

Inventory Management in Private Merchandising Business: Bridging Identified Gaps Through Cost-Efficiency Framework

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ABSTRACT

This study examined inventory management practices in a private hard-discount merchandising business and developed an integrated framework for improving operational efficiency and cost efficiency. A mixed-methods design combined a structured employee survey with qualitative accounts of inventory and supply-chain practices. Quantitative analysis assessed real-time data and tracking, predictive modeling for demand forecasting, and sustainability and cost reduction, while qualitative thematic analysis examined waste reduction, continuous improvement, demand-pull practices, and supplier integration. The reported results show consistently high assessments of the three data-driven inventory dimensions. Predictive modeling was the strongest reported predictor of inventory management performance, followed by sustainability and cost reduction and real-time data and tracking. Qualitative findings indicate that waste reduction and continuous improvement were practiced but remained largely manual and reactive, while supplier coordination was often informal and vulnerable to delays. The study proposes an Integrated Smart Inventory Management Framework that combines data-driven inventory optimization with lean supply-chain practices to support proactive replenishment, waste reduction, supplier coordination, and long-term cost efficiency.

Keywords: Inventory Management; Demand Forecasting; Real-Time Tracking; Lean Supply Chain; Cost Efficiency; Merchandising Business

INTRODUCTION

Inventory management is central to merchandising performance because firms must maintain product availability while controlling holding costs, stockouts, waste, and working capital. The challenge is particularly important for discount-oriented retailers operating with narrow margins and fluctuating demand. Traditional or predominantly manual inventory practices can limit visibility, slow replenishment decisions, and make it difficult to respond quickly to changes in customer demand.

This study focuses on a private merchandising business operating in a highly price-sensitive urban retail environment. To protect confidentiality, the participating company is referred to throughout this article only as the “participating merchandising business.” The article evaluates inventory management through two complementary perspectives: Data-Driven Inventory Optimization and Lean Supply Chain Management (LSCM). The former emphasizes real-time data, predictive demand forecasting, and sustainability-oriented cost reduction; the latter emphasizes waste reduction, continuous improvement, demand pull, and supplier integration.

The study addressed three questions: (1) How is the current inventory management system assessed in terms of real-time data and tracking, predictive modeling for demand forecasting, and sustainability and cost reduction? (2) How do employees describe their experiences, challenges, and suggestions for improving inventory management to achieve cost efficiency? and (3) What integrated strategies can address the identified gaps?

Literature and Conceptual Basis

Data-Driven Inventory Optimization

Data-driven inventory optimization uses timely operational information and analytical models to align stock levels with demand. Real-time tracking improves inventory visibility and supports faster responses to stock movements and supply disruptions. Predictive modeling uses historical and contextual data to estimate future demand, while automation can reduce manual errors and improve replenishment speed. In the manuscript's literature base, these practices are consistently linked with improved forecasting accuracy, lower excess inventory, fewer stockouts, and stronger operational decision-making.

Lean Supply Chain Management

LSCM complements data-driven inventory management by emphasizing the removal of non-value-adding activities and the continuous refinement of supply-chain processes. Its relevant dimensions in this study are waste reduction, continuous improvement, demand-pull replenishment, and supplier integration. Together, these practices are intended to reduce excess inventory, shorten delays, align replenishment with actual demand, and strengthen coordination with suppliers.

Sustainability and Cost Reduction

The reviewed literature emphasizes that effective and sustainable inventory management depends on integrating cost-efficiency, waste reduction, demand responsiveness, supplier collaboration, data-driven technologies, and lean supply chain practices. Studies show that sustainability-oriented inventory systems can reduce waste, excess stock, spoilage, and environmental impacts while improving resource utilization and long-term economic performance. Demand-pull approaches and accurate forecasting help businesses align inventory with actual customer needs, while strong supplier integration improves coordination, responsiveness, risk management, and operational performance. Moreover, real-time analytics, predictive modeling, IoT, and automated replenishment can reduce stockouts, overstocking, inventory costs, and waste while improving decision-making. Finally, lean supply chain practices—including waste minimization, continuous improvement, demand-driven replenishment, and supplier collaboration—further enhance inventory turnover, cost efficiency, customer satisfaction, sustainability, and overall supply chain performance.

Integrated Conceptual Framework

The conceptual logic of the study is that real-time data and tracking, predictive demand forecasting, and sustainability-oriented cost reduction strengthen inventory decisions, while lean practices address process waste, continuous improvement, demand responsiveness, and supplier coordination. Their integration is expected to improve cost efficiency by moving inventory management from a reactive system toward a proactive and continuously improving system.

METHODOLOGY

Research Design and Participants

The study used a mixed-methods design. Quantitative data were gathered through a structured survey, while qualitative data were obtained from personnel involved in inventory and supply-chain activities and analyzed thematically. The manuscript reports a population of 380 personnel across 38 stores in the study area and a quantitative sample of 191 respondents.

Instrument and Scale

The quantitative instrument measured three dimensions of Data-Driven Inventory Optimization: real-time data and tracking, predictive modeling for demand forecasting, and sustainability and cost reduction. The source manuscript contains an internal inconsistency: the methodology describes a 5-point Likert scale, while the

reliability section and archived appendix display a 4-point response format. Because the reported means range above 4.00 (up to 4.45), those descriptive statistics cannot arise from a four-point scale. For this blinded journal version, the quantitative results are therefore reported as based on the manuscript's stated 5-point scale (1 = Strongly Disagree to 5 = Strongly Agree). Before journal submission, the author should verify this against the original administered questionnaire and raw dataset; if the administered instrument was actually four-point, the descriptive statistics must be recomputed from the raw responses rather than relabeled.

Validity, Reliability, Ethics, and Analysis

The instrument underwent validity review and pilot reliability testing. The manuscript states that 15 respondents who were not part of the primary sample participated in the pilot test and that Cronbach's alpha was used to assess internal consistency. Participation was voluntary, respondents were assured of anonymity and confidentiality, and data were intended for academic use. Quantitative analysis used descriptive statistics and regression-based hypothesis testing, while qualitative responses were organized through thematic analysis.

RESULTS

Descriptive Assessment of Data-Driven Inventory Practices

Table 1. Overall assessment of Data-Driven Inventory Optimization dimensions

Dimension	Overall Mean	SD	Interpretation
Real-Time Data and Tracking	4.38	.520	Strongly Agree
Predictive Modeling for Demand Forecasting	4.39	.520	Strongly Agree
Sustainability and Cost Reduction	4.40	.524	Strongly Agree

All three dimensions received high overall ratings. Sustainability and cost reduction had the highest overall mean ($M = 4.40$, $SD = .524$), followed by predictive modeling for demand forecasting ($M = 4.39$, $SD = .520$) and real-time data and tracking ($M = 4.38$, $SD = .520$). The pattern suggests that respondents perceived data-driven and sustainability-oriented inventory practices as strongly embedded in the participating merchandising business.

Regression Results

Table 2. Multiple regression coefficients for the Data-Driven Inventory Optimization dimensions

Predictor	β	t	p	Decision	Interpretation
Real-Time Data and Tracking	0.32	4.85	0.000	Reject H_0	Significant positive effect
Predictive Modeling for Demand Forecasting	0.41	6.12	0.000	Reject H_0	Significant positive effect
Sustainability and Cost Reduction	0.36	5.38	0.000	Reject H_0	Significant positive effect

All three predictors were reported as statistically significant at $\alpha = .05$. Predictive modeling for demand forecasting had the largest standardized coefficient ($\beta = .41$, $t = 6.12$, $p < .001$), followed by sustainability and cost reduction ($\beta = .36$, $t = 5.38$, $p < .001$) and real-time data and tracking ($\beta = .32$, $t = 4.85$, $p < .001$).

Table 3. Overall model summary for the combined Data-Driven Inventory Optimization predictors

Model	R ²	F	p	Interpretation
Real-time data + predictive modeling + sustainability/cost reduction → inventory management system	.79	112.45	< .001	Overall model statistically significant

The original manuscript duplicated the coefficient output when presenting the relationship test. To avoid reporting the same regression coefficients twice, the journal version separates the coefficient table from the overall model summary. The manuscript reports $R^2 = .79$ and $F = 112.45$ ($p < .001$), indicating that the combined predictors accounted for 79% of the reported variation in the inventory management outcome. A true correlation matrix cannot be reconstructed without the raw respondent-level dataset; therefore, no unverified Pearson r values have been invented.

Table 4. Predictive modeling and reported inventory-performance outcomes

Outcome	Predictor	β	t	p	Decision	Interpretation
Inventory Efficiency	Predictive Modeling for Demand Forecasting	0.41	6.12	0.000	Reject H_0	Significant positive influence
Stock Availability	Predictive Modeling for Demand Forecasting	0.39	5.88	0.000	Reject H_0	Significant positive influence
Cost Reduction	Predictive Modeling for Demand Forecasting	0.37	5.45	0.000	Reject H_0	Significant positive influence

Predictive modeling was reported to have a significant positive influence on inventory efficiency ($\beta = .41$), stock availability ($\beta = .39$), and cost reduction ($\beta = .37$), with all reported p-values below .001. The manuscript further reports $R^2 = .76$ and $F = 98.32$ ($p < .001$) for the overall predictive-modeling performance model.

Qualitative Findings

Table 5. Condensed thematic findings

Theme	Observed practices	Condensed interpretation
Waste reduction	Stock monitoring, stock rotation, manual checking, basic digital tracking	Practices existed but were largely manual and reactive; overstocking, damage, expiry, and forecasting errors remained concerns.
Continuous improvement	Incremental process adjustments, monitoring, employee reporting and suggestions	Improvement occurred mainly through experience-based adjustments rather than a formal continuous-improvement system.

Demand pull	Sales-based replenishment, customer-driven stocking, seasonal adjustments	Demand-pull practices were partially implemented, but stock adjustments were often reactive and dependent on informal tracking.
Supplier integration	Calls/messages, periodic ordering, trust-based coordination, delivery scheduling	Supplier coordination was present but informal; inconsistent delivery performance and limited structured integration created vulnerability.

DISCUSSION

The quantitative findings suggest that the participating merchandising business had already adopted several elements associated with data-driven inventory management. Respondents particularly recognized the value of predictive modeling, which emerged as the strongest reported predictor. This is consistent with the study's conceptual position that improved demand forecasting can reduce both overstocking and stockouts by enabling more timely replenishment decisions.

The sustainability findings should be interpreted as operational inventory practices rather than as training or simulation activities. The results consistently concern waste reduction, energy use, packaging, storage costs, inventory optimization, profitability, and environmental responsibility. The high overall mean indicates favorable employee perceptions, although the comparatively lower rating for direct operational-cost savings suggests that some financial benefits may take longer to become visible.

The qualitative findings qualify the strong quantitative ratings. Although technology-supported and lean practices were recognized, day-to-day waste reduction, process improvement, demand adjustment, and supplier coordination remained partly manual, informal, and reactive. This gap between favorable perceptions and operational practice supports the need for an integrated framework that links forecasting and real-time information with standardized lean routines and more formal supplier collaboration.

Proposed Integrated Smart Inventory Management Framework

The proposed framework combines four operational layers. First, real-time inventory visibility should provide a common view of stock levels, movement, and exceptions. Second, predictive demand forecasting should guide replenishment quantities and timing. Third, lean operating routines should formalize waste reduction, continuous improvement, and demand-pull replenishment. Fourth, supplier integration should establish clearer information-sharing, delivery expectations, and performance monitoring. Sustainability and cost-efficiency indicators should cut across all four layers so that inventory decisions are evaluated not only by availability but also by waste, storage cost, resource use, and profitability.

CONCLUSION AND RECOMMENDATIONS

The study indicates that data-driven inventory practices can contribute to stronger inventory management in a private merchandising business, with predictive demand forecasting showing the strongest reported influence. However, qualitative evidence shows that several lean practices remain manual, reactive, or informally coordinated. The proposed integrated framework addresses this gap by linking real-time visibility and predictive analytics with waste reduction, continuous improvement, demand-pull replenishment, and supplier integration.

For implementation, the participating merchandising business should prioritize standardized data capture, forecast review routines, exception-based replenishment, supplier performance monitoring, and measurable waste- and cost-reduction targets. For research reporting, the author should retain strict company masking and verify the original Likert response format against the administered questionnaire and raw data. If raw respondent-level data are available, the relationship hypothesis should be rerun using the intended statistic (for example, a correlation matrix if the hypothesis is relational) and reported separately from regression coefficients.

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