Uncertain Supply Chain Management 14 (2026) ****_****

Contents lists available at GrowingScience

Uncertain Supply Chain Management

homepage: www.GrowingScience.com/uscm

Optimizing inventory management in food processing: A conceptual model linking supply chain costs and complexity to sales, quality, and customer satisfaction

Mst. Nasima Bagum[a], Poritosh Kumer Paul[a], Choudhury Abul Anam Rashed[a*], Md. Mehedi Hasan Kibria[a] and Rafid Ahmed Chowdhury[a]

[a]*Shahjalal University of Science & Technology, Bangladesh*

Article history:
Received September 16, 2024
Received in revised format October 25, 2024
Accepted January 9 2025
Available online January 9 2025

Keywords:
Inventory management
Cost
Supply complexity
Customer satisfaction
Sales
Quality

A B S T R A C T

In food processing factories, especially when dealing with perishable items, managing inventory is crucial as it impacts sales, quality, and customer satisfaction. However, inventory management is often complicated by the costs and intricacies of the supply chain. This research aims to create a conceptual model that connects the costs and complexities of the supply chain with satisfaction, sales, and quality through optimized inventory management. The study involves a case analysis of thirteen food processing factories, using a structured questionnaire for data collection. To validate the proposed framework, PLS-SEM was employed. The framework addressed five key research questions, and the results confirmed that inventory management is essential for maintaining quality, sales, and satisfaction, and that supply chain costs and complexity influence inventory management.

1. Introduction

The food industry is characterized by perishable goods, changing demand, and complex supply networks. Inventory optimization is required to maintain cost efficiency, reduce waste and increase customer satisfaction in the food industry. However, it is becoming increasingly challenging due to several cost-related and supply chain issues that can have a big effect on operational efficiency and profitability. Traditional techniques often fail to manage these complexities effectively, resulting in higher cost and possible financial losses.

Due to the lack of real-time data feedback, traditional inventory management in meat and poultry farms leads to increased logistic costs and inefficiencies. Using data analytics to optimize inventories, operational efficiency can be improved by up to 37%. This will result in cost savings and increased customer satisfaction (Kler et al., 2022). Retailers must change prices to offset losses when holding costs rise because doing so reduces order quantities and overall profitability (Wei et al., 2020). Reducing overall inventory costs in Vendor-Managed Inventory (VMI) systems requires optimizing ordering, holding, and transportation costs (Sadeghi et al., 2014). Promotional cost-sharing and wholesale prices must be balanced to optimize inventory optimization and maximize profitability throughout the supply chain (Ahmadini et al., 2021; Chen, 2018).

Supply chain complexity increases the difficulty of inventory management. Inventory strategies and the overall performance of the supply chain are impacted by detail and dynamic complexities (Bozarth et al., 2009; Serdarasan, 2013). Advanced coordination and risk mitigation strategies are required to meet these challenges, particularly in cross-channel logistics and high-end manufacturing environments (Aqlan and Lam, 2016; Ivanov et al., 2019). According to Dai and Tseng (2012), inventory accuracy is important, and technologies like RFID greatly improve inventory management in multi-stage supply chains.

* Corresponding author
E-mail address rashed-ipe@sust.edu (C.A.A. Rashed)

ISSN 2291-6830 (Online) - ISSN 2291-6822 (Print)

doi: 10.5267/j.uscm.2025.1.001

Product availability and customer satisfaction are major factors in effective inventory management, which boosts sales (Atnafu and Balda, 2018; Panigrahi, 2013). Better sales and customer experiences are the outcome of optimized inventory practices in retail and supermarket settings (Ahmad and Zabri, 2016; Charles and Jackson, 2021).

The intersection of cost management and supply chain complexities presents both challenges and opportunities for inventory optimization in the food industry. By leveraging advanced data analytics, robust coordination mechanisms, and innovative inventory management techniques, businesses can navigate these complexities to enhance operational efficiency, reduce costs, and ultimately improve customer satisfaction.

1.1 Research Questions

✓ **Cost Management in Inventory Optimization**

In the food industry, cost management is essential to inventory optimization because it affects operational efficiency and profitability. Research has shown that different cost components—like holding costs, ordering costs, transportation costs, and promotional costs—have a substantial impact on decision-making processes. Kler et al. (2022) point out that traditional meat and poultry farms are inefficient because they do not receive real-time data feedback, which drives up logistic costs. They also point out that implementing data analytics can increase efficiency by up to 37%, which lowers costs and improves customer satisfaction. Wei et al. (2020) show that higher holding costs result in lower order quantities and profitability, which forces retailers to adjust prices to offset. According to Sadeghi et al. (2014), vendor-managed inventory (VMI) systems reduce overall inventory costs by coordinating ordering and holding strategies between vendors and retailers.

Chen (2018) examines how wholesale price and promotional cost-sharing affect inventory selections, emphasizing how these two factors have different effects on manufacturers' and retailers' profits. Ahmadini et al. (2021) highlight the necessity for optimization to optimize profitability and sustainability by identifying key cost components in inventory management, such as holding and ordering costs, production costs, and waste disposal costs. greater production rates result in greater holding costs, which affect overall cost structures and highlight the importance of return rates in cost reduction, as demonstrated by Motla et al. (2023). As mentioned by Abaku et al. (2024), supply chain complexity presents problems such as nonlinear cost functions and demand fluctuation. This requires advanced computational methods to find the best answers. To efficiently reduce total costs, Van Horenbeek et al. (2013) recommend integrated spare parts and maintenance optimization. Chinello et al. (2020) recommend ABC analysis for inventory optimization, particularly in managing stock levels to balance cost efficiency and service goals. Garcia and You (2015) emphasize that efficient inventory optimization in line with economic and environmental goals requires supply chain design to take holding, ordering, and transportation costs into account.

RQ 1: How does cost management affect the Optimization of Inventory?

✓ **Supply Chain Complexities in Inventory Optimization**

Supply chain complexity poses serious obstacles to inventory optimization, which affects cost control, efficiency, and general supply chain performance. Addressing these challenges needs sophisticated strategies and technologies to enhance inventory management across various industries. Daniel and Rajendran (2005) explore the impact of supply chain complexities on inventory optimization by modeling serial supply chains and using genetic algorithms to minimize total supply chain cost. Their results emphasize how important it is to optimize inventory levels while taking into account a variety of complexities, including supply delays, demand fluctuation, and production constraints. Serdarasan (2013) delves deeper into supply chain complexity, identifying static, dynamic, and decision-making complexities that affect process control, synchronization, and decision-making. These complexities directly affect demand adaptive supply chain strategies and inventory optimization efforts because of shifting consumer needs and market pressures.

Eckstein et al. (2014) explore product complexity's effects on inventory optimization, noting that increased product variety leads to higher holding costs, reduced service levels, and delivery reliability issues. This complexity necessitates distinct organizational requirements for manufacturing and information management, complicating inventory optimization efforts. Wu and Golbasi (2004) also address how faster technical innovation and more market responsiveness affect inventory optimization. These factors increase the operational dependencies in supply chains, which makes conventional inventory management techniques more difficult and calls for more flexible solutions. Aqlan and Lam (2015) identify material shortages, machine failures, order cancellations, and quality issues as key complexities impacting inventory optimization in high-end server manufacturing environments. For efficient handling of these issues, they recommend risk reduction techniques such as push-pull production, on-site supplier hubs, and redundant suppliers. Diabat and Al-Salem (2015) emphasize the significance of environmental considerations and demand uncertainty in inventory optimization. They recommend genetic algorithms being used to offer reliable optimisation solutions and more environmentally friendly supply chains.

Hartwig et al. (2015) discuss the role of strategic inventories in supply chains, which can empower buyers and reduce wholesale prices, enhancing overall supply chain performance. Non-cooperative behaviors can lead to inefficiencies, but strategic interactions across periods can mitigate these issues, optimizing inventory levels. Wang et al. (2011) address time-sensitive deterioration rates in industries such as agriculture and manufacturing, emphasizing the importance of developing integrated inventory policies to manage these complexities. Reducing supply chain costs overall requires coordination systems for delivery amounts and timing. Jemai et al. (2020) focus on supply chain management for highly perishable goods such as blood platelets. Efficient control of collection and distribution processes is crucial to minimize environmental effects and total costs, emphasizing the need for innovative solutions in green healthcare supply-chain management. Similarly, Zheng et al. (2019) investigate how supply chain complexities influence supply chain network design decisions, especially regarding inventory costs. They found that rising inventory costs can change the quantity of distribution centers. It emphasizes how closely supply chain structure and inventory optimization are related. Managing supply chain complexities involves considering stochastic demand and suppliers' imperfect quality, which can result in additional costs such as external failure and holding costs. Supply disruptions can also affect suppliers' lead times, resulting in delivery delays. These complexities influence inventory optimization strategies. Supplier selection and inventory management must be integrated during disruptions to reduce the risks associated with supply chain complexities. This integration entails implementing a reactive strategy to address disruptions in the proactive stage of the supply chain (Saputro et al., 2021).

Technology's role in mitigating supply chain complexities is evident in Dai and Tseng (2012), who emphasize RFID technology's importance in reducing inventory inaccuracies and enhancing management in multi-stage supply chains. Ivanov et al. (2019) on the rise of digitalization and Industry 4.0 suggests that better visibility and accuracy through RFID implementation can optimize inventory management in complex supply chains. These developments affect disruption propagation and optimization methods by increasing the complexity of coordinating in cross-channel logistics. Abaku et al. (2024) emphasize that handling nonlinear cost functions, complex production processes, and fluctuating demand curves requires advanced computational resources. Efficiency of the supply chain, identification of bottlenecks, and inventory strategy optimization depend heavily on simulation modeling. This is consistent with the findings of Bozarth et al. (2009) who differentiate between dynamic complexity and detail in supply chains, both of which have a major impact on inventory management. These complexities must be taken into consideration in effective strategies in order to maintain service levels and minimize costs. Supply chain complexities, both structural and dynamic, can have an impact on inventory management operations and firms' ability to respond properly to disruptions. Longer lead times due to structural complexity can result in a much greater bullwhip effect, affecting inventory management operations and resilience. Big data analytics (BDA) can help to mitigate the effect of supply chain complexities on supply chain resilience. BDA contributes to the management of various types of supply chain complexity, including structural and dynamic complexities, and can improve supply chain resilience (Iftikhar et al., 2023).

RQ 2: How is Supply Chain Complexity linked with the Optimization of Inventory?

✓ **Impact of Inventory Optimization on Customer Satisfaction and Sales**

Effective inventory management is critical for increasing customer satisfaction and sales, as indicated by several studies across different sectors. Inventory optimization and customer satisfaction are primarily motivated by the capacity to maintain product availability, minimize operational costs, and improve service levels. Both Atnafu and Balda (2018) and Panigrahi (2013) underline the importance of efficient inventory management in ensuring product availability and accurate demand forecasting, which are critical for satisfying customer expectations and increasing satisfaction. When products are consistently available, customers receive timely order fulfillment. This promotes loyalty and repeat business. Takim (2014) further supports this idea by demonstrating how inventory management may minimize operational costs, give accurate demand projections, and enable shorter production turnover cycles. These operational improvements improve customer service by ensuring that products are available when needed, resulting in significant long-term savings and higher customer satisfaction.

The retail sector likewise benefits significantly from effective inventory management. Ahmad and Zabri (2016) found that adequate inventory control boosts sales and profitability by addressing consumer needs more effectively. Charles and Jackson (2021) investigate technological advancements such as electronic scanners and mobile payments. These solutions streamline inventory processes, ensuring that products are precisely tracked and easily accessible, hence improving the shopping experience for customers. Tripathi and Tiwari (2014) underline that inventory management approaches have a substantial impact on retailers' financial success, resulting in shorter lead times, greater supplier flexibility, and faster product delivery to customers, eventually improving service delivery quality.

In the food industry, Martin and Iravo (2014) show that inventory management decreases product deterioration and assures effective storage and retrieval systems. This leads to increased satisfaction among retailers and customers since products are delivered in optimal condition, improving the overall quality of goods received. Perishables are the key factor driving supermarket profitability. The assortment and shelf availability of fresh food strongly impact customer choices. Grocery stores might lose up to 15% of their perishable items due to breakage and spoilage (Ferguson and Ketzenberg, 2006). Castro and Jaimes (2017) reinforce this by showing how successful inventory optimization in the perishable food supply chain assures item freshness and availability, which has a direct impact on sales and consumer satisfaction. Uthayakumar and Priyan (2013) emphasize the importance of good inventory policies and service levels throughout the pharmaceutical supply chain. Proper inventory management eliminates pharmaceutical shortages and reduces unnecessary costs, resulting in higher customer satisfaction and financial performance. Efficient inventory systems maintain product availability, reduce operational costs, and improve service levels across a variety of industries. Businesses may build strong inventory policies that boost sales and foster long-term customer loyalty by combining technological advancements, employee training, and strategic optimization. Effective inventory management, driven by data analytics, technological advancements, and strategic optimization, emerges as a key subject for improving operational efficiencies, lowering costs, and fulfilling consumer expectations. The interrelated findings emphasize the importance of integrated, responsive approaches to inventory management that handle different challenges posed by dynamic market demands and supply chain complexities. This thorough understanding paves the way for future research and practical applications aimed at optimizing inventory systems to ensure long-term corporate success.

RQ 3: How does the optimization of inventory affect customer satisfaction?

RQ 4: What is the impact of optimized inventory on sales?

✓ **Inventory Optimization Techniques and Quality**

Inventory optimization techniques are critical in reducing costs, increasing efficiency, and maintaining product availability throughout supply chains. Several strategies have been investigated to handle specific supply chain challenges, each providing unique benefits tailored to different operational requirements. Chinello et al. (2020) underline the significance of product classification, specifically ABC analysis, which helps in prioritizing inventory management activities based on product value and turnover rates. This method ensures that high-priority items are consistently provided while low-priority items are managed more conservatively, balancing costs and service objectives. This fundamental technique serves as a baseline for more complex optimization strategies. Simchi-Levi et al. (2018) present a dynamic approach to inventory management that takes process flexibility into account, building on the requirement for flexible methods. Their two-stage robust optimization issue demonstrates that firms should allocate more inventory to high-variability products when flexibility is limited. As process flexibility grows, inventory allocation shifts toward low-variability products. This strategy enables firms to dynamically alter their inventory strategies in response to changing operational situations, resulting in optimal overall inventory levels.

Duan and Liao (2013) offer the 'old inventory ratio' (OIR) policy, which addresses the unique issues of perishable goods. This strategy considers both stock levels and the age distribution of inventory items in order to reduce the predicted system outdate rate while maintaining a set maximum permissible shortage level. This strategy is especially useful in supply chains dealing with highly perishable products, where timely inventory control is essential. Motla et al. (2023) discuss the effects of production and remanufacturing rates on inventory costs. They suggest lowering the amount of material produced to reduce holding costs while emphasizing the profitability of incorporating returned products into the inventory system. This method not only reduces costs, but also improves supply chain sustainability by encouraging material reuse.

Rashed et al. (2024) showed that integration of 4IR technologies promotes open and transparent information exchange, enabling quicker decision-making and proactive market adjustments, thus enhancing total supply chain agility. Sadeghi et al. (2014) demonstrate that Vendor Managed Inventory (VMI) models reduce demand fluctuation and cut total inventory costs by allowing vendors to manage inventory levels at the retailer's location. They extend this concept to impulse purchase products, demonstrating how VMI models reduce stockouts while increasing profitability. Each strategy provides personalized solutions to specific supply chain challenges, ranging from foundational methods like ABC analysis to dynamic approaches that take into account process flexibility, age-based policies for perishable goods, and VMI models augmented by modern technologies.

RQ 5: Does the use of optimization techniques in inventory management result in enhanced quality?

2. Methodology

This research is based on a case study approach conducted within food processing factories, specifically those that produce perishable items. Initially, three factories were visited for a pilot study, where face-to-face interviews were conducted with relevant personnel with a semi-structured questionnaire. Following the pilot, ten additional factories were interviewed, and the developed questionnaire was finalized. Insights from these interviews, along with an extensive literature review, were used to develop a conceptual model. A conceptual model represents a system of ideas intended to help people understand, simulate, or gain deeper insight into the topic it depicts. This model is often presented using a graphical diagram to visually or systematically represent the system. In this study, six key concerns were the focus: Costs, Supply Chain Complexity, Optimizing Inventory Management, Quality, Sales, and Customer Satisfaction. The study's structure is illustrated in Fig. 1 (the developed conceptual model). Costs and Supply Chain Complexity are identified as independent variables, Optimizing

Inventory Management serves as the mediating variable, and Quality, Sales, and Customer Satisfaction are the dependent variables.

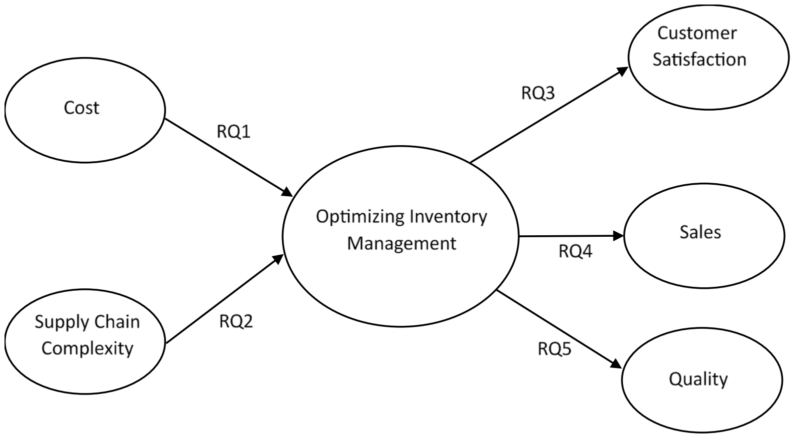

Fig. 1. Conceptual Model

The developed model, as shown in Fig. 1, outlines the study's research questions, with five questions being formulated and tested. The subfactors of the input, mediating, and output variables are presented in Table 1. The study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) techniques to analyze the data using SmartPLS4. PLS-SEM is a widely recognized method frequently employed in management, information technology (IT), and statistical fields. It is known for delivering reliable and credible results (Avkiran and Ringle, 2018). It is a non-parametric approach that focuses on explaining the variance in latent variables, which are not directly observable. Unlike covariance-based SEM (COV-SEM), Smart PLS-SEM requires fewer assumptions about residual distributions, measurement scales, and sample sizes (Hair et al. 2019).

The objective of the developed model of the current study is to assess the impact of cost and supply chain complexity through optimization of inventory management on sales, quality, and customer satisfaction. The data analysis is divided into two primary sections, i.e., examination of the structural model and evaluation of the measurement model. The Structural Model involves analyzing the relationships between the latent variables, including the coefficient of determination (R^2) and path coefficients, and identifying the indicators with the strongest influence on the variables. The Measurement Model focuses on assessing the indicators' reliability and validity. A thorough discussion of the findings is presented based on the results obtained. Finally, based on the validation of the model, a firm conclusion is drawn.

Table 1
Components of the factors of the developed conceptual model.

Cost	Supply Chain Complexity	Customer Satisfaction	Sales	Quality	Optimizing Inventory Management
Demand Variation (DV)	Inadequate Transportation Facilities (TF)	Inaccurate Demand Forecasting (DF)	On time Replenishment (OR)	Inadequate Storage Facilities (SF)	Demand Variation (DV)
Lack of Real-Time Data (RT)	Bullwhip Effect (Improper Co-ordination) (BW)	Inadequate Technology (IT)	Absence of Modern Inventory Related Software (IS)	Fluctuation in Temperature & Time (TT)	Inadequate Technology (IT)
		Inability to Manage Uncertain / Excess Demand (UD)			Inadequate Storage Facilities (SF)
					Fluctuation in Temperature & Time (TT)
					On time Replenishment (OR)

3. Analysis and Results

3.1 Measurement Model

The quality of the constructs in the study was evaluated by examining the measurement model. The process starts with an analysis of the factor loadings, followed by an assessment of construct reliability and validity.

3.1.1 Identification of key Indicators (Factor Loadings)

Factor loadings illustrate how each item's correlation matrix aligns with the principal component. These values range from -1.0 to +1.0, with higher absolute values indicating a stronger correlation between the item and the underlying factor (Pett et al., 2003). Table 2 displays the factor loading values for the indicators.

Table 2
Factor Loadings of Key Indicators.

	Cost	Customer Satisfaction	Optimizing Inventory Management	Quality	Sales	Supply Chain Complexity
Demand Variation (DV)	0.94		0.858			
Lack of Real-Time Data (RT)	0.807					
Inadequate Technology (IT)		0.926	0.862			
Inaccurate Demand Forecasting (DF)		0.711				
Inability to Manage Uncertain / Excess Demand (UD)		0.802				
Inadequate Storage Facilities (SF)			0.776	0.774		
Fluctuation in Temperature & Time (TT)			0.725	0.976		
Ontime Replenishment (OR)			0.848		0.899	
Absence of Modern Inventory Related Software (IS)					0.911	
Bullwhip Effect (BW)						0.913
Inadequate Transportation Facilities (TF)						0.935

3.1.2 Multicollinearity of Indicators

The Variance Inflation Factor (VIF) measures the degree of multicollinearity among the indicators (Fornell and Bookstein, 1982). A VIF value below five is recommended (Monecke and Leisch, 2012). The VIF values for the indicators in this study, shown in Table 3, fall within the acceptable range.

Table 3
Variance Inflation Factor values for Indicators

	VIF
Demand Variation (DV)	1.451
Inaccurate Demand Forecasting (DF)	1.66
Inadequate Storage Facilities (SF)	1.613
Fluctuation in Temperature & Time (TT)	1.613
Ontime Replenishment (OR)	1.689
Absence of Modern Inventory Related Software (IS)	1.689
Bullwhip Effect (BW)	2.007
Inadequate Transportation Facilities (TF)	2.007
Lack of Real-Time Data (RT)	1.451
Inadequate Technology (IT)	1.598
Inability to Manage Uncertain / Excess Demand (UD)	2.168
Fluctuation in Temperature & Time vs Optimizing Inventory	2.16
Ontime Replenishment vs Optimizing Inventory	3.172
Inadequate Storage Facilities vs Optimizing Inventory	2.39
Inadequate Technology vs Optimizing Inventory	2.644
Demand Variation vs Optimizing Inventory	3.156

3.1.3 Analysis of Reliability and Validity

To thoroughly analyze the structural model, it is important to ensure the reliability and validity of the latent variables. Cronbach's Alpha (CA) is a widely used metric for assessing the consistency and reliability of a measurement scale. It produces a score between 0 and 1, with higher values indicating greater internal consistency. Generally, a Cronbach's Alpha of 0.7 or above is considered acceptable, while values above 0.8 indicate high reliability, as recommended by Hair et al. (2011).

Another measure of reliability is Composite Reliability (CR), which also ranges from 0 to 1, with higher values reflecting more reliable measurements. Like Cronbach's Alpha, higher CR values are desirable. Both CA and CR provide valuable insights into the reliability of the measurements, and in this study, as shown in Table 4, both metrics exceeded the recommended threshold of 0.70, confirming the reliability of the measurements (Hair et al., 2011, 2019).

Additionally, suppose the Average Variance Extracted (AVE) is 0.50 or higher. In that case, it indicates that the items effectively capture the key concepts of interest and are reliable, as recommended by Fornell and Larcker (1981).

Table 4
Analysis of Reliability and Validity among the latent variables.

Variables	CA	CR	AVE	Fornell-Larcker					
				1	2	3	4	5	6
1. Cost	0.716	0.868	0.768	0.876					
2. Customer Satisfaction	0.788	0.857	0.669	0.464	0.818				
3. Optimizing Inventory Management	0.874	0.908	0.665	0.683	0.539	0.816			
4. Quality	0.763	0.872	0.776	0.399	0.021	0.564	0.881		
5. Sales	0.780	0.901	0.819	0.651	0.171	0.601	0.432	0.905	
6. Supply Chain Complexity	0.829	0.921	0.854	-0.342	0.182	0.388	-0.053	-0.189	0.924

3.1.4 Heterotrait and Monotrait Ratio (HTMT)

The HTMT ratio is used to assess Discriminant Validity, with a recommended threshold of 0.85 or below (Martynova et al., 2018). As shown in Table 5, the HTMT ratios for all constructs fall within the acceptable range.

Table 5
HTMT values of the constructs.

	Cost	CS	OIM	Quality	Sales	Q^2
Cost						0.301
Customer Satisfaction (CS)	0.561					0.279
Optimizing Inventory Management (OIM)	0.796	0.586				0.446
Quality	0.434	0.233	0.587			0.360
Sales	0.761	0.418	0.697	0.485		0.436
Supply Chain Complexity (SCC)	0.481	0.458	0.498	0.192	0.324	0.397

3.2 Examination of the Structural Model

Evaluating the structural model is crucial in the Structural Equation Modeling (SEM) process. It ensures that the analysis results are valid, reliable, and informative while also revealing the strength of relationships within the model. Several methods are used to assess the structural model in SEM, including:

(i) **Multicollinearity**: Checking for multi-collinearity among predictor variables, often using the Variance Inflation Factor (VIF), ensures that predictors are not excessively correlated. These values are presented in Table 3.

(ii) **R-Squared Values**: The R-squared values, which indicate the proportion of variance explained by the model for the dependent variables, reflect the model's predictive strength. Higher R-squared values suggest better predictive power. These values are shown in Table 6.

(iii) **Cross-Validated Redundancy Values (Q-Squared)**: The Q-squared values assess how well the model predicts outcomes for endogenous variables, providing a measure of predictive accuracy. These values are also presented in Table 6.

(iv) **Significance and Magnitude of Path Coefficients**: Evaluating the significance of path coefficients helps to understand the strength and relationships of the hypotheses. The β values, which represent these path coefficients, are shown in Table 7.

(v) **Bootstrap Confidence Intervals**: Bootstrap confidence intervals are calculated to determine the precision and reliability of the estimated path relationships. The confidence interval values are displayed in Table 7.

Table 6
R-square and Q-square values

	R-square	R-square adjusted	Q-square
Customer Satisfaction	0.29	0.226	0.075
Optimizing Inventory Management	0.903	0.884	0.522
Quality	0.318	0.256	0.098
Sales	0.361	0.303	0.208

Table 7
Findings of Research Questions.

	Path Coefficient (β)	STDEV	T statistics	P values	Confidence Interval	
					2.50%	97.50%
RQ1: Cost → OIM	0.923	0.248	3.728	0.000	0.447	1.128
RQ2: SCC → OIM	0.704	0.325	2.165	0.030	-0.121	1.049
RQ3: OIM → CS	0.539	0.16	3.374	0.001	0.322	0.847
RQ4: OIM → Sales	0.601	0.201	2.992	0.003	0.200	0.885
RQ5: OIM → Quality	0.564	0.273	2.065	0.039	-0.415	0.884

** OIM = Optimizing Inventory Management, SCC = Supply Chain Complexity, CS = Customer Satisfaction

All the research questions are supported as shown in Table 7. The β (path coefficient) values, T statistics and P values support the research questions. The findings of the research questions and their sub-factors values are shown in Fig. 2.

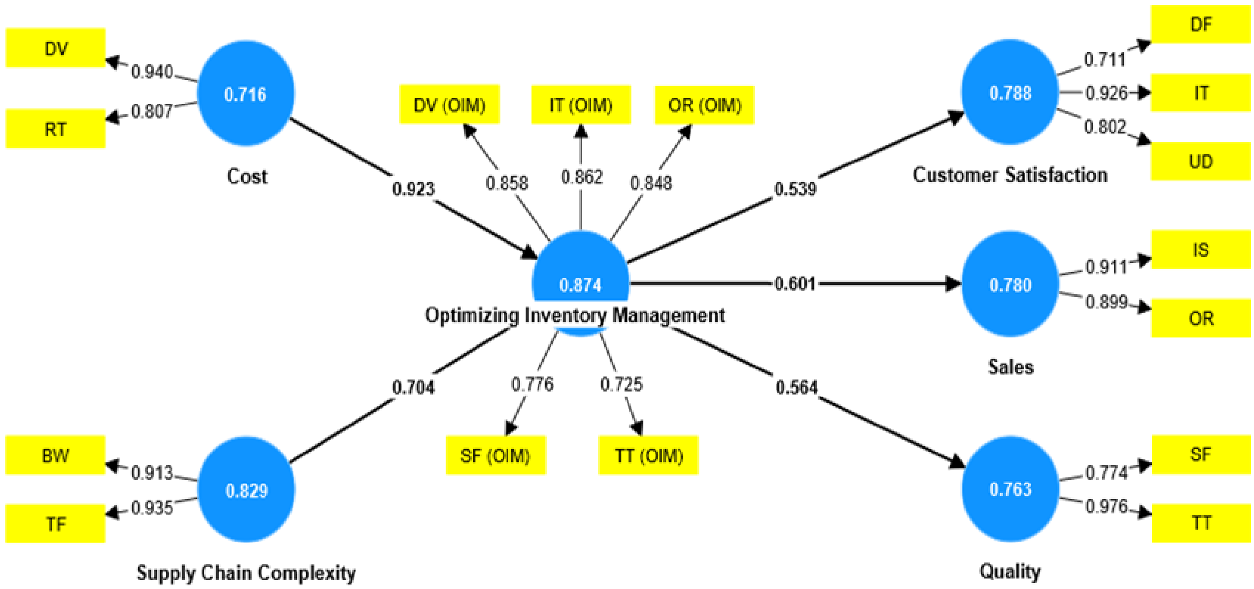

Fig. 2. PLS-SEM with path coefficients of Optimized Inventory and its linked elements

4. Discussion

The current research sought to investigate and factorize the challenges and establish the reliability and validity of the variables pertaining to inventory management of perishable food items made of dairy products using Partial Least Squares Structural Equation Modeling (PLS-SEM) and propose effective solutions to address these issues.

A conceptual model was developed based on the identification of challenges in proper inventory management and its effect on customer satisfaction, sales and quality of the product. The developed model was validated and addressed five research questions through hypothesis testing. The results presented in Table 7 and Figure 2 indicated that all the generated research questions are justified.

Through a comprehensive analysis of the food industry's inventory management processes, it is identified that several critical challenges that impede customer satisfaction, sales and quality. Based on the analysis of Factor Loading and R-Square values obtained from PLS-SEM model, it can be concluded that, Firstly, demand variation and inadequate demand forecasting emerged as a significant obstacle, leading to either excess inventory, resulting in storage and spoilage costs, or stock-outs, causing customer dissatisfaction and revenue loss. Secondly, inadequate transportation facilities disrupt the seamless flow of dairy products through the distribution network, cause delays, product damage, and inconsistent delivery schedules, impacting customer satisfaction. Thirdly, fluctuation in temperature and time leads to product spoilage and reduced shelf life for food products.

Moreover, the lack of real-time data and integrated information systems hindered decision-making, making it difficult for dairy companies to optimize their inventory levels effectively. Additionally, fluctuations in seasonal demand posed a challenge to maintaining an optimal inventory balance throughout the year.

In response to these challenges, the present study recommends several solutions aimed at enhancing dairy product inventory management. Employing advanced demand forecasting techniques, such as machine learning algorithms and historical sales data analysis, using modern software can significantly improve the accuracy of predicting future demands, thus enabling companies to optimize their inventory levels more efficiently.

To address supply chain complexities, fostering strong and transparent collaborations with suppliers, implementing vendor-managed inventory (VMI) systems, and integrating technology for real-time tracking of goods can help ensure a smooth and continuous supply flow.

Furthermore, investing in robust and integrated information systems that provide real-time data on inventory levels, sales trends, and customer preferences will empower decision-makers to make informed choices swiftly and proactively manage inventory in response to changing market demands.

Lastly, the research highlights the importance of adopting a responsive and flexible inventory management strategy that accounts for seasonal fluctuations in demand. By strategically planning production and inventory allocation, dairy companies can minimize costs and better meet customer needs, even during peak seasons.

5. Conclusions

From the literature review and field data it is evident that cost and complexity are two vital challenges to optimize the inventory that hinders the satisfaction of customers, sales volume and quality of the products. From the obtained results it could be concluded that

- The developed conceptual framework that links inventory management with costs and supply chain complexity is validated. Moreover, the inventory management effect on satisfaction, sales quantity and quality is also justified.

By applying PLS-SEM to identify and factorize the challenges of perishable food product inventory management and proposing feasible solutions, this research contributes to the body of knowledge in supply chain management. The findings of this study can serve as a valuable guide for food industry stakeholders seeking to enhance their inventory management practices, improve operational efficiency, quality and customer satisfaction and ultimately achieve sustainable growth in an increasingly competitive market.

Acknowledgement
The authors are thankful to the Department of Industrial and Production Engineering, SUST and food processing factories for providing the support during data collection.

References

Abaku, E. A., Edunjobi, T. E., & Odimarha, A. C. (2024). Theoretical approaches to AI in supply chain optimization: Pathways to efficiency and resilience. *International Journal of Science and Technology Research Archive*, *6*(1), 092–107. https://doi.org/10.53771/ijstra.2024.6.1.0033

Ahmad, K., & Zabri, S. (2016). Inventory management practices among Malaysian micro retailing enterprises. *Journal of Business and Retail Management Research*, *11*(1), 103–115. https://doi.org/10.24052/JBRMR/247

Ahmadini, A. A. H., Modibbo, U. M., Shaikh, A. A., & Ali, I. (2021). Multi-objective optimization modelling of sustainable green supply chain in inventory and production management. *Alexandria Engineering Journal*, *60*(6), 5129–5146. https://doi.org/10.1016/j.aej.2021.03.075

Aqlan, F., & Lam, S. S. (2016). Supply chain optimization under risk and uncertainty: A case study for high-end server manufacturing. *Computers and Industrial Engineering*, *93*, 78–87. https://doi.org/10.1016/j.cie.2015.12.025

Atnafu, D., & Balda, A. (2018). The impact of inventory management practice on firms' competitiveness and organizational performance: Empirical evidence from micro and small enterprises in Ethiopia. *Cogent Business and Management*, *5*(1), 1–16. https://doi.org/10.1080/23311975.2018.1503219

Avkiran, N. K., & Ringle, C. M. (Eds.). (2018). *Partial least squares structural equation modeling: Recent advances in banking and finance* (Vol. 239). Berlin/Heidelberg, Germany: Springer International Publishing.

Bozarth, C. C., Warsing, D. P., Flynn, B. B., & Flynn, E. J. (2009). The impact of supply chain complexity on manufacturing plant performance. *Journal of Operations Management*, *27*(1), 78–93. https://doi.org/10.1016/j.jom.2008.07.003

Castro, J. A. O., & Jaimes, W. A. (2017). Dynamic impact of the structure of the supply chain of perishable foods on logistics performance and food security. *Journal of Industrial Engineering and Management*, *10*(4 Special Issue), 687–710. https://doi.org/10.3926/jiem.2147

Charles, N., & Jackson, N. (2021). Influence of electronic point of sale on inventory optimization in major supermarkets in Nairobi City County, Kenya. *Journal of Procurement and Management*, *5*(2), 633–653.

Chen, Z. (2018). Optimization of production inventory with pricing and promotion effort for a single-vendor multi-buyer system of perishable products. *International Journal of Production Economics*, *203*, 333–349. https://doi.org/10.1016/j.ijpe.2018.06.002

Chinello, E., Lee Herbert-Hansen, Z. N., & Khalid, W. (2020). Assessment of the impact of inventory optimization drivers in a multi-echelon supply chain: Case of a toy manufacturer. *Computers and Industrial Engineering*, *141*. https://doi.org/10.1016/j.cie.2019.106232

Dai, H., & Tseng, M. M. (2012). The impacts of RFID implementation on reducing inventory inaccuracy in a multi-stage supply chain. *International Journal of Production Economics*, *139*(2), 634–641. https://doi.org/10.1016/j.ijpe.2012.06.005

Daniel, J. S. R., & Rajendran, C. (2005). A simulation-based genetic algorithm for inventory optimization in a serial supply chain. *International Transactions in Operational Research*, *12*(1), 101–127. https://doi.org/10.1111/j.1475-3995.2005.00492.x

Diabat, A., & Al-Salem, M. (2015). An integrated supply chain problem with environmental considerations. *International Journal of Production Economics*, *164*, 330–338. https://doi.org/10.1016/j.ijpe.2014.12.004

Duan, Q., & Liao, T. W. (2013). A new age-based replenishment policy for supply chain inventory optimization of highly perishable products. *International Journal of Production Economics*, *145*(2), 658–671. https://doi.org/10.1016/j.ijpe.2013.05.020

Eckstein, D., Goellner, M., Blome, C., & Henke, M. (2014). The performance impact of supply chain agility and supply chain adaptability: The moderating effect of product complexity. *International Journal of Production Research*, *53*(10), 3028–3046. https://doi.org/10.1080/00207543.2014.970707

Ferguson, M., & Ketzenberg, M. E. (2006). Information Sharing to Improve Retail Product Freshness of Perishables. *Production and Operations Management*, *15*(1), 57–73. https://doi.org/10.1111/j.1937-5956.2006.tb00003.x

Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, *19*(4), 440-452. https://doi.org/10.1177/002224378201900406

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Garcia, D. J., & You, F. (2015). Supply chain design and optimization: Challenges and opportunities. *Computers and Chemical Engineering*, *81*, 153–170. https://doi.org/10.1016/j.compchemeng.2015.03.015

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. http://dx.doi.org/10.1108/EBR-11-2018-0203

Hartwig, R., Inderfurth, K., Sadrieh, A., & Voigt, G. (2015). Strategic Inventory and Supply Chain Behavior. *Production and Operations Management*, *24*(8), 1329–1345. https://doi.org/10.1111/poms.12325

Iftikhar, A., Purvis, L., Giannoccaro, I., & Wang, Y. (2023). The impact of supply chain complexities on supply chain resilience: the mediating effect of big data analytics. *Production Planning & Control*, *34*(16), 1562–1582. https://doi.org/10.1080/09537287.2022.2032450

Ivanov, D., Dolgui, A., Das, A., & Sokolov, B. (2019). Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility. In *International Series in Operations Research and Management Science* (Vol. 276, pp. 309–332). Springer New York LLC. https://doi.org/10.1007/978-3-030-14302-2_15

Jemai, J., Chung, B. Do, & Sarkar, B. (2020). Environmental effect for a complex green supply-chain management to control waste: A sustainable approach. *Journal of Cleaner Production*, *277*. https://doi.org/10.1016/j.jclepro.2020.122919

Kler, R., Gangurde, R., Elmirzaev, S., Hossain, M. S., Vo, N. V. T., Nguyen, T. V. T., & Kumar, P. N. (2022). Optimization of Meat and Poultry Farm Inventory Stock Using Data Analytics for Green Supply Chain Network. *Discrete Dynamics in Nature and Society*, *2022*. https://doi.org/10.1155/2022/8970549

Martin, M., & Iravo, Dr. A. (2014). Effect of inventory control management on mumias sugar retailers satisfaction level: A survey of mumias sugar retailers in Kiambu County, Kenya. *International Journal of Academic Research in Business and Social Sciences*, *4*(12), 83–100. https://doi.org/10.6007/ijarbss/v4-i12/1330

Martynova, E., West, S. G., & Liu, Y. (2018). Review of principles and practice of structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(2), 325-329. https://doi.org/10.1080/10705511.2017.1401932

Monecke, A., & Leisch, F. (2012). semPLS: structural equation modeling using partial least squares. *Journal of statistical software*, *48*, 1-32. https://doi.org/10.18637/jss.v048.i03

Motla, R., Kumar, A., Saxena, N., & Sana, S. S. (2023). Inventory optimization in a green environment with two warehouses. *Innovation and Green Development*, *2*(4). https://doi.org/10.1016/j.igd.2023.100087

Panigrahi, A. (2013). Relationship between inventory management and profitability: An empirical analysis of Indian cement companies. *Asia Pacific Journal of Marketing & Management Review*, *2*(7).

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research*. Sage.

Rashed, C. A. A., Bagum, M. N., Kibria, M. M. H., Chowdhury, R. A., & Islam, M. A. (2024). Integrating Supply Chain Partners through Implementing Industry 4.0 Technologies to Enhance Competitiveness. *Jordan Journal of Mechanical and Industrial Engineering*, *18*(2), 351–363. https://doi.org/10.59038/jjmie/180208

Sadeghi, J., Sadeghi, S., & Niaki, S. T. A. (2014a). A hybrid vendor managed inventory and redundancy allocation optimization problem in supply chain management: An NSGA-II with tuned parameters. *Computers and Operations Research*, *41*(1), 53–64. https://doi.org/10.1016/j.cor.2013.07.024

Sadeghi, J., Sadeghi, S., & Niaki, S. T. A. (2014b). Optimizing a hybrid vendor-managed inventory and transportation problem with fuzzy demand: An improved particle swarm optimization algorithm. *Information Sciences*, *272*, 126–144. https://doi.org/10.1016/j.ins.2014.02.075

Saputro, T. E., Figueira, G., & Almada-Lobo, B. (2021). Integrating supplier selection with inventory management under supply disruptions. *International Journal of Production Research*, *59*(11), 3304–3322. https://doi.org/10.1080/00207543.2020.1866223

Serdarasan, S. (2013). A review of supply chain complexity drivers. *Computers and Industrial Engineering*, *66*(3), 533–540. https://doi.org/10.1016/j.cie.2012.12.008

Simchi-Levi, D., Wang, H., & Wei, Y. (2018). Increasing Supply Chain Robustness through Process Flexibility and Inventory. *Production and Operations Management*, *27*(8), 1476–1491. https://doi.org/10.1111/poms.12887

Takim, S. A. (2014). Optimization of Effective Inventory Control and Management in Manufacturing Industries: Case Study of Flour Mills Company Calabar, Nigeria. *Journal of Emerging Trends in Engineering and Applied Sciences (JETEAS)*, *5*(4), 265–276.

Tripathi, P., & Tiwari, D. (2014). A study of inventory management techniques applied by organized retailers' and its effect on customer satisfaction and retailer's financial performance with special reference to Bhopal and Indore City. *International Journal of Innovation and Applied Studies*, *8*(2), 788–799. http://www.ijias.issr-journals.org/

Uthayakumar, R., & Priyan, S. (2013). Pharmaceutical supply chain and inventory management strategies: Optimization for a pharmaceutical company and a hospital. *Operations Research for Health Care*, *2*(3), 52–64. https://doi.org/10.1016/j.orhc.2013.08.001

Van Horenbeek, A., Buré, J., Cattrysse, D., Pintelon, L., & Vansteenwegen, P. (2013). Joint maintenance and inventory optimization systems: A review. *International Journal of Production Economics*, *143*(2), 499–508. https://doi.org/10.1016/j.ijpe.2012.04.001

Wang, K. J., Lin, Y. S., & Yu, J. C. P. (2011). Optimizing inventory policy for products with time-sensitive deteriorating rates in a multi-echelon supply chain. *International Journal of Production Economics*, *130*(1), 66–76. https://doi.org/10.1016/j.ijpe.2010.11.009

Wei, J., Liu, Y., Zhao, X., & Yang, X. (2020). Joint optimization of pricing and inventory strategy for perishable product with the quality and quantity loss. *Journal of Industrial and Production Engineering*, *37*(1), 23–32. https://doi.org/10.1080/21681015.2020.1719222

Wu, S. D., & Golbasi, H. (2004). Multi-Item, Multi-Facility Supply Chain Planning: Models, Complexities, and Algorithms *. *Computational Optimization and Applications*, *28*, 325–356. https://doi.org/10.1023/B:COAP.0000033967.18695.9d

Zheng, X., Yin, M., & Zhang, Y. (2019). Integrated optimization of location, inventory and routing in supply chain network design. *Transportation Research Part B: Methodological*, *121*, 1–20. https://doi.org/10.1016/j.trb.2019.01.003