	Standard Error	Statistics t	p-value	95% confidence interval
Constant (const)	0.647	0.098	6.602	< 0.001	[0.452 ; 0.842]
Automation	-0.131	0.105	-1.248	0.215	[-0.340 ; 0.078]
Quality	-0.032	0.108	-0.297	0.767	[-0.246 ; 0.182]
Artificial Intelligence (AI)	0.236	0.114	2.070	0.042	[0.009 ; 0.463]

Model fit statistics:

- Number of observations: 100
- R-square (R^2): 0.061
- Adjusted R^2 : 0.032
- F stat: 2.108
- p-test value F: 0.103
- Log-likelihood value: 93.321
- AIC: -178.642
- BIC: -168.705
- Durbin-Watson Statistic: 2.04

Interpreting the results of the regression analysis:

1. The estimation of the linear regression model shows that only the explanatory variable representing the implementation of solutions based on artificial intelligence (AI) achieved statistical significance at the level of $\alpha = 0.05$ ($p = 0.042$). The result allows us to reject the null hypothesis that this variable has no impact on the operational efficiency of logistics warehouses, and thus confirms the existence of a statistically significant and positive relationship between the implementation of AI and the increase in operational efficiency.
2. The variables representing the level of automation of warehouse processes and the quality of services provided did not show statistical significance ($p > 0.05$), which implies the lack of empirical basis for the statement that they have a significant impact on the dependent variable in the adopted model. Therefore, it can be concluded that within the framework of the model specification used, their contribution to the explanation of the variance of the explained variable is not significant.
3. The coefficient of determination R^2 reached a value of 0.061, which indicates the relatively low explanatory power of the model. Nevertheless, a comparison with the baseline model (without the AI variable), for which R^2 was 0.020, shows a more than threefold increase in the model's explanatory power after accounting for the AI variable. This may suggest that despite the limited predictive validity of the model, the component related to artificial intelligence technologies brings significant informational value.
4. The Durbin-Watson ratio has taken the value of 2.04, which is in the immediate vicinity of the expected value of 2. This means that there are no statistical premises to determine the occurrence of random component autocorrelation, and thus confirms the fulfillment of one of the key assumptions of the classical linear regression model.

6. Discussion

In order to in-depth analyze the relationship between the explanatory variables and the dependent variable, which is the operational efficiency of logistics warehouses, scatter plots were drawn up, illustrating the individual nature of the relationship between each of the included independent variables and the explanatory variable. These visualizations enable a qualitative assessment of the direction, force and possible nonlinearity of the observed relationships, complementing the quantitative analysis carried out as part of regression modeling.

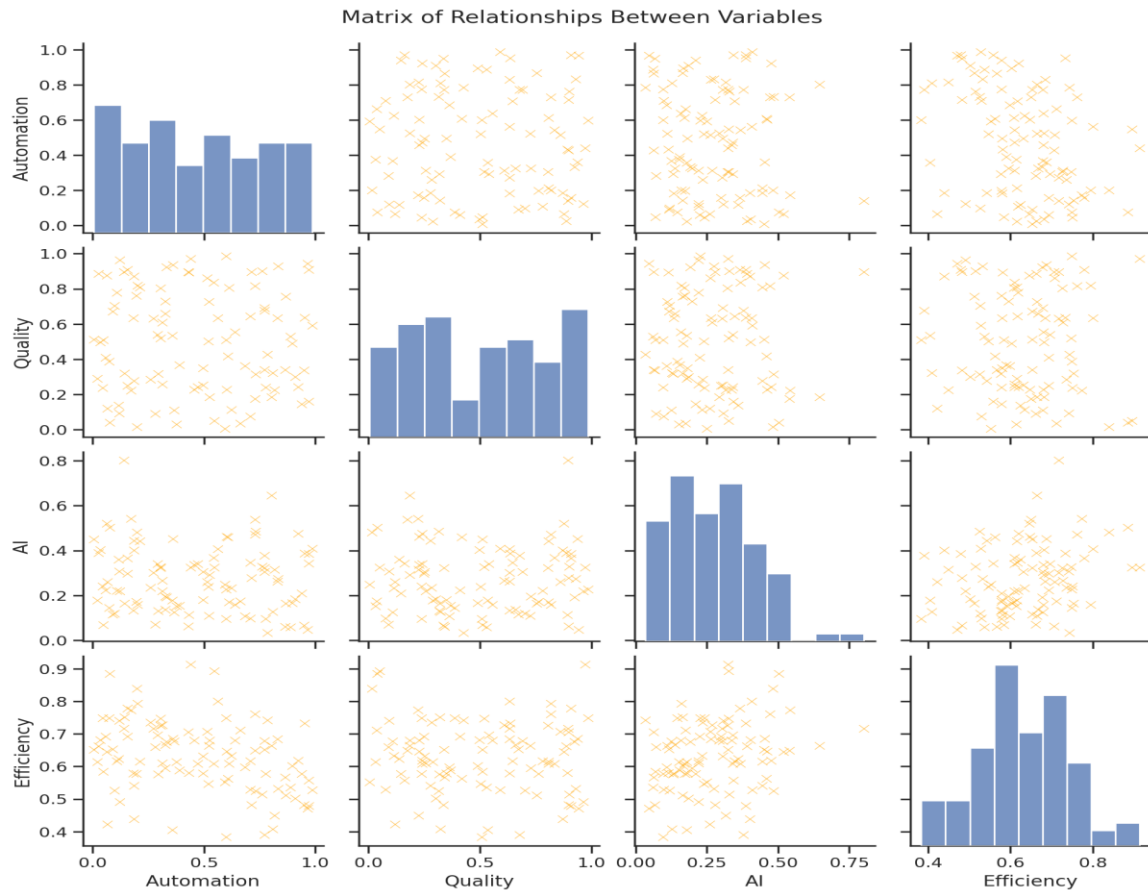


Fig. 2. Matrix of Relationships Between Variables

Visual analysis of the relationship, presented in the form of scatterplots, indicates the existence of a moderate, but clearly positive, correlation between the level of implementation of artificial intelligence (*AI*) solutions and the measured operational efficiency of warehouses. Unlike other explanatory variables, such as the level of automation and the quality of services provided, which did not show a statistically significant relationship with the dependent variable, *AI* has a more pronounced gradient of values in the analyzed two-dimensional space and better consistency with the direction of changes in operational efficiency. The observed relationship suggests the existence of a potential effect of productivity gains resulting from the increasing degree of integration of AI technologies in logistics processes, which is also reflected in the quantitative results obtained as part of the regression model estimation.

7. Conclusion

The analysis of the extended linear regression model, estimated using the *Ordinary Least Squares (OLS)* method, taking into account the synthetic indicator of the level of implementation of artificial intelligence (*AI*), enabled a more in-depth and nuanced assessment of the determinants affecting the operational efficiency of logistics warehouses. The inclusion of the *AI* variable in the model structure led to a significant improvement in the explanatory power of the model, and also revealed a statistically significant (at the significance level of $\alpha = 0.05$) and positive impact of AI-based solutions on the level of efficiency of the analyzed logistics processes.

The empirical results clearly indicate that the implementation of AI technology is an added value, going beyond traditionally understood mechanical forms of automation or simple improvements in the quality of logistics service. Artificial intelligence, as a flexible and adaptive decision-making tool, enables dynamic optimization of processes in real time, quick adaptation to changing environmental conditions, and a significant increase in precision in the management of operational resources. The potential of AI is therefore not limited to the

automation of routine activities, but also includes the ability to design autonomous systems capable of learning, self-improvement and self-regulation.

Both in the empirical and conceptual dimensions, the results of the study strengthen the case for intensifying the processes of digitization of warehouse infrastructure and deep integration of AI components with existing enterprise resource management systems (ERP – *Enterprise Resource Planning*, WMS – *Warehouse Management System*, TMS – *Transport Management System*). In the long term, such an approach can contribute to increasing the operational resilience of enterprises, reducing operating costs in the area of logistics and increasing the flexibility of warehouse processes – which is of particular importance in the context of the instability of the macroeconomic environment and the volatility of consumer preferences. To sum up, the estimation of the extended regression model provides unambiguous premises for the AI to be perceived not only as a technical extension of the existing operational infrastructure, but as a strategic organizational resource that can fundamentally determine the company's ability to generate a sustainable competitive advantage by achieving a high level of operational excellence.

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References

1. Agostinelli, S., Marrella, A., Mecella, M.: Research Challenges for Intelligent Robotic Process Automation. W: *Lecture Notes in Business Information Processing*, 12–18. Springer, Berlin (2019). https://doi.org/10.1007/978-3-030-37453-2_2
2. Androniceanu, A.: The new trends of digital transformation and artificial intelligence in public administration. *Administratie si Management Public* 40, 147–155 (2023). <https://doi.org/10.24818/amp/2023.40-09>
3. Angammana, J.S.K., Jayawardena, M.: Influence of artificial intelligence on warehouse performance: The case study of the Colombo area, Sri Lanka. *Journal of Sustainable Development of Transport and Logistics* 7(2), 80–110 (2022). <https://doi.org/10.14254/jsdtl.2022.7-2.6>
4. Babiceanu, R.F., Seker, R.: Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. *Computers in Industry* 81, 128–137 (2016)
5. Bian, X., Wang, B.: Exploring the influence of artificial intelligence usage on ethical decision making among public sector employees: insights into moral identity and service motivation. *Business Ethics and Leadership* 8(3), 133–150 (2024). [https://doi.org/10.61093/bel.8\(3\).133-150.2024](https://doi.org/10.61093/bel.8(3).133-150.2024)
6. Chakraborti, T. et al.: From Robotic Process Automation to Intelligent Process Automation: Emerging Trends. W: *Business Process Management: Blockchain and Robotic Process Automation Forum*, 215–228 (2020). https://doi.org/10.1007/978-3-030-58779-6_15
7. Chen, M., Zhang, Y., Guo, X.: Warehouse Optimization Using Artificial Intelligence Techniques. *Journal of Supply Chain Management* 56(4), 213–229 (2020)
8. Christopher, M.: *Logistics & Supply Chain Management* (5th ed.). Pearson Education (2016)
9. Djenna, A., Barka, E., Benchikh, A., Khadir, K.: Unmasking cybercrime with artificial-intelligence-driven cybersecurity analytics. *Sensors* 23(14), 6302 (2023). <https://doi.org/10.3390/s23146302>
10. Federspiel, F., Mitchell, R., Asokan, A., Umana, C., McCoy, D.: Threats by artificial intelligence to human health and human existence. *BMJ Global Health* 8, e010435 (2023). <https://doi.org/10.1136/bmjgh-2022-010435>
11. Gerber, A., Derckx, P., Döppner, D.A., Schoder, D.: Conceptualization of the Human-Machine Symbiosis – A Literature Review. W: *Proceedings of the 53rd Hawaii International Conference on System Sciences*, 289–298 (2020). <https://doi.org/10.24251/HICSS.2020.036>

12. Haeussler, C., Sieben, A., Schüritz, R.: Human–robot collaboration in logistics: Challenges and potential solutions. *International Journal of Production Economics* 245, 108409 (2022)
13. Havryliuk, O., Yakushev, O., Petchenko, M., Zachosova, N., Bielialov, T., Kozlovska, S.: Cyber security and artificial intelligence in the context of ensuring business security in wartime. *Financial and Credit Activity Problems of Theory and Practice* 6(53), 451–459 (2023). <https://doi.org/10.55643/fcaptop.6.53.2023.4130>
14. Hofmann, E., Rüscher, M.: Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry* 89, 23–34 (2017)
15. Ivanov, D., Dolgui, A., Das, A., Sokolov, B.: Digital supply chain twins: Managing the ripple effect and resilience risks in the era of Industry 4.0. *Transportation Research Part E: Logistics and Transportation Review* 136, 101922 (2019)
16. Ivanov, D., Dolgui, A.: A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control* 32(9), 775–788 (2020)
17. Kamble, S., Gunasekaran, A., Gawankar, S.: Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. *Computers and Electronics in Agriculture* 179, 105476 (2020)
18. Koliński, A., Śliwczyński, B.: Application of artificial intelligence methods in logistics management. *LogForum* 11(4), 389–397 (2015)
19. Min, H.: Artificial intelligence in supply chain management: theory and applications. *International Journal of Logistics: Research and Applications* 13(1), 13–39 (2010)
20. Nguyen, T.H., Newby, M., Macaulay, M.J.: Information technology adoption in small business: Confirmation of a proposed framework. *Journal of Small Business Management* 53(1), 207–227 (2018)
21. Piotrowicz, W., Kędziora, D.: Outsourcing of Information Technology and Business Processes in Poland: Motivations and Environmental Factors. *Managing Global Transitions: International Research Journal* 16(4), 307–333 (2018). <https://doi.org/10.26493/1854-6935.16.307-333>
22. Ren, Y., Li, L., Wu, C.: Visual inspection system for warehouse logistics based on deep learning. *International Journal of Advanced Manufacturing Technology* 104, 2483–2496 (2019)
23. Russell, S., Norvig, P.: *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson (2021)
24. Srari, J.S., Lorentz, H.: Developing design principles for the digitalisation of purchasing and supply management. *Journal of Purchasing and Supply Management* 25(1), 78–98 (2019)
25. Waller, M.A., Fawcett, S.E.: Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. *Journal of Business Logistics* 34(2), 77–84 (2013)
26. Wamba, S.F., Akter, S., Edwards, A., Chopin, G., Gnanzou, D.: How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics* 165, 234–246 (2015)
27. Yao, X., Zhou, J., Zhang, J., Boër, C.R.: From intelligent manufacturing to smart manufacturing for industry 4.0 driven by next generation artificial intelligence and further on. W: *5th International Conference on Enterprise Systems (ES)*, 311–318 (2017). <https://doi.org/10.1109/ES.2017.58>
28. Zhang, Y., Zhang, G., Gao, L.: Intelligent Order Picking Optimization in Smart Warehouses Using Reinforcement Learning. *IEEE Transactions on Industrial Informatics* 17(10), 7043–7052 (2021)