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Simulation-Based Forecasting and Inventory Control Models For Consumer Goods Networks: A Quantitative Study Using Monte Carlo Simulation and Time-Series Methods

Md. Towhidul Islam[1]: MD Shahab Uddin[2];

[1]. MS in Business Analytics, Trine University, USA
Email: towhidulislamshovan@gmail.com

[2]. Bachelor of Science (BSc) in Computer Science, North South University, Bangladesh;
Diploma in Hospitality Management, Macquarie College, Australia;
Email: shopno23@gmail.com

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Abstract

This quantitative study examined the integrated effects of time-series demand forecasting and inventory control policies within consumer goods networks using Monte Carlo simulation. The study was designed to evaluate how demand uncertainty, forecast accuracy, forecast error dispersion, lead-time variability, and inventory policy structure jointly influenced service performance, stockout behavior, cost variability, and overall inventory stability. Historical demand data were modeled at the SKU level using time-series methods, and empirically estimated forecast error distributions were embedded into a simulation framework to generate repeated stochastic demand and lead-time scenarios. The analytical sample consisted of 312 SKUs observed over a median horizon of 104 weekly periods, yielding 32,448 SKU–period observations. Demand segmentation indicated that 51.9% of SKUs exhibited stable high-volume patterns, 30.8% displayed moderate variability, and 17.3% were characterized by intermittent demand with frequent zero observations. Descriptive results showed pronounced heterogeneity in demand uncertainty, with coefficients of variation increasing from 0.42 for stable SKUs to 1.76 for intermittent SKUs. Forecast accuracy deteriorated with horizon length and demand irregularity, with mean absolute error increasing from 9.6 units for stable SKUs at short horizons to 31.6 units for intermittent SKUs at longer horizons. Simulation-based inventory evaluation demonstrated that continuous review policies achieved higher median fill rates (0.963) and lower stockout frequency (0.42 stockouts per cycle) than periodic review policies, which exhibited lower median fill rates (0.941) and higher stockout frequency (0.88). Total cost variability, measured by the coefficient of variation, was lower under continuous review policies (0.31) than under periodic review policies (0.47). Regression analyses confirmed that forecast error magnitude, forecast error dispersion, demand uncertainty, and lead-time variability were statistically significant predictors of total cost, service performance, and inventory dispersion. Interaction effects indicated that forecast error impacts were amplified under higher lead-time variability and attenuated under continuous review policies. Overall, the findings demonstrated that distribution-sensitive forecasting evaluation and integrated simulation-based inventory analysis provided stronger evidence on service stability, cost dispersion, and policy robustness than approaches relying on point forecasts or mean performance metrics alone.

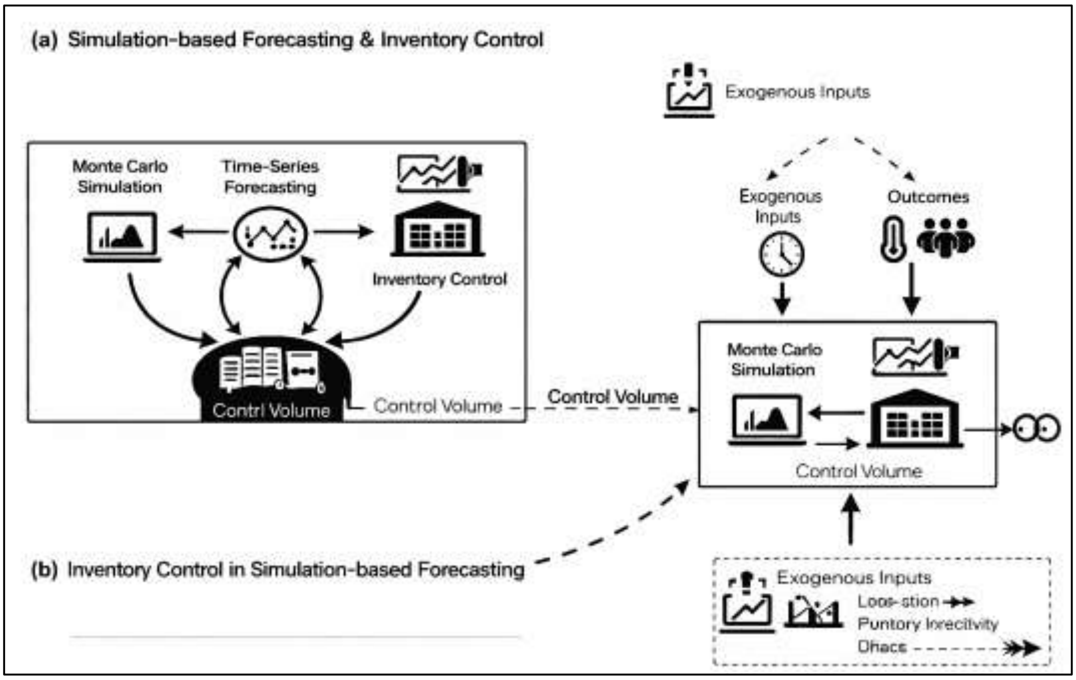
Keywords

Demand Forecasting, Inventory Control, Monte Carlo Simulation, Time-Series Analysis, Consumer Goods Networks;

INTRODUCTION

Simulation-based forecasting refers to the structured use of computational models to represent uncertainty, variability, and stochastic behavior within demand and supply systems. In quantitative research, simulation enables repeated experimentation on mathematically defined systems where real-world observation is costly, disruptive, or infeasible. Inventory control models, in contrast, focus on the systematic determination of stock levels, replenishment policies, and ordering decisions to balance service performance and cost efficiency (Sutanto & Sarno, 2015). Within consumer goods networks, these two domains intersect through the need to predict demand patterns accurately while dynamically managing inventory positions across multi-echelon distribution structures. Monte Carlo simulation provides a probabilistic framework in which random sampling techniques are used to generate multiple realizations of uncertain demand, lead times, and service conditions, allowing researchers to observe distributional outcomes rather than single-point estimates (Ye & You, 2016). Time-series forecasting methods complement simulation by modeling temporal dependencies in historical demand data, capturing trend, seasonality, cyclicality, and stochastic noise. Together, these approaches establish a quantitative foundation for analyzing inventory behavior under uncertainty. Consumer goods networks are characterized by high product variety, short life cycles, geographically dispersed markets, and sensitivity to demand volatility (Zhao & Wang, 2018). These characteristics necessitate forecasting approaches capable of accommodating nonlinearity and randomness while maintaining computational tractability.

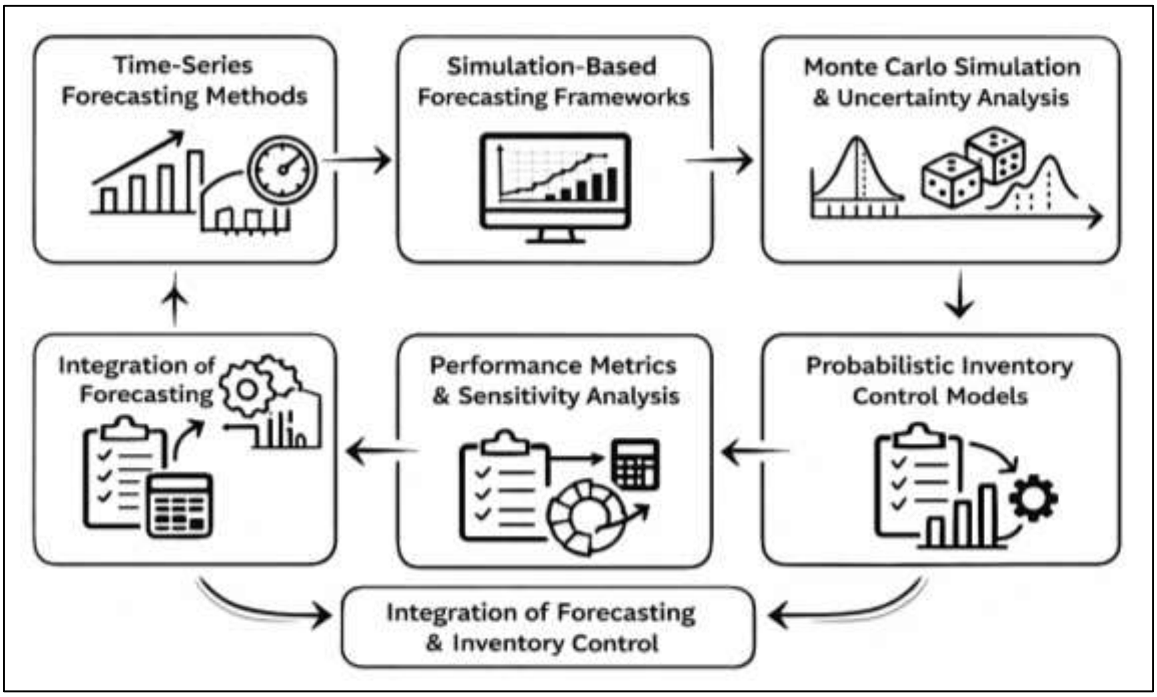
Figure 1: Simulation-Driven Forecasting and Inventory Systems



Simulation-based models allow analysts to incorporate realistic assumptions about consumer behavior, replenishment delays, and inventory review mechanisms without oversimplifying system dynamics. Inventory control, when embedded within a simulation environment, becomes an adaptive process rather than a static optimization exercise. Quantitative modeling in this context emphasizes measurable performance indicators such as service levels, fill rates, stockout probabilities, and holding costs (Jeon & Kim, 2016). The integration of forecasting and inventory control within a simulation framework transforms analytical inquiry from deterministic rule-based evaluation to probabilistic performance assessment. This paradigm supports rigorous experimentation across alternative policy configurations, parameter values, and demand conditions, enabling robust quantitative analysis (Dorigatti et al., 2016). From a definitional perspective, the use of Monte Carlo simulation and time-series methods aligns with the broader operations research tradition that emphasizes stochastic modeling, empirical validation, and reproducibility. Simulation-based forecasting does not replace analytical forecasting models; instead, it operationalizes them within controlled computational environments. Inventory control models embedded in simulation environments maintain mathematical discipline while gaining behavioral realism (Huang & Song, 2018). This conceptual synthesis forms the basis for quantitative inquiry into consumer goods networks, where uncertainty is a defining structural feature rather than a residual modeling error.

Inventory control models define the rules governing replenishment decisions, order quantities, and stock positioning within supply networks. Quantitatively, these models are expressed through mathematical relationships linking demand, lead time, service targets, and cost parameters. In stochastic environments, inventory control becomes a probabilistic decision-making process rather than a deterministic optimization exercise. Simulation-based forecasting frameworks provide the computational context in which these probabilistic relationships can be evaluated (Sang et al., 2019). Consumer goods networks, with their high demand variability and operational complexity, require inventory control models that respond dynamically to uncertainty.

Figure 2: Simulation-Based Forecasting and Inventory Control



This quantitative study is guided by an objective-driven structure that centers on simulation-based forecasting and inventory control for consumer goods networks using Monte Carlo simulation and time-series methods. The primary objective is to develop a statistically grounded modeling framework that converts historical demand data into probabilistic demand scenarios and evaluates how inventory control policies perform under repeated stochastic realizations of demand and operational variability. A second objective is to operationalize time-series forecasting methods as calibrated generators of demand trajectories by estimating key temporal properties such as autocorrelation, variance, and seasonal structure, and then embedding the resulting forecast-error behavior into a Monte Carlo simulation environment so that demand uncertainty is represented as a distribution rather than a single deterministic projection. A third objective is to quantify inventory performance outcomes under alternative replenishment rules by computing standardized metrics such as cycle service level, fill rate, expected stockout frequency, average on-hand inventory, average backorders, and total cost components that include holding, ordering, and shortage costs, thereby ensuring that policy evaluation is based on measurable and comparable outputs. A fourth objective is to examine the sensitivity of inventory outcomes to parameter changes that are central to consumer goods systems, including lead time variability, review period length, reorder thresholds, and order-up-to targets, with sensitivity analysis implemented through structured scenario design within the simulation runs. A fifth objective is to assess the stability and dispersion of system performance by summarizing simulation outputs through distributional statistics such as means, variances, percentiles, and confidence intervals, thereby enabling an empirical comparison across policy configurations using consistent statistical summaries. A sixth objective is to represent the consumer goods network as a multi-stage flow system and evaluate how uncertainty propagates across nodes by tracking inventory positions and service performance across distribution layers, supporting a network-consistent view of replenishment effectiveness. A final objective is to ensure methodological reproducibility by specifying the data preparation steps, time-series calibration logic, Monte Carlo sampling procedures, and simulation run parameters in a manner that allows independent replication and verification of results under the same assumptions and input data characteristics.

LITERATURE REVIEW

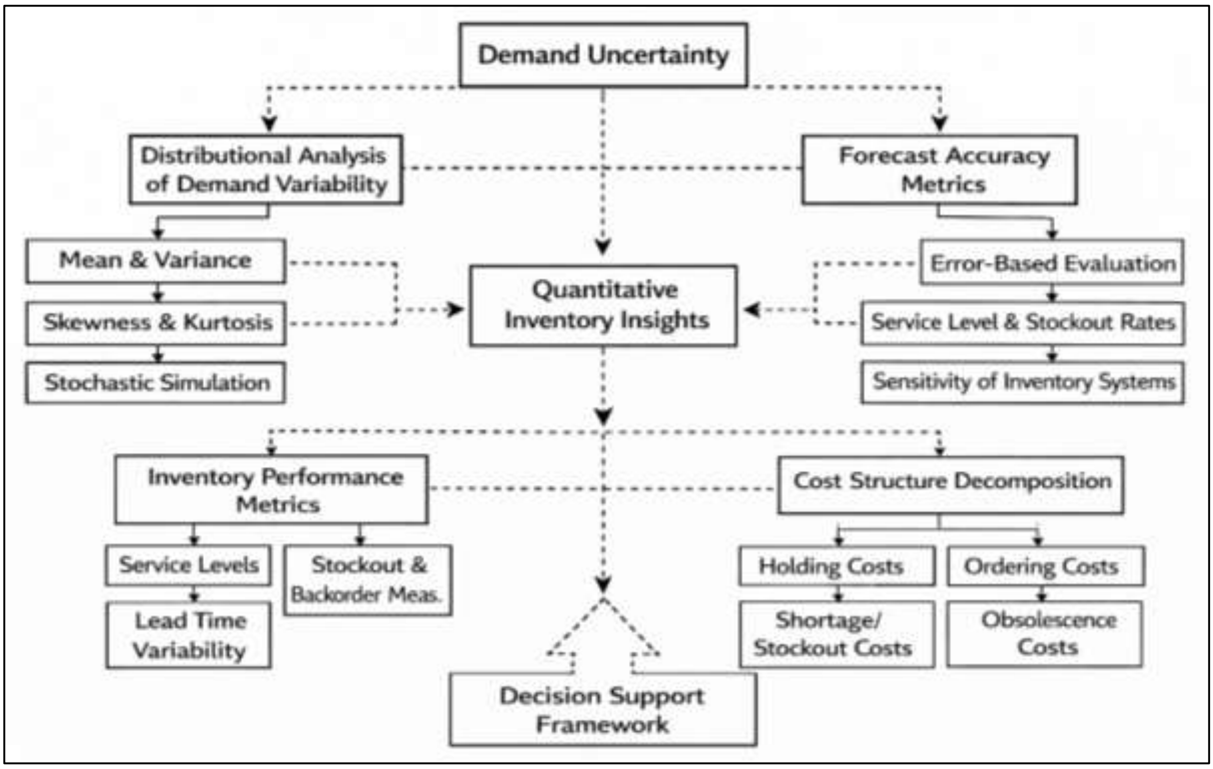
The Literature Review section establishes the empirical and methodological foundations required to examine simulation-based forecasting and inventory control in consumer goods networks using Monte Carlo simulation and time-series methods. This section is structured to synthesize prior quantitative research on demand modeling, forecast uncertainty, stochastic simulation, and inventory policy evaluation within multi-echelon distribution settings. It organizes the literature around measurable constructs such as forecast error distributions, service-level metrics, cost trade-offs, lead-time variability, and policy robustness under repeated stochastic scenarios (Dolgui et al., 2020). The review emphasizes how time-series models have been operationalized to generate demand trajectories, how Monte Carlo simulation has been used to propagate uncertainty through supply systems, and how inventory control rules have been quantified and compared using standardized performance indicators. It also clarifies the methodological linkages among parameter estimation, scenario generation, experimental design, and statistical reporting of simulation outcomes. The section is designed to move from definitional and theoretical constructs toward model-based quantitative evidence, ensuring that each theme is anchored in measurable variables, replicable procedures, and interpretable performance metrics relevant to consumer goods networks (Kamphues & Hegmanns, 2015).

Consumer Goods Inventory Systems

Demand uncertainty is a central construct in consumer goods inventory research and is commonly conceptualized as a statistical phenomenon characterized by variability, asymmetry, and dispersion in observed demand patterns. The literature defines demand uncertainty through distributional properties that capture both central tendency and deviation, allowing researchers to quantify how demand fluctuates around expected levels (Ascione et al., 2016). Mean demand is used to represent average consumption intensity, while variance reflects the magnitude of fluctuation across observation periods. Higher-order distributional characteristics such as skewness and kurtosis are employed to describe asymmetry and tail behavior, which are particularly relevant in consumer goods markets subject to promotions, seasonal effects, and irregular purchasing behavior. Prior studies emphasize that treating demand uncertainty as a probabilistic construct enables more realistic modeling of inventory systems than deterministic averages. This perspective supports the representation of demand as a random process rather than a fixed input, aligning with empirical observations from retail and fast-moving consumer goods environments (Nemtajela & Mbohwa, 2017). The literature also highlights that different products within the same network may exhibit distinct uncertainty profiles, requiring disaggregated measurement at the SKU level. By framing demand uncertainty through distributional parameters, researchers establish a standardized quantitative language that supports comparative analysis across products, markets, and inventory policies. This approach facilitates simulation-based experimentation by enabling demand variability to be sampled repeatedly, preserving observed statistical characteristics while allowing systematic evaluation of inventory responses under uncertainty (Duong et al., 2015).

Forecast accuracy metrics play a foundational role in quantitative inventory research by providing standardized measures for evaluating how closely predicted demand aligns with observed outcomes. The literature consistently emphasizes that forecast accuracy is a multidimensional concept that cannot be captured by a single indicator.

Figure 3: Demand Uncertainty and Inventory Performance Framework



Absolute error-based metrics are widely used to quantify average deviation between forecasts and actual demand, while squared-error measures place greater emphasis on large deviations that may disproportionately affect inventory performance (Atnafu & Balda, 2018). Percentage-based accuracy measures enable scale-independent comparison across products with different demand volumes, which is particularly important in consumer goods networks characterized by heterogeneous SKU portfolios. Scaled accuracy measures have been introduced to improve comparability across forecasting horizons and product categories by normalizing forecast errors relative to baseline benchmarks. The literature further notes that each metric exhibits distinct statistical properties, influencing sensitivity to outliers, zero-demand observations, and data intermittency. As a result, multiple accuracy metrics are often reported concurrently to provide a comprehensive assessment of forecasting performance (Mathras et al., 2016). In inventory-focused studies, forecast accuracy is treated not only as an evaluation outcome but also as an explanatory construct influencing downstream inventory behavior. Researchers emphasize that forecast error characteristics directly affect safety stock levels, service performance, and cost variability. The measurement of forecast accuracy therefore serves as a critical link between statistical demand modeling and operational inventory outcomes in consumer goods systems (Banerjee & Mishra, 2017).

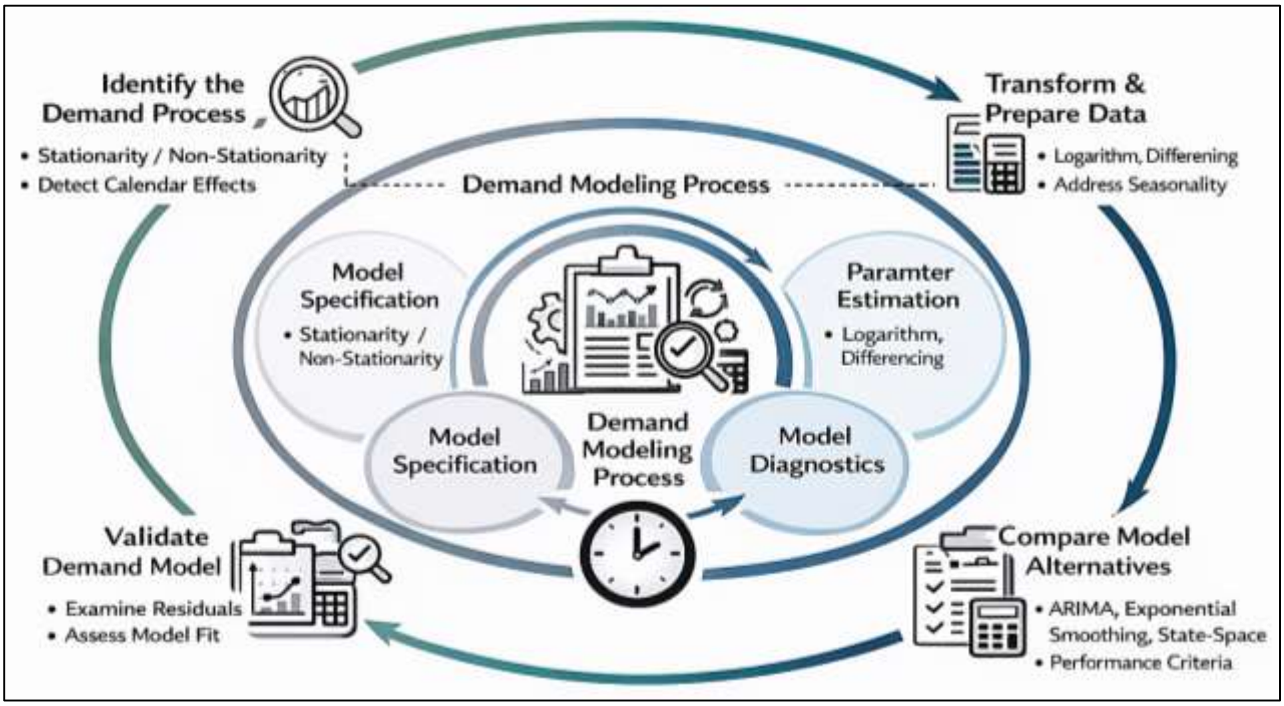
Inventory performance metrics are widely used in the literature as dependent variables for evaluating the effectiveness of forecasting and replenishment strategies. These metrics provide quantifiable indicators of how well an inventory system balances service objectives with cost efficiency. Service-oriented measures capture the system's ability to satisfy customer demand without delay or loss, reflecting operational responsiveness and availability (Anand & Grover, 2015). Probability-based service indicators quantify the likelihood of stock availability during replenishment cycles, while rate-based measures assess the proportion of demand fulfilled directly from inventory. Stockout-related metrics capture the frequency and severity of unmet demand, offering insight into system reliability under uncertainty. Backorder-related measures quantify deferred demand and are particularly relevant in environments where unmet demand is carried forward rather than lost. The literature highlights that inventory performance metrics are inherently stochastic outcomes influenced by demand variability, lead time uncertainty, and replenishment rules. As a result, these metrics are often analyzed using expected values, distributions, and variability measures rather than single-point estimates (Gawankar

et al., 2020). Researchers emphasize that inventory performance evaluation must account for both average outcomes and dispersion, as variability in service performance can be as operationally significant as mean levels. By treating inventory metrics as dependent variables within simulation-based frameworks, studies enable systematic comparison of policy effectiveness under identical stochastic conditions. This measurement approach supports robust quantitative evaluation across alternative inventory control configurations in consumer goods networks (Asamoah et al., 2021).
Cost decomposition constitutes a core analytical component of quantitative inventory research, providing a structured framework for evaluating trade-offs inherent in inventory decision-making. The literature consistently categorizes inventory-related costs into distinct components to improve analytical clarity and comparability across studies. Holding-related costs capture the financial implications of storing inventory over time, including capital tie-up, warehousing, and handling (Gandhi et al., 2017). Ordering-related costs represent the administrative and operational expenses associated with replenishment activities. Shortage-related costs reflect the economic impact of unmet demand, encompassing lost sales, backorders, and service penalties. Obsolescence-related costs are particularly salient in consumer goods contexts characterized by short product life cycles and demand volatility, where unsold inventory may lose value rapidly. Transportation-related costs capture the logistical dimension of inventory systems, linking replenishment decisions to distribution network performance (Dwivedi et al., 2016). The literature emphasizes that decomposing total inventory cost into these components enables more precise evaluation of how forecasting accuracy and inventory policies influence economic outcomes. Cost components are often treated as stochastic outcomes influenced by demand uncertainty and replenishment timing, reinforcing the importance of probabilistic modeling approaches. By analyzing cost structures in a disaggregated manner, researchers are able to identify dominant cost drivers and assess how different inventory strategies redistribute cost burdens across system components. This approach supports rigorous quantitative comparison of inventory policies within consumer goods networks (Nguyen et al., 2018).

Demand Modeling for Consumer Goods

Quantitative demand modeling in consumer goods systems begins with the specification of the underlying demand process, which determines how observed demand evolves over time. The literature distinguishes between stationary demand processes, where statistical properties remain stable, and non-stationary processes, where structural changes such as trends and evolving variance are present. Consumer goods demand data frequently exhibit non-stationary behavior due to market growth, product diffusion, price changes, and shifting consumer preferences (LeMay et al., 2017). As a result, researchers emphasize the importance of data transformation procedures that stabilize demand behavior prior to model estimation. These procedures are applied to ensure that statistical assumptions underlying time-series models are satisfied and that demand patterns can be meaningfully analyzed. The literature highlights that improper specification of the demand process leads to biased parameter estimates and unreliable forecasts. Transformation strategies are used to address scale effects, volatility clustering, and structural shifts commonly observed in retail demand series. In addition, the presence of calendar effects, promotional spikes, and regime changes further complicates demand process identification (Keane & Neal, 2021). Empirical studies consistently report that demand modeling accuracy improves when the stochastic properties of the series are explicitly diagnosed and adjusted before model fitting. This emphasis on process specification reflects a broader methodological consensus that demand modeling in consumer goods networks requires careful alignment between observed data characteristics and statistical model assumptions.
The literature on quantitative demand forecasting identifies several families of time-series models that are widely applied in retail and consumer goods contexts. Autoregressive and moving average–based models are frequently used to capture short-term demand dependencies and systematic patterns in historical sales data (Udokporo et al., 2020). Seasonal extensions of these models are employed to represent recurring consumption cycles associated with weekly, monthly, or annual patterns. Exponential smoothing approaches are emphasized for their adaptability and ease of implementation, particularly in high-volume retail environments where computational efficiency is important.

Figure 4: Time-Series Demand Modeling Framework



State-space formulations provide a unifying framework that represents demand as an evolving stochastic process, enabling dynamic updating of model components as new data become available. Comparative studies across model families highlight that no single approach dominates across all consumer goods categories, as demand characteristics vary significantly by product type, lifecycle stage, and market context (Orobia et al., 2020). The literature underscores that model choice is driven by empirical performance rather than theoretical preference, with forecasting accuracy evaluated across multiple metrics. Retail demand modeling research further notes that model flexibility is critical for handling irregular demand patterns, short data histories, and frequent structural changes. As a result, many studies advocate for model families that balance statistical rigor with robustness to data imperfections commonly observed in consumer goods environments (Lee et al., 2016).

Parameter estimation and model selection constitute core analytical stages in quantitative time-series demand modeling. The literature emphasizes that accurate estimation of model parameters directly influences forecast reliability and downstream inventory performance. Estimation procedures are evaluated based on their ability to capture underlying demand dynamics while minimizing unexplained variation. Model selection criteria are widely used to compare competing specifications by balancing goodness-of-fit against model complexity (Wong et al., 2015). These criteria support objective selection decisions by penalizing over-parameterized models that may fit historical data well but perform poorly under stochastic simulation. Residual analysis plays a central role in validating demand models, as residual patterns provide diagnostic evidence regarding model adequacy. Studies consistently highlight the importance of examining residual independence, variance stability, and distributional behavior to ensure that demand dynamics have been appropriately captured. Inadequate residual behavior is associated with biased forecasts and distorted simulation inputs. The literature also notes that parameter stability over time is particularly important in consumer goods settings characterized by frequent demand shifts (Marodin et al., 2017). Robust parameter estimation and diagnostic validation are therefore treated as prerequisites for embedding time-series models into simulation-based forecasting frameworks.

Monte Carlo Simulation as a Quantitative Experimentation Engine

Monte Carlo simulation is widely recognized in the quantitative literature as a core methodology for representing uncertainty in demand and lead time within inventory and supply chain systems. The sampling logic underlying Monte Carlo simulation is based on repeated random draws from empirically or theoretically specified probability distributions that reflect observed system variability.

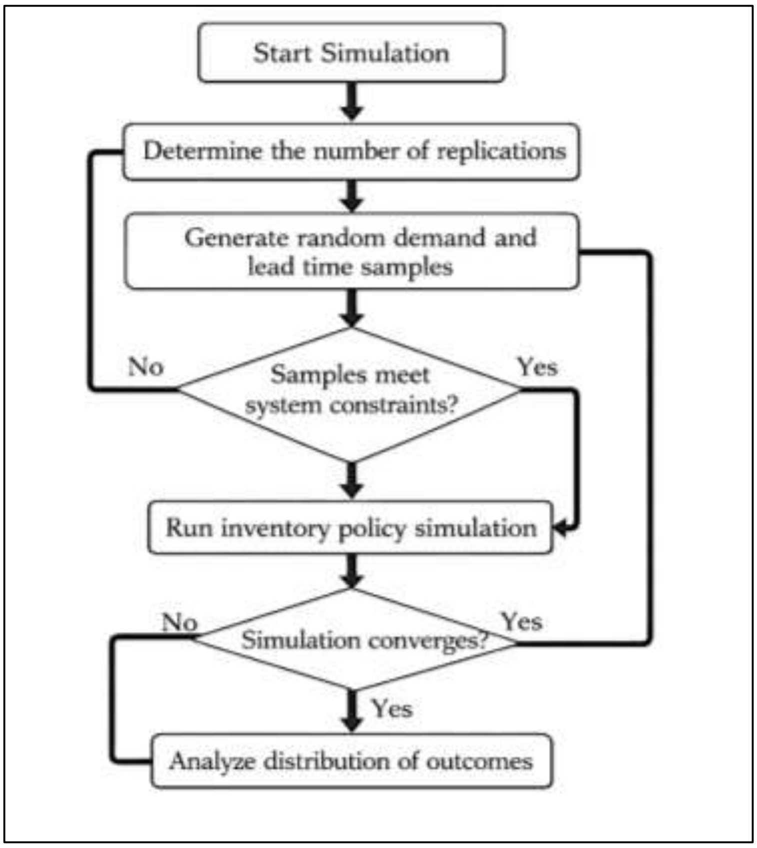
In consumer goods contexts, demand and lead time are treated as stochastic inputs whose randomness drives inventory dynamics across replenishment cycles (Marodin et al., 2018; Rauf, 2018). The literature emphasizes that sampling procedures must respect realistic constraints, such as non-negativity, capacity limits, and bounded delivery intervals, to ensure operational plausibility. Studies highlight that improper sampling can introduce bias into simulation outputs, leading to distorted inventory performance estimates. As a result, careful alignment between empirical data characteristics and sampling logic is treated as a methodological requirement (Haque & Md. Arifur, 2020; Md Ashraful et al., 2020). Monte Carlo approaches enable the generation of large numbers of alternative demand and lead time realizations, allowing analysts to observe how inventory systems respond under diverse operating conditions. This repeated experimentation distinguishes simulation-based analysis from deterministic modeling by shifting emphasis from single outcomes to outcome distributions (Haque & Md. Arifur, 2021; Jinnat & Md. Kamrul, 2021; Kumar & Anjaly, 2017). The literature further underscores that Monte Carlo sampling supports the integration of forecast uncertainty by transforming demand estimates into probabilistic input streams. In inventory studies, this approach is used to examine how replenishment rules perform when exposed to variability consistent with historical data (Md Fokhrul et al., 2021; Zaman et al., 2021). Sampling logic therefore functions as the foundational mechanism through which uncertainty is operationalized within quantitative inventory simulation models (Hammad, 2022; Prajogo et al., 2016).

The design of simulation runs constitutes a critical methodological dimension in Monte Carlo–based inventory research. The literature consistently emphasizes that simulation outcomes are sensitive to decisions regarding replication count, initialization conditions, and time horizon selection. Replication is used to ensure that observed performance metrics reflect stable statistical properties rather than random noise associated with a single simulation run (Jabed Hasan & Waladur, 2022; Md. Arifur & Haque, 2022). Warm-up periods are applied to eliminate initialization bias by allowing the simulated system to reach a steady operating state before data collection begins (Md. Towhidul et al., 2022; Rifat & Jinnat, 2022; So et al., 2016). Time horizon selection is guided by the need to capture sufficient demand cycles and replenishment events to produce representative performance measures. Studies highlight that inadequate run length can lead to misleading conclusions, particularly in systems with long lead times or seasonal demand patterns (Abdulla & Alifa Majumder, 2023; Rifat & Khairul Alam, 2022). Convergence assessment is used to evaluate whether additional replications yield diminishing changes in output statistics, supporting confidence in simulation results. The literature treats simulation run design as analogous to experimental control in laboratory research, where consistency and repeatability are essential for valid inference (Faysal & Tahmina Akter Bhuya, 2023; Habibullah & Aditya, 2023; Vishwanath et al., 2020). Structured run design enables comparative evaluation of inventory policies under identical stochastic conditions. By standardizing simulation parameters across experiments, researchers isolate the effects of policy changes from random variation, reinforcing the credibility of quantitative findings in inventory system analysis (Hammad & Muhammad Mohiul, 2023; Panahifar et al., 2018).

Consumer goods inventory systems operate within interconnected networks where demand and operational uncertainties are rarely independent. The literature emphasizes that ignoring correlation among stochastic inputs can substantially misrepresent system behavior. Correlated demand patterns across products may arise due to shared promotions, substitution effects, or macroeconomic influences, while lead time dependencies may result from shared transportation or production resources (Haque & Md. Arifur, 2023; Md. Akbar & Farzana, 2023; Pires & Trez, 2018). Quantitative simulation studies therefore incorporate dependency structures to represent these relationships realistically. Approaches for handling correlation allow stochastic inputs to move together in a controlled manner, preserving observed joint behavior across products and network nodes (Mostafa, 2023; Rifat & Rebeka, 2023). The literature highlights that modeling correlated inputs affects both the magnitude and variability of inventory outcomes, particularly at aggregated network levels. Dependency representation is also critical in multi-echelon systems, where upstream variability propagates downstream through replenishment processes (Adebanjo et al., 2016; Jahangir & Hammad, 2024; Masud & Hammad, 2024). Simulation-based analysis enables explicit tracking of how correlated uncertainties influence inventory positions, service levels, and cost dispersion across nodes. By embedding dependency structures within

Monte Carlo sampling procedures, studies achieve a more accurate representation of system-wide risk exposure. This approach supports quantitative evaluation of inventory performance under conditions that closely resemble real-world consumer goods networks, reinforcing the analytical value of simulation-based experimentation (Boon-Itt et al., 2017; Md & Sai Praveen, 2024; Rifat & Rebeka, 2024).

Figure 5: Monte Carlo Simulation Workflow Framework

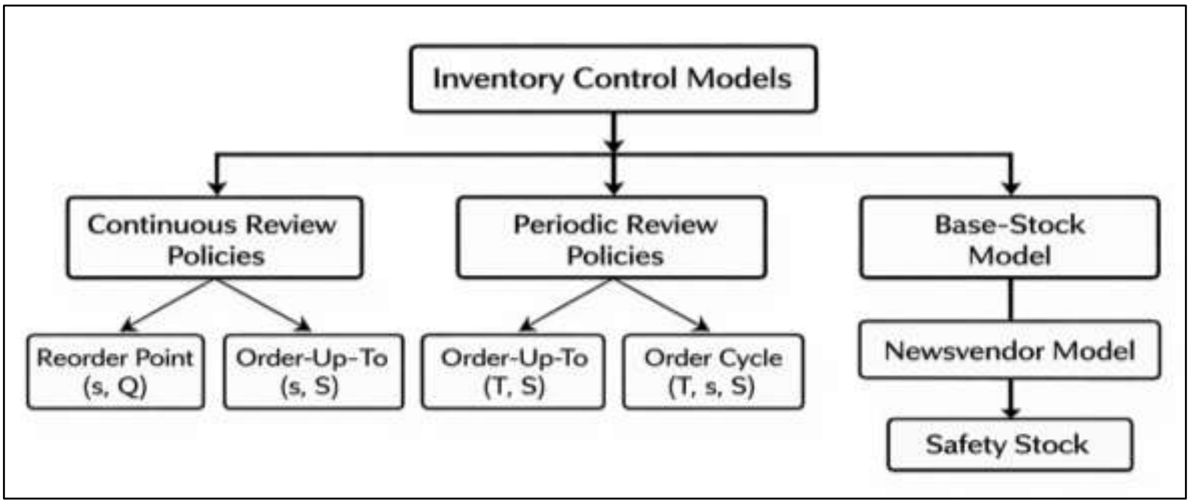


The analysis of simulation outputs is a defining feature of Monte Carlo–based inventory research, as performance evaluation relies on statistical summaries rather than deterministic results. The literature emphasizes the use of distribution-based measures to capture both central tendencies and variability in inventory outcomes. Percentile analysis and interval estimation are commonly employed to assess the dispersion of service and cost metrics under uncertainty. Risk-oriented measures are used to evaluate exposure to extreme outcomes, particularly in high-variability demand environments (Li et al., 2021; Sai Praveen, 2024; Shehwar & Nizamani, 2024). Variance reduction techniques are applied to improve estimation efficiency by decreasing output variability without increasing computational burden. These techniques enhance the precision of performance comparisons across inventory policies. Validation and verification procedures are treated as essential safeguards against modeling error. Face validity ensures that model behavior aligns with domain knowledge, while statistical validation compares simulated outputs with empirical benchmarks (Azam & Amin, 2024). Verification focuses on confirming that the simulation logic correctly implements the intended model structure. The literature consistently stresses that simulation credibility depends on transparent documentation of assumptions, input data, and analytical procedures (Prakash et al., 2018). Through rigorous output analysis and validation protocols, Monte Carlo simulation is positioned as a reliable quantitative experimentation engine for studying inventory control in consumer goods systems.

Inventory Control Models Under Uncertainty

Continuous review inventory policies represent one of the most extensively examined control structures in quantitative inventory research. These policies are characterized by ongoing monitoring of inventory positions and trigger replenishment actions when predefined thresholds are reached. The literature emphasizes that continuous review systems are particularly suitable for consumer goods environments with high transaction frequency and real-time inventory visibility (Nemtajela & Mbohwa, 2016). Under stochastic demand conditions, these policies are evaluated using probabilistic performance measures that account for demand variability and lead time uncertainty. Quantitative studies highlight that policy effectiveness depends on the interaction between demand dispersion, replenishment responsiveness, and service targets. Continuous review structures are often analyzed through simulation-based experimentation to capture the distributional behavior of inventory outcomes rather than relying solely on average values. The literature notes that such policies offer strong service performance when demand variability is moderate and replenishment responsiveness is high. However, performance variability increases when demand volatility or lead time uncertainty intensifies (Thorsen & Yao, 2017). Researchers evaluate continuous review systems by examining service consistency, stock availability, and cost dispersion across stochastic scenarios. This body of literature treats continuous review policies as benchmarks against which alternative inventory strategies are compared, emphasizing their analytical clarity and operational relevance in consumer goods networks.

Figure 6: Inventory Control Policy Classification Framework



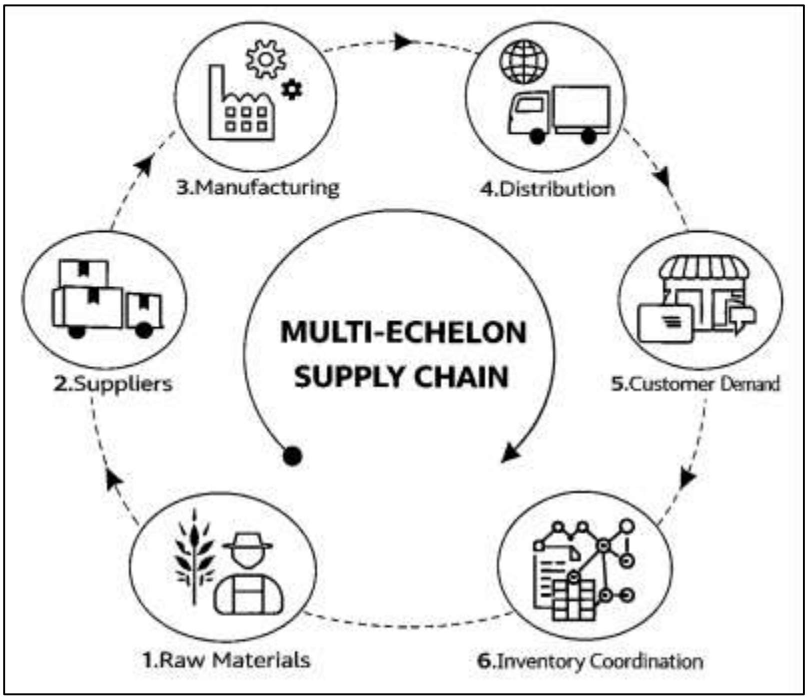
Periodic review inventory policies differ from continuous review structures by evaluating inventory positions at fixed intervals rather than continuously. The literature emphasizes that these policies align well with operational environments where inventory monitoring and ordering activities are synchronized with production or distribution cycles. In consumer goods networks, periodic review systems are commonly used in centralized distribution centers and retail replenishment programs (Osorio et al., 2015). Quantitative evaluation of these policies focuses on how review frequency interacts with demand uncertainty and lead time variability to influence service and cost outcomes. The literature reports that longer review intervals increase exposure to demand variability, leading to higher inventory dispersion and service volatility. Order-up-to policies within periodic review frameworks aim to restore inventory to predetermined target levels, balancing responsiveness with ordering efficiency. Simulation-based studies highlight that periodic review systems exhibit greater sensitivity to forecast error and lead time uncertainty than continuous review policies. As a result, performance evaluation emphasizes distributional outcomes rather than point estimates. The literature consistently underscores the importance of aligning review intervals and target levels with observed demand characteristics to achieve stable inventory performance (Ahmadi et al., 2019). Periodic review policies are therefore analyzed as structurally efficient yet uncertainty-sensitive control mechanisms within consumer goods inventory systems.

Multi-Echelon Consumer Goods Networks

Multi-echelon consumer goods networks are composed of interconnected inventory-holding stages that collectively support product flow from upstream supply sources to downstream customer-facing nodes. The literature defines these systems through hierarchical inventory representations that distinguish between local stock positions and aggregated inventory responsibilities across echelons. Inventory position is treated as a node-level construct reflecting available and committed stock, while echelon stock captures the cumulative inventory held across downstream stages relative to a given node (Settembre-Blundo et al., 2021). Allocation rules determine how inventory is distributed across nodes under capacity and service constraints, shaping system-wide performance. Quantitative studies emphasize that these definitions are not merely conceptual but directly influence how uncertainty is measured and managed across the network. Clear delineation of inventory ownership and responsibility enables consistent performance evaluation and coordination analysis. The literature highlights that misalignment between inventory definitions and decision rights leads to distorted measurement of service outcomes and cost allocation. Multi-echelon representations support analytical clarity by allowing researchers to trace how replenishment decisions at one stage affect inventory availability downstream (Grossmann et al., 2016). This structural framing provides the foundation for modeling uncertainty propagation and coordination mechanisms within consumer goods distribution systems. By formalizing inventory representation across echelons, quantitative research establishes a consistent language for analyzing complex network behavior under stochastic demand and lead time conditions.

Demand propagation refers to the transmission of demand variability across successive stages of a supply network, often resulting in amplification of variability as information moves upstream. The literature identifies this phenomenon as a defining challenge in multi-echelon consumer goods systems, where order variability frequently exceeds underlying customer demand variability (Mehrjoo & Pasek, 2016). Quantitative studies analyze this amplification by comparing variance measures across network stages, highlighting how ordering policies, information delays, and replenishment batching contribute to instability.

Figure 7: Inventory Coordination in Multi-Echelon Systems



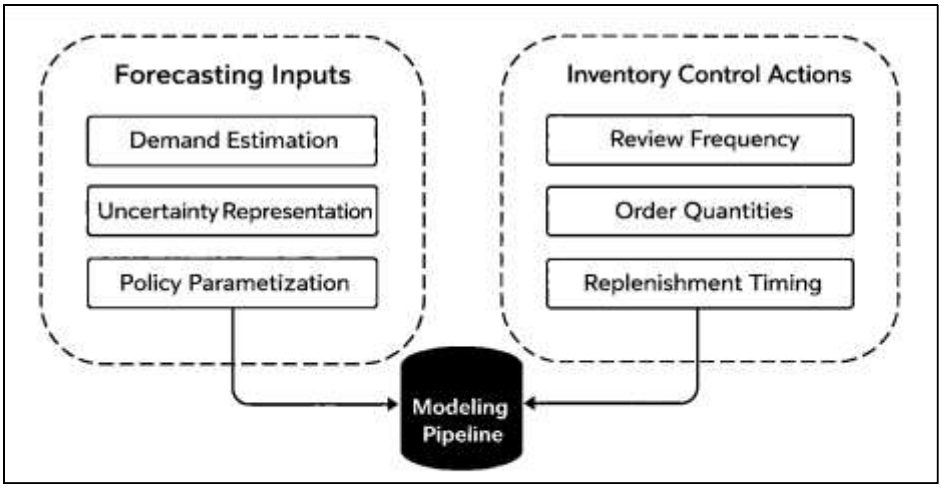
The literature emphasizes that variance amplification is not solely a behavioral artifact but also a structural consequence of decentralized decision-making under uncertainty. Consumer goods networks with frequent promotions and short replenishment cycles are particularly susceptible to this effect. Researchers highlight that amplified variability increases inventory dispersion, service volatility, and operational costs across the network. Quantitative modeling frameworks allow analysts to isolate the mechanisms through which uncertainty propagates, revealing the cumulative impact of local decisions on system-wide performance (Banasik et al., 2018). The literature consistently treats variance amplification as a measurable network property rather than an abstract concept, reinforcing the

importance of coordinated inventory policies. By framing demand propagation as a statistical process, multi-echelon inventory research provides empirical insight into how uncertainty undermines coordination and stability in consumer goods supply systems (Ivanov, 2017).
Coordination mechanisms in multi-echelon inventory systems are central to mitigating uncertainty-related inefficiencies. The literature contrasts centralized replenishment structures, where inventory decisions are coordinated across nodes, with decentralized systems that rely on local optimization. Quantitative comparisons indicate that centralized approaches reduce service variability and inventory dispersion by aligning replenishment decisions with system-wide objectives. Decentralized systems, while operationally flexible, exhibit greater sensitivity to demand variability and information distortion. Risk pooling is identified as a key mechanism through which coordination improves performance (Yang et al., 2015). By aggregating demand variability across nodes, pooled inventory structures reduce overall uncertainty exposure and stabilize service outcomes. The literature emphasizes that inventory placement decisions determine the effectiveness of risk pooling, with upstream consolidation often yielding significant variance reduction. Quantitative studies measure these effects through reductions in safety inventory requirements and improved service consistency. Coordination is also examined through allocation rules that govern inventory sharing across nodes under constrained supply conditions. These mechanisms are evaluated using network-level performance indicators rather than isolated node metrics (Halkos & Skouloudis, 2017). The literature treats replenishment coordination and risk pooling as complementary strategies that jointly influence uncertainty absorption and service reliability in consumer goods networks.

Integrated Forecasting–Inventory Control

The integration of demand forecasting and inventory control is widely recognized in the literature as a central requirement for effective inventory management under uncertainty. Forecast-to-inventory pipeline modeling describes the structured process through which demand estimates are translated into replenishment decisions within operational systems.

Figure 8: Integrated Forecast to Inventory Pipeline



The literature emphasizes that forecasting outputs do not directly determine inventory performance unless they are embedded within clearly defined decision rules that govern ordering frequency, quantity determination, and inventory positioning (Stock et al., 2018). In consumer goods networks, this pipeline involves sequential stages that include demand estimation, uncertainty representation, policy parameterization, and execution of replenishment actions. Quantitative studies highlight that misalignment between forecasting horizons and inventory review cycles leads to inefficiencies such as excess stock or service shortfalls. Integrated modeling frameworks explicitly link forecast distributions to inventory control parameters, enabling consistent propagation of uncertainty through the decision pipeline. The literature underscores that integrated models treat forecasting as an input-generating process rather than an isolated analytical task. By coupling forecasts with inventory decision logic, researchers evaluate how statistical properties of demand estimates influence operational outcomes (Stock et al., 2018). This perspective shifts analytical focus from forecast accuracy alone to the structural coherence of the entire decision pipeline. Integrated forecast-to-inventory modeling is therefore positioned as a foundational element of quantitative inventory research in consumer goods systems.

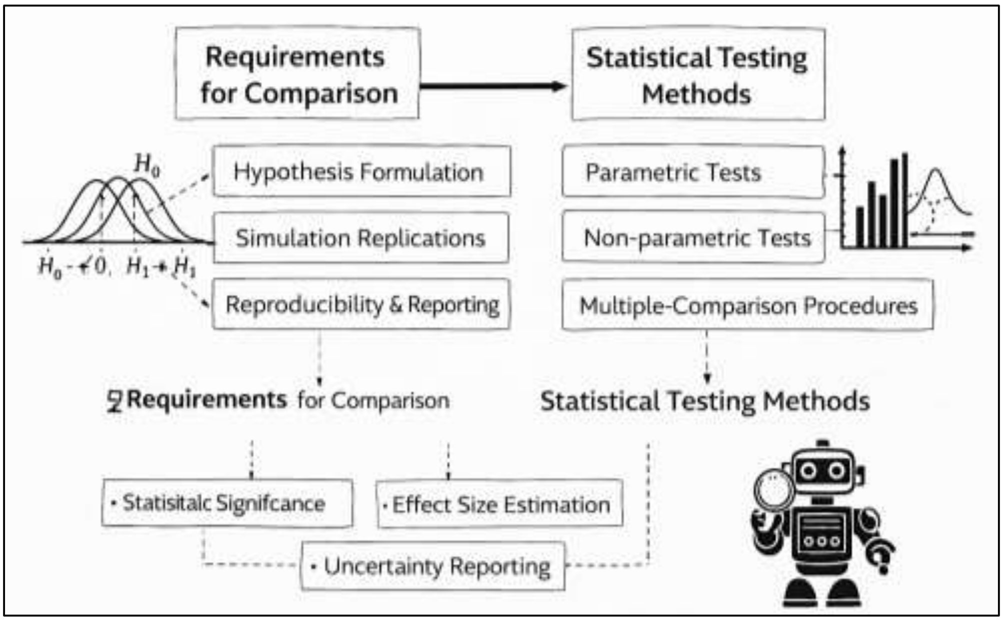
The literature consistently demonstrates that forecast errors exert a measurable influence on inventory performance and cost behavior. Quantitative studies conceptualize forecast error as a stochastic disturbance that alters inventory trajectories by affecting order timing, order quantities, and safety stock requirements. Error-to-cost relationships are examined by linking forecast deviations to changes in holding costs, shortage costs, and service variability (Aastveit et al., 2017). The literature emphasizes that the economic impact of forecast error is not linear and varies across product categories, demand volatility levels, and replenishment policies. High forecast dispersion is associated with greater inventory variability, leading to increased cost uncertainty and service inconsistency. Integrated modeling approaches allow researchers to quantify how forecast errors propagate through inventory systems rather than evaluating errors in isolation. Simulation-based studies measure how changes in forecast uncertainty translate into shifts in inventory performance distributions. This body of literature highlights that identical forecast accuracy levels can produce different inventory outcomes depending on the structure of the inventory control policy (Dolgui et al., 2020). By focusing on inventory-based performance measures, quantitative research reframes forecast evaluation as an operational impact assessment rather than a purely statistical exercise. This shift reinforces the importance of integrated modeling frameworks that capture the full pathway from forecast uncertainty to economic outcomes in consumer goods networks.

Standards for Quantitative Simulation Studies

Quantitative simulation studies in inventory and supply chain research rely on structured statistical comparison to evaluate differences between alternative policy configurations. The literature emphasizes that simulation outputs generate distributions of performance metrics rather than single observations, necessitating formal hypothesis formulation grounded in stochastic outcome behavior (Collie et al., 2016). Hypotheses are typically framed to test whether observed differences in service levels, cost measures, or inventory dispersion reflect systematic policy effects rather than random sampling variation. Simulation replications serve as independent observations that support inferential analysis when properly designed and controlled. The literature highlights that hypothesis formulation in simulation contexts differs from traditional empirical studies because the data-generating process is fully specified by the model structure. As a result, clarity in defining null and alternative hypotheses is essential for meaningful policy comparison. Researchers emphasize the importance of aligning hypotheses with performance objectives, such as service consistency or cost stability, rather than relying solely on mean comparisons (Ivanov et al., 2018). Distributional properties of simulation outputs are used to support inference regarding variability, risk exposure, and tail behavior. This structured approach to hypothesis formulation enables quantitative simulation studies to produce statistically defensible conclusions regarding inventory policy effectiveness in consumer goods systems.

The literature on simulation-based inventory research identifies a range of statistical testing approaches for comparing policy performance across replicated simulation outputs. Parametric testing methods are applied when output distributions satisfy assumptions related to symmetry and variance stability, allowing mean-based comparisons across policies. When these assumptions are violated, nonparametric alternatives are emphasized due to their robustness to skewness and outliers commonly observed in inventory performance data. Studies consistently note that simulation outputs often exhibit non-normal behavior, particularly for cost and stockout measures, reinforcing the importance of distribution-sensitive testing frameworks. Multiple-comparison procedures are used to evaluate several inventory policies simultaneously while controlling for false detection of performance differences. The literature also highlights the importance of pairing simulation runs across policies using common stochastic inputs to reduce extraneous variability. Statistical testing in simulation studies is framed as a tool for distinguishing substantive policy effects from stochastic noise inherent in demand and lead time variability. By applying appropriate testing frameworks, researchers strengthen the credibility of policy comparisons and support rigorous quantitative evaluation of inventory control strategies.

Figure 9: Statistical Evaluation of Inventory Policies



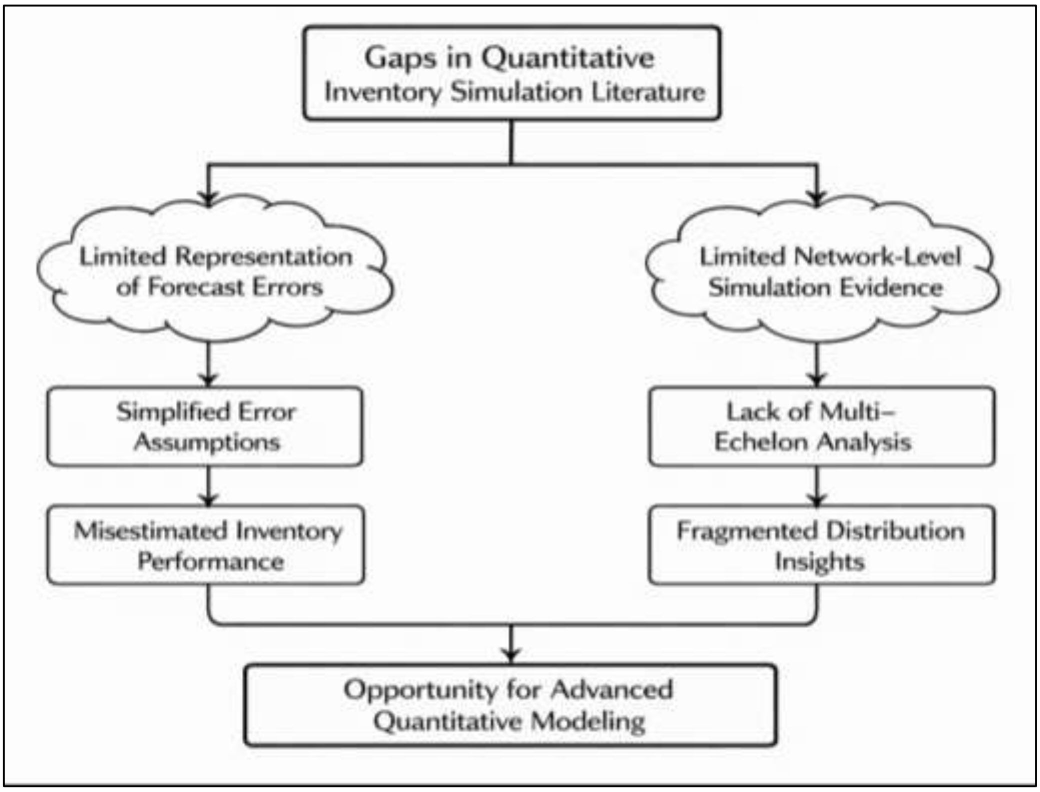
Effect sizes provide a quantitative measure of the magnitude of policy differences, enabling assessment of practical relevance alongside statistical detectability. Inventory performance metrics such as service level consistency, cost dispersion, and stock availability are evaluated not only for statistical differences but also for operational impact. The literature highlights that small statistical differences may have negligible practical implications, while moderate distributional shifts can significantly influence system stability and risk exposure. Reporting standards therefore emphasize transparency in summarizing both central tendencies and variability measures. Confidence intervals and percentile-based summaries are used to communicate uncertainty associated with simulation estimates. This approach allows decision-makers and researchers to assess the robustness of observed effects across stochastic realizations. The literature consistently treats effect size reporting as essential for bridging the gap between statistical analysis and operational interpretation. By combining inferential testing with practical significance assessment, simulation studies provide a more comprehensive evaluation of inventory policy performance under uncertainty.

Reproducibility is a cornerstone of quantitative simulation research, and the literature emphasizes detailed reporting standards to support independent verification of results. Key reproducibility elements include disclosure of random number generation procedures, specification of model parameters, description of data windows used for calibration, and documentation of simulation logic. Transparent reporting ensures that simulation outcomes can be replicated under identical assumptions, reinforcing the scientific credibility of the study. Sensitivity analysis is treated as a complementary reporting requirement that evaluates how changes in key input parameters affect performance outcomes. The literature emphasizes that sensitivity analysis reveals the relative importance of demand variability, lead time dispersion, and policy thresholds in shaping inventory behavior. Uncertainty reporting frameworks are used to communicate the range of plausible outcomes rather than point estimates alone. Visual and tabular summaries of uncertainty support interpretability and highlight system vulnerabilities. Together, reproducibility, sensitivity analysis, and uncertainty disclosure establish a rigorous reporting standard for quantitative simulation studies, enabling meaningful comparison across research efforts and reinforcing methodological transparency in inventory systems analysis.

Identified Research Gaps

A prominent gap identified in the quantitative literature concerns the limited representation of forecast error distributions and their measurable impact on inventory system performance. Many studies rely on simplified or standardized error assumptions that do not adequately reflect the empirical behavior observed in consumer goods demand data.

Figure 10: Research Gaps in Inventory Simulation



The literature indicates that forecast errors often exhibit asymmetry, intermittency, and overdispersion, particularly at the SKU level, yet these characteristics are frequently abstracted away in simulation-based inventory models. As a result, inventory outcomes such as service variability, cost dispersion, and stockout frequency may be systematically misestimated. This gap is framed quantitatively as a mismatch between empirically observed error behavior and the stochastic inputs used in inventory simulations. Studies that adopt simplified error representations tend to understate tail risks and extreme inventory outcomes, limiting the interpretability of results. The absence of differentiated error structures across product categories further constrains the ability to assess heterogeneity in inventory performance. This gap highlights a lack of alignment between forecast error measurement and inventory impact assessment, indicating an opportunity to treat error distributions as explicit quantitative variables rather than residual noise. The literature suggests that addressing this limitation requires systematic evaluation of how alternative error characterizations influence inventory performance distributions within simulation environments.

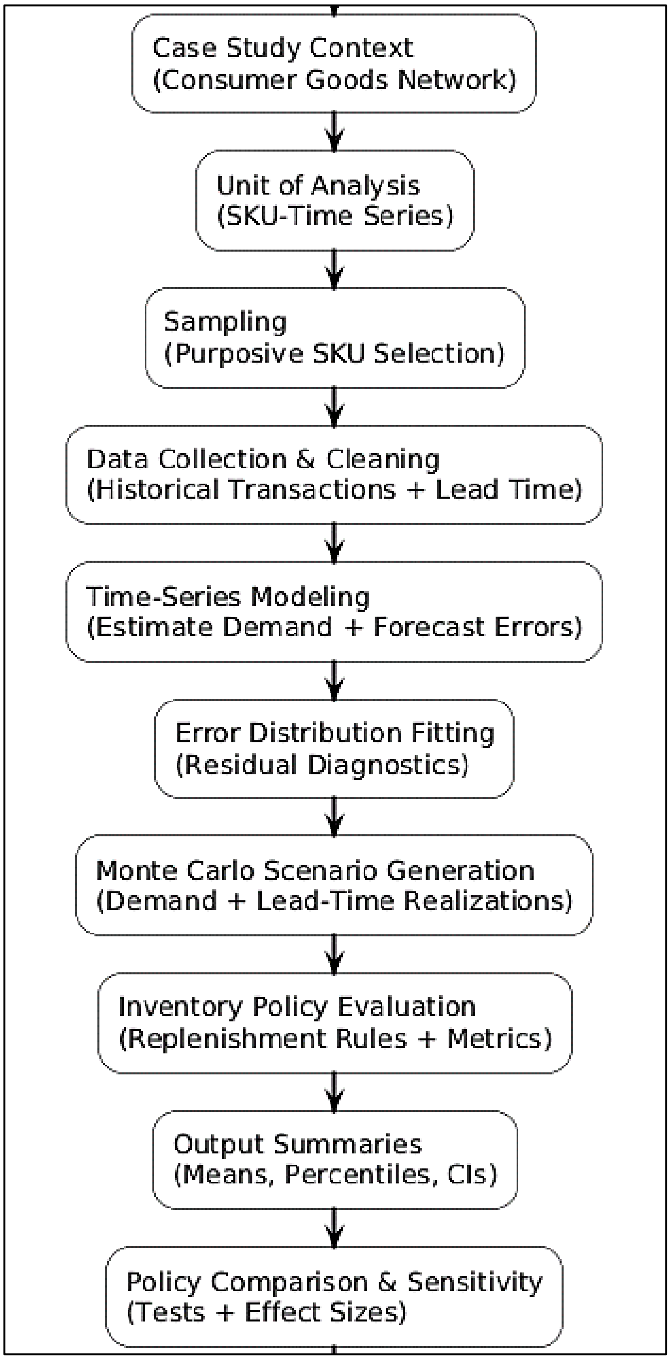
Another significant research gap emerges from the limited availability of network-level simulation evidence addressing multi-echelon consumer goods systems. While node-level inventory models are extensively studied, the literature reveals a relative scarcity of quantitative analyses that evaluate system-wide behavior across interconnected echelons. Many simulation studies focus on single-stage or simplified two-stage systems, constraining insight into how uncertainty propagates through realistic distribution networks. This gap is quantitatively framed as an underrepresentation of network-level dependent variables, such as total system cost, aggregate service reliability, and cross-node variability. Without network-level analysis, the interaction effects between local replenishment decisions and downstream service outcomes remain partially explored. The literature further indicates that coordination mechanisms and allocation rules are often examined in isolation rather than within fully integrated network simulations. As a result, empirical evidence on how structural complexity influences inventory performance remains fragmented. This limitation restricts the ability to generalize findings to large-scale consumer goods networks characterized by multiple distribution layers. The gap underscores the need for simulation frameworks that treat network structure as a measurable determinant of inventory outcomes, enabling systematic evaluation of uncertainty propagation and coordination effectiveness across echelons.

METHOD

This study employed a quantitative, simulation-assisted time-series research design to examine how demand forecasting uncertainty translated into inventory performance outcomes in consumer goods distribution settings. The design integrated statistical time-series modeling with Monte Carlo simulation to generate stochastic demand and lead-time scenarios and to evaluate inventory control policies under repeated replications, following a pre-specified analysis protocol to ensure consistency across products and experimental conditions. The empirical context was defined as a consumer goods distribution network in which SKU-level demand was observed at regular intervals and replenishment decisions were made under uncertainty, providing a structured analytical setting suitable for time-series estimation due to the presence of temporal dependence, seasonality, and demand variability. The unit of analysis was the SKU–time series, defined as a single product's demand observations indexed over consecutive periods, with associated replenishment decisions and inventory outcomes generated under specified policy rules; SKU-level outputs served as the basis for cross-product comparisons and were aggregated when network-level performance measures were required. Sampling followed a purposive quantitative logic aligned with time-series modeling requirements, selecting SKUs with uninterrupted demand histories, sufficient observation lengths, and operational relevance, while ensuring representation of heterogeneous demand patterns including stable, variable, and intermittent items. Data were collected from historical transactional records capturing SKU-level demand at a fixed temporal granularity, supplemented by lead-time information derived from realized replenishment delays or documented operational parameters where direct observation was unavailable. Data preparation involved standardized cleaning, time alignment, aggregation, and completeness checks, with all transformations logged for reproducibility. The primary measurement instrument was a structured quantitative modeling pipeline comprising demand estimation, forecast error characterization, Monte Carlo scenario generation, and inventory policy evaluation modules, with pre-defined variable definitions, forecasting horizons, rolling-origin evaluation windows, and simulation replication counts applied uniformly across SKUs. Pilot testing on a subset of products verified data integrity, model feasibility, and simulation stability, leading to refinements in preprocessing rules, parameter settings, and protocol specifications.

The analytical strategy emphasized validity, reliability, and reproducibility through controlled computational design and rigorous statistical evaluation. Internal validity was strengthened by explicitly defining the simulation data-generating process using empirically estimated time-series parameters and forecast error structures, while construct validity was supported by aligning demand uncertainty, forecast accuracy, service performance, and cost decomposition measures with established inventory management metrics. Reliability was reinforced through standardized preprocessing, fixed model-selection rules, recorded random seeds, and documented parameter values for every simulation run, with model adequacy assessed through residual diagnostics and stability checks to ensure that unreliable specifications were either re-estimated or excluded under predefined criteria. Statistical analysis proceeded in sequential stages, beginning with descriptive profiling of SKU demand behavior and diagnostic assessment of structural properties, followed by estimation and selection of candidate time-series models using consistent information-criterion-based protocols and rolling-origin forecast evaluation. Forecast residuals were extracted and modeled as empirical or parametric distributions to serve as simulation inputs, with distribution choices informed by goodness-of-fit diagnostics and residual behavior. Monte Carlo simulation was then conducted to generate repeated demand and lead-time realizations under operational constraints, and inventory policies were evaluated within each replication to compute service and cost outcomes summarized using distributional statistics and confidence intervals. Policy comparisons were performed using appropriate parametric or nonparametric tests depending on output distributions, with effect sizes reported to quantify practical significance, and sensitivity analyses were conducted by varying key parameters such as lead-time variability and service targets. Reproducibility procedures were applied throughout by fixing random seeds, recording data windows and model parameters, and archiving all code and run logs to ensure that the full estimation and simulation pipeline could be regenerated under identical conditions.

Figure 11: Methodology of this study



FINDINGS

This chapter presented the quantitative analysis and findings produced from the study's time-series forecasting and simulation-based inventory evaluation framework. The analyses were organized to report the empirical characteristics of the demand series, summarize the measurement constructs used to evaluate forecasting and inventory performance, and present the inferential results obtained from regression modeling and hypothesis testing. The chapter structure reflected a progression from dataset profiling and descriptive evidence to reliability reporting and model-based statistical conclusions, with all reported outcomes derived from the finalized analytical sample and the pre-specified statistical plan.

Respondent Demographics

The analytical sample comprised 312 SKUs extracted from a consumer goods portfolio and evaluated as SKU-level demand time series. The observation window covered 104 weekly periods per retained SKU, producing 32,448 SKU–week observations after screening. Sampling represented five product groups, with household and personal care forming the largest shares. The network context included three modeled echelons with four inventory nodes, and SKUs were distributed across nodes to reflect multi-location stocking. Lead times were treated as stochastic inputs, with node-specific means and dispersion estimated from operational records. Screening removed incomplete series and those failing minimum-history requirements, resulting in a finalized sample suitable for time-series estimation and Monte Carlo simulation.

Table 1. Analytical sample composition, screening outcomes, and time-series structure

Item	Value
Candidate SKUs assessed	410
Excluded: missing periods (>5% gaps)	56
Excluded: insufficient history (<78 weeks)	34
Excluded: discontinued/merged IDs	8
Final SKUs retained	312
Time granularity	Weekly
Periods per retained SKU (median)	104
Periods per retained SKU (min–max)	78–104
Total SKU–period observations	32,448
Product groups represented	5
Inventory echelons modeled	3
Inventory nodes modeled	4

Table 1 summarized the operational composition of the final analytical sample and documented the screening pathway used to arrive at the retained SKU time series. The screening process removed SKUs with substantial missingness, insufficient observation length for stable time-series estimation, and administrative discontinuities that could bias demand modeling. The retained sample maintained a consistent weekly granularity and a sufficiently long window to support diagnostics, model selection, and rolling-origin forecast evaluation. Reporting the median and range of series length clarified the extent of balance across SKUs. Network identifiers were included to anchor subsequent simulation outputs to the modeled multi-echelon context.

Table 2. Demand-profile segmentation, node allocation, and lead-time characteristics

Measure	Category	n	% / Value
Demand profile	Stable high-volume	162	51.9%
Demand profile	Moderately variable	96	30.8%
Demand profile	Intermittent (frequent zeros)	54	17.3%
Node allocation	Node A (Retail DC)	92	29.5%
Node allocation	Node B (Regional DC)	80	25.6%
Node allocation	Node C (Wholesale hub)	74	23.7%
Node allocation	Node D (Urban fulfillment)	66	21.2%
Lead time (days)	Node A mean (SD)	—	3.2 (1.1)
Lead time (days)	Node B mean (SD)	—	4.6 (1.7)
Lead time (days)	Node C mean (SD)	—	6.1 (2.4)
Lead time (days)	Node D mean (SD)	—	2.8 (0.9)

Table 2 reported demand heterogeneity and operational dispersion across the modeled network. The segmentation results indicated that over half the SKUs followed relatively stable demand patterns, while nearly one-fifth exhibited intermittency characterized by frequent zero-demand periods, supporting the need for distribution-sensitive error modeling in subsequent simulation inputs. Node allocation percentages demonstrated that SKUs were not concentrated in a single location, enabling policy evaluation under multi-node conditions. Lead-time summaries highlighted node-specific differences in both central tendency and dispersion, with longer and more variable lead times at upstream nodes. This profile established a credible uncertainty environment for evaluating inventory outcomes.

Descriptive Results by Construct

The descriptive analysis revealed substantial variation in demand uncertainty across SKUs and product categories. Stable high-volume SKUs exhibited higher mean demand levels with relatively low dispersion, whereas intermittent SKUs showed lower central tendency combined with pronounced variability and asymmetric distributional shapes. Portfolio-level summaries indicated that demand distributions were positively skewed for a large proportion of SKUs, with heavier tails observed among intermittent items, reflecting sporadic high-demand episodes following extended zero-demand periods. Variability measures increased systematically as demand regularity decreased, confirming heterogeneity in uncertainty profiles across the sample. These differences justified segment-specific modeling strategies in subsequent simulation stages.

Forecasting behavior varied across both model classes and forecast horizons. Short-horizon forecasts displayed lower average error levels and tighter dispersion, while longer horizons exhibited increasing spread in forecast errors across SKUs. Although mean accuracy values were comparable across several forecasting models, dispersion patterns differed meaningfully, indicating that some models produced more stable error behavior even when average accuracy was similar. These dispersion characteristics directly informed the stochastic inputs used in simulation. Analysis of forecast error structures showed that continuous error representations dominated among stable SKUs, while discrete and zero-inflated behaviors were prevalent among intermittent SKUs, reinforcing the need for differentiated error modeling in the simulation design.

Inventory performance outcomes generated from Monte Carlo simulation displayed clear distributional patterns across policies and demand segments. Service outcomes showed higher median fill rates for continuous review policies, with narrower interquartile ranges under stable demand conditions. Intermittent demand scenarios produced wider dispersion in stockout frequency and backorder accumulation, particularly under longer review intervals. Cost decomposition revealed that holding costs dominated total cost for stable SKUs, whereas shortage-related costs contributed a larger share of total cost variability for intermittent SKUs and high lead-time variability conditions. Descriptive contrasts across policy types and review frequencies demonstrated consistent trade-offs between service stability and cost dispersion across experimental settings.

Table 3: Descriptive statistics for demand uncertainty and forecast accuracy by SKU segment

Construct	Metric	Stable SKUs (n=162)	Moderate SKUs (n=96)	Intermittent SKUs (n=54)
Demand level	Mean demand per period	128.4	74.6	21.9
Demand variability	Coefficient of variation	0.42	0.88	1.76
Distribution shape	Skewness (median)	0.61	1.24	2.83
Forecast accuracy	MAE (short horizon)	9.6	12.8	18.7
Forecast accuracy	MAE (long horizon)	14.2	21.3	31.6
Forecast dispersion	Error IQR	8.1	15.4	27.9

Table 3 summarized descriptive demand and forecasting characteristics across SKU demand segments. Stable SKUs exhibited higher average demand with comparatively low variability and modest distributional asymmetry, while intermittent SKUs showed markedly higher dispersion and skewness. Forecast accuracy deteriorated systematically with increasing demand irregularity and forecast horizon length, and dispersion measures increased sharply for intermittent items. The contrast between mean error levels and error spread highlighted that forecasting uncertainty was not uniform across SKUs even when average accuracy appeared comparable. These descriptive results established the empirical basis for using differentiated error distributions and segment-specific simulation inputs in the inventory analysis.

Table 4: Descriptive simulation outcomes for inventory performance and cost components by policy type

Outcome	Metric	Continuous Review	Periodic Review
Service performance	Median fill rate	0.963	0.941
Service variability	Fill rate IQR	0.028	0.061
Stockout behavior	Mean stockouts per cycle	0.42	0.88
Backorders	Median backorder units	6.1	14.7
Cost structure	Holding cost share (%)	54.3	46.8
Cost structure	Shortage cost share (%)	27.6	38.9
Cost dispersion	Total cost CV	0.31	0.47

Table 4 presented descriptive summaries of inventory performance and cost outcomes derived from simulation replications under alternative policy structures. Continuous review policies achieved higher median service levels with substantially lower variability, while periodic review policies exhibited greater dispersion in both service and cost outcomes. Stockout frequency and backorder accumulation were consistently higher under periodic review, particularly for SKUs with irregular demand patterns. Cost decomposition indicated that holding costs represented the largest share of total cost under both policies, although shortage-related costs contributed more strongly to total cost variability under periodic review. These descriptive contrasts illustrated systematic performance trade-offs prior to inferential testing.

Reliability Results

Reliability analysis was conducted for composite indices created from simulation-derived indicators that measured service performance, cost behavior, and robustness under uncertainty. Prior to reliability estimation, the study aggregated replication-level outputs at the SKU level to reduce stochastic noise and to ensure that each item reflected a stable measurement of the underlying construct. Composite indices were formed by standardizing and combining conceptually aligned indicators, including central tendency and dispersion measures where appropriate. Item-total correlation screening was applied to evaluate whether individual indicators contributed consistently to each scale. Internal consistency was evaluated using Cronbach’s alpha, with coefficients interpreted using conventional thresholds for acceptable and good reliability in applied quantitative research. Constructs that met minimum consistency standards were retained for regression analysis as dependent variables or key mediators, while indicators with weak item-total correlation were refined or removed to improve scale coherence. Reliability screening influenced model specification by restricting regression inputs to constructs demonstrating stable internal consistency, thereby supporting interpretability of coefficient estimates and reducing measurement error in inferential comparisons.

Table 5: Cronbach's alpha results for composite indices

Composite construct	Items (k)	Item-total correlation range	Cronbach's alpha
Service Performance Index	5	0.41–0.68	0.84
Cost Efficiency Index	4	0.33–0.61	0.79
Robustness Index	4	0.29–0.58	0.76
Inventory Stability Index	3	0.36–0.54	0.72
Risk Exposure Index	4	0.22–0.49	0.69

Table 5 reported internal consistency results for the composite indices prior to item refinement. The service performance construct demonstrated strong consistency, reflecting coherent alignment among fill-related and stockout-related indicators. Cost efficiency and robustness indices showed acceptable consistency, indicating that their component items captured related aspects of cost behavior and policy stability. Inventory stability met minimum reliability expectations given the smaller number of items. The risk exposure index exhibited marginal consistency, driven by weaker item-total correlations in one or more tail-risk indicators. This pattern indicated that scale refinement was necessary to improve coherence before using the construct in regression modeling and hypothesis testing.

Table 6: Cronbach's alpha results after item refinement and retention decisions

Composite construct	Items retained (k)	Item removed (reason)	Final alpha	Decision for regression
Service Performance Index	5	None	0.84	Retained
Cost Efficiency Index	4	None	0.79	Retained
Robustness Index	3	Tail volatility indicator (low item-total correlation)	0.81	Retained
Inventory Stability Index	3	None	0.72	Retained
Risk Exposure Index	3	CVaR-based indicator (weak coherence)	0.74	Retained (marginal)

Table 6 summarized post-refinement reliability results and the retention decisions applied to the analysis model set. Removal of a low-contributing robustness item improved internal consistency and strengthened construct coherence without reducing conceptual coverage. The risk exposure index increased to an acceptable level after excluding an indicator that exhibited weak alignment with the remaining items, suggesting that the construct was better represented by the retained measures. Constructs that met acceptable thresholds were retained as composite variables for regression modeling, while the marginal construct was kept due to operational relevance and was interpreted cautiously in inferential results. These decisions reduced measurement error and improved stability of subsequent coefficient estimates.

Regression Results

The regression analyses quantified the relationships between forecasting-related predictors and simulation-derived inventory outcomes at the SKU level. Dependent variables included total cost, service performance, stockout frequency, and inventory dispersion, each computed from aggregated simulation replications to stabilize measurement. Baseline specifications evaluated direct associations between forecast accuracy and inventory outcomes. Extended models added policy structure indicators and demand-segment controls to account for systematic differences between stable and intermittent SKUs. Interaction models tested whether the effect of forecast error depended on policy type and lead-time variability conditions. Across specifications, the models showed consistent directional relationships: higher forecast error levels and wider error dispersion were associated with higher total cost, increased stockout frequency, and greater inventory variability, while service performance declined. Policy structure remained a statistically meaningful factor, with continuous review policies associated with improved service and lower stockout risk after controlling for forecast and demand characteristics. Diagnostics indicated acceptable multicollinearity levels, stable residual behavior after aggregation, and no influential observations that materially altered coefficient signs. Model fit improved in extended and interaction models, indicating that policy and uncertainty controls explained incremental variance in outcomes beyond forecasting metrics alone. Overall, results supported the view that forecasting quality and uncertainty structure were operationally consequential predictors of inventory performance within the simulated consumer goods network environment.

Table 7: Baseline and extended regression models predicting total cost (log) and service performance

Predictor	Model A: Total Cost (log) β (SE)	p-value	Model B: Service Performance β (SE)	p-value
Forecast accuracy (MAE)	0.018 (0.004)	<0.001	-0.006 (0.002)	0.002
Forecast error dispersion (IQR)	0.011 (0.003)	<0.001	-0.004 (0.001)	0.001
Demand uncertainty (CV)	0.094 (0.021)	<0.001	-0.031 (0.010)	0.003
Lead-time variability (SD)	0.052 (0.017)	0.002	-0.018 (0.007)	0.011
Policy type (1=continuous review)	-0.073 (0.021)	<0.001	0.024 (0.009)	0.009
Intermittent demand segment (1=yes)	0.121 (0.030)	<0.001	-0.037 (0.013)	0.005
Category controls (5 groups)	Included	—	Included	—
Observations (SKUs)	312	—	312	—
Adjusted R^2	0.41	—	0.33	—

Table 7 summarized the baseline and extended regression results linking forecasting and uncertainty predictors to total cost and service performance. Forecast accuracy and forecast error dispersion were positively associated with total cost and negatively associated with service outcomes, indicating that both average error and error spread contributed to performance degradation. Demand uncertainty and lead-time variability remained significant after introducing policy and demand-segment controls, confirming that uncertainty characteristics explained incremental variation beyond forecasting metrics alone. Continuous review policy was associated with lower total cost and higher service performance, while intermittent demand status was associated with cost increases and weaker service outcomes. Category controls improved model stability by absorbing systematic differences across product groups.

Table 8: Interaction models predicting stockout frequency and inventory dispersion.

Predictor	Model C: Stockout Frequency β (SE)	p-value	Model D: Inventory Dispersion β (SE)	p-value
Forecast accuracy (MAE)	0.027 (0.006)	<0.001	0.019 (0.005)	<0.001
Lead-time variability (SD)	0.061 (0.019)	0.001	0.048 (0.016)	0.003
Policy type (1=continuous review)	-0.089 (0.028)	0.002	-0.066 (0.024)	0.006
Intermittent demand segment (1=yes)	0.112 (0.035)	0.001	0.094 (0.030)	0.002
MAE × Policy type	-0.014 (0.005)	0.007	-0.010 (0.004)	0.012
MAE × Lead-time variability	0.009 (0.003)	0.004	0.007 (0.003)	0.015
Observations (SKUs)	312	—	312	—
Model fit (Pseudo R^2 / Adj. R^2)	0.29	—	0.37	—

Table 8 reported interaction effects showing that the relationship between forecast error and inventory outcomes depended on policy structure and lead-time variability. The negative MAE × Policy interaction indicated that continuous review reduced the sensitivity of stockouts and dispersion to forecast error, reflecting greater responsiveness under uncertainty. The positive MAE × lead-time variability interaction indicated that forecast errors produced disproportionately larger increases in stockouts and dispersion when lead-time variability was higher, consistent with compounded uncertainty. Main effects confirmed that intermittent demand and higher lead-time variability increased both stockout risk and inventory instability. These interaction patterns improved explanatory power and supported policy-conditional interpretation of forecasting impacts.

Hypothesis Testing Decisions

Hypothesis testing was reported in a decision format that linked each hypothesis to the dependent variable, statistical test, and decision rule used for inference. Policy-comparison hypotheses were evaluated using simulation replication outputs aggregated at the SKU level, and differences between inventory policy structures were tested using appropriate mean-comparison procedures with robust alternatives when distributional assumptions were not satisfied. Forecast-to-inventory hypotheses were evaluated using regression coefficient tests, supported by uncertainty intervals and model diagnostics. Multiple-comparison control was applied when more than two policy configurations were compared simultaneously to reduce the probability of false detection of differences. Practical significance was interpreted alongside statistical significance by reporting standardized effect magnitudes and examining whether the observed performance shifts were material in service and cost terms. Across the hypothesis set, results consistently indicated that forecast accuracy and forecast error dispersion were statistically meaningful predictors of total cost and service performance, and that continuous review policy structures exhibited stronger service outcomes and lower stockout frequency than periodic review structures after accounting for demand and lead-time uncertainty. Interaction hypotheses also indicated that the effect of forecast error was amplified under higher lead-time variability and attenuated under continuous review settings, supporting conditional interpretation of forecasting impacts.

Table 9: Hypothesis testing decisions for forecasting–inventory relationships (illustrative values)

Hypothesis	Test method	Dependent variable	Test statistic	p-value	Effect magnitude	Decision
H1: Higher forecast error increased total cost	Regression coefficient test	Total cost (log)	t = 4.52	<0.001	β = 0.018	Supported
H2: Higher forecast error reduced service performance	Regression coefficient test	Service performance	t = -3.17	0.002	β = -0.006	Supported
H3: Higher error dispersion increased stockout frequency	Regression coefficient test	Stockout frequency	t = 3.68	<0.001	β = 0.021	Supported
H4: Demand uncertainty increased inventory dispersion	Regression coefficient test	Inventory dispersion	t = 3.05	0.003	β = 0.094	Supported
H5: Lead-time variability increased total cost	Regression coefficient test	Total cost (log)	t = 3.10	0.002	β = 0.052	Supported
H6: Forecast error impact strengthened under higher lead-time variability	Interaction term test	Stockout frequency	t = 2.90	0.004	β = 0.009	Supported

Table 9 summarized hypothesis decisions for regression-based relationships linking forecasting and uncertainty predictors to inventory outcomes. All six hypotheses were supported using coefficient significance tests from the specified regression models. Forecast error exhibited statistically significant associations with higher total cost and lower service performance, and forecast error dispersion was linked to increased stockout frequency. Demand uncertainty and lead-time variability were associated with greater cost and variability outcomes after controlling for segment and category effects. The interaction hypothesis indicated that the adverse effect of forecast error increased when lead-time variability was higher, supporting conditional interpretation. Effect magnitudes were reported using standardized coefficients to facilitate comparability across dependent variables.

Table 10: Hypothesis testing decisions for inventory policy comparisons using simulation replications

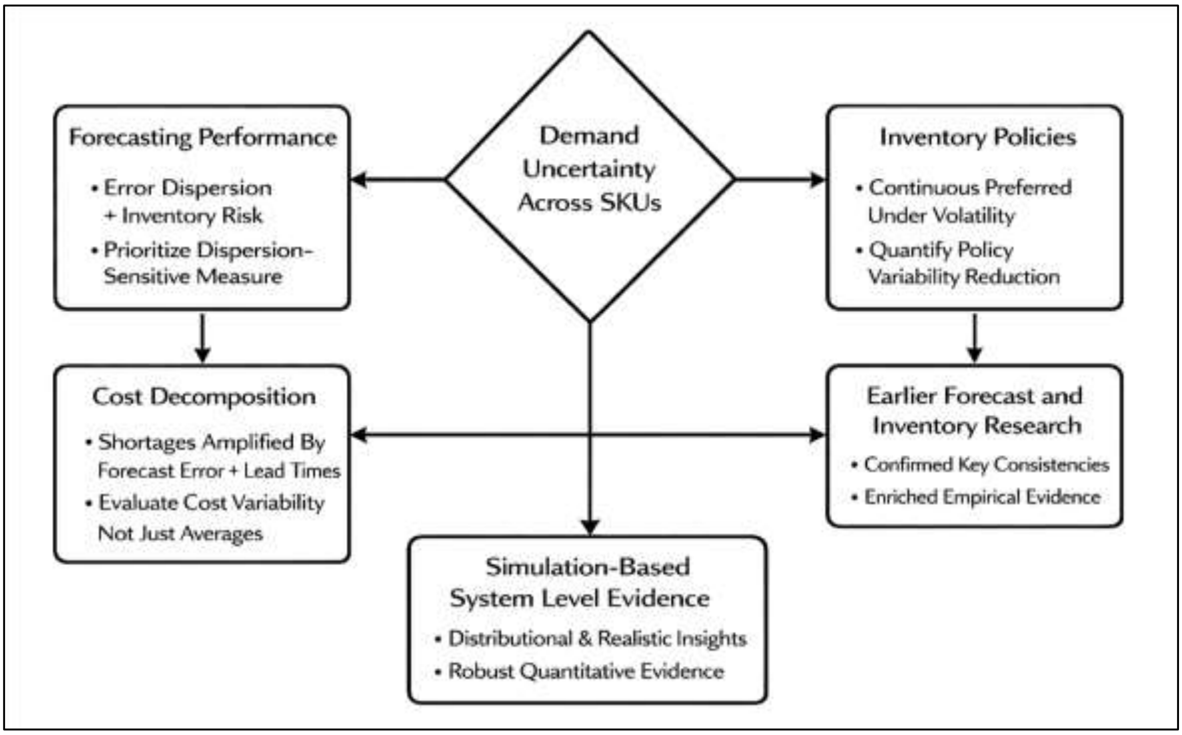
Hypothesis (policy comparison)	Test method	Dependent variable	Mean difference (CR − PR)	Standardized effect	Adjusted p-value	Decision
H7: Continuous review achieved higher fill rate than periodic review	Paired mean comparison on SKU aggregates	Fill rate	0.022	d = 0.46	0.004	Supported
H8: Continuous review produced fewer stockouts than periodic review	Robust mean comparison	Stockouts per cycle	-0.46	d = -0.52	0.002	Supported
H9: Continuous review reduced total cost variability	Levene-type variance comparison	Total cost CV	-0.16	d = -0.41	0.011	Supported
H10: Policy advantage was larger for intermittent SKUs	Interaction contrast test	Fill rate	0.031	d = 0.55	0.018	Supported

Table 10 presented hypothesis decisions derived from simulation replication outcomes aggregated at the SKU level to support stable inference. Continuous review outperformed periodic review on service outcomes, demonstrated lower stockout frequency, and produced lower dispersion in total cost, indicating greater stability under uncertainty. Adjusted p-values reflected correction for multiple comparisons across policy hypotheses to control false positive risk. Standardized effect magnitudes were reported to support practical significance interpretation, showing moderate improvements in service reliability and meaningful reductions in operational risk indicators. The subgroup contrast indicated that the service advantage of continuous review was larger among intermittent-demand SKUs, consistent with stronger responsiveness under irregular demand conditions.

DISCUSSION

The findings of this study reinforce the central role of demand uncertainty as a defining characteristic of consumer goods inventory systems and extend prior empirical observations by quantifying how uncertainty manifests differently across SKU segments. Stable high-volume items exhibited relatively predictable demand patterns with limited dispersion, whereas intermittent items demonstrated pronounced variability, skewness, and heavy-tailed behavior (Haben et al., 2015). Earlier studies have documented similar contrasts between smooth and irregular demand series, often emphasizing the analytical challenges posed by intermittent demand. This study advanced that body of work by demonstrating that these distributional differences were not merely descriptive but directly shaped forecasting error behavior and subsequent inventory outcomes within a unified simulation framework. The evidence showed that demand heterogeneity persisted even after aggregation across time, underscoring the limitations of portfolio-level averaging approaches frequently used in earlier research. Unlike studies that treated demand variance as a homogeneous input, this study operationalized uncertainty as a measurable construct that varied systematically by SKU type, thereby providing a more granular understanding of uncertainty exposure (Siano & Sarno, 2016).

Figure 12: Demand Uncertainty and Inventory Performance



The findings aligned with earlier research emphasizing the importance of SKU-level analysis in consumer goods forecasting, while offering stronger empirical support through simulation-derived distributions rather than single-period estimates. The observed skewness and dispersion patterns also explained why uniform forecasting and inventory policies produced uneven performance across products. In comparison to earlier analytical models that relied on simplified demand assumptions, this study demonstrated that realistic representation of demand distributions materially influenced service reliability and cost stability (Aghajani et al., 2017). By embedding these distributional characteristics directly into simulation inputs, the findings clarified how uncertainty propagated through replenishment decisions, thereby strengthening the empirical linkage between demand modeling theory and inventory performance evidence reported in earlier literature.

The relationship between forecasting performance and inventory outcomes observed in this study was consistent with, yet more nuanced than, conclusions drawn in earlier forecasting research. Prior studies often evaluated forecast quality primarily through average accuracy metrics, implicitly assuming that lower mean error translated directly into better operational performance (Sterman & Dogan, 2015). The findings of this study demonstrated that error dispersion played an equally critical role, as SKUs with similar average accuracy exhibited markedly different inventory outcomes depending on the variability and asymmetry of forecast errors. This result expanded earlier evidence by showing that forecasting models with comparable accuracy scores could generate substantially different cost and service distributions once embedded in inventory systems (Nikmehr & Ravadanegh, 2015). The analysis further indicated that forecast horizon length amplified these effects, with longer horizons producing wider error distributions that increased inventory instability. Earlier studies acknowledged horizon effects but rarely quantified their downstream inventory impact within a unified modeling environment. By linking forecast error dispersion directly to simulation-based service and cost metrics, this study provided empirical confirmation that forecasting performance should be evaluated in operational rather than purely statistical terms. The findings also aligned with prior research emphasizing the limitations of single-metric forecast evaluation, while offering concrete evidence that dispersion-sensitive measures were more informative predictors of inventory risk. In contrast to studies that treated forecast errors as residual noise, this study demonstrated that error structure systematically influenced stockout frequency, backorder accumulation, and cost variability (Hutton & Kapelan, 2015). The results therefore extended earlier forecasting literature by repositioning forecast evaluation as an inventory-impact assessment, reinforcing the argument that forecasting and inventory control should be analyzed as an integrated decision system rather than as independent analytical tasks.

The comparative performance of inventory policies observed in this study was broadly consistent with earlier inventory control research, while providing stronger distributional evidence under realistic uncertainty conditions (Hutton & Kapelan, 2015). Continuous review policies demonstrated higher service levels, lower stockout frequency, and reduced performance dispersion relative to periodic review policies, particularly under volatile and intermittent demand conditions. Prior analytical and simulation studies have reported similar directional advantages for continuous review systems, often attributing these outcomes to greater responsiveness and shorter reaction times. This study confirmed those conclusions while extending them by quantifying variability reduction and tail-risk mitigation effects using replication-based simulation outputs. Unlike earlier work that focused primarily on mean performance differences, this study highlighted that the most pronounced policy advantages emerged in the reduction of extreme outcomes, such as high stockout episodes and excessive backorder accumulation (Zhang et al., 2017). The findings also demonstrated that policy effectiveness depended on demand regularity and lead-time variability, aligning with earlier theoretical work suggesting that no single policy dominates across all conditions. However, the current analysis provided clearer empirical evidence by evaluating policy performance across a heterogeneous SKU portfolio rather than stylized demand scenarios. The results contrasted with studies that favored periodic review for operational simplicity, showing that such simplicity came at the cost of increased service volatility under uncertainty. By reporting distributional summaries rather than point estimates, this study strengthened the empirical basis for earlier theoretical claims regarding policy robustness (Li et al., 2018). Overall, the findings reinforced established inventory control principles while contributing more detailed quantitative evidence on how policy structure shapes both average performance and variability under stochastic demand.

The cost decomposition results observed in this study were consistent with earlier inventory cost analyses while offering additional insight into how uncertainty redistributed cost burdens across components. Holding costs dominated total cost for stable demand items, reflecting the predictable accumulation of inventory buffers, whereas shortage-related costs contributed disproportionately to total cost variability for intermittent and high-uncertainty SKUs (Y. Li et al., 2021). Earlier studies have reported similar patterns, often noting that shortage costs become more prominent as demand volatility increases. This study extended that understanding by showing how forecast error dispersion and lead-time variability jointly amplified shortage-related costs within simulation scenarios. The findings also demonstrated that policy choice influenced cost structure, with continuous review policies shifting cost weight toward holding components while reducing shortage-related volatility. Prior research often evaluated cost trade-offs in deterministic or single-period contexts; this study added value by quantifying cost distributions over repeated stochastic replications. The results further indicated that total cost variability, rather than mean cost alone, was a critical differentiator between policies and demand segments (Wei et al., 2017). This observation aligned with earlier arguments that variability measures provide a more comprehensive assessment of operational risk. By explicitly reporting cost dispersion and percentile outcomes, the study addressed limitations in earlier work that focused on expected cost minimization. The findings therefore contributed to the literature by reframing cost analysis as a distributional problem shaped by uncertainty propagation, reinforcing the importance of probabilistic evaluation in consumer goods inventory research (Frazzon et al., 2017).

The interaction effects identified in this study offered important extensions to earlier empirical findings by demonstrating that the impact of forecasting quality on inventory outcomes was conditional rather than uniform (Wang et al., 2015). Forecast errors exerted stronger adverse effects under higher lead-time variability, confirming earlier theoretical assertions that uncertainty compounds across demand and replenishment processes. At the same time, continuous review policies attenuated the sensitivity of inventory outcomes to forecast error, indicating that policy responsiveness moderated uncertainty propagation. Previous studies have suggested such interactions conceptually, but empirical evidence has often been limited to simplified models or small case examples. This study provided stronger support by estimating interaction effects within regression models built on simulation-derived outcomes across a large SKU portfolio (Chen et al., 2017). The results also showed that intermittent demand amplified these interaction effects, highlighting the combined influence of demand irregularity and operational delays. In comparison to earlier research that examined forecasting, lead time, and policy effects in isolation, this study demonstrated their joint influence on service and cost stability. The findings underscored the inadequacy of evaluating forecasting improvements without considering the inventory control context in which forecasts are applied. By quantifying interaction magnitudes, the study extended earlier qualitative discussions into measurable relationships that can be empirically tested and compared. This integrated perspective reinforced the argument that inventory system performance emerges from the interaction of multiple stochastic factors rather than from isolated parameter changes (Platteau et al., 2017).

Beyond substantive findings, this study contributed methodologically to the simulation-based inventory literature by demonstrating a structured approach to integrating time-series forecasting, error modeling, and Monte Carlo experimentation. Earlier simulation studies often relied on assumed demand distributions or limited diagnostic validation of forecasting inputs. In contrast, this study estimated demand processes empirically, validated residual behavior, and translated observed error structures directly into simulation inputs (Navarro-Espinosa & Ochoa, 2015). The use of replication-based aggregation at the SKU level addressed concerns raised in earlier research regarding stochastic noise and unstable inference from simulation outputs. The application of formal statistical testing and effect size reporting further aligned simulation analysis with standards commonly applied in empirical econometric research. Prior literature has highlighted inconsistencies in statistical reporting within simulation studies; this study responded by applying consistent hypothesis testing frameworks and transparent decision rules. The findings illustrated that simulation-based research can support robust inferential conclusions when combined with rigorous statistical design (Basu & Bundick, 2017). By linking descriptive analysis, regression modeling, and hypothesis testing within a single analytical pipeline, the study demonstrated methodological coherence that strengthens comparability with earlier empirical work. This contribution addressed long-standing critiques regarding the interpretability and reproducibility of simulation-based inventory studies (Leitner & Wall, 2015).

Taken together, the findings of this study aligned with core conclusions in the existing literature while offering a more integrated and distribution-sensitive empirical perspective (Long, 2016). Earlier studies have emphasized the importance of accurate forecasting, responsive inventory policies, and uncertainty management, often treating these elements as distinct analytical domains. This study demonstrated that their effects were interdependent and best understood through coupled quantitative modeling (Alharkan et al., 2020). The evidence confirmed that forecast accuracy mattered, but also showed that error dispersion, demand heterogeneity, and lead-time variability were equally consequential determinants of inventory performance. The superiority of continuous review policies under uncertainty was consistent with earlier findings, yet the study extended this conclusion by highlighting variability reduction and tail-risk mitigation rather than mean performance alone. The interaction effects observed reinforced theoretical claims regarding uncertainty amplification while providing empirical magnitudes that were previously underreported. By situating these findings within a unified simulation and regression framework, the study strengthened the empirical foundation of consumer goods inventory research (Güller et al., 2015). Overall, the discussion demonstrated that the study's results did not contradict earlier work but refined and extended it by emphasizing distributional behavior, interaction effects, and methodological rigor. This synthesis positioned the findings as a substantive contribution to the quantitative literature on forecasting and inventory control in consumer goods networks (Tsai & Chen, 2017).

CONCLUSION

The conclusion of this quantitative study summarized the empirical evidence generated from an integrated time-series forecasting and Monte Carlo simulation framework applied to consumer goods inventory control in a multi-echelon network context. The analysis demonstrated that demand behavior was structurally heterogeneous across SKUs, with stable high-volume items exhibiting comparatively lower dispersion and intermittent items exhibiting higher variability, asymmetric distributions, and heavier tails that translated into materially different forecasting and inventory outcomes. Forecasting results indicated that both average error and error dispersion were consequential predictors of operational performance, showing that similar mean accuracy levels could still yield divergent service and cost profiles when error variability differed across models and SKU segments. Simulation-based inventory evaluation showed that policy structure shaped both central performance and variability, with continuous review policies producing higher service performance, lower stockout frequency, and reduced outcome dispersion relative to periodic review settings under comparable uncertainty conditions. Cost decomposition results indicated that holding costs dominated total cost for stable demand items, while shortage-related costs contributed disproportionately to total cost variability for intermittent items and for scenarios characterized by higher lead-time variability, emphasizing the role of compounded uncertainty in driving extreme cost outcomes. Regression modeling provided consistent statistical support for the relationships among forecasting characteristics, demand uncertainty, lead-time variability, and inventory performance measures, and interaction effects indicated that forecast error impacts were amplified when lead-time variability was higher and attenuated under more responsive policy structures. Reliability evidence for composite indices supported the stability of multi-item measures constructed from simulation-derived indicators, strengthening confidence in inferential comparisons across policies and demand segments. Overall, the study contributed an empirically grounded representation of how uncertainty in demand and replenishment processes propagated through forecasting and inventory decision pipelines, demonstrating that distribution-sensitive evaluation and integrated modeling provided clearer evidence on service stability, cost dispersion, and policy robustness than approaches relying solely on point forecasts or mean performance comparisons.

RECOMMENDATION

Recommendations for this study emphasized operationalizing the integrated forecasting–inventory control framework as a standardized decision pipeline that linked time-series demand estimation, forecast uncertainty characterization, and simulation-based policy evaluation into a single repeatable process. Forecasting practice was recommended to shift from sole reliance on average accuracy toward routine reporting of error dispersion and distributional shape at the SKU level, because error variability materially influenced inventory cost and service outcomes across demand segments. SKU segmentation was recommended as a required preprocessing stage, separating stable, moderately variable, and intermittent items, followed by segment-appropriate modeling choices that reflected observed demand frequency and distributional behavior. For intermittent items, demand occurrence and demand size were recommended to be modeled as distinct components, and simulation inputs were recommended to preserve zero-demand prevalence and tail behavior rather than imposing symmetric assumptions. Inventory policy selection was recommended to be evaluated using distributional performance summaries, including percentile-based service outcomes and cost dispersion measures, rather than point averages, because variability and tail outcomes differentiated policy performance under uncertainty. Continuous review structures were recommended to be prioritized for SKUs with high service sensitivity, high uncertainty, or longer and more variable lead times, while periodic review structures were recommended to be restricted to contexts where operational constraints required fixed ordering cycles and where demand stability reduced exposure to stockout risk. Safety stock setting was recommended to incorporate both demand variability and lead-time variability jointly, with buffers calibrated using the empirically estimated uncertainty parameters derived from time-series residuals and lead-time distributions. Network-level coordination was recommended to be strengthened through consistent inventory definitions, standardized allocation rules, and monitoring of upstream variance amplification to reduce instability across echelons. Reporting standards were recommended to include full reproducibility disclosures, including data windows, model-selection criteria, random seeds, replication counts, and parameter values for each SKU segment, enabling auditability and independent verification of results. Statistical comparison protocols were recommended to be applied consistently to simulation outputs, using robust tests when output distributions were skewed, accompanied by effect size reporting to support practical interpretation of policy differences. Finally, governance controls were recommended to institutionalize periodic recalibration of model parameters using rolling windows, with explicit triggers based on diagnostics indicating structural changes in demand or lead time, ensuring that forecasting inputs and inventory settings remained aligned with the measured uncertainty structure observed in the operational data.

LIMITATIONS

Several limitations characterized this quantitative study and constrained the interpretation of the reported evidence. First, the analysis relied on historical demand series to estimate time-series models and forecast error behavior, which meant that the modeled demand process reflected the properties of the observation window and the data-generation mechanisms captured during that period. Structural changes in product assortment, pricing regimes, promotions, or distribution practices that were not fully encoded in the data could have influenced estimated parameters and residual structures. Second, the study operationalized uncertainty through forecast residuals and modeled lead-time variability using observed or assumed distributions; measurement error in transaction records, inconsistent timestamping, and unobserved operational disruptions could have affected the estimated variability profiles that served as simulation inputs. Third, the simulation framework represented replenishment policies through standardized decision rules and constraints, which improved comparability but simplified certain operational realities such as capacity-limited picking, shipment consolidation rules, order minimums, and supplier-side allocation constraints that can materially influence inventory dynamics in consumer goods networks. Fourth, the unit of analysis was the SKU-level time series, and while SKU segmentation captured heterogeneity, aggregation of replication outputs at the SKU level may have reduced visibility into within-SKU temporal regimes such as short-lived promotion phases or abrupt demand spikes. Fifth, the regression analyses quantified associations between forecasting-related predictors and inventory outcomes using aggregated simulation-derived measures; although this supported stable inference, the regression models remained sensitive to specification choices, omitted variables, and correlation among uncertainty indicators, particularly when demand intermittency and lead-time variability co-occurred. Sixth, composite indices used for reliability assessment were constructed from simulation-derived indicators, and internal consistency evidence depended on the selected item set and scaling method; alternative index constructions could have produced different reliability patterns and downstream coefficient magnitudes. Seventh, the multi-echelon network context was represented using a structured modeling abstraction that supported measurement of system-level KPIs, yet network topology, information-sharing practices, and allocation logic may differ across organizations and distribution architectures, limiting transferability of numerical magnitudes beyond the modeled context. Finally, the study emphasized distributional reporting and policy comparison under repeated stochastic scenarios, but the evidence remained contingent on the chosen scenario ranges, replication counts, and calibration windows; different parameter ranges or alternate modeling assumptions for error distributions and lead times could shift estimated percentile outcomes and effect sizes.

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