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Analysis of Artificial Intelligence on Warehouse Management in the Peruvian Pharmaceutical Sector: A Quantitative Study

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Abstract*– This study analyzes the impact of artificial intelligence (AI) in optimizing warehouse management in the Peruvian pharmaceutical sector. A quantitative, non-experimental, cross-sectional design was used, with a sample of 80 companies in the sector. Statistical analyzes were applied to evaluate the relationship between AI and logistics efficiency. The results indicate that AI significantly improves cost reduction and time optimization in the supply chain. Three key areas were identified: process automation, systems integration and data analysis. The strongest influence was found in data analysis, with a 44.6% impact on cost reduction and 46.6% on time optimization. Automation contributed 31% to cost reduction, while systems integration improved time by 26%. Additionally, it was observed that companies that implemented AI achieved a 20% reduction in frozen stock and an 18% decrease in delivery delays. The correlation between time optimization and cost reduction was high (85.8%), showing that the use of AI generates comprehensive improvements in logistics. It is concluded that AI is a key tool to improve the efficiency and competitiveness of the pharmaceutical sector, facilitating data-based decision making and optimizing warehouse management.

***Keywords*-- Logistics Chain Optimization, Artificial intelligence, Pharmaceutical Warehouses, Automation Processes, Integrated Systems.**

I. Introduction

Currently [1] artificial intelligence (AI) has become an essential technological tool in all types of sectors, since it has managed to revolutionize all areas, due to its great data processing capacity, which It allows decision-making in a strategic, precise and anticipated manner [2]. According to [3] and [4] its impact has transcended not only the medical, financial, manufacturing industry, but it has also positively impacted the logistics sector, where its implementation has contributed positively in several aspects, especially in its operational part, optimizing in this way your inventory management, avoiding shortages and increasing the precision in your distribution and supply routes. Its use has allowed the reduction of costs and minimizing errors, generating a positive impact on both clients and suppliers since their deliveries are faster and more precise [5].

The Peruvian pharmaceutical sector has represented one of the fundamental pillars of the Peruvian economy and health in recent years, where [6] point out that this sector has generated income of over four billion dollars for the country, despite [7] points out that this industry faces many challenges related to its supply management, poor inventory controls, and excessive costs in operational times. In this scenario [8] highlights the use of new technologies where artificial intelligence stands out for its ability to optimize processes, thereby guaranteeing correct warehouse management. The correct use of artificial intelligence, in addition to the optimization of processes, also has the ability to handle and process large amounts of data so that all the information collected can be used in a more accurate analysis, thereby being able to make a more informed decision making [9].

According to [10] maintain that the use of artificial intelligence within the Peruvian pharmaceutical sector has become a primary tool, allowing to guarantee the correct and timely supply of medicines and other products related to this area. Another advantage of its use is that you can have a complete and real-time view of your entire supply line, and may even be able to prevent possible logistical problems that may occur along the way, your dispatch or others that may occur [11]. Furthermore, according to [12] artificial intelligence can optimize reception, distribution and return times between suppliers and customers. Its implementation according to [13] can ensure timely anticipation of shortages and overstock of inventories, allowing it to be maintained with great precision, thereby optimizing warehouse management in this type of sector.

The purpose of this research was to analyze to what extent artificial intelligence contributes to optimizing the management of warehouses in the pharmaceutical sector in Peru. The statistical approach used in this research is based on a multiple linear regression model and correlation analysis, thereby allowing us to analyze the multiple relationships between the variables and thus be able to evaluate the impact generated by artificial intelligence in real time, contributing in a way essential in making strategic decisions in this type of industry, thereby improving its competitiveness and efficiency.

II. LITERARY REVIEW

A. Artificial Intelligence

[14] artificial intelligence is the ability of machines to execute roles and tasks that would necessarily require being executed by human beings. [15] maintains that these functions include learning, the development of problems and with the processed data they can have the ability to make decisions, thus allowing them to optimize their performance based on their experience. According to [16] and [17] maintain that artificial intelligence has developed significantly in recent years, and can be applied in various sectors such as finance, commerce, health and logistics.

In the logistics sector, [12] maintain that artificial intelligence stands out in the optimization of operations, thereby allowing the reduction of costs and the increase in the precision of its inventory management and its distribution chain. According to [18], companies use artificial intelligence to optimally address the challenges that exist in a highly competitive market with personalized solutions. In the development of this research, [19] identify three essential dimensions of the application of artificial intelligence in logistics: automation processes; integrated systems and collection; and data analysis. Where each dimension will play an essential role in the optimization of logistics management, allowing companies to improve their performance and allowing their adaptation and better performance in the market.

B. Automatization Process

According to [20], it refers to the use of advanced technologies capable of executing repetitive tasks in a more optimal and efficient manner, thereby reducing errors due to human intervention and optimizing their usefulness. Thus allowing, as [21] points out, the supply chain to be much more agile, more efficient and with an efficient margin of precision. According to [22], these processes include three key areas in logistics: dispatches, order preparation, and loading and unloading operations. Improving automation, in addition to improving productivity in the company, generates a positive impact on its customers and suppliers by reducing times, costs and waiting times.

C. Integrated Systems

According to [23] are technological tools capable of coordinating and centralizing logistics processes in an organization. As noted by [24] the main objective of integrated systems is to be able to improve their traceability, thus contributing to the optimization of resources and the synchronization of each of the activities carried out in the supply chain. Likewise, [25] maintain that the implementation of technologies such as warehouse management systems and radio frequency identification will reduce delays in the execution of processes, thus achieving more efficient administration of resources, avoiding problems and the loss of materials due to expiration or lack of stock. Its correct implementation will allow all types of organizations to optimize their performance and thus be able to ensure an efficient experience for both their clients and their suppliers.

D. Data Collection and Analysis

According to [26], it is one of the most important dimensions of artificial intelligence since its objective is focused on the collection, processing and optimal use of the information collected. Likewise, [27] has the ability to obtain information in real time which allows companies to monitor their inventories and analyze fluctuating market trends. Finally, [28] points out that its use effectively contributes to the optimization of demand forecasts since it will allow companies to have an efficient and correct allocation of resources.

E. Logistic Chain Optimization

According to [29], it refers to the constant evolution of those processes related to supply, storage and distribution. Its primary objective according to [30] is the constant search to be able to optimize the operational efficiency of its processes, guaranteeing that the associated costs are used optimally. In this sense, [12] point out that the optimization of the logistics chain can be achieved with the automation of its processes, this will ensure that resources are used efficiently, thereby reducing losses or waste in inventories, as well as agility. and availability will achieve an efficient supply chain, thereby guaranteeing that operations are more agile and that waiting times are reduced, thus improving supplier and consumer satisfaction.

According to [31] the optimization of the logistics chain is divided into two main dimensions, which are: costs and times. Where the costs focus mainly on the efficiency of the use of the resources assigned in the supply chain without having to compromise the quality of the inputs and the service requested or provided, on the other hand, the time dimension refers mainly to the measurement of the speed and precision with which logistics operations are carried out [28]. Both dimensions seek to improve the competitiveness and sustainability of operations.

III. METHODOLOGY

A. Sample

The present study employs a quantitative, cross-sectional, and non-experimental research design, which allows for the systematic examination of the relationship between artificial intelligence and logistics chain optimization without manipulating variables. A non-probabilistic convenience sampling method was applied, selecting a sample of 80 pharmaceutical companies in Peru, chosen for their extensive experience and proven expertise in the sector. This strategic sampling approach ensures that the selected participants possess in-depth knowledge and practical insights into logistics operations, thus enhancing the study's internal validity and the robustness of the findings.

Table I presents the main variables analyzed in the study, organized according to their corresponding dimensions and indicators. The optimization of logistics chain costs (OLCC) is addressed from the cost dimension, with key indicators such as the quantity of immobilized stock in dollars, the annual percentage of rejected inputs, and the warehouse occupancy rate. These indicators allow for the evaluation of the economic efficiency of logistics management, focusing on reducing costs associated with inventory immobilization and efficient space management. On the other hand, the optimization of logistics chain time (OLCT) is measured through indicators related to quarterly picking accuracy, the number of collected products, and the punctuality of deliveries by suppliers, which are critical factors for improving operational efficiency and ensuring customer satisfaction.

TABLE I
MAIN VARIABLES

Variable	Dimension	Indicator
Optimization of the logistics chain costs (OLCC)	Cost	Quantity of immobilized stock in $
		Annual percentage of rejected inputs
		Warehouse occupancy rate
Optimization of the logistics chain time (OLCT)	Time	Picking accuracy per quarter
		Quarterly picking
		Number of products not delivered on time
Automation processes	Automation processes	Shipments made per hour
		Order fulfillment accuracy
Integrated systems	Integrated systems	Reduction of idle time per month
		Loss of inputs due to expiration per month
Data collection and analysis	Data collection and analysis	Product search time per order
		Stockouts

The table indicates that automation in logistics processes is quantified through the frequency of orders placed for a period of one hour and subsequently measures the accuracy in the execution of its dispatch, thus demonstrating the role that artificial intelligence plays in improving and reducing times and costs of logistics management. Likewise, system integration is analyzed through the reduction of idle time per month and the loss of inputs due to expiration, indicators that provide key information on the effectiveness of warehouse management systems. Finally, data collection and analysis are examined through the product search time per order and the incidence of stockouts, metrics that help identify improvement opportunities in inventory management and data-driven decision-making. These findings are crucial for understanding the impact of artificial intelligence on optimizing the supply chain in the Peruvian pharmaceutical sector.

The table presented indicates how automated processes are evaluated through the number of shipments made per hour and their accuracy in fulfilling orders, which shows the potential that artificial intelligence has to make logistics operations more efficient. Likewise, the articulation of their systems is examined by reducing monthly unproductive time and the waste of inputs generated by their expiration date, parameters that provide significant evidence on the performance of warehouse management systems. Finally, the obtaining and processing of information is analyzed through the time required to search for products per order and the frequency of stock outages due to shortages, indicators that contribute to detecting opportunities in the optimization of inventory management and in the process of making strategic decisions based on data. The results obtained are essential to understand the impact of artificial intelligence on the efficiency of the supply chain in the pharmaceutical sector of Peru.

B. *Regression models*

To obtain the results, a multiple linear regression model and also a correlation analysis were used to identify the impact between the variables and their statistical significance. For this, the estimation method will be ordinary least squares, since it is the method that is very important to make a consistent estimate if it meets the conventional assumptions.

$$y_i = \beta_{i,0} + \beta_{i,1}x_1 + \beta_{i,2}x_2 + \beta_{i,3}x_3 + u_i, \quad \text{for } i = \text{OLCC}, \text{OLCT} \quad (1)$$

Where

y_{OLCC}: Optimization of the logistics chain costs
y_{OLCT}: Optimization of the logistics chain time
x_1: Automation processes
x_2: Integrated systems
x_3: Data collection and analysis
u_i: Disturbance term, $u_i \sim iid(0, \sigma^2)$

The formula represents the estimation process through Ordinary Least Squares (OLS), aiming to obtain unbiased, efficient, and consistent parameter estimates under the standard classical assumptions.

$$SSR = (y_i^T - \beta_i^T X^T)(y_i - X\beta_i) \quad (2)$$

Where SSR is sum square of residuals, $\beta_i = [\beta_{0,1}, \beta_{i,1}, \beta_{i,2}, \beta_{i,3}]^T$ and $X = [1, x_1, x_2, x_3]$.

$$\beta_i = (X^T X)^{-1} X^T y_i \quad (3)$$

This methodological approach ensures a rigorous and reliable analysis, facilitating a deeper understanding of the relationships between the variables and their influence within optimization of the logistics chain.

IV. RESULTS

A. *Descriptive statistics*

Table II presents the descriptive statistics of five key dimensions related to the optimization of the logistics chain through artificial intelligence in the Peruvian pharmaceutical sector. The results show that the mean values across the analyzed dimensions range from 3.422 to 3.508, indicating a homogeneous perception among respondents regarding the benefits of AI implementation in logistics management. The medians (P_{50}) reflect values similar to the means, suggesting a balanced distribution of responses without significant biases. The dispersion of the data, represented by the Standard Deviation (SD), is moderate across all dimensions, being highest in Data collection and analysis (0.736) and lowest in Integrated systems (0.613), indicating greater variability in perceptions of data system effectiveness compared to technological integration.

TABLE II
DESCRIPTIVE STATISTICS

Stats	OLCC	OLCT	Automation processes	Integrated systems	Data collection and analysis
N	80	80	80	80	80
Max	4.8	5	5	4.75	5
Min	2	2.2	2	2.5	2
Mean	3.508	3.455	3.463	3.422	3.422
SD	0.720	0.691	0.734	0.613	0.736
Variance	0.518	0.477	0.539	0.376	0.542
P_{50}	3.4	3.4	3.5	3.375	3.375
Skewness	-0.010	0.169	0.044	0.220	0.085
Kurtosis	2.045	2.017	2.272	2.056	1.969

Regarding the shape of the data distribution, skewness values close to zero suggest that the variables exhibit symmetrical distributions, without pronounced deviations towards extreme values, indicating that the data are representative of the selected sample. Kurtosis values range from 1.969 to 2.272, suggesting slightly platykurtic distributions, implying a lower concentration of values around the mean compared to a normal distribution. These results reinforce the validity of the collected data, ensuring their relevance for subsequent statistical analysis. The information obtained provides a solid basis for evaluating the impact of AI on the operational efficiency of the pharmaceutical sector, with opportunities to optimize strategic decision-making based on data-driven insights.

B. *Statistical analysis*

The correlation matrix presented in Table III illustrates the relationships between key variables related to logistics chain optimization through artificial intelligence in the Peruvian pharmaceutical sector. The results indicate strong positive correlations among all dimensions, suggesting a high degree of interdependence. Notably, the correlation between OLCC and OLCT is 0.858, implying that cost optimization tends to align closely with time efficiency improvements. Similarly, automation processes exhibit a strong correlation with integrated systems (0.848), indicating that the implementation of automated solutions is closely linked to the effectiveness of integrated systems within logistics operations.

TABLE III
CORRELATION MATRIX

	OLCC	OLCT	Automation processes	Integrated systems	Data collection and analysis
OLCC	1.000	-	-	-	-
OLCT	0.858	1.000	-	-	-
Automation processes	0.818	0.802	1.000	-	-
Integrated systems	0.788	0.798	0.848	1.000	-
Data collection and analysis	0.836	0.845	0.806	0.791	1.000

The strongest correlation is observed between data collection and analysis and OLCT (0.845), underscoring the pivotal role of accurate, data-driven insights in enhancing operational efficiency. These high correlation values indicate a holistic interconnection in the implementation of AI-based logistics solutions, suggesting that improvements in one area are likely to generate positive effects throughout the entire logistics chain. The findings emphasize the importance of adopting an integrated approach to logistics optimization, combining automation, data analytics, and system integration to achieve sustainable and long-term operational improvements.

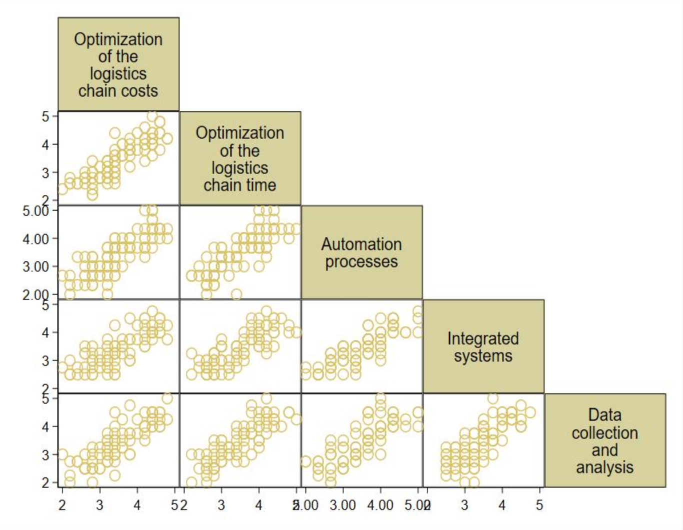

Fig. 1 Scatterplot matrix

Figure 1 presents a scatterplot matrix illustrating the relationships between key dimensions related to logistics chain optimization through artificial intelligence in the Peruvian pharmaceutical sector. The scatterplots reveal strong positive linear relationships between all pairs of variables, supporting the findings from the correlation analysis. The clusters of data points exhibit a consistent upward trend, indicating that improvements in one dimension, such as automation processes, are associated with enhancements in other areas, such as OLCC and OLCT. The relatively tight clustering of data points in most scatterplots suggests a high degree of association, with minimal dispersion, reflecting the strong interdependence among the studied variables. Notably, the relationship between data collection and analysis and OLCT appears to have a particularly strong linear trend, emphasizing the critical role of data-driven decision-making in achieving operational efficiency. These results highlight the necessity of an integrated approach to logistics management, where the implementation of AI-driven solutions across multiple dimensions can lead to synergistic improvements in performance and cost efficiency.

C. *Modelling*

Considering the data previously obtained, and according to the objectives proposed, multiple regression models will be carried out where the impact between the dimensions and their significance will be determined.

TABLE IV
OLS RESULTS

	(1) OLCC	(2) OLCT
Automation processes	0.310** (2.74)	0.194 (1.80)
Integrated systems	0.188 (1.43)	0.260* (2.08)
Data collection and analysis	0.446*** (4.56)	0.466*** (5.01)
Constant	0.268 (1.18)	0.301 (1.39)
F statistic (3,76)	82.53	84.28
Adjusted R-squared	0.756	0.760

t statistics in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV presents the results of the Ordinary Least Squares (OLS) regression analysis, examining the impact of automation processes, integrated systems, and data collection and analysis on the optimization of logistics chain costs and time. In the first model, which explains the optimization of logistics chain costs, data collection and analysis emerges as the most significant predictor ($\beta_{OLCC,3} = 0.446$, $p < 0.001$), indicating a strong positive influence. Automation processes also show a statistically significant effect ($\beta_{OLCC,1} = 0.310$, $p < 0.01$), suggesting that implementing automated solutions contributes significantly to cost optimization. However, integrated systems do not exhibit a statistically significant relationship with cost optimization ($\beta_{OLCC,2} = 0.188$, $p > 0.05$), implying that their direct impact may be limited or indirect. The model demonstrates a strong explanatory power, with an adjusted R-squared value of 0.756, indicating that approximately 75.6% of the variability in logistics chain costs is explained by the independent variables.

In the second model, which focuses on the optimization of logistics chain time, data collection and analysis once again proves to be the strongest predictor ($\beta_{OLCT,3} = 0.466$, $p < 0.001$), reinforcing its critical role in enhancing operational efficiency. Integrated systems also show a statistically significant impact ($\beta_{OLCT,2} = 0.260$, $p < 0.05$), suggesting that system integration positively contributes to reducing logistics time. However, automation processes, despite having a positive coefficient ($\beta_{OLCT,1} = 0.194$), do not reach statistical significance ($p > 0.05$), indicating that their influence on time optimization may be less pronounced compared to their impact on cost reduction. The adjusted R-squared value of 0.760 demonstrates that 76% of the variance in logistics chain time is explained by the model, reflecting a high degree of model fit. Overall, these findings underscore the importance of data-driven decision-making and integrated systems in achieving logistics efficiency, while highlighting the need for further exploration of automation's role in time management.

TABLE V
MODEL SPECIFICATION BY REGRESSION MODELS P-VALUES

	Heteroscedasticity		Autocorrelation		Normality	Multi-collinearity
Test	Breusch-Pagan	White	Durbin-Watson	Breusch-Godfrey	Jarque-Bera	Mean VIF
Model 1	0.6774	0.4487	2.2146	0.6357	0.3545	3.85
Model 2	0.2898	0.7654	2.1978	0.6236	0.7302	

Table V presents the diagnostic test results for the OLS regression models, assessing key assumptions such as heteroscedasticity, autocorrelation, normality, and multicollinearity. For Model 1, the p-values from the Breusch-Pagan (0.6774) and White (0.4487) tests indicate no presence of heteroscedasticity, confirming that the variance of the residuals remains constant across observations, ensuring the efficiency of the model's estimators. Similarly, Model 2 also exhibits no heteroscedasticity concerns, with p-values of 0.2898 (Breusch-Pagan) and 0.7654 (White), further supporting the homoscedasticity assumption. In terms of autocorrelation, the Durbin-Watson statistic for both models (2.2146 for Model 1 and 2.1978 for Model 2) falls within the acceptable range, indicating no significant first-order autocorrelation. Furthermore, the Breusch-Godfrey test results (0.6357 for Model 1 and 0.6236 for Model 2) confirm the absence of higher-order serial correlation, ensuring the validity of the regression results.

Regarding normality, the Jarque-Bera test results (0.3545 for Model 1 and 0.7302 for Model 2) suggest that the residuals are normally distributed, satisfying one of the fundamental assumptions for OLS regression. This normality ensures that hypothesis testing and confidence interval estimations remain valid and reliable. Additionally, the mean variance inflation factor (VIF) of 3.85 for Model 1 suggests that multicollinearity is within acceptable limits, indicating that the independent variables are not highly correlated. The absence of a reported VIF for Model 2 might require further investigation to confirm its multicollinearity levels. Overall, the diagnostic results demonstrate that both models meet key assumptions, with Model 2 potentially having a slight edge in terms of homoscedasticity and normality, making them suitable for further interpretation and policy implications.

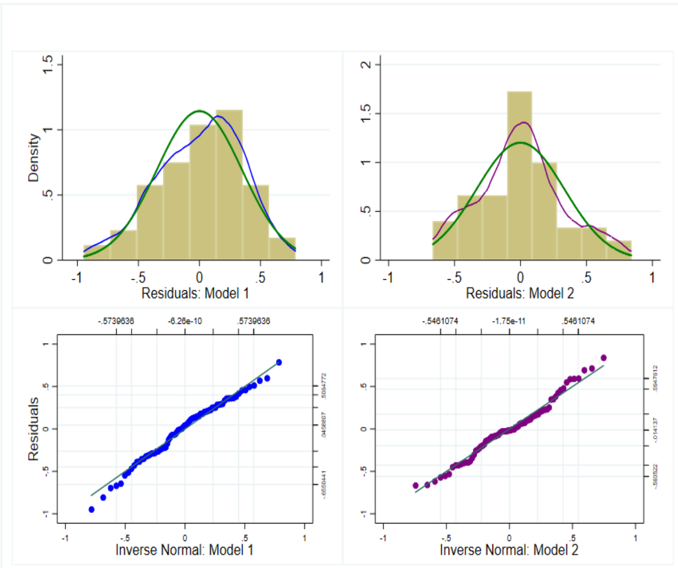

Fig. 2 Estimated kernel density and Q-Q plots. The normal distribution is represented by the green line. Grid lines are 5, 10, 25, 50, 75, 90, and 95 percentiles.

Figure 2 presents kernel density estimations and Q-Q plots to evaluate the normality of residuals for both Model 1 and Model 2. The kernel density plots (top row) compare the distribution of residuals against a normal distribution, represented by the green line. For Model 1, the residuals exhibit a relatively close fit to the normal distribution, with slight deviations in the tails, suggesting minor departures from normality. In Model 2, the residual distribution follows the normal curve more closely, indicating a better approximation to normality. The blue and purple kernel density lines provide a smoothed estimate of the residual distribution, visually confirming the alignment with the expected normal shape in both models. These results support the assumption of normality for residuals, which is crucial for ensuring the validity of statistical inference in OLS regression.

The Q-Q plots (bottom row) further validate the normality assumption by comparing the observed residuals against an ideal normal distribution. In Model 1, the residuals largely align with the theoretical quantiles, with slight deviations at the extremes, suggesting potential minor outliers but no significant departures from normality. Model 2 exhibits an even better fit, with residuals closely following the diagonal reference line, indicating a stronger adherence to normality assumptions. These findings align with the Jarque-Bera test results reported in Table 5, reinforcing the conclusion that both models satisfy the normality assumption, with Model 2 displaying a slightly better fit. Overall, the results suggest that the models are appropriate for hypothesis testing and reliable interpretation of results.

V. LIMITATIONS

Although the study provides consistent empirical evidence on the influence of artificial intelligence on logistics optimization, its scope is limited by the cross-sectional nature of the design, which prevents inferring robust causal relationships between the variables analyzed. The choice of non-probability convenience sampling, although suitable for exploratory studies, restricts the generalization of the results to broader contexts and could be biased toward companies with greater technological readiness.

Additionally, the use of self-reported instruments poses risks of response and perception bias, potentially affecting the accuracy of the collected data. Furthermore, the proposed model focuses on specific operational variables, ignoring critical factors such as organizational change management, companies' digital maturity, and cyber resilience, whose interaction with artificial intelligence could substantially modify the observed results. These limitations open up relevant avenues for future longitudinal and comparative studies.

V. CONCLUSIONS

The results of the study show that the adoption of artificial intelligence in the logistics chain of the pharmaceutical sector in Peru significantly impacts its operational optimization, effectively contributing to the reduction of costs and operational times.Likewise, the multiple linear regression analysis identifies the dimension of data collection and analysis as the most determining dimension in the optimization of costs and times, which highlights the relevance of efficiently managing information for correct and strategic decision making.

The automation of logistics processes by mitigating human intervention allows a significant effect on cost optimization, thereby additionally achieving the reduction of logistics times. On the other hand, integrated systems promote interaction between the different areas of the logistics chain, streamlining their integration and thereby improving the flow of operations. This allows the minimization of times and ensures more profitable and competitive logistics.

From a methodological approach, the efficient application of econometric models and compliance with fundamental statistical assumptions such as homoscedasticity, the absence of autocorrelation and normality, guarantee the precision, reliability and representativeness of the estimates obtained, strengthening the validity of the econometric analysis. The results achieved in the model specification tests indicate that the residuals comply with a normal distribution, according to the Jarque-Bera test, and also do not present a significant serial correlation according to the Durbin-Watson test. Thus, ensuring the reliability of the econometric analysis.

Finally, as a result, this research provides solid and consistent evidence on the effectiveness of artificial intelligence in logistics optimization, highlighting its impact to optimize the competitiveness of the pharmaceutical sector in Peru. Likewise, the findings obtained indicate that the adoption of these technologies not only allows reducing costs and operating times, but also manages to strengthen those capacities in the sector to be able to adapt to any eventual change in demand and in the logistics chain, thus strengthening its efficiency and sustainability.

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