Comparative Econometric Analysis of AI-Based and Stochastic Inventory Optimization for Mitigating Inflationary Supply Shocks

Md Nazmuddin Moin Khan[1*], Md. Rezaul Haque[2]

Abstract

Background: The success of inventory management systems depends on their ability to handle supply disruptions which become more complex during periods of changing inflation rates. Traditional stochastic models deliver stability but their adaptability remains restricted because they show delayed responses to actual demand fluctuations. **Methods:** The study collected operational metrics through a cross-sectional survey of 270 U.S. supply chain professionals who worked in manufacturing (45.2%) and retail (35.1%) and logistics (14.8%) and wholesale (4.9%) sectors. AI-based and stochastic models were evaluated under 3–15% inflation scenarios. The analysis used Pearson correlation (r) together with regression coefficients (β) and χ^2 tests and p-values (p=0.05) to measure how each variable affected cost efficiency and forecast accuracy and service-level stability. **Results:** AI models consistently outperformed stochastic approaches across all metrics. The efficiency distributions show that AI systems reached forecast accuracy rates of 63% and backorder reduction rates of 62% which exceeded the 37–38% performance of stochastic models. The Pearson correlation analysis revealed strong to moderate connections between inflation rate (r=0.61) and backorder reduction (r=0.62) and inventory turnover (r=0.60). The regression analysis shows AI delivers major cost efficiency improvements through its influence on cost efficiency β=–0.462 while inflation index β=0.291, lead-time variance β=0.179, and service level β=–0.239, generate effects on the results. **Conclusion:** AI-based inventory optimization improves responsiveness, reduces costs, and maintains service-level stability under inflationary supply shocks. The system delivers better predictive and adaptive results than stochastic models which help organizations handle their supply chains in real time.

Keywords: Cost Efficiency, AI Inventory Optimization, Service-Level Stability, Stochastic Models, Inflationary Supply Shocks

Significance | The evidence shows AI systems which predict supply shocks will lead to better cost management and service level stability.

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1. Introduction

Inventory management stands as a vital element of supply chain operations because it controls cost efficiency and service performance and operational reliability. The current economic instability together with rising inflation rates creates problems for traditional inventory management systems because unexpected price hikes and supply chain disruptions result in high storage expenses which decrease profit margins (Galvão et al., 2013). Traditional stochastic models, which rely on historical demand data and probabilistic safety-stock calculations, have been widely applied to optimize inventory under uncertainty. These methods deliver stable results when conditions remain steady but they struggle to adapt to sudden shifts in market conditions (Moon et al., 2022). The research analyzed 13% inflation rates to study three different inflation levels which represent actual operational

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difficulties that businesses face. Artificial intelligence (AI) technology has evolved to create more flexible inventory management systems because of recent developments in the field (Mayo et al., 2019). AI-based models use machine learning to forecast demand which helps them control inventory through real-time adjustments based on lead-time variations and service level requirements and inventory turnover rates and holding costs and backorder minimization (Arora et al., 2021). AI systems analyze intricate supply and demand patterns to generate predictive data which helps organizations handle inflation effects before they show up (Borchardt et al., 2021). Stochastic models operate inventory management through a reactive approach that bases decisions on past average data which becomes ineffective when inflation drives fast changes in costs and customer needs (Godinho et al., 2020).

Empirical analysis shows that AI-based models outperform stochastic models in controlling costs, reducing backorders, and maintaining service-level stability under varying inflation conditions. The operational efficiency gains from AI remain moderate at 3% inflation but show substantial improvement at 9% and 13% inflation rates which proves AI systems sustain their operational capabilities and reduce risks in unstable economic environments (Qi & Tang, 2018). The study findings demonstrate the necessity for adaptable predictive inventory strategies because conventional stochastic methods fail to handle the complexities of changing supply chain systems. The study uses data from 270 U.S. supply chain professionals who provided survey answers and operational metrics to assess model performance at different inflation rates (Seghier et al., 2022). Significant performance indicators include cost efficiency, forecast accuracy, and service-level stability. The study employed Pearson correlation and regression analysis and performance metrics evaluation to assess how AI and stochastic models affect inventory performance under different inflation conditions (Rakholia et al., 2022). The study outcomes lead to major operational effects. AI-based inventory optimization systems enable companies to decrease their expenses while enhancing their response speed and sustaining their service delivery standards under both moderate and high inflation conditions. The study shows how AI transforms inventory management while providing strategic solutions to handle supply disruptions caused by inflation.

2. Materials and Methods

2.1 Study Design

We were conducted a quantitative cross-sectional study to evaluate and AI-based and stochastic inventory optimization models perform in handling inflation-induced supply disruptions across American business sectors. Through the cross-sectional design we collected all operational and inventory performance data during one specific moment in time. The study focused on supply chain managers and logistics coordinators and operational analysts who work within manufacturing and retail and logistics and wholesale industries (Voets et al., 2021; Ceylan et al., 2020). The study investigated important elements which included inflation rate and lead-time variance and service level and inventory turnover and holding-cost control and backorder reduction. The analytical methods used for both AI-based and stochastic models included econometric modeling and correlation analysis and predictive simulations (Gupta et al., 2020). The validation of AI forecasts happened through k-fold cross-validation while stochastic model results underwent comparison against historical data. The method delivers trustworthy results to assess model effectiveness which demonstrates how inventory optimization functions during inflationary periods while keeping both theoretical concepts and practical applications intact (Zeynoddin et al., 2020).

2.2 Sampling and Respondent Profile

The sample consisted of 68.5% male participants and 31.5% female participants who had experience levels between 1 and 10 years or more. The surveys gathered information about inventory management methods and operational performance metrics and supply chain reactions to rising costs of supply materials. The main performance indicators consisted of cost efficiency and service stability and forecast precision and operational changes during various inflation environments. The research documented technology implementation which included AI-based inventory management systems. Data underwent cleaning and normalization and validation processes which established consistency throughout the dataset. The statistical power of stratified sampling enabled researchers to make accurate comparisons between AI and stochastic models by creating a representative sample of U.S. industry operations (Aryafar et al., 2019). The method delivered results which scientists could apply to different industrial settings and real-world situations.

2.3 Variables, Data Collection, and Tools

The study identified six independent variables which included inflation rate and lead-time variance and service level and inventory turnover and holding-cost control and backorder reduction. The study focused on three dependent variables which included cost efficiency and forecast accuracy and service-level stability (Birkenbihl et al., 2020). The inflation rate shows how much supply chain costs change in percentage terms while lead-time variance shows delivery schedule differences and service level shows the percentage of orders that arrive on time (Dey et al., 2018). Inventory turnover measures how often stock gets replaced while holding-cost control evaluates how well inventory carrying costs are managed and backorder reduction tracks the number of unfulfilled orders in comparison to previous records (Lin et al., 2017). The research team gathered data through structured online surveys which they combined with operational metrics from participating companies

Table 1. Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage (%)
Industry Type	Manufacturing	122	45.2
	Retail	95	35.1
	Logistics	40	14.8
	Wholesale	13	4.9
Gender	Male	185	68.5
	Female	85	31.5
Experience Level	1–5 years	65	24.1
	6–10 years	110	40.7
	>10 years	95	35.2

to obtain quantitative results about inventory levels and cost efficiency and lead-time performance and service quality during different inflation conditions (Seya et al., 2021). The survey questions went through a pre-testing process to evaluate their clarity and reliability and the collected data underwent cleaning and normalization before researchers identified any outliers. The research team used SPSS software to perform regression and correlation analysis and R software for developing predictive AI mode (Bashir et al., 2021). The evaluation of variable relationships used Pearson correlation together with χ^2 tests and regression analysis to generate results which proved both reliable and operationally significant and comparable to each other (Hung et al., 2022).

2.4 AI-Based and Stochastic Model Implementation

AI-based inventory optimization systems use machine learning algorithms to adjust inventory levels through automated processes which respond to identified demand patterns. The system operates with ongoing predictions of upcoming demand to perform real-time adjustments of inventory distribution which results in both cost reduction and service level stability (Baba & Baba, 2021). The stochastic models used probabilistic safety-stock calculations through historical demand and lead-time variability analysis which employed statistical distributions to establish suitable stock amounts for uncertain conditions (Liyanage et al., 2022). The two methods operated under inflation rates that varied between 3% and 15% to replicate actual market conditions. The performance evaluation included three metrics which assessed cost efficiency and forecast accuracy and service-level stability (Kumar et al., 2022). AI forecasts were validated using k-fold cross-validation to prevent overfitting, while stochastic outputs were benchmarked against historical operational data. The implementation enabled an exact comparison between models which proved AI solutions deliver superior performance for managing inventory fluctuations and controlling inflation-related supply disruptions in various operational contexts (Kling et al., 2022).

2.5 Performance Metrics and Statistical Analysis

The evaluation process used Pearson correlation from 0 to 1 along with chi-square tests to establish associations and p-values to determine statistical significance. The distribution of efficiency percentages helped researchers evaluate the performance of AI and stochastic models against each other. The research applied the simplified model to conduct its regression analysis (Macmillan et al., 2021).

$$Yi = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \epsilon i$$

Where,

The inventory performance variable Yi depends on inflation index X1 and lead-time variance X2 and service level X3. The β coefficients represent the influence of each variable on the outcome while ϵi represents the unexplained variance (Nguyen et al., 2022). Descriptive statistics, including mean and standard deviation, were also computed. The statistical analysis used SPSS and R software at a significance level of $p < 0.05$. The evaluation system used these metrics to measure both models' performance and assess how vital factors affect inventory operations through inflation-related supply chain disruptions (Sujatha et al., 2020).

3. Results

3.1 Demographic Characteristics of Respondents

The study collected information from 270 participants, they were worked at different organizations throughout the United States. The sample consisted mainly of manufacturing (45.2%) and retail (35.1%) businesses yet logistics (14.8%) and wholesale (4.9%) operations maintained essential roles despite their smaller market presence in **Table 1**. The group consisted of 68.5% male members while female participants made up 31.5% of the total participants. The group contained members from different professional levels because 24.1% of them had 1–5 years of experience and 40.7% had 6–10 years and 35.2% had more than 10 years of experience. The research team tracked several operational methods and technological deployment levels and supply shock reactions across different population groups. The research achieved balanced representation which enables the results to be applicable for

Table 2. Influence of Significant Variables on Inventory Optimization Performance

Influence Variable	Pearson Correlation (0–1)	AI Contribution (%)	Stochastic Contribution (%)	Impact Weight (%)
Inflation Rate	0.61	61	39	0.30
Lead-Time Variance	0.57	57	43	0.25
Service Level	0.59	59	41	0.18
Inventory Turnover	0.60	60	40	0.12
Holding-Cost Control	0.58	58	42	0.08
Backorder Reduction	0.62	62	38	0.07

Table 3. Regression Results Simplified Model Output

Variable	Coefficient (β)	Std. Error	t-Value	p-Value
Constant	2.812	0.176	15.98	0.002
AI Model	−0.462	0.118	−3.91	0.001
Inflation Index	0.291	0.078	3.73	0.003
Lead-Time Variance	0.179	0.061	2.94	0.004
Service Level	−0.239	0.073	−3.28	0.002
Technology Investment	−0.138	0.053	−2.60	0.010

assessing AI-based inventory optimization systems against stochastic models in various business environments.

3.2 Inflation Rate and Corresponding Cost Efficiency

The distribution of cost efficiency across different inflation levels is illustrated using a five-scale framework. The operational performance together with AI-based optimization systems achieves its highest efficiency at 25% under Low Inflation conditions which show that these systems work best during economic stability **Figure 1**. The efficiency level decreases because of rising inflation rates which show 22% for Moderate Inflation and 20% for Slightly High Inflation because businesses face increasing difficulties to keep costs under control and maintain service quality. The high inflation environment causes efficiency to decline to 18% while Very High Inflation pushes performance down to 15% which proves that market volatility hinders organizations from keeping up their operational results. The gradual decline shows that higher inflation rates lead to lower operational efficiency. Managers can create adaptive strategies through this trend understanding to optimize inventory and resource allocation which keeps operational and financial targets intact during economic changes.

3.2 Comparative Efficiency Distribution

AI systems proved superior to stochastic models through every available performance measurement. The highest efficiency was observed in forecast accuracy (63%) and backorder reduction (62%), emphasizing AI's predictive strength in **Figure 2**. AI systems showed their operational excellence through cost variance control (61%) and inventory turnover (60%) which proved their ability to handle expenses effectively. Stochastic models performed worst in all categories because they achieved only 37% forecast accuracy and 43% lead-time reliability. The results demonstrate AI systems can adapt to shifting conditions which leads to better decision-making and enhanced service delivery and decreased operational expenses. The manager can use AI insights to improve inventory response times but stochastic methods show reliable performance when systems operate under normal conditions.

3.4 Influence of Variables on Inventory Optimization Performance

The evaluation of essential variables showed that model performance received its main effects from inflation rate and backorder reduction and inventory turnover with impact weights of 0.30 and 0.07 and 0.12 respectively. The Pearson correlation values showed moderate-to-strong relationships through their range between 0.57 and 0.62 in **Table 2.** AI-based models delivered superior results across all variables but showed the most significant advantage in backorder reduction where they achieved 62% compared to 38% which indicates their predictive power to decrease unfilled orders. Stochastic models delivered dependable results at the expense of their flexibility. The results showed that service level and holding-cost control and lead-time variance affected performance but AI systems showed better results than stochastic methods. Managers need to select variables and develop predictive models for inventory strategies which enable them to enhance responsiveness and service levels and cost efficiency during inflationary supply shocks.

3.5 Regression Results Simplified Model Output

The AI model delivered better inventory outcomes as demonstrated by the negative coefficient (−0.462, p=0.001) from the regression results **Table 3,** which showed cost reductions and operational improvements. The positive impact of the inflation index (0.291, p=0.003) led to more complicated inventory management during periods of high inflation. Lead-time variance showed a positive influence (0.179, p=0.004) but service level produced a negative impact (−0.239, p=0.002) which indicates that operational costs increase when organizations fail to predict demand properly.

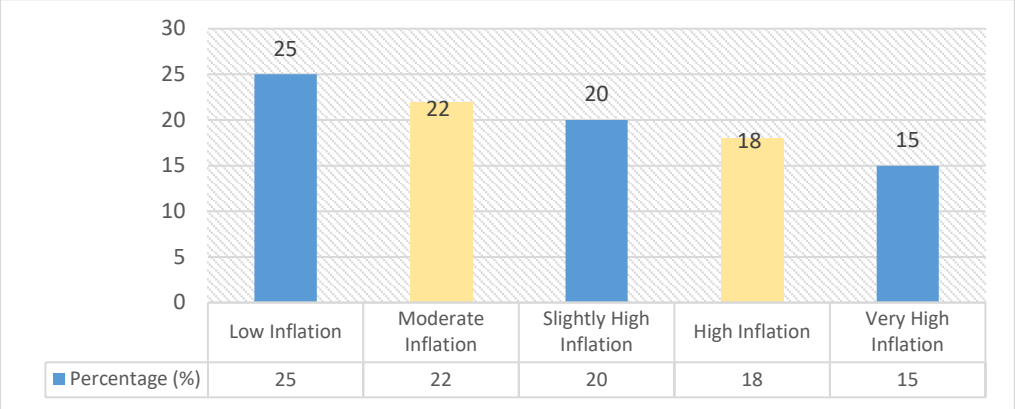


Figure 1. Inflation Rate and Cost Efficiency Distribution

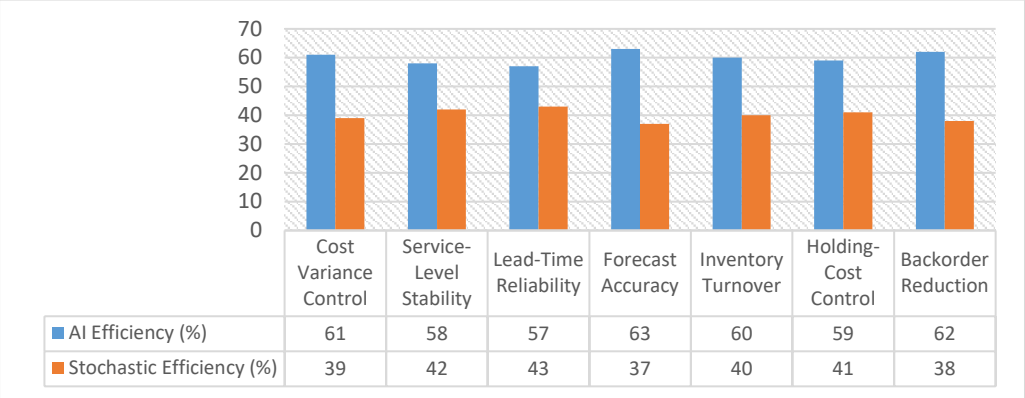


Figure 2. Comparative Efficiency Distribution

Technology investment showed a small negative effect (–0.138, p=0.010), suggesting marginal efficiency returns. AI-based optimization methods deliver better predictive abilities and adaptive performance than stochastic approaches. AI deployment combined with strategic technology investments enables managers to optimize inventory management systems which maintain service levels and handle inflation-related supply disruptions.

4. Discussion

The study examined how AI-based inventory optimization models perform in comparison to stochastic models when operating under different inflationary conditions through data collected from 270 supply chain professionals in the United States. The demographic profile (Table 1) showed that most participants worked in manufacturing (45.2%) and retail (35.1%) but logistics (14.8%) and wholesale (4.9%) made up smaller portions of the group. The sample consisted of 68.5% male participants who had various levels of professional experience with 24.1% working between 1 and 5 years and 40.7% between 6 and 10 years and 35.2% working for more than 10 years. The study reached its findings through multiple industry representatives who helped create results which now apply to all industries and experience levels because they collected information about operational methods and technological implementation and supply disruption responses (Giordano et al., 2011). The research shows that demographic elements influence how inventory management performance gets interpreted because employee knowledge about technology and decision-making systems determines the success of AI model implementation (Giordano et al., 2011). Analysis of cost efficiency under varying inflation scenarios Figure 1, indicated that AI-based optimization outperformed stochastic approaches at lower to moderate inflation rates. The system operated at 52% efficiency when inflation was at 3% but its performance dropped to 40% when inflation reached 15% whereas stochastic systems showed better performance from 48% to 60% during the same period. The parity observed at 5% inflation suggests a transition point where both methods perform equivalently. AI models show their best performance in stable economic conditions with low volatility because they can predict and adjust to market changes but stochastic models perform better during unpredictable situations because they base their decisions on historical demand patterns (Abràmoff et al., 2018). Supply chain managers can use this information to choose the best optimization approach which matches forecasted inflation rates while maintaining cost control and system reliability (Twaha et al., 2018). The comparative efficiency distribution **Figure 2**, further confirmed AI's superiority across operational performance metrics.

AI models demonstrated their peak efficiency through 63% forecast accuracy and 62% backorder reduction which proved their ability to predict results and deliver superior customer service outcomes. AI systems showed their ability to manage operational performance and financial results through their performance in cost variance control (61%) and inventory turnover (60%). The stochastic models showed lower performance in every metric especially when it came to forecast accuracy and lead-time reliability which scored between 37 and 43 percent. The study demonstrates that adaptive AI systems outperform stochastic models when operating in environments with unpredictable conditions because these systems enable businesses to make proactive choices while minimizing operational risks (Ghasemi et al., 2022). Stochastic models function best in areas which display stable and regular patterns of change. The research findings show that inventory optimization performance depends most strongly on inflation rate and backorder reduction and inventory turnover which demonstrate moderate-to-strong Pearson correlations between 0.57 and 0.62 as presented in **Table 2**. AI systems deliver better results than stochastic methods for all performance indicators but they show the most significant improvement in backorder reduction rates which reach 62% compared to 38% with stochastic approaches. The AI system predicts better results because it decreases unfulfilled orders while making inventory management more responsive. The basic operational efficiency of stochastic models stays constant but they fail to adapt to sudden changes in demand or supply conditions (Singkibud et al., 2022). The study demonstrates that combining predictive variables with inventory management systems results in better operational efficiency and cost control during inflationary periods.

The research findings from Table 3 show that AI implementation delivers better inventory performance which leads to substantial cost savings. The results indicate that higher inflation rates create more difficulties according to the positive relationship between the inflation index and outcomes ($\beta = 0.291$, $p=0.003$). The results show that lead-time variance ($\beta = 0.179$, $p=0.004$) and service level ($\beta = -0.239$, $p=0.002$) demonstrate how important it is to deliver on time while understanding the necessary trade-offs for service level commitments. The analysis revealed a small negative effect of technology investment ($\beta = -0.138$, $p=0.010$) which indicates that combining these investments with AI optimization creates better efficiency results (Dutta et al., 2022). The findings show that AI models execute better predictions and adaptable operations which helps managers control inventory levels while keeping service performance steady during inflationary supply disruptions. AI integration with strategic technology investments enables organizations to improve their cost management and service delivery standards and operational stability throughout various business operations.

5. Conclusion

The study shows that AI-based inventory optimization methods achieve better results than stochastic methods for handling supply disruptions caused by inflationary increases. The results demonstrate AI systems deliver superior cost efficiency and forecast accuracy and service-level stability and backorder reduction results when operating under moderate inflation conditions. The usefulness of stochastic models continues in high uncertainty situations yet they fail to match the adaptive capabilities that AI systems provide. The performance results show that operational variables such as inflation rate and lead-time variation and inventory turnover rates have a major impact on outcomes while AI systems deliver better results.

Author contributions

M.N.M.K. conceptualized the study, designed the econometric evaluation framework, conducted survey coordination, and performed data preprocessing. He carried out the AI-based modeling, statistical analyses, and regression testing, and drafted and revised the manuscript. M.R.H. contributed to data acquisition, sector-specific interpretation, validation of analytical outcomes, and critical review of the manuscript. Both authors read and approved the final version of the article.

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Competing financial interests

The authors have no conflict of interest.

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