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Predicting Stock Requirement in Organised Retail: A Case Study of DMart

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ABSTRACT
The organised retail sector in India has witnessed unprecedented growth over the past two decades, with hypermarket chains like DMart (Avenue Supermarts Ltd.) emerging as dominant players through superior supply chain efficiency and cost leadership. Accurate stock requirement prediction remains a critical determinant of profitability, customer satisfaction, and operational efficiency in this capital-intensive industry. This paper examines the methodologies, frameworks, and challenges associated with stock prediction at DMart, using secondary data sourced from published annual reports, academic literature, industry databases, and institutional research. The study analyses DMart's proprietary EDLC-EDLP (Every Day Low Cost – Every Day Low Price) model, its vendor-managed inventory arrangements, and seasonal demand patterns across product categories. The paper discusses quantitative tools including Economic Order Quantity (EOQ), ABC–VED analysis, Moving Average and Exponential Smoothing models, and emerging AI-driven demand forecasting approaches. Findings indicate that DMart's stock prediction advantage stems from a combination of centralised procurement, data-driven reorder policies, stringent shrinkage controls, and long-term supplier relationships. The study contributes to management literature by synthesising best practices applicable to organised retail in emerging markets and offers strategic recommendations for improving forecast accuracy. This research is intended for academic publication at the postgraduate MBA level.

INTRODUCTION

The Indian retail industry is one of the largest and fastest-growing sectors in the global economy, projected to reach USD 2 trillion by 2032 (IBEF, 2023). Within this expansive landscape, organised retail characterised by professionally managed chains, standardised formats, and formal procurement systems accounts for a rapidly expanding share, growing from approximately 8% of total retail in 2012 to nearly 25% in 2023 (Deloitte, 2023). DMart, operated by Avenue Supermarts Limited, has been at the vanguard of this transformation since its inception in 2002 under the stewardship of Mr. Radhakrishna Damani.

Unlike most global hypermarket chains, DMart follows a distinctive own-and-operate model — it owns the real estate it operates from, thereby avoiding the volatility of rental costs and enabling long-term strategic planning. Coupled with its EDLC-EDLP philosophy, which promises consumers consistently low prices, DMart's entire operational architecture is built around cost compression at every node of the supply chain. Central to this model is the ability to predict stock requirements with precision — ensuring that shelves remain adequately stocked without accumulating excessive inventory that ties up working capital.Inventory management in retail is a complex, multi-variable challenge. Consumer demand is influenced by seasonality, promotional events, macroeconomic conditions, regional preferences, and competitive dynamics. The consequences of poor stock prediction are twofold and equally damaging:

stockouts result in lost sales, customer dissatisfaction, and erosion of brand trust, while overstocking leads to increased carrying costs, product spoilage (particularly in perishables), and eventual markdowns that dilute margins.This paper undertakes a systematic secondary-data analysis to understand how DMart approaches stock requirement prediction, what analytical frameworks it employs, how its supply chain architecture supports forecasting accuracy, and what lessons can be drawn for the broader organised retail sector. The research is structured as follows: Section 2 reviews the relevant literature; Section 3 outlines the research methodology; Section 4 profiles DMart as an organisation; Section 5 examines stock prediction frameworks; Section 6 presents findings and analysis; Section 7 discusses implications; Section 8 concludes with recommendations

The study is guided by the following specific objectives:

To examine the theoretical frameworks and quantitative models employed in stock requirement prediction within organised retail.

To analyse DMart's supply chain architecture and inventory management philosophy in the context of demand forecasting.

To identify key factors influencing stock prediction accuracy at DMart across product categories.

To evaluate the role of technology and data analytics in enhancing forecast reliability.

To derive strategic recommendations for improving stock prediction practices in organised retail chains operating in emerging markets.

SCOPE OF STUDY

The study is confined to secondary data sources and does not involve primary data collection through surveys or interviews. The analysis is based on publicly available annual reports of Avenue Supermarts Ltd., peer-reviewed academic literature, SEBI filings, industry reports from IBEF, Deloitte, McKinsey, and KPMG, and news articles from credible financial publications. The findings, while analytically rigorous, are subject to the limitations inherent in secondary research, including potential data lags and restricted access to proprietary operational metrics.

REVIEW LITRATURE

Inventory management retail

The foundations of inventory management in retail are rooted in operations research literature dating back to Harris (1913), who first formalised the Economic Order Quantity (EOQ) model. Subsequent contributions by Wilson (1934), Arrow, Harris and Marschak (1951), and Silver and Meal (1973) extended EOQ theory to account for probabilistic demand, lead time uncertainty, and multi-period planning horizons. The classic EOQ model, despite its simplifying assumptions, Chopra and Meindl (2016) emphasise that effective supply chain management requires balancing the cost of holding inventory against the risk of stockouts, a trade-off that is particularly acute in high-SKU, high-velocity retail environments. Their framework of cycle stock, safety stock, and pipeline inventory provides a useful lens for understanding DMart's replenishment architecture.

Demand forecasting Method

Demand forecasting constitutes the cornerstone of stock prediction. Makridakis, Wheelwright, and Hyndman (1998) categorise forecasting methods into qualitative (expert opinion, Delphi method, market surveys) and quantitative approaches (time series models, causal models). In retail, quantitative methods have gained primacy due to the availability of large transactional datasets through point-of-sale (POS) systems.

Time series methods — including Simple Moving Average (SMA), Weighted Moving Average (WMA), Single and Double Exponential Smoothing, and the Holt-Winters Seasonal Model — have been extensively applied in retail forecasting. Box and Jenkins (1970) introduced ARIMA models, which account for autocorrelation in demand patterns and have shown strong predictive performance across multiple product categories (Syntetos et al., 2016).

More recently, machine learning and artificial intelligence have transformed demand forecasting. Carbonneau, Laframboise, and Vahidov (2008) demonstrated that recurrent neural networks outperform traditional statistical methods when demand patterns are irregular. Fildes et al. (2019) reviewed over 200 forecasting studies in retail and found that hybrid models — combining statistical and machine learning components — consistently delivered superior accuracy.

Indian Organised Retail of DMart

Research specifically examining Indian organised retail is relatively nascent but growing. Kumar and Kulkarni (2019) analysed the emergence of hypermarket chains in India, identifying supply chain efficiency as the primary differentiator between successful and failed retail ventures. Their study highlighted DMart's model as exemplary, attributing its success to disciplined procurement, zero-debt growth, and concentrated store presence in high-density urban clusters.

Sharma and Mehta (2021) examined DMart's financial performance from 2012–2020, documenting an inventory turnover ratio consistently exceeding 12x annually — significantly above the industry average of 8–9x — as evidence of superior demand prediction capability. Verma (2022) studied the EDLC-EDLP model's dependency on vendor relationships, finding that DMart's practice of early supplier payments (within 11–12 days versus the industry standard of 30–45 days) translates into procurement discounts that fund its price competitiveness.

Research Gap

While considerable literature exists on inventory management theory and demand forecasting methods, there is a conspicuous absence of published research that comprehensively examines stock prediction practices at DMart through a secondary data lens at the MBA research level. Most case studies on DMart focus on financial performance or competitive strategy, with limited attention to the operational mechanics of inventory forecasting. This paper addresses that gap.

Research Methodology

Research Design

This study adopts a descriptive and analytical research design. Given the secondary nature of data, the research follows a systematic literature review (SLR) approach combined with case study methodology. The case study method, as advocated by Yin (2014), is particularly suited to the study of contemporary organisational phenomena within real-world contexts where the boundary between phenomenon and context is not clearly evident.

Data Source

Secondary data for this study was collected from the following sources:

SOURCE CATEGORY	SPECIFIC SOURCES
Company Filings	Avenue Supermarts Ltd. Annual Reports (2017–2023), SEBI Disclosures, BSE/NSE Filings

Academic Literature	Peer-reviewed journals: IJRM, JOM, EJOR, SCM: An International Journal
Industry Reports	IBEF Retail Sector Report 2023, Deloitte India Retail Outlook, KPMG Consumer Markets
Financial Databases	Capitaline, Ace Equity, Bloomberg (secondary access via institution repositories)
News & Media	The Economic Times, Business Standard, Mint, Forbes India (2018–2023)

Analytical Framework

The study employs a thematic content analysis framework to synthesise information from diverse secondary sources. Quantitative tools such as EOQ, ABC Analysis, and Moving Average models are explained and contextualised using DMart-specific financial metrics derived from published annual reports. Trend analysis of key inventory metrics (inventory turnover ratio, days inventory outstanding, gross margin return on inventory) over a seven-year period (FY 2017–FY 2023) forms the empirical backbone of the analytical sections.

DMART: COMPANY PROFILE AND RETAIL MODEL

Background and growth

Avenue Supermarts Limited, the holding entity of DMart, was incorporated in 2000 and opened its first store in Powai, Mumbai, in 2002. By March 2023, the company operated 327 stores across 22 states and union territories, with a total retail business area exceeding 13.5 million square feet (Avenue Supermarts Annual Report, 2023). Revenue from operations grew from INR 11,903 crore in FY 2017 to INR 42,840 crore in FY 2023, representing a compound annual growth rate (CAGR) of approximately 23.6%. DMart's financial model is distinguished by its asset-heavy approach: unlike competitors such as Reliance Retail and Big Bazaar which predominantly lease retail space, DMart owns a majority of its store premises. This strategy, while capital-intensive in the short term, substantially reduces long-term occupancy costs and provides operational stability that directly supports inventory planning certainty.

Product Portfolio and store format

DMart's product portfolio spans three broad categories: (i) Food and Grocery (approximately 52% of revenues), encompassing staples, packaged foods, dairy, and fresh produce; (ii) Non-Food FMCG (approximately 20% of revenues), including personal care, home care, and over-the-counter healthcare products; and (iii) General Merchandise and Apparel (approximately 28% of revenues), covering kitchenware, home furnishings, and basic clothing. The company deliberately limits its SKU count to fast-moving items, maintaining approximately 3,500–4,000 SKUs per store — significantly lower than international hypermarket benchmarks of 10,000–15,000 SKUs (McKinsey, 2022).

THE EDLC-EDLP MODEL

The philosophical bedrock of DMart's operations is the EDLC-EDLP (Every Day Low Cost – Every Day Low Price) model. This strategy diverges fundamentally from the High-Low pricing approach adopted by most Indian retailers wherein promotional deep discounts alternate with regular pricing. EDLC-EDLP requires that cost savings be achieved structurally — through procurement efficiency, minimal wastage, lean staffing, and inventory velocity — rather than through periodic markdowns.

For stock prediction, the EDLC-EDLP model creates both opportunities and imperatives. Since demand is not artificially stimulated by promotions, DMart's demand patterns are smoother and more predictable than those of promotional retailers, facilitating more accurate baseline forecasting. However, it also means that inefficiencies in stock prediction cannot be offset by promotional clearances — errors must be corrected through tighter operational discipline.

STOCK PREDICTION FRAMEWORK AT DMART

Economic order quantity (EOQ)

The EOQ model determines the optimal order quantity that minimises the total cost of inventory, which is the sum of ordering costs and holding costs. The classical EOQ formula is expressed as (EOQ = sqrt((2 x D x S) / H))

Where D = Annual demand (units), S = Ordering cost per order (INR), H = Annual holding cost per unit (INR). For DMart's high-velocity FMCG products with stable demand, EOQ provides a reliable baseline for replenishment quantities. The Reorder Point (ROP) is computed as: ROP = (Average daily demand x Lead time in days) + Safety Stock. DMart's centralised distribution centres (DCs) typically maintain lead times of 24–48 hours for replenishment to stores, a structural advantage that allows significantly lower safety stock levels relative to competitors

ABC – VED Analysis

DMart applies ABC analysis — a form of Pareto analysis — to classify its SKUs into three tiers based on annual consumption value. Category A items (approximately top 10% of SKUs, contributing ~70% of sales value) receive the most intensive forecasting attention and tighter reorder controls. Category B items (next 20% of SKUs, ~20% of value) are managed with moderate oversight, while Category C items (remaining 70% of SKUs, ~10% of value) are managed with simpler periodic review systems.

This classification is complemented by VED (Vital, Essential, Desirable) analysis, which assesses items based on their criticality to the customer experience rather than purely their financial contribution. Staple categories like rice, wheat flour (atta), edible oil, and salt — though sometimes low-margin — are classified as Vital because their stockout would immediately drive customers to competitors, undermining DMart's core value proposition of one-stop convenience.

ABC Analysis Framework Applied at DMart

Category	% of SKUs	% of Sales Value	Control Mechanism	Review Frequency
A – High Value	~10%	~70%	Tight reorder controls, daily monitoring	Daily
B – Medium Value	~20%	~20%	Moderate oversight, automated alerts	Weekly
C – Low Value	~70%	~10%	Periodic review, bulk ordering	Monthly

MOVING AVERAGE ABD EXPONENTIONAL SMOTHING

For time series-based demand forecasting, DMart's procurement teams are reported to use simple and weighted moving averages for stable-demand product categories. The Simple Moving Average (SMA) for period t is calculated as the arithmetic mean of demand over the preceding n periods. Weighted Moving Average (WMA) assigns greater weight to more recent periods, improving responsiveness to demand

shifts. The WMA forecast is: F(t) = sum of [w(i) x D(t-i)] for i=1 ton, where the weights sum to 1.0 and are assigned in decreasing order from the most recent period.
Exponential Smoothing (ES) provides a computationally efficient alternative that assigns exponentially decreasing weights to historical observations. The single ES formula is: F(t+1) = alpha x D(t) + (1 - alpha) x F(t), where alpha (the smoothing constant, 0 < alpha < 1) controls the speed of adaptation. For seasonal products — such as woollens in winter or air coolers in summer — Holt-Winters Triple Exponential Smoothing, which decomposes the series into level, trend, and seasonal components, provides substantially better forecast accuracy.

VENDEOR MANAGED INVENTORY (VMI) INTEGRATION

distinguishing feature of DMart's supply chain is its extensive VMI arrangements with key FMCG suppliers. Under VMI, the supplier — not the retailer — takes responsibility for monitoring stock levels at DMart's distribution centres and initiating replenishment when inventory falls below agreed trigger levels. This model transfers forecasting responsibility to entities with superior product-level demand visibility and reduces DMart's administrative burden while improving service levels.
VMI at DMart is enabled by Electronic Data Interchange (EDI) connections with major FMCG companies. Real-time point-of-sale data is shared with vendors, allowing them to build predictive models at the SKU-store level. This collaborative forecasting approach aligns with the CPFR (Collaborative Planning, Forecasting, and Replenishment) framework advocated by the Voluntary Interindustry Commerce Solutions (VICS) association and is considered a global best practice in retail supply chain management (Cachon and Fisher, 2000).

SEASONAL AND PROMOTIONAL DEMAND ADJUSTMENT

Despite its non-promotional pricing philosophy, DMart experiences significant seasonal demand patterns tied to Indian festive cycles (Diwali, Navratri, Eid, Pongal, Dussehra), agricultural income cycles, and school calendar events. Stock prediction for these periods requires multiplicative seasonal adjustment factors derived from historical sell-through rates by store cluster and product category.
For example, edible oil consumption spikes by an estimated 35–45% in the October–November festive period, gift packaging and dry fruits by 150–200%, and apparel by 60–80% (KPMG Consumer Markets Report, 2022). DMart's regional supply chain teams develop 'festive stock plans' 8–12 weeks in advance, working with suppliers to secure incremental inventory within pre-negotiated capacity constraints. This forward planning is enabled by the supplier relationship stability that DMart's early payment practices foster.

TECHNOLOGY AND AI DEMAND FORECOSTING

Avenue Supermarts has been progressively investing in technology infrastructure to enhance forecast precision. The company's ERP backbone — reportedly based on SAP platform modules customised for Indian retail — integrates POS data, procurement records, warehouse management, and supplier EDI feeds into a unified data environment. This data infrastructure forms the foundation for advanced analytics applications.
Emerging applications in DMart's analytical arsenal reportedly include: (i) Machine Learning-based demand prediction models that incorporate external variables such as weather data, local event calendars, and commodity price indices alongside internal sales history; (ii) Automated replenishment trigger

systems that generate purchase orders without manual intervention for Category A items; and (iii) Exception-based reporting dashboards that flag SKUs with unusual velocity patterns for human review. These capabilities are consistent with the broader digital transformation underway in Indian organised retail (Technopak, 2022).

6.FINDING AND ANALYSIS

INVENTORY TURNOVER PERFORMANCE

Inventory turnover ratio (ITR) is the most direct quantitative indicator of stock prediction effectiveness. A high ITR indicates that inventory is selling quickly relative to what is held, implying accurate demand prediction and efficient replenishment. Table 3 presents DMart's ITR alongside industry benchmarks over the seven-year study period.

DMart Inventory Turnover Ratio vs Industry Average (FY 2017–2023)

Financial Year	DMart Revenue (INR Crore)	DMart Inventory (INR Crore)	DMart ITR (Times)	Industry Avg ITR (Times)
FY 2017	11,903	837	14.2	8.1
FY 2018	15,009	1,002	15.0	8.4
FY 2019	19,916	1,279	15.6	8.6
FY 2020	24,143	1,507	16.0	8.3
FY 2021	21,792	1,438	15.2	7.8
FY 2022	30,977	1,871	16.6	8.9
FY 2023	42,840	2,503	17.1	9.2

The data reveals a consistent and widening gap between DMart's inventory turnover performance and the industry average. DMart's ITR improved from 14.2x in FY 2017 to 17.1x in FY 2023, representing a 20% improvement over the period. Even during FY 2021, when pandemic-related supply disruptions caused industry-wide inventory challenges, DMart maintained an ITR of 15.2x — nearly double the industry average of 7.8x. This sustained outperformance is a strong empirical indicator of superior stock prediction capability.

DAYS INVENTORY OUTSTANDING (DIO)

Days Inventory Outstanding (DIO) measures the average number of days a unit of inventory is held before being sold. DIO is the inverse of ITR expressed in days: DIO = 365 / ITR. DMart's DIO for FY 2023 stands at approximately 21.3 days, compared to the industry average of approximately 39.7 days. This 18-day advantage translates directly into reduced holding costs, lower spoilage rates, and improved working capital efficiency.

For a company with annual inventory levels of approximately INR 2,503 crore, a one-day reduction in DIO frees approximately INR 69 crore in working capital — a compelling financial motivation for continued investment in stock prediction accuracy.

SKU RATIONALISATION AND ITS IMPACT ON FORECOST ACCURACY

One of DMart's most consequential — and often underappreciated — inventory management strategies is aggressive SKU rationalisation. By maintaining 3,500–4,000 SKUs per store versus international norms of 10,000–15,000, DMart fundamentally reduces the complexity of its forecasting problem. Academic research confirms that forecast accuracy deteriorates non-linearly with SKU proliferation due to demand cannibalization, inter-SKU substitution effects, and the increased likelihood of intermittent demand patterns at the individual SKU level (Syntetos et al., 2016).

DMart's SKU discipline also benefits suppliers: concentrated purchasing volumes across fewer products allow suppliers to plan production runs more efficiently, reducing lead time variability — a key source of safety stock requirements — and enabling more reliable delivery schedules that support DMart's replenishment accuracy.

SUPPLY CHAIN ARCHIECTURE SUPPORTING PREDICTION

DMart operates a hub-and-spoke distribution architecture, with large distribution centres (typically 100,000–200,000 sq. ft.) strategically located to serve clusters of 15–25 stores within a 100–150 km radius. As of FY 2023, the company operated approximately 49 distribution and packing centres. This architecture provides two critical forecasting advantages: (i) it enables inventory pooling across multiple stores, reducing the statistical variability of aggregate demand and thereby lowering required safety stock levels; and (ii) it shortens store replenishment lead times to 24–48 hours, enabling reactive adjustment to unexpected demand surges without excessive buffer inventory.

SHRINKAGE CONTROL AND ITS FORECASTING LINK

Retail shrinkage — inventory loss due to theft, administrative errors, vendor fraud, and product damage — directly undermines stock prediction accuracy by creating a divergence between system-recorded and physically available inventory. DMart's annual reports indicate a shrinkage rate of approximately 0.15–0.20% of revenues, compared to the Indian retail industry average of 1.3–1.8% (Retailers Association of India, 2022). This extraordinarily low shrinkage rate reflects disciplined store operations and significantly improves the reliability of inventory data on which forecasting models are built.

DISCUSSION AND IMPLICATIONS

THEORETICAL IMPLICATION

The DMart case offers several important theoretical insights for inventory management and retail operations literature. First, it demonstrates that classical models such as EOQ and ABC analysis, when implemented with discipline and supported by robust data infrastructure, can deliver competitive advantages even in the age of machine learning. DMart's outperformance relative to technologically more sophisticated global retailers underscores that model sophistication is a necessary but not sufficient condition for forecasting excellence — organisational discipline and data quality are equally critical.

Second, the case illustrates the forecasting benefits of supply chain design choices. DMart's decisions to own its stores (reducing disruption from lease renegotiations), to operate dedicated distribution centres (enabling inventory pooling), and to maintain a curated SKU portfolio (reducing forecast complexity) collectively create a structural forecasting advantage that is difficult for competitors to replicate without fundamental business model changes.

MANAGERIAL IMPLICATIONS

For retail managers and supply chain professionals, the DMart case yields several actionable insights:
SKU rationalisation is a powerful lever for improving forecast accuracy. Retailers should periodically audit their product portfolios to identify slow-moving or redundant SKUs whose elimination would reduce forecasting complexity without materially impacting customer satisfaction.
Supplier relationship quality has direct forecasting implications. Practices that strengthen supplier trust — such as prompt payment, transparent demand sharing, and long-term purchase commitments — translate into shorter and more reliable lead times that reduce safety stock requirements.
Distribution centre consolidation enables inventory pooling benefits that systematically reduce aggregate demand variability, allowing more accurate network-level stock positioning.
Data quality — particularly shrinkage control and inventory record accuracy — is a foundational prerequisite for advanced forecasting. Investment in forecasting technology is unlikely to deliver expected returns if the underlying data is unreliable.
The integration of external variables (weather, local events, commodity prices) into forecasting models is increasingly accessible through commercial data APIs and should be incorporated into retail forecast systems to improve accuracy for weather-sensitive and event-driven product categories.

POLICY IMPLICATIONS

From a policy perspective, the DMart case highlights the importance of supply chain infrastructure in enabling retail sector efficiency. Government investments in cold chain logistics, rural road connectivity, and digital trade facilitation platforms would disproportionately benefit organised retail chains that have the capability to leverage these assets for improved stock prediction and replenishment. Additionally, regulatory frameworks that facilitate easier access to large retail properties and streamline multi-state GST compliance would reduce the operational friction that currently inflates lead times and inventory buffers for many organised retailers.

CONCLUSION AND RECOMMENDATIONS

This study has examined the stock prediction practices of DMart through a comprehensive secondary data analysis, drawing on annual reports, academic literature, and industry research spanning the period FY 2017–FY 2023. The findings establish DMart as a benchmark practitioner of inventory management within Indian organised retail, evidenced by its consistently superior inventory turnover ratio (17.1x in FY 2023), ultra-low days inventory outstanding (21.3 days), and shrinkage rates that are a fraction of the industry average.
DMart's stock prediction advantage is not attributable to any single tool or technology, but rather to the mutually reinforcing alignment of its business model, supply chain architecture, supplier relationships, and operational discipline. The EDLC-EDLP philosophy creates stable, promotionally undistorted demand patterns that are inherently more forecastable. The owned-store model eliminates lease disruptions. The hub-and-spoke DC network enables inventory pooling and rapid replenishment. Aggressive SKU rationalisation reduces forecast complexity. And early supplier payments build the relational capital that translates into supply reliability.

STRTEGIC RECOMMENDATIONS

INVEST IN INTEGRETED DATA PLATFORMS

Retailers should prioritise the integration of POS, WMS, and procurement systems into a unified analytics environment to enable real-time demand sensing and automated replenishment triggering.

Adopt Hybrid forecasting models

Statistical models (ARIMA, Exponential Smoothing) should be augmented with machine learning algorithms trained on external variables to capture demand drivers beyond historical sales patterns.

Implement Collaborative Forecasting

VMI and CPFR arrangements should be expanded, particularly for Category A items, to leverage supplier demand intelligence and reduce the bullwhip effect.

Rationalise SKU Portfolio Regularly

Annual SKU productivity reviews should be conducted to eliminate long-tail SKUs with intermittent demand that disproportionately inflate forecasting error.

Build Safety Stock Scientifically

Safety stock calculations should explicitly account for both demand variability and lead time variability, using statistical methods such as the standard deviation of demand during lead time rather than rule-of-thumb multiples of average demand.

Invest in Shrinkage Control

Inventory record accuracy is a forecasting prerequisite. Investment in anti-theft technology, cycle counting processes, and vendor quality checks yields outsized returns in forecast reliability.

Future Research Direction

Future research could extend this study by:

1. conducting primary research with DMart supply chain professionals to validate secondary findings and identify operational nuances not captured in public data
2. comparing DMart's inventory prediction practices with global hypermarket benchmarks such as Walmart and Costco
3. examining the impact of DMart Ready (the company's e-commerce platform) on demand forecasting complexity
4. developing a quantitative simulation model of DMart's replenishment system to evaluate the sensitivity of inventory performance to forecasting accuracy improvements.

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