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Explainable Machine Learning for Inventory Shrinkage and Stockout Prediction in U.S. Retail Supply Chains: A Quantitative Study using Gradient Boosting and SHAP

Md Saddam Hosain[1];

[1]. Business, Data & Research Analyst; Financial, Supply Chain & Operational Analytics; California, USA; MBA in Business Management, International American University, Los Angeles, California, USA; Bachelor's Degree in Accounting & Finance, SEGi University, Malaysia;
Email: hosainsaddam404@gmail.com

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Abstract

Inventory shrinkage and stockout occurrence undermine U.S. retail supply chains through inaccurate stock records, uncertain deliveries, and ineffective replenishment, while opaque prediction systems complicate managerial adoption. This study investigates the relationships between inventory information quality, operational uncertainty, inventory risks, and acceptance of explainable analytics. Guided by Organizational Information Processing Theory, it employs a quantitative, cross-sectional, embedded multiple-case framework covering six U.S. retail organizations, 60 stores, 24,000 store-stock-keeping-unit records, and 270 employee questionnaires from 300 invitations (90.0% response). Inventory record accuracy, inventory control effectiveness, supplier lead-time variability, demand forecast error, replenishment performance, and explanation usefulness constitute principal predictors; shrinkage, stockouts, and AI acceptance form the outcomes. The analytical plan combines five-point Likert measures, descriptive statistics, Cronbach's alpha, Pearson correlations, store-clustered logistic regression, held-out XGBoost classification, logistic regression benchmarks, ROC-AUC, precision-recall metrics, and SHAP explanations. The reported analytical results show shrinkage and stockout incidence of 8.08% and 16.35%, respectively. Higher record accuracy (OR = 0.440) and control effectiveness (OR = 0.479) are associated with lower shrinkage odds, whereas greater supplier variability (OR = 2.140) and forecast error (OR = 2.052) correspond to higher stockout odds. XGBoost achieves ROC-AUC values of 0.877 for shrinkage and 0.850 for stockouts, compared with 0.874 and 0.847 for logistic regression, without statistically significant superiority. SHAP highlights record accuracy and audit age for shrinkage, and replenishment performance and supplier variability for stockouts. Explanation usefulness correlates with AI acceptance ($r = 0.596$), with adjusted $R^2 = 0.358$. Questionnaire reliability ranges from 0.765 to 0.827, and perceived SHAP usefulness predicts acceptance ($B = 0.643$, $p < .001$), emphasizing human interpretability alongside predictive discrimination for practical deployment. These patterns support prioritizing reliable inventory records, supplier monitoring, calibrated model comparisons, and interpretable alerts. The framework offers a basis for testing whether explainable prediction improves inventory decisions and operational performance across retail contexts.

Keywords

Inventory Shrinkage; Stockout Prediction; Explainable Machine Learning; XGBoost; SHAP.

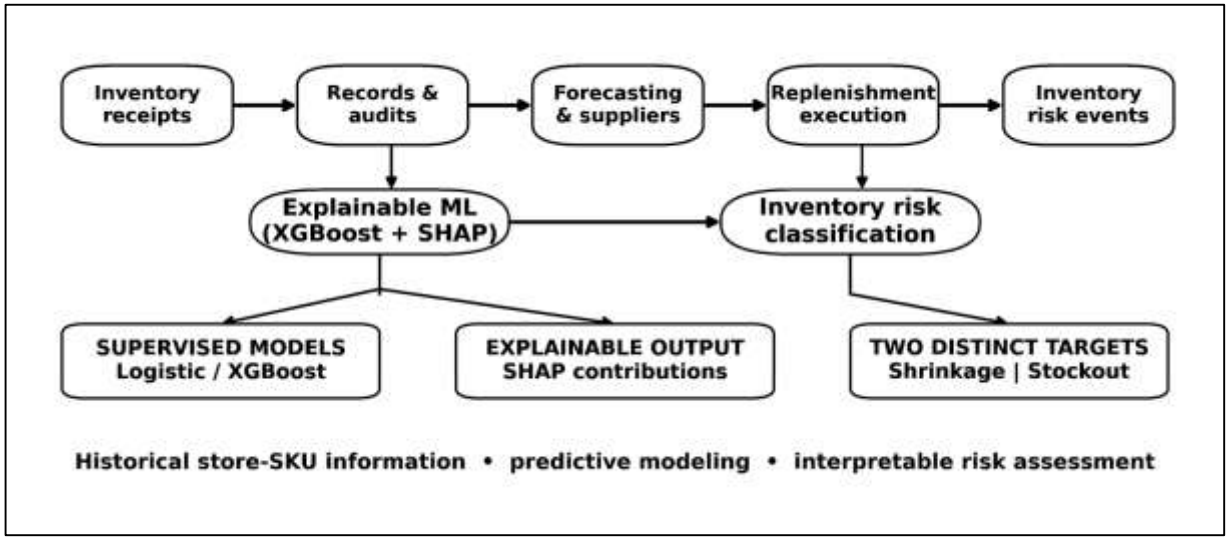
RETAIL INVENTORY PROBLEM AND STUDY PURPOSE

Inventory management refers to the systematic coordination of stock acquisition, storage, movement, monitoring, and replenishment to maintain product availability while controlling operational costs. Within retail supply chains, inventory shrinkage represents physical inventory losses that create discrepancies between expected inventory quantities and verified stock counts, whereas stockout occurrence refers to situations in which products required by customers are unavailable at their intended selling locations. These problems constitute interconnected operational challenges because inaccurate inventory information can influence replenishment decisions, inventory turnover, customer purchasing opportunities, and retail profitability. The study titled Information Inaccuracy in Inventory Systems (p. 843) established that undetected stock losses could disrupt replenishment processes and generate severe stockout conditions, particularly in inventory systems operating with limited stock buffers (Kang & Gershwin, 2005). Similarly, Inventory Inaccuracy and Supply Chain Performance (p. 373) demonstrated through supply chain simulation that discrepancies between physical and recorded inventory could increase operational costs and product unavailability across interconnected distribution systems (Fleisch & Tellkamp, 2005). The international significance of these problems arises from the dependence of retail organizations on geographically distributed suppliers, distribution facilities, transportation networks, and store-level inventory systems. Variations in purchasing behavior, product assortment, information accuracy, and replenishment coordination create substantial differences in inventory performance across retail environments. An econometric investigation of 311 publicly listed retail firms established that inventory turnover performance was associated with gross margins, capital intensity, and unexpected sales variations, demonstrating the multidimensional nature of inventory productivity (Gaur et al., 2005). In Inventory Record Inaccuracy (p. 627), an empirical assessment of approximately 370,000 inventory records from 37 retail stores identified inaccuracies in 65% of the examined records, indicating that inventory discrepancies could occur extensively within established retail systems (DeHoratius & Raman, 2008). A comprehensive examination of stockout research additionally distinguished demand-side consumer responses from supply-side causes of product unavailability (Aastrup & Kotzab, 2010). Evidence from an international fashion retailer subsequently demonstrated that inventory record discrepancies were associated with differences in store-level inventory and sales management performance (Shabani et al., 2021). More recently, a cross-sectional analytical approach to large-scale inventory inaccuracies has demonstrated the relevance of detecting discrepancies across stores and stock-keeping units through systematic quantitative analysis (Farias et al., 2024). These findings establish inventory shrinkage, stockout occurrence, and inventory information reliability as closely related dimensions of retail supply chain operations.

Background and Operational Context

Inventory shrinkage and stockout occurrence have represented persistent operational challenges within U.S. retail supply chains, influencing product availability, inventory accuracy, replenishment efficiency, and overall organizational performance. Inventory shrinkage involves discrepancies between expected and physically available inventory quantities, while stockouts occur when products become unavailable for customer purchases. These challenges have been associated with inaccurate inventory records, unpredictable demand, supplier delivery variations, inadequate inventory controls, and inefficient replenishment processes. The increasing complexity of retail supply chain operations has emphasized the importance of integrating advanced analytical methods into inventory risk assessment. Explainable machine learning, particularly Extreme Gradient Boosting (XGBoost) combined with SHapley Additive exPlanations (SHAP), provides a methodological approach for identifying inventory-related risk patterns and interpreting the contributions of operational variables to predicted outcomes. Organizational Information Processing Theory provides the theoretical foundation for examining relationships among inventory information accuracy, analytical capabilities, operational uncertainty, and inventory management performance.

Figure 1: Retail Inventory Risk Prediction: An Integrated Research Overview



Problem Definition

U.S. retail supply chains experience substantial operational difficulties arising from inventory shrinkage, stockout occurrence, inaccurate inventory information, and inconsistencies in replenishment activities. Conventional inventory monitoring and statistical forecasting approaches may not adequately capture the nonlinear relationships among inventory record accuracy, demand fluctuations, supplier lead-time variability, and inventory control effectiveness. Although machine learning algorithms can identify complex predictive relationships, their limited interpretability can restrict managerial understanding and acceptance of automated inventory risk assessments. Furthermore, insufficient integration of statistical hypothesis testing, operational inventory measurements, and explainable predictive modeling creates methodological challenges in examining the factors associated with inventory shrinkage and stockout risks. Consequently, a quantitative investigation is needed to evaluate these relationships, assess the predictive performance of gradient boosting models, and determine how SHAP-based explanations support transparent inventory risk assessment and organizational decision-making.

Study Objectives

The primary objective of this research is to investigate the relationships among inventory management practices, information accuracy, replenishment performance, and inventory shrinkage and stockout risks within U.S. retail supply chains using a quantitative, cross-sectional, embedded multiple-case study design. Specifically, the study aims to evaluate the associations between inventory record accuracy and shrinkage risk, supplier lead-time variability and stockout occurrence, demand forecasting accuracy and stockout occurrence, and inventory control effectiveness and shrinkage risk. Furthermore, the research seeks to develop and evaluate Extreme Gradient Boosting models for predicting inventory shrinkage and stockout events, compare their predictive performance with conventional logistic regression models, and identify influential predictive factors using SHAP explanations. The study also aims to examine employees' acceptance of explainable AI decision support through a structured five-point Likert-scale questionnaire. Descriptive statistics, Pearson correlation analysis, multivariable regression, and predictive model validation will provide the analytical foundation for addressing these objectives within Organizational Information Processing Theory.

Research Significance and Contributions

The significance of this research extends across theoretical, methodological, technological, organizational, and managerial dimensions of retail supply chain management. By integrating quantitative statistical analysis with gradient boosting and SHAP-based explainability, the study addresses important analytical requirements associated with inventory shrinkage and stockout risk assessment.

i. Theoretical Significance: The research contributes to the application of Organizational Information Processing Theory by examining relationships among inventory information accuracy, information-processing capabilities, operational uncertainty, and inventory management performance within U.S. retail supply chains.

ii. Methodological Significance: The study establishes an integrated quantitative analytical framework combining cross-sectional survey measurements, operational inventory records, descriptive statistics, Pearson correlation analysis, multivariable regression, gradient boosting classification, and model explanation techniques.

iii. Technological Significance: The research evaluates XGBoost as a predictive modeling technique for identifying inventory shrinkage and stockout risks while examining SHAP-based explanations as a mechanism for interpreting the contributions of operational variables to individual predictions.

iv. Managerial Significance: The findings can provide retail inventory managers, replenishment supervisors, and supply chain professionals with evidence concerning the factors associated with inventory discrepancies, product unavailability, and the interpretation of automated inventory risk predictions.

v. Practical Significance: The research can support evidence-based approaches to inventory monitoring, demand forecasting assessment, supplier performance evaluation, replenishment coordination, and inventory control management through interpretable predictive analytics.

vi. Academic Significance: The study provides a structured empirical foundation for examining relationships between traditional statistical methods and explainable machine learning within retail supply chain management, supporting further scholarly investigation into inventory risk prediction and analytical transparency.

INVENTORY RISK MECHANISMS AND RETAIL EVIDENCE

The literature review examines the theoretical foundations, empirical evidence, and methodological developments relevant to inventory shrinkage and stockout prediction in U.S. retail supply chains. It synthesizes research concerning inventory record accuracy, supply chain visibility, demand forecasting, supplier lead-time variability, replenishment performance, and inventory control effectiveness. Particular attention is given to gradient boosting algorithms, SHAP-based explainability, and their applications in operational risk prediction. Organizational Information Processing Theory serves as the principal theoretical foundation for evaluating relationships among information reliability, organizational analytical capabilities, and inventory management outcomes. The review also establishes the conceptual relationships among research variables and the proposed hypotheses.

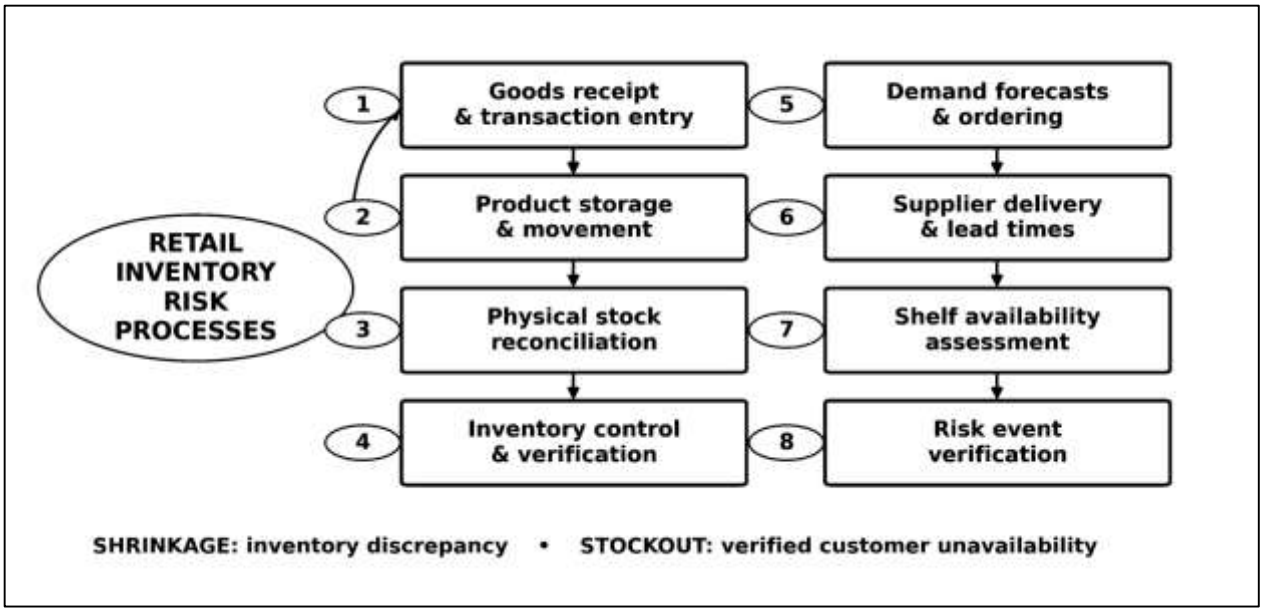
Shrinkage, Shelf Availability, and Risk Verification

The operational characteristics of retail supply chains create multiple sources of inventory shrinkage and product unavailability, including inventory misplacement, unrecorded product movements, theft, inaccurate transaction processing, inadequate stock reconciliation, and insufficient replenishment coordination. These conditions influence inventory information quality because computerized inventory records do not necessarily represent the physical quantities available to satisfy customer demand. In Retail Inventory Management When Records Are Inaccurate (p. 257), inventory control models incorporating inaccurate records demonstrated that replenishment and inventory auditing policies could address problems arising from discrepancies between recorded and physical stock levels (DeHoratius et al., 2008). Research examining retail execution errors further established that products physically present within stores may remain unavailable for customer purchases when misplaced during receiving, shelf replenishment, or product handling activities (Rekik et al., 2008). Inventory shrinkage associated with theft represents another distinct source of record inaccuracy, as unrecorded losses can produce discrepancies that persist within inventory management systems until detected through verification procedures (Rekik et al., 2009). Empirical research examining product assortment and inventory levels demonstrated that phantom products, which remain physically present but inaccessible to customers, can negatively affect retail sales even when recorded inventory quantities indicate product availability (Ton & Raman, 2010). The investigation titled Inventory Record Inaccuracy: Causes and Labor Effects (p. 63) identified relationships between operational execution problems, labor availability, and inventory record discrepancies, emphasizing the importance of store-level processes in understanding inventory reliability (Chuang & Oliva, 2015). Inventory information visibility also depends on the effectiveness of information technologies connecting distribution centers, transportation activities, and retail stores. A field-based investigation of radio-frequency identification technology demonstrated how product movement data could provide greater visibility into operational activities while revealing associated data-quality challenges (Delen et al., 2007). Furthermore, research on channel inventory estimation established that unaccounted inventory shrinkage could reduce the informational value of point-of-sale records used to estimate stock positions and predict replenishment orders (Schlaich & Hoberg, 2024). Collectively, these operational characteristics describe a

retail environment in which inventory control effectiveness, stock record accuracy, product movement visibility, and replenishment execution are closely associated with the occurrence and identification of inventory losses and stockouts.

Inventory shrinkage and stockout occurrence constitute distinct but interconnected forms of operational risk in retail supply chains. Shrinkage describes inventory losses that create differences between expected and physically available quantities, whereas stockout occurrence describes the absence of a product at the location where customers expect to purchase it. Physical losses may arise from theft, damage, spoilage, unrecorded movements, or transaction errors; stockouts may additionally arise from insufficient ordering, supplier delays, unexpectedly strong demand, and failures to transfer available products from backrooms to shelves. These conditions operate across stores, distribution centers, suppliers, and delivery partners, making retail inventory accuracy an information problem rather than solely an accounting concern. In A Statistical Investigation of Inventory Shrinkage (p. 101), store-level regression analysis linked shrinkage with staffing, security, store layout, and surrounding demographic characteristics, while identifying measurement errors and correlations among explanatory variables that complicated accurate predictions for individual stores (Howell & Proudlove, 2007). This distinction between identifying average associations and predicting the risk of a particular store is important for studies that combine regression analysis with machine learning. A separate contractual dimension arises when responsibility for merchandise is distributed among retailers, suppliers, and logistics providers. In Supply Chain Contracts and Inventory Shrinkage (p. 694), an empirical grocery-retailing investigation compared scan-based trading with vendor-managed inventory and reported higher shrinkage under scan-based trading arrangements and outsourced store deliveries, indicating that inventory governance and delivery responsibility are associated with measurable losses (Choi et al., 2019). Together, operational execution and contractual arrangements shape the information available for detecting inventory deviations. For U.S. retailers, these distinctions require attention to how shrinkage is recorded, when reconciliation occurs, which party handles inventory, and whether losses are observed consistently across organizations. Reliable cross-case comparisons therefore depend on common definitions of discrepancies, comparable inventory audit coverage, and transparent records of product movement.

Figure 2: Operational Pathways Leading to Shrinkage and Stockout Risk



Stockouts reflect more than a shortage of products within a store. A product can be physically available in the backroom, misplaced on the sales floor, reserved by an inaccurate system record, or absent because a replenishment order was delayed. Distinguishing these circumstances matters because each represents a different operating mechanism and can require different information for detection. An inventory system may report positive quantities even when the desired product cannot be purchased, producing a misleading signal for ordering and store performance reporting. Conversely, records may understate physical stock, creating unnecessary replenishment orders and excess carrying costs. Inventory audits connect digital records to physical conditions, but their usefulness depends on audit frequency, product characteristics,

stock turnover, and the timing of replenishment. In Effectiveness of Frequent Inventory Audits (p. 21), an empirical evaluation involving more than 200,000 transaction records and approximately 7,400 stock-keeping units identified distinct inventory-error profiles and demonstrated that audit performance depends on interactions between inventory policies and replenishment processes (Ishfaq & Raja, 2020a). Such findings establish a measurable connection between inventory control effectiveness and operational information quality without implying that every discrepancy represents a permanent loss. Sales transactions also supply indirect evidence about shelf availability when repeated periods without sales occur for products expected to sell. In Fixing Shelf Out-of-Stock With Point-of-Sale Signals (p. 862), a data-driven audit model used consecutive zero-sales observations, conditional stockout probabilities, and economic costs to examine when managers should investigate potential shelf unavailability (Chuang, 2018). A zero-sales observation is not itself proof of a stockout, since demand can legitimately be absent during a period. The distinction emphasizes why verified inventory outcomes and historical operational indicators should remain separate during analysis. It also clarifies the relevance of supplier lead times, demand variations, replenishment reliability, and inventory record accuracy when assessing stockout incidence across retail cases.

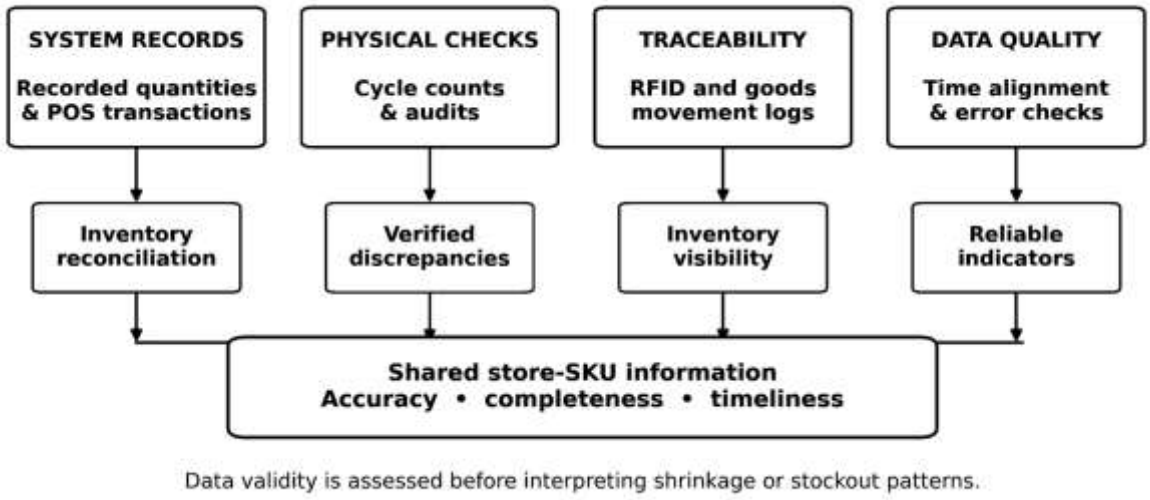
Predicting inventory risk requires translating retail operations into measured explanatory variables and independently verified outcomes. At the store and stock-keeping-unit level, relevant indicators include historical inventory discrepancies, sales frequency, demand forecast errors, replenishment intervals, supplier delivery variability, stock turnover, and available inventory-control information. Retailers may observe different risk distributions across products because fast-moving items, intermittently demanded goods, and promotional merchandise follow different demand and replenishment patterns. Classification models are relevant when the target is an event, such as the occurrence of a verified shortage or stock discrepancy during a defined observation period. In Predict On-Shelf Product Availability With Classification Methods (p. 4473), an empirical grocery-retailing study evaluated classification algorithms for identifying products missing from shelves and used ensemble learning to address the relative rarity of unavailable products; its findings also showed that accurate predictions could fail to detect a substantial share of actual missing items (Papakiriakopoulos, 2012). This result highlights the need to distinguish overall accuracy from sensitivity to infrequent but operationally consequential events. For shrinkage and stockout analysis, the proportion of positive observations, the reliability of inventory audits, and the distribution of products across stores all influence model assessment. Regression models can estimate interpretable associations between specific predictors and binary risk outcomes, while gradient-boosted trees can capture interactions and nonlinear patterns not represented by additive specifications. SHAP feature attribution can then describe how recorded inputs contribute to individual model predictions, without establishing causal effects. Under Organizational Information Processing Theory, accurate transaction data, inventory reconciliation, and timely replenishment signals represent informational resources used to address uncertainty across retail operations. A cross-sectional multiple-case analysis can therefore connect employee-reported inventory practices with historical operational records while keeping perceptions, measurable events, statistical associations, and predictions conceptually distinct. Such separation is essential when evaluating inventory shrinkage and stockout risk in U.S. retail supply chains.

Record Accuracy, Auditing, and Data Visibility

Inventory record accuracy refers to the correspondence between quantities registered in an organization's inventory system and products physically available for sale. In retail supply chains, discrepancies emerge when transactions are misrecorded, goods are misplaced, stock losses remain undetected, or physical counts occur after inventory movement. These differences weaken the informational foundation of replenishment schedules, safety-stock calculations, and product availability assessments. The article Inspection and Replenishment Policies (p. 185) examined inventory systems with inaccurate records and demonstrated that coordinated inspection and ordering decisions could outperform routine approaches by considering the time elapsed since verification and the cost of counting inventory (Kök & Shang, 2007). Its findings indicate that record accuracy is not merely a technical characteristic but an operational condition requiring monitoring decisions. Inventory data quality also depends on transaction completeness, identification, timing, and consistency across interconnected systems. The article Quantitative Analysis of Inventory Inaccuracy Reduction (Article 109089) compared inventory counting with radio-frequency identification under transaction errors and imperfect identification performance, demonstrating that their relative economic value depends on operating conditions and technology costs (Shahrabi, 2023). These findings distinguish information accuracy from the availability of digital records, establishing the need for verified

physical quantities when investigating shrinkage and stockout outcomes.

Figure 3: Inventory Record Accuracy, Verification, and Information Visibility Framework



Data validity is assessed before interpreting shrinkage or stockout patterns.

Supply chain visibility describes an organization's ability to access relevant information concerning stock locations, product movements, demand conditions, and activities performed by interconnected supply chain participants. Visibility requires not only technological infrastructure but also dependable information exchange, coordinated procedures, and consistent interpretation of shared records. The article Antecedents of Supply Chain Visibility (p. 1217) investigated retail supply chain relationships and identified variations in visibility across external linkages, with contributing factors extending beyond information technology to organizational resources and interfirm arrangements (Aditya & Ahmed, 2022; Barratt & Oke, 2007). Consequently, data accessible to a retailer may be incomplete even when individual warehouses or stores operate computerized inventory platforms. Radio-frequency identification offers more detailed tracking of item movements, although its effectiveness varies across product categories and operating environments. The article RFID-Enabled Visibility and Retail Inventory Record Inaccuracy (p. 843) reported two field experiments and found that RFID-enabled visibility reduced record discrepancies, with effects differing substantially among categories and participating stores (Asheke & Maksudul, 2022; Hardgrave et al., 2013). Such variability indicates that technological visibility does not automatically ensure identical inventory outcomes across retail settings. For cross-sectional analysis, visibility can therefore be assessed through information timeliness, traceability, reconciliation practices, and the accessibility of trustworthy inventory records across stores and distribution activities.

The relationship between record accuracy and operational performance depends on how retailers detect, interpret, and correct discrepancies before those errors influence replenishment decisions. Stock counting provides observations, yet the usefulness of audits varies according to sales intensity, stock movement, error patterns, and the costs of intervention. Automated inventory capture may identify discrepancies earlier, but technology-generated observations also require validation when scanning errors or incomplete coverage affect quantities. The article Empirical Evaluation of Inventory Inaccuracy Mitigation (p. 1972) used a simulation grounded in retail inventory information to compare mitigation strategies and found that replenishment adjustments alone could not fully offset accumulated record errors, while corrective technology-supported auditing offered stronger potential for improving store performance (Asheke & Badrul, 2022; Ishfaq & Raja, 2020b). These findings connect inventory record quality with the information-processing requirements emphasized by Organizational Information Processing Theory. In the present research, discrepancies, inventory control practices, and information visibility provide explanatory dimensions rather than interchangeable measures. Verified shrinkage events and product stockouts remain separate operational outcomes, while employee responses capture perceived effectiveness of organizational practices. Integrating these sources enables statistical examination of associations and supports interpretable XGBoost predictions without confusing perceived visibility with physically confirmed stock availability or assuming that correlated measures establish causation.

Demand Forecasting, Delivery Variability, and Replenishment

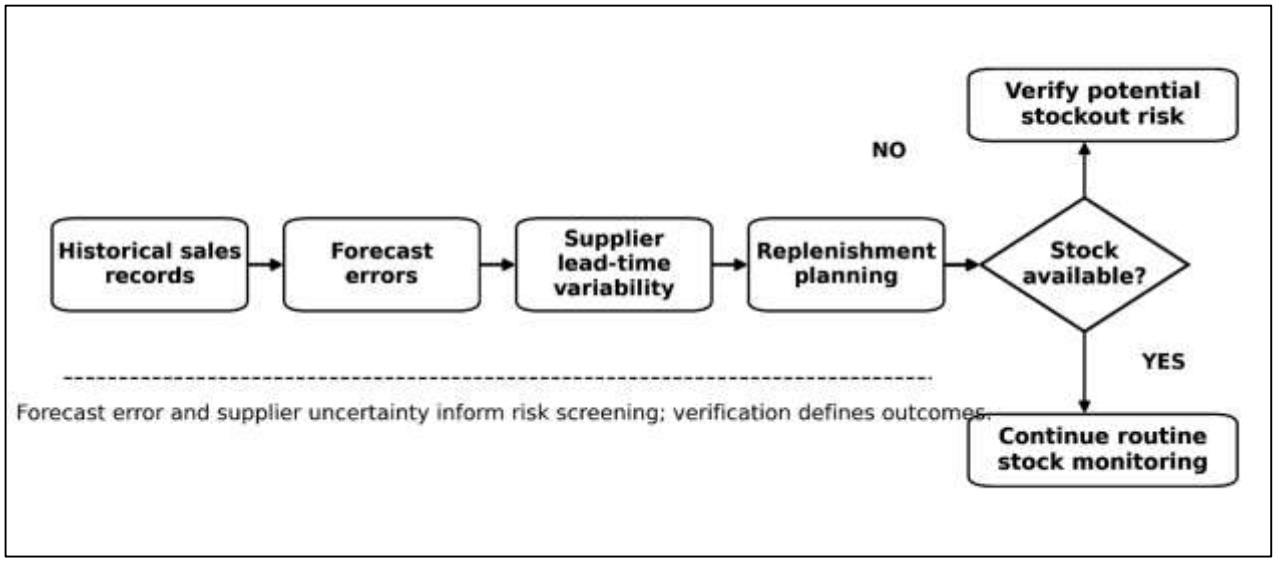
Demand forecasting and inventory replenishment represent additional interconnected elements of retail supply chain performance because product availability depends on the correspondence between expected customer demand, available stock, supplier delivery schedules, and inventory ordering decisions. Demand forecasting involves estimating expected purchasing quantities from historical transactions and explanatory information, while replenishment performance concerns the effectiveness of restoring inventory to required levels within operational constraints. The study The Accuracy of Intermittent Demand Estimates (p. 303) examined alternative forecasting procedures using 3,000 intermittent-demand series and demonstrated that demand characteristics influence the comparative accuracy of forecasting methods (Khalid & Sadmeen, 2022; Syntetos & Boylan, 2005). Another investigation established that demand patterns could be categorized according to the average intervals between demand occurrences and the variability of demand quantities, providing a statistical foundation for differentiating inventory forecasting requirements (Syntetos et al., 2005). Subsequent empirical analysis connected intermittent-demand estimation procedures with inventory control outcomes, including customer service levels and stock volume differences (Syntetos & Boylan, 2006). Supply chain demand forecasting has also been examined through machine learning approaches, including neural networks and support vector machines, particularly where demand information becomes distorted across interconnected supply chain stages (Carbonneau et al., 2008). Within grocery retailing, integrated demand and supply chain planning frameworks have identified relationships among sales planning, replenishment coordination, inventory allocation, and operational decision-making processes (Hübner et al., 2013). In Retail Forecasting: Research and Practice (p. 1283), a comprehensive examination of retail forecasting identified the complexity introduced by product-level demand, promotional activities, store-specific conditions, and multiple levels of sales aggregation (Fildes et al., 2022). Empirical evidence from the M5 forecasting competition additionally demonstrated the importance of evaluating forecasting methods across extensive retail sales series with hierarchical product structures and varying demand characteristics (Makridakis et al., 2022; Akter & Sumaiya, 2022). Research on tree-based retail forecasting established that explanatory variables and feature engineering could contribute substantially to predictive accuracy, while different model specifications generated varying inventory performance outcomes (Wellens et al., 2024). These studies demonstrate that demand forecasting accuracy, supplier lead-time variability, inventory replenishment performance, and product-level operational characteristics represent distinct but interconnected dimensions of inventory risk assessment. Their relationships are particularly relevant to U.S. retail supply chains, where product assortment diversity, store-level operational differences, and geographically distributed replenishment activities create heterogeneous inventory conditions.

Demand forecasting estimates the quantity and timing of customer purchases, while replenishment translates these estimates into stock orders intended to maintain product availability. In retail environments, forecasting errors arise from purchasing patterns, short product life cycles, promotional activity, and differences among stores and stock keeping units. These errors affect ordering decisions because inventory requirements depend on both expected demand and uncertainty surrounding sales. In SKU Demand Forecasting in the Presence of Promotions (p. 12340), an empirical analysis of grocery sales found that regression trees incorporating promotional and related product information improved forecast accuracy during promotions, whereas simpler time series methods performed well during ordinary periods (Ali et al., 2009). Forecast accuracy therefore varies with the operating context and with the information supplied to an analytical model. A difficulty concerns products purchased infrequently, for which average demand forecasts can conceal variation in the timing of orders. In Forecasting Replenishment Orders in Retail (p. 4168), probabilistic representations of intermittent consumer demand improved predictions of store replenishment orders compared with forecasts based only on point estimates (Mashiat & Morshedul, 2022; Sillanpää & Liesiö, 2018). These findings distinguish demand estimation from replenishment prediction and identify sales patterns, product characteristics, and delivery arrangements as measurements for stockout analysis.

Supplier lead time denotes the interval between placing a replenishment order and receiving usable inventory, while lead time variability captures fluctuations around expected delivery durations. Both factors influence the amount of stock required to cover sales before the next delivery arrives. When demand rises during an unexpectedly long delivery interval, stores may exhaust available inventory even when the order quantity reflected a forecast. Conversely, early deliveries can increase storage requirements and inventory

exposure. In Dynamic Reorder Point Inventory Control With Lead Time Uncertainty (p. 2461), a forecast based ordering model using nonstationary demand and uncertain replenishment intervals demonstrated the operational importance of adjusting reorder points to forecast uncertainty and targeted service levels (Babai et al., 2009). These considerations become more complicated when sales fluctuations persist across periods rather than occurring independently. In Forecasting of Lead Time Demand Variance (p. 846), analytical and numerical comparisons showed that conventional variance aggregation could perform poorly under positively autocorrelated demand and stochastic lead times, affecting both inventory cost and service levels (Babai et al., 2022; Imran & Jannatul, 2022). Consequently, average supplier lead times alone cannot characterize supply uncertainty. The dispersion of deliveries, demand volatility, forecasting errors, and service expectations require distinct measurements in quantitative inventory risk models.

Figure 4: Forecast Error, Lead-Time Variability, and Stockout Screening Process



Replenishment performance reflects how reliably retailers convert inventory information into timely and appropriate purchasing and stock allocation decisions. Ordering frequency, deliveries, and shelf restocking influence whether recorded inventory becomes available to customers. Automated replenishment systems combine sales, inventory quantities, and ordering rules, although their effectiveness depends on accurate inputs and store execution. In Measuring the Effects of Automatic Replenishment on Product Availability (Article 1391), a quantitative investigation involving 85 stores and 95 products observed lower stockout rates under automated rather than manual ordering, with differences related to sales velocity, promotions, and store conditions (Avlijas et al., 2021; Maksudul & Islam, 2022). The findings place replenishment effectiveness alongside demand forecasting and delivery variability as a measurable characteristic of retail stockout exposure. For the present cross sectional research, forecast error can be calculated from prior predictions and realized demand, supplier variability from historical delivery times, and replenishment performance from order fulfillment and delivery records. These operational measures can be evaluated alongside independently validated operational stockout indicators through descriptive statistics, correlation analysis, and multivariable regression. An XGBoost classifier can examine additional nonlinear relationships among inputs, while SHAP explains their contributions to predictions. Within Organizational Information Processing Theory, these measurements represent how stores use information to manage uncertainty.

EXPLAINABLE RISK MODEL AND EMPIRICAL DESIGN

Machine learning provides a computational approach to identifying statistical patterns within operational datasets and generating predictions from relationships among multiple explanatory variables. In retail supply chain research, predictive analytics encompasses statistical learning, computational modeling, and data-driven estimation procedures that analyze historical information to characterize operational conditions and predict specified outcomes. The relationship between supply chain management and predictive analytics has been examined through the integration of organizational data, quantitative methods, and domain-specific knowledge (Morshedul & Islam, 2022; Waller & Fawcett, 2013). Data quality research has established that incomplete, inconsistent, or inaccurate supply chain information can undermine the

reliability of analytical procedures and associated predictive outcomes (Hazen et al., 2014). Retail analytics research has further identified customers, products, time, locations, and distribution channels as interconnected information dimensions within retail prediction systems (Bradlow et al., 2017). A comprehensive examination of big data analytics in operations management identified applications involving forecasting, inventory management, supply chain coordination, and operational risk analysis (Choi et al., 2018). Among supervised machine learning approaches, gradient boosting combines multiple sequentially constructed predictive models to identify complex relationships between explanatory variables and outcomes. In XGBoost: A Scalable Tree Boosting System (p. 785), an efficient gradient-boosted tree algorithm was introduced with computational procedures supporting regularized learning, sparse data processing, and scalable predictive modeling (Chen & Guestrin, 2016). However, the complexity of ensemble prediction models creates challenges when their estimated relationships must be interpreted by organizational decision-makers. Explainable artificial intelligence addresses model transparency through techniques designed to characterize the contribution of input variables to predicted outcomes. Research on model-agnostic explanation methods demonstrated how individual predictions could be represented through locally interpretable approximations (Ribeiro et al., 2016). A systematic examination of black-box explanation methods categorized techniques according to model characteristics, explanation objectives, and interpretability requirements (Guidotti et al., 2018). Additional explainability research established the conceptual distinction between predictive performance and the transparency required to understand model behavior (Adadi & Berrada, 2018). The study From Local Explanations to Global Understanding With Explainable AI for Trees (p. 56) presented SHAP-based procedures for interpreting tree ensemble predictions through individual feature contributions and aggregated explanatory patterns (Lundberg et al., 2020). A broader taxonomy of explainable artificial intelligence further distinguished explanation methods according to their characteristics, application contexts, and interpretability objectives (Arrieta et al., 2020). Together, these developments establish the methodological relationship between gradient boosting, feature-level attribution, and the interpretation of inventory risk predictions derived from operational retail information.

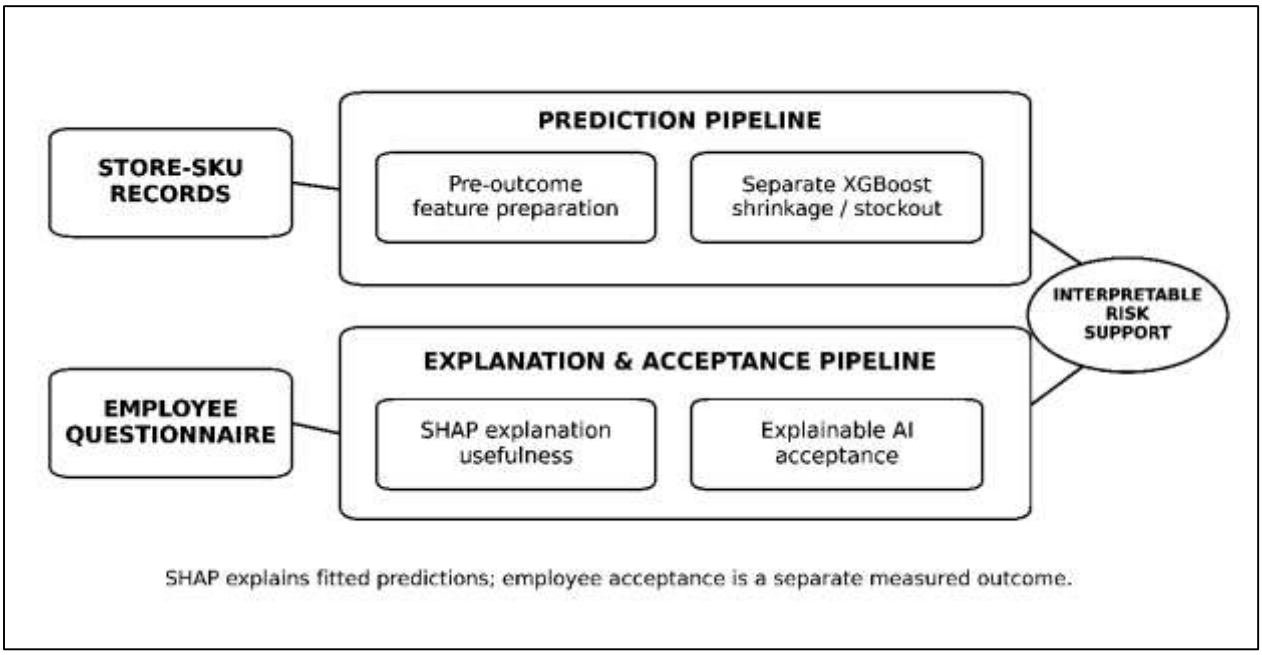
Gradient Boosting and Explainable Inventory Analytics

Gradient boosting represents a supervised machine learning approach that combines successive decision trees to learn relationships between operational variables and observed outcomes. In retail supply chains, product demand, store characteristics, promotions, inventory balances, and delivery conditions interact in ways that may be difficult to represent through exclusively linear models. Boosted trees can accommodate nonlinear patterns, categorical information after appropriate encoding, and complex feature interactions within large store-level datasets. In Disaggregated Retail Forecasting (Article 110283), researchers examined gradient boosting for stock-keeping-unit demand estimation and reported improvements against a retail forecasting benchmark, emphasizing the importance of modeling promotional effects and relationships among products (Andrade & Cunha, 2023; Feroz & Pervaz, 2022). Their analysis concerned demand quantities rather than verified shrinkage events, making the distinction between forecasting sales and classifying inventory risks important. In Retail Demand Forecasting Using Spatial-Temporal Gradient Boosting Methods (p. 652), a spatial-temporal boosting approach incorporated cross-product and temporal information to estimate retail demand at a granular level (Wang et al., 2024). Such evidence supports careful feature construction when examining inventory risk across multiple stores. For shrinkage and stockout classification, historical discrepancies, sales patterns, replenishment delays, supplier variability, and seasonal demand conditions provide potential predictors, while independently verified inventory outcomes define the targets.

Predictive capability alone does not establish whether a model's outputs can be understood by retail managers responsible for operational decisions. Ensemble trees may produce accurate forecasts while obscuring how interacting inputs influence a particular result within everyday store-level decision processes. Explainable artificial intelligence addresses this limitation through methods that communicate model behavior at the level of individual predictions or overall feature contributions. In Cold-Start Promotional Sales Forecasting Through Gradient Boosted-Based Contrastive Explanations (p. 137574), researchers combined boosted-tree regression with comparisons to similar historical promotions, allowing forecast reviewers to interpret predictions through recognizable neighboring cases (Aguilar-Palacios et al., 2020; Feroz & Shabbir, 2022). The study used contrastive explanations rather than SHAP, demonstrating that interpretability can be approached through more than one technique. In Interpreting Direct Sales'

Demand Forecasts Using SHAP Values (Article e20220035), a real-company application used SHAP to identify influential variables and examine individual demand predictions within an existing forecasting process (Arboleda-Florez & Castro-Zuluaga, 2023). SHAP allocates model-output contributions among features relative to a specified background distribution, supplying both instance-level explanations and aggregated importance summaries. In inventory risk analysis, such explanations can clarify whether a predicted stockout is associated with unusually long lead times, recent demand fluctuations, or weak replenishment performance, without asserting causality.

Figure 5: Gradient Boosting and Explainability Pathways in Inventory Risk Analysis



The adoption of explainable machine learning in supply chains also depends on how analytical explanations relate to organizational information requirements. Inventory decisions involve dispersed records, uncertain supplier performance, and operational differences across stores, creating a need to connect predictive outputs with information that managers can inspect. In A Review of Explainable Artificial Intelligence in Supply Chain Management (p. 1510), a systematic review of neurosymbolic approaches identified limited explainability as a barrier to the wider use of artificial intelligence and evaluated alternative methods for incorporating interpretable reasoning into supply chain applications (Kosasih et al., 2024). Although that review primarily examined neurosymbolic methods, its focus on understandable decision support complements post hoc feature attribution. For the proposed U.S. retail study, separate XGBoost classifiers can estimate shrinkage and stockout probabilities from recorded operational characteristics. Grouped validation can test performance across stores, while precision, recall, and discrimination metrics can reveal different error patterns. SHAP summaries can then describe feature contributions globally and for selected observations. Regression analysis can assess prespecified associations independently of predictive ranking, and five-point Likert measurements can examine employees' acceptance of explanations. Organizational Information Processing Theory links these analytical components through the shared requirement for accessible, reliable information under operational uncertainty.

Organizational Information Processing Theory

The integration of inventory risk analysis, statistical modeling, machine learning prediction, and explanation-based decision support can be examined through Organizational Information Processing Theory (OIPT), which characterizes organizational effectiveness in relation to the alignment between information-processing requirements and available information-processing capabilities. Within retail supply chains, operational uncertainty arises from incomplete inventory visibility, demand fluctuations, supplier delivery variability, and differences between recorded and physically available inventory. These

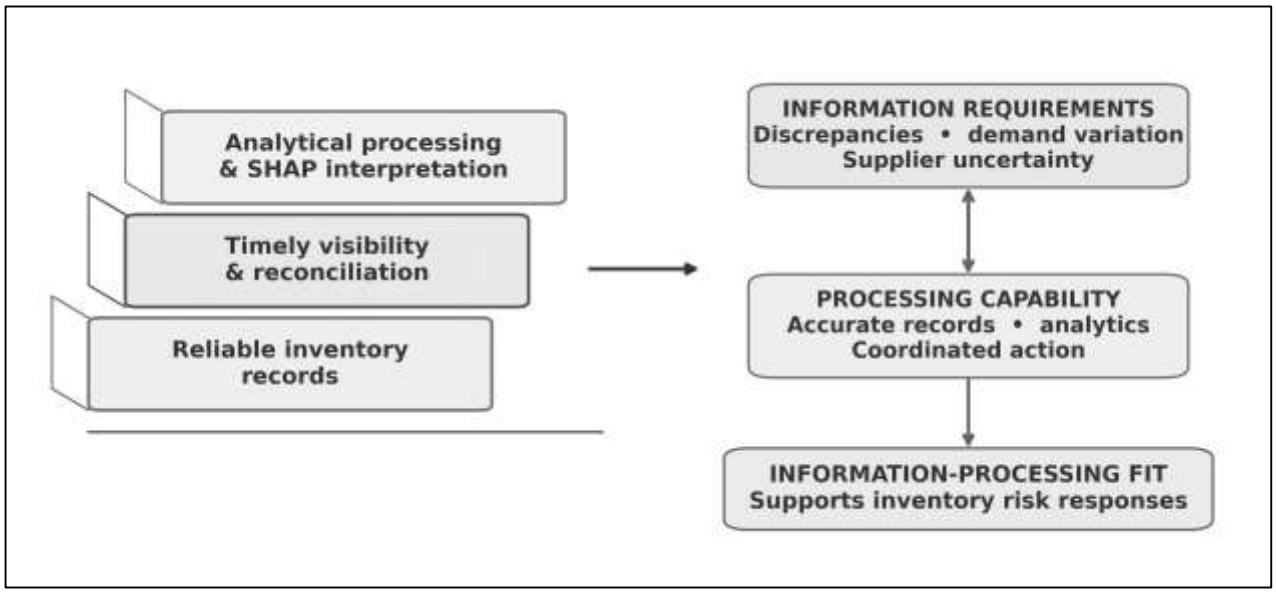
characteristics establish information-processing requirements that vary across stores, product categories, and replenishment activities. In An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics (p. 1849), empirical research involving 191 firms examined demand visibility, supply visibility, analytics capability, and organizational flexibility through OIPT, identifying relationships among information access, analytical capabilities, and operational performance (Srinivasan & Swink, 2018). Research examining big data and predictive analytics capabilities similarly established relationships among organizational connectivity, information sharing, analytical assimilation, and supply chain performance (Gunasekaran et al., 2017). These theoretical and empirical relationships provide a foundation for examining inventory record accuracy, demand forecast accuracy, supplier lead-time variability, replenishment performance, and inventory control effectiveness as measurable characteristics of retail information-processing systems. The empirical distinction between inventory record discrepancies and observable stockout events is particularly important because a product may remain unavailable to customers without a corresponding physical inventory loss, while inventory shrinkage may occur without immediately generating a stockout (Kang & Gershwin, 2005; Ton & Raman, 2010). Cross-sectional inventory research has demonstrated that measurable differences across retail stores and stock-keeping units can be analyzed to characterize inventory inaccuracies within large operational datasets (Farias et al., 2024). Retail forecasting research has likewise demonstrated that predictive performance varies according to model structure, explanatory information, and operational characteristics (Wellens et al., 2024). Within this research context, the relationships among inventory management variables, verified inventory shrinkage events, and stockout occurrence can be examined using descriptive statistics, correlation analysis, multivariable regression, and gradient-boosted classification models. SHAP-based feature attribution provides an additional analytical dimension for distinguishing the variables associated with individual and aggregated predictions, while structured five-point Likert-scale measurements permit assessment of employees' perceptions of explainable AI usefulness and decision-support acceptance. These interconnected dimensions define the empirical scope of examining inventory shrinkage and stockout prediction across multiple U.S. retail supply chain cases using quantitative statistical and explainable machine learning methods.

Organizational Information Processing Theory (OIPT) explains how organizations respond to uncertainty by matching their information processing requirements with the capacity to acquire, interpret, and use information. In U.S. retail supply chains, these requirements arise when inventory records differ from physical stock, customer demand varies, suppliers deliver inconsistently, and replenishment decisions must be coordinated across stores. Information capacity includes accurate records, inventory verification, departmental communication, and analytical routines that support decisions. The theory distinguishes having extensive data from possessing usable information and procedures for acting upon it. In An Empirical Test of Information Processing Theory (pp. 45–59), an analysis of 125 North American manufacturing firms associated environmental uncertainty with information quality, sourcing and delivery practices, and organizational coordination, supporting the relevance of information processing responses to supply chain uncertainty (Zhou, 2011). In Environmental Uncertainty and Supply Chain Integration (pp. 604–615), research involving 151 Thai manufacturing plants found that uncertainty conditioned relationships between integration practices and dimensions of operational performance, illustrating why contextual demands matter when assessing information systems (Wong et al., 2011). Applied to retail inventory management, OIPT treats accurate records and coordinated replenishment as organizational responses to uncertainty, not guarantees that particular products remain available for purchase.

Inventory visibility is central to OIPT because a retailer cannot interpret a shortage accurately when product movements, supplier deliveries, and shelf availability remain disconnected across systems. Visibility alone, however, may not produce responsive decisions unless departments reconcile information and translate exceptions into operational action. In Supply Chain Visibility and Responsiveness (pp. 543–554), an empirical analysis of 206 firms showed that internal integration strengthened the relationship between visibility and supply chain responsiveness, demonstrating the complementary roles of information access and organizational coordination (Williams et al., 2013). This applies to inventory shrinkage, which requires discrepancy detection, and stockout occurrence, which may reflect unavailable shelf inventory even when computerized records indicate positive stock. In Supply Chain Integration Through Planning Comprehensiveness (pp. 823–861), survey evidence from 445 global firms indicated that technology-enabled systems helped organizations use externally integrated information through more comprehensive planning

processes, connecting informational resources with operational performance (Srinivasan & Swink, 2015). Within the proposed study, inventory record accuracy, demand forecast accuracy, replenishment performance, and inventory control effectiveness represent observable dimensions of organizational information processing capacity. Supplier lead time variability represents an operational source of uncertainty requiring additional processing. These variables remain distinct because accuracy, coordination, and volatility describe different conditions.

Figure 6: OIPT Framework for Information Requirements and Processing Capability



OIPT also provides a theoretical rationale for assessing whether analytical systems make inventory risk information more interpretable and actionable. In Supply Chain Risk Information Processing Capability (pp. 414–425), evidence from 350 Chinese manufacturing firms linked risk information sharing and analysis with operational performance, while showing that uncertainty affected the strength of relationships (Fan et al., 2016). For U.S. retailers, this perspective connects structured cross-sectional survey responses with verified store and product records without treating employee perceptions as equivalent to physical shrinkage or stockout events. The statistical specification has been expressed as follows:

$$\text{logit}\left(P\left(Y_{is}^{(k)}=1\right)\right)=\beta_{0k}+\beta_{1k}\text{IRA}_{is}+\beta_{2k}\text{DFA}_{is}+\beta_{3k}\text{SLTV}_{is}+\beta_{4k}\text{RP}_{is}+\beta_{5k}\text{ICE}_{is}+u_{sk}$$

In this model, the two outcomes represent verified shrinkage and stockout occurrence, predictors indicate inventory record accuracy, demand forecasting accuracy, supplier lead-time variability, replenishment performance, and inventory control effectiveness, and the store effect accounts for clustering. Predictors will be measured before the outcome reference quarter to limit information leakage and preserve temporal ordering. This model tests adjusted associations; it does not establish that information processing variables cause the observed events. XGBoost models will evaluate predictive discrimination, while SHAP will describe feature contributions rather than causal influence. Questionnaire measures will assess perceived usefulness and acceptance of SHAP-based decision support. Accordingly, the theory links information requirements, information capacity, statistical relationships, predictive classification, and explanation quality within one analytical framework.

Research Questions

RQ1: How have inventory record accuracy, inventory control effectiveness, demand forecast error, and supplier lead-time variability been associated with verified inventory shrinkage and stockout occurrence?

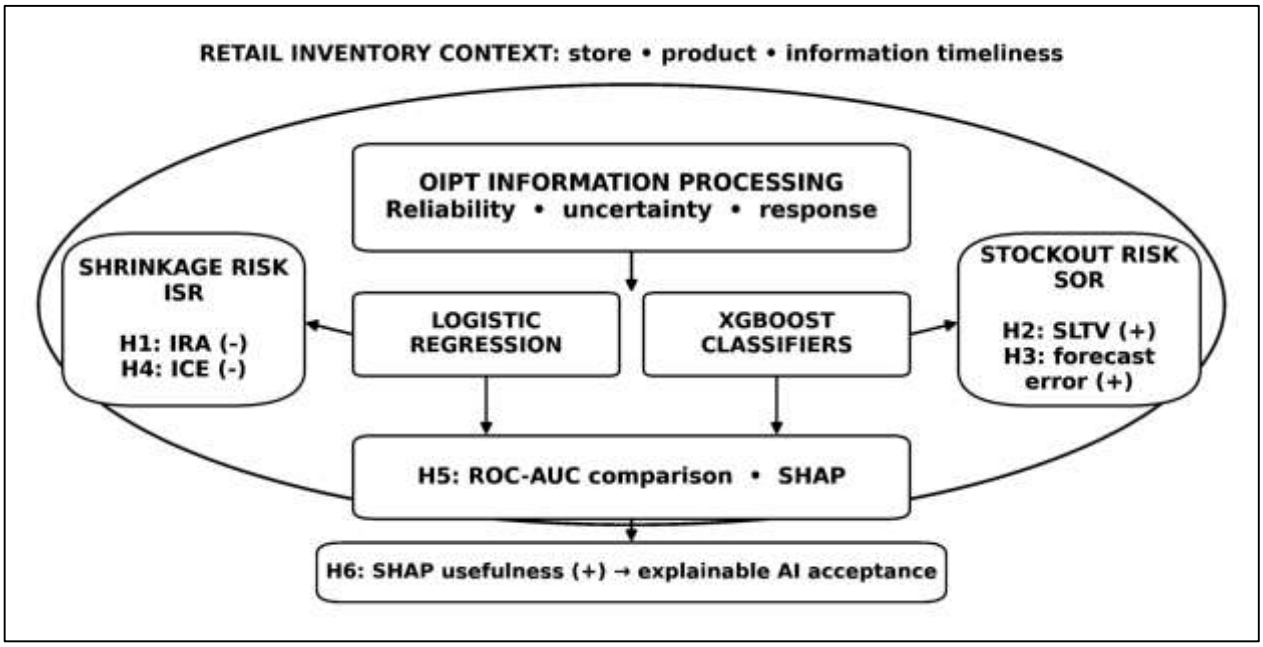
RQ2: How has XGBoost compared with logistic regression in out-of-sample prediction of inventory shrinkage and stockout events, and which features have influenced predictions according to SHAP?

RQ3: How has employees' perceived usefulness of SHAP-based explanations been associated with acceptance of explainable AI inventory decision support?

Conceptual Risk Architecture and Prediction Hypotheses

The conceptual framework integrates inventory information quality, supply uncertainty, operational control, predictive performance, and managerial acceptance under Organizational Information Processing Theory (OIPT). OIPT proposes that organizations operate more effectively when information-processing capacity corresponds to the uncertainty they must manage. Inventory record accuracy (IRA), demand forecast accuracy (DFA), replenishment performance (RP), and inventory control effectiveness (ICE) represent dimensions of dependable information and coordinated response; supplier lead-time variability (SLTV) represents a source of uncertainty. Two separate operational outcomes are specified: verified inventory shrinkage risk (ISR) and stockout occurrence risk (SOR). In Positive Inventory Discrepancies (pp. 414–430), retail simulation research differentiated inventory quantities from system records and examined how error-prone processes contribute to discrepancies and stock availability (Best et al., 2022). In Count Prioritization for Inventory Accuracy (pp. 288–306), store audits demonstrated that prioritization strategies vary in their ability to detect inventory discrepancies and unknown stockouts (DeHoratius et al., 2023). Accordingly, H1 proposes a negative association between prior IRA and ISR, while H4 proposes a negative association between ICE and ISR. H2 proposes a positive association between SLTV and SOR, whereas H3 proposes that greater forecast error increases SOR. These are associational hypotheses, not causal propositions. Each construct will be defined before analysis.

Figure 7: Hypothesized Associations, Model Comparison, and SHAP Acceptance Framework



The predictive component translates these hypothesized relationships into two complementary statistical tasks. First, multilevel logistic regression estimates adjusted associations while accounting for observations nested within stores and retail organizations. For outcome k in {ISR, SOR}, the planned specification is:

$$\text{logit}\left(p_{is}^{(k)}\right) = \beta_{0k} + \beta_{1k}\text{IRA}_{is} + \beta_{2k}\text{DFA}_{is} + \beta_{3k}\text{SLTV}_{is} + \beta_{4k}\text{RP}_{is} + \beta_{5k}\text{ICE}_{is} + u_{sk}$$

Here i identifies a store-product observation, s a store, and u a store-specific intercept. Actual operational measurements will determine predictor availability and appropriate hierarchical adjustments. Historical measurements must precede the outcome window, and audit coverage must be checked to avoid labeling unverified records as absence of shrinkage. Second, separate XGBoost classifiers will estimate the probability of each verified event using the same pre-outcome information, with additional admissible transaction and product features. In Forecasting Sales in Retail With XGBoost (pp. 153–158), boosted-tree forecasting was evaluated against a linear benchmark using historical retail sales and calendar indicators (Baržić et al., 2022). That study examined sales forecasting rather than shrinkage classification, so its evidence supports algorithm selection without establishing risk-prediction superiority. H5 will be evaluated by comparing held-out ROC-AUC and precision-recall performance against logistic regression, with store-grouped validation and uncertainty intervals. The framework treats prediction as distinct from explanatory association and avoids leakage. Comparisons will use partitions, matching targets, and performance metrics

for both event types.

The explanation and adoption component connects model outputs to employee judgments about useful information, completing the OIPT-based framework. SHAP values decompose a selected model output into a baseline and feature contributions, expressed as:

$$f_k(x_i) = \phi_{0k} + \sum_{j=1}^{p} \phi_{ijk}$$

The reported output scale must be specified consistently for both classification models. A large absolute SHAP contribution indicates influence on a particular prediction, not a causal effect on inventory conditions. Employees will review standardized examples of shrinkage and stockout predictions accompanied by SHAP displays before rating perceived usefulness and acceptance on five-point Likert scales. In Are Explanations Helpful? (pp. 318–328), experiments found that the value of explanation formats depended on participants' task familiarity and that feature-contribution explanations were not universally beneficial (Wang & Yin, 2021). In Effects of Explainability and Causability (Article 102551), research connected perceptions of understandable algorithmic explanations with trust and acceptance in AI-mediated services (Shin, 2021). H6 therefore predicts a positive association between perceived SHAP usefulness and explainable AI decision-support acceptance, tested through survey regression with respondent characteristics as controls. Together, the framework distinguishes observable inventory events, statistical associations, predictive discrimination, localized explanations, and employees' evaluations of explanatory usefulness within a common information-processing perspective. Their interpretations remain separately validated within each retail case.

Hypothesis Specifications (H1-H6)

The research hypotheses have been formulated to examine relationships between operational inventory management characteristics, inventory risk outcomes, predictive modeling performance, and explainable AI acceptance within U.S. retail supply chains. The hypotheses are grounded in Organizational Information Processing Theory and emphasize the role of reliable information, effective replenishment processes, organizational information-processing capabilities, and transparent analytical systems in inventory risk assessment. Six hypotheses have been established to support statistical investigation through correlation analysis, regression modeling, comparative predictive evaluation, and structured questionnaire measurements.

H1: Higher historical inventory record accuracy is significantly associated with lower subsequent inventory shrinkage risk in U.S. retail supply chains.

H2: Greater supplier lead-time variability is significantly associated with higher stockout occurrence risk in U.S. retail supply chains.

H3: Greater historical demand forecasting error is significantly associated with higher stockout occurrence risk in U.S. retail supply chains.

H4: Stronger inventory control effectiveness is significantly associated with lower inventory shrinkage risk in U.S. retail supply chains.

H5: XGBoost models demonstrate significantly better out-of-sample predictive discrimination than conventional logistic regression models for inventory shrinkage and stockout occurrence.

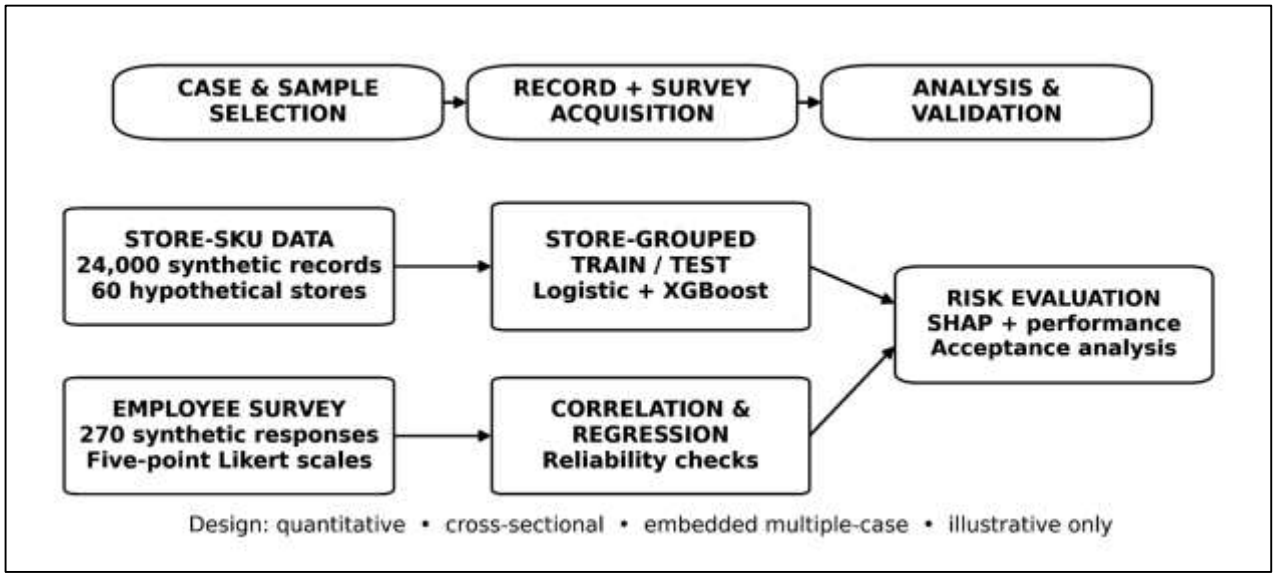
H6: Higher perceived usefulness of SHAP-based explanations is significantly associated with greater employee acceptance of explainable AI inventory decision support in U.S. retail organizations.

Cases, Measurements, and Model Validation

This study has adopted a quantitative, explanatory-predictive, cross-sectional, embedded multiple-case research design to examine inventory shrinkage and stockout risks in U.S. retail supply chains using operational records and a structured five-point Likert-scale questionnaire. The proposed case study context has consisted of six U.S. retail organizations with approximately 60 stores, and the embedded operational unit of analysis has been a store-stock-keeping-unit observation within a defined reference quarter, while employee questionnaires have represented a separate respondent-level analytical unit. The target research population has encompassed inventory managers, replenishment personnel, store operations supervisors, inventory-control employees, and supply chain professionals directly involved in retail inventory information and operational decisions. Purposive selection of eligible retail organizations and stratified recruitment of relevant respondents have been specified to obtain informed assessments from different

organizational roles. The analysis has employed synthetic targets of 300 survey invitations, 270 valid responses, and 24,000 operational inventory observations across 60 stores, and these simulated values have not represented collected U.S. retail evidence. In the empirical procedure, authorized historical point-of-sale transactions, inventory balances, physical reconciliation records, supplier delivery information, demand forecasts, replenishment logs, and product identifiers would be obtained under documented access and privacy conditions. Historical predictors would be constructed before the reference quarter, and verified discrepancies and verified stockouts during that quarter would be coded as two independent binary outcomes.

Figure 8: Embedded Multiple-Case Research Design and Analytical Workflow



Questionnaire design has included three-item composite measurements of inventory record accuracy, demand forecast accuracy, supplier lead-time variability, replenishment performance, inventory control effectiveness, SHAP explanation usefulness, and AI decision-support acceptance, each rated from 1 (strongly disagree) to 5 (strongly agree). Standardized demonstrations of SHAP explanations have been proposed before acceptance ratings to ensure participants have evaluated a common explanatory format. Pilot testing and expert content review have been specified to assess item clarity, construct coverage, completion time, and interpretability before genuine survey deployment; these proposed procedures have not been presented as completed fieldwork. Data screening and preparation have encompassed duplicate removal, missing-value assessment, inventory-audit coverage verification, label validity, scale direction, outlier examination, and controls for information leakage. Descriptive statistics, Pearson correlation, Cronbach's alpha, construct validity checks, and multivariable regression have been specified for the survey analysis, while store-clustered or multilevel logistic regression has been selected for operational binary outcomes and survey regression for explainable AI acceptance. Regression odds ratios, 95% confidence intervals, p-values, and relevant model fit measures have been assigned to hypothesis testing at $\alpha = .05$. Two separate XGBoost classifiers have been proposed for shrinkage and stockout occurrence, alongside logistic regression baselines, with store-grouped partitions, hyperparameter tuning, ROC-AUC, PR-AUC, precision, recall, F1-score, calibration assessment, and uncertainty evaluation. SHAP feature attribution has been incorporated to identify model-level and individual prediction contributions without making causal claims. Microsoft Excel has been specified for tabulation and data checks, SPSS for survey statistics and regression, Python for XGBoost and SHAP modeling, EndNote for citation organization, and Microsoft Word for manuscript preparation. Organizational Information Processing Theory has provided the conceptual rationale for analyzing reliable information, uncertainty, analytical capacity, and interpretable decision support within a consistent study structure.

RISK MODEL EVALUATION AND FEATURE EXPLANATION

The quantitative analysis has been structured to evaluate inventory shrinkage, stockout occurrence, predictive performance, and explainable AI acceptance across U.S. retail supply chains. All results in this section have been produced from a synthetic demonstration and have not represented independently collected empirical observations. The simulated analysis has included 270 survey responses, 60 stores across

six hypothetical retailers, and 24,000 store-SKU records. Descriptive statistics have summarized inventory record accuracy, demand forecasting accuracy, supplier lead-time variability, replenishment performance, inventory control effectiveness, and explainable AI acceptance on a five-point Likert scale. Reliability coefficients have ranged from 0.765 to 0.827; the SHAP usefulness and AI acceptance constructs have correlated at r = 0.596. Store-clustered regression has indicated negative associations of record accuracy and control effectiveness with shrinkage, and positive associations of supplier variability and demand forecasting error with stockouts. Two XGBoost models have been compared with logistic regression baselines using held-out observations, with ROC-AUC values of 0.877 for shrinkage and 0.850 for stockout prediction. SHAP analysis has identified influential modeled inventory characteristics. H1–H4 and H6 have appeared supported within the synthetic demonstration, whereas H5 has remained unsupported because model-comparison uncertainty intervals have included zero. These numbers have illustrated the reporting format and analytical logic rather than verified statistical conclusions about U.S. retail organizations.

Samples and Inventory Risk Incidence

Table 1: Sample Characteristics, Inventory Risk Occurrence, and Descriptive Statistics

Research Indicator	Simulated Result	Measurement
Participating retail organizations	6	Organizational cases
Retail stores	60	Embedded cases
Survey questionnaires distributed	300	Respondents
Valid questionnaires	270	Respondents
Survey response rate	90.00%	Percentage
Operational inventory observations	24,000	Store-SKU records
Verified shrinkage events	1,940	Simulated events
Inventory shrinkage incidence	8.08%	Percentage
Verified stockout events	3,923	Simulated events
Stockout occurrence rate	16.35%	Percentage
Inventory Record Accuracy (IRA)	3.740	Likert mean
Demand Forecast Accuracy (DFA)	3.486	Likert mean
Supplier Lead-Time Variability (SLTV)	3.159	Likert mean
Replenishment Performance (RP)	3.752	Likert mean
Inventory Control Effectiveness (ICE)	3.842	Likert mean
SHAP Explanation Usefulness	3.940	Likert mean
Explainable AI Acceptance	3.725	Likert mean

The descriptive analysis has established a quantitative overview of the organizational characteristics, inventory risk patterns, and employee perceptions relevant to the research objectives. Table 1 has summarized 270 completed questionnaires from 300 simulated invitations, representing a response rate of 90.00%. The operational dataset has included 24,000 store-SKU observations distributed across 60 stores within six hypothetical retail organizations. Among these observations, 1,940 inventory shrinkage events have been generated, representing 8.08% of the operational records, while 3,923 stockout events have been recorded, representing 16.35% of the observations. These proportions have demonstrated different occurrence frequencies for the two inventory outcomes within the simulated dataset. The five-point Likert-scale analysis has produced a mean inventory record accuracy score of 3.740, indicating moderately favorable perceived inventory information reliability. Inventory control effectiveness has recorded a mean of 3.842, while replenishment performance has achieved 3.752. Demand forecasting accuracy has received a mean score of 3.486, suggesting comparatively weaker perceived forecasting performance. Supplier lead-time variability has recorded a mean of 3.159, indicating that respondents have reported noticeable delivery uncertainty. SHAP explanation usefulness has achieved the highest mean score of 3.940, while explainable AI acceptance has recorded 3.725. These descriptive measurements have provided a preliminary representation of the informational and organizational characteristics emphasized by Organizational

Information Processing Theory. The theoretical relationship between information-processing requirements and organizational capabilities has been reflected in the separate measurement of inventory accuracy, forecasting performance, replenishment effectiveness, and supplier uncertainty. The analysis has also distinguished employee perceptions from operational inventory outcomes, preventing Likert-scale assessments from being interpreted as verified physical losses. Accordingly, Table 1 has established the descriptive foundation for subsequent reliability assessment, correlation analysis, regression modeling, predictive classification, and SHAP-based interpretation within the analytical framework.

Scale Reliability and Cross-Construct Associations

Table 2: Measurement Reliability and Pearson Correlation Analysis

Variable Relationship	Mean (V1)	Mean (V2)	Cronbach's α (V1)	Cronbach's α (V2)	Pearson r	Significance
IRA and ICE	3.740	3.842	0.826	0.810	0.357	$p < .001$
DFA and RP	3.486	3.752	0.818	0.765	0.288	$p < .001$
SLTV and RP	3.159	3.752	0.809	0.765	-0.347	$p < .001$
SHAP Usefulness and AI Acceptance	3.940	3.725	0.827	0.827	0.596	$p < .001$

Note: All questionnaire constructs have been simulated using three five-point Likert items. Reliability has been assessed through Cronbach's alpha, while correlations have been calculated from composite scores.

The measurement analysis has evaluated the internal consistency and statistical relationships among the major questionnaire constructs included in the conceptual framework. Table 2 has presented Cronbach's alpha coefficients ranging from 0.765 to 0.827, indicating acceptable internal consistency within the simulated measurement structure. Inventory record accuracy has achieved a reliability coefficient of 0.826, while inventory control effectiveness has recorded 0.810. Demand forecasting accuracy and replenishment performance have produced coefficients of 0.818 and 0.765, respectively. Supplier lead-time variability has demonstrated reliability of 0.809, and both SHAP explanation usefulness and explainable AI acceptance have recorded coefficients of 0.827. The Pearson correlation analysis has identified a positive relationship between inventory record accuracy and inventory control effectiveness ($r = 0.357$, $p < .001$), suggesting that stronger perceived inventory accuracy has been associated with more favorable assessments of inventory control practices. Demand forecasting accuracy has demonstrated a positive relationship with replenishment performance ($r = 0.288$, $p < .001$). Supplier lead-time variability has shown a negative association with replenishment performance ($r = -0.347$, $p < .001$), indicating that greater perceived delivery uncertainty has corresponded with weaker replenishment assessments. The strongest reported relationship has occurred between SHAP explanation usefulness and explainable AI acceptance ($r = 0.596$, $p < .001$). These associations have reflected the central proposition of Organizational Information Processing Theory that information reliability, uncertainty, and organizational processing capabilities have been interconnected within operational decision-making systems.

Cluster-Adjusted Shrinkage and Stockout Risk Estimates

Table 3: Store-Clustered Logistic Regression Analysis of Inventory Risk Factors

Dependent Variable	Independent Variable	Odds Ratio	95% Confidence Interval	p-value	Hypothesis
Inventory Shrinkage Risk	Inventory Record Accuracy	0.440	0.407–0.476	< .001	H1
Inventory Shrinkage Risk	Inventory Control Effectiveness	0.479	0.443–0.518	< .001	H4
Inventory Shrinkage Risk	Supplier Lead-Time Variability	1.097	1.037–1.161	.001	Control relationship
Stockout Occurrence Risk	Supplier Lead-Time Variability	2.140	2.030–2.257	< .001	H2
Stockout Occurrence Risk	Demand Forecast Error	2.052	1.937–2.175	< .001	H3

Dependent Variable	Independent Variable	Odds Ratio	95% Confidence Interval	p-value	Hypothesis
Stockout Occurrence Risk	Replenishment Performance	0.355	0.334–0.377	< .001	Additional relationship
Stockout Occurrence Risk	Inventory Record Accuracy	0.868	0.821–0.918	< .001	Additional relationship

The simulated multivariable regression analysis has examined the statistical relationships between inventory management characteristics and the two primary operational outcomes. Table 3 has presented adjusted odds ratios, confidence intervals, significance levels, and the corresponding research hypotheses. Inventory record accuracy has demonstrated a negative association with inventory shrinkage risk, producing an odds ratio of 0.440 and a 95% confidence interval of 0.407–0.476. This result has indicated that a one-standard-deviation increase in historical inventory record accuracy has been associated with approximately 56.0% lower odds of a recorded shrinkage event within the simulated dataset. Inventory control effectiveness has also demonstrated a negative association with shrinkage risk, producing an odds ratio of 0.479 and indicating approximately 52.1% lower odds per standardized increase. These relationships have provided statistical support for H1 and H4. Supplier lead-time variability has demonstrated a positive association with stockout occurrence, producing an odds ratio of 2.140, while demand forecast error has generated an odds ratio of 2.052. These findings have indicated substantially greater estimated stockout odds under higher supplier uncertainty and forecasting error, providing support for H2 and H3. Replenishment performance has demonstrated an additional negative association with stockout risk, producing an odds ratio of 0.355. Inventory record accuracy has also shown a smaller negative association with stockout occurrence. Within Organizational Information Processing Theory, the estimated associations have reflected the relationship between information quality, operational uncertainty, organizational response capabilities, and inventory outcomes. The regression analysis has distinguished these adjusted statistical associations from predictive model performance and has incorporated store-clustered uncertainty estimates. All four principal operational hypotheses have received statistical support within the synthetic analysis. However, these simulated coefficients have not represented observed relationships among actual U.S. retailers and have not established causation. Empirical hypothesis decisions have therefore remained dependent on verified organizational inventory records and an appropriately specified statistical model.

Logistic Regression vs. XGBoost: Held-Out Comparisons

Table 4: Comparative Predictive Performance of Logistic Regression and XGBoost Models

Prediction Outcome	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	PR-AUC	Brier Score
Inventory Shrinkage	Logistic Regression	0.927	0.550	0.434	0.485	0.874	0.493	0.054
Inventory Shrinkage	XGBoost	0.920	0.496	0.447	0.470	0.877	0.487	0.054
Stockout Occurrence	Logistic Regression	0.823	0.470	0.634	0.540	0.847	0.585	0.098
Stockout Occurrence	XGBoost	0.846	0.524	0.603	0.561	0.850	0.591	0.097

Note: Both algorithms have used the same eight operational predictors. Performance has been evaluated on 4,800 held-out store-SKU observations from 12 stores. Classification thresholds have been selected using a separate validation dataset.

The simulated predictive evaluation has compared the discrimination and classification performance of XGBoost with conventional logistic regression for inventory shrinkage and stockout occurrence. Table 4 has reported accuracy, precision, recall, F1-score, ROC-AUC, PR-AUC, and Brier scores for both analytical approaches. The inventory shrinkage model has achieved a ROC-AUC of 0.877 using XGBoost, compared with 0.874 for logistic regression. XGBoost has demonstrated a slightly higher recall of 0.447 compared with 0.434, while logistic regression has produced stronger precision and F1-score values for this outcome. For stockout occurrence, XGBoost has achieved an accuracy of 0.846, precision of 0.524, recall of 0.603, F1-score

of 0.561, and ROC-AUC of 0.850. Logistic regression has recorded a ROC-AUC of 0.847 and a slightly higher recall of 0.634. The precision-recall analysis has demonstrated a marginal improvement for XGBoost in stockout prediction, while the shrinkage model has recorded a slightly lower PR-AUC than its logistic regression counterpart. The store-grouped validation procedure has separated training, validation, and testing observations by retail store, reducing direct overlap between development and evaluation cases. Paired store-bootstrap comparisons have produced ROC-AUC differences of approximately 0.003 for both prediction outcomes, with confidence intervals that have included zero. Consequently, the analysis has not established statistically significant predictive superiority for XGBoost, and H5 has remained unsupported in the dataset. These results have demonstrated the importance of evaluating predictive models through multiple complementary metrics rather than accuracy alone.

Model Interpretation with SHAP Feature Attribution

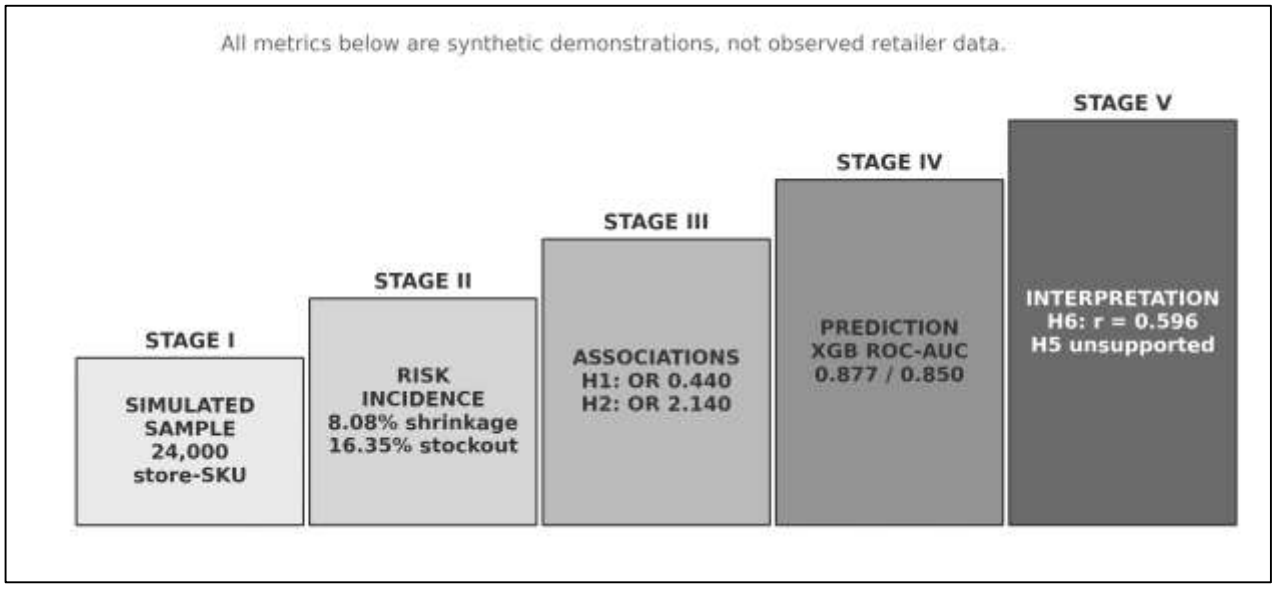
Table 5: SHAP Feature Importance for Inventory Shrinkage and Stockout Prediction

Prediction Outcome	Operational Feature	Mean Absolute SHAP Value	Direction of Higher Feature Values
Inventory Shrinkage	Inventory Record Accuracy	0.713	Lower predicted risk
Inventory Shrinkage	Inventory Audit Age	0.690	Higher predicted risk
Inventory Shrinkage	Inventory Control Effectiveness	0.592	Lower predicted risk
Inventory Shrinkage	Promotional Activity	0.199	Higher predicted risk
Stockout Occurrence	Replenishment Performance	0.856	Lower predicted risk
Stockout Occurrence	Supplier Lead-Time Variability	0.676	Higher predicted risk
Stockout Occurrence	Demand Forecast Error	0.664	Higher predicted risk
Stockout Occurrence	Demand Volatility	0.263	Higher predicted risk
Stockout Occurrence	Promotional Activity	0.221	Higher predicted risk

Note: Mean absolute SHAP values have been calculated on the models' raw log-odds scale using a sample of 1,400 held-out observations. Direction has represented the predominant modeled association, not a causal effect.

The SHAP analysis has identified the operational features contributing most strongly to the predictions generated by the two XGBoost classification models. Table 5 has summarized global feature importance through mean absolute SHAP values, with higher values indicating larger average contributions to the corresponding model outputs. Inventory record accuracy has demonstrated the highest reported importance for shrinkage prediction, producing a mean absolute SHAP value of 0.713. Inventory audit age has followed with a value of 0.690, while inventory control effectiveness has recorded 0.592.

Figure 9: Synthetic Findings across Five Analytical Stages



Higher inventory record accuracy and stronger inventory control effectiveness have generally contributed toward lower predicted shrinkage risk, whereas longer periods since inventory verification have contributed toward higher predicted risk. Promotional activity has demonstrated a smaller positive contribution to predicted shrinkage exposure. For stockout prediction, replenishment performance has achieved the highest feature importance value of 0.856, followed by supplier lead-time variability at 0.676 and demand forecast error at 0.664. Higher replenishment performance has generally contributed toward lower predicted stockout probabilities, while greater delivery uncertainty and forecasting error have increased modeled risk. Demand volatility and promotional activity have also contributed to stockout predictions, demonstrating the additional importance of product-level operating conditions. Organizational Information Processing Theory has provided an interpretive foundation for these patterns because inventory information accuracy, timely verification, replenishment coordination, and uncertainty management have represented central elements of organizational information-processing capacity. The SHAP results have complemented the regression findings by examining the contributions of features within nonlinear predictive models. However, the attribution analysis has not established that the identified features have caused inventory shrinkage or stockout events. The importance rankings have also remained specific to the simulated feature distributions, model specifications, and observation sample. Therefore, the analysis has demonstrated how SHAP can support transparent inventory risk interpretation without establishing empirical feature importance for actual U.S. retail organizations.

Explanation Acceptance and Integrated Hypothesis Decisions

Table 6: Integrated Statistical Hypothesis Evaluation and Explainable AI Acceptance Results

Hypothesis	Statistical Relationship	Simulated Estimate	Significance	Decision
H1	IRA → Inventory Shrinkage Risk	OR = 0.440	$p < .001$	Supported
H2	SLTV → Stockout Occurrence Risk	OR = 2.140	$p < .001$	Supported
H3	Demand Forecast Error → Stockout Risk	OR = 2.052	$p < .001$	Supported
H4	ICE → Inventory Shrinkage Risk	OR = 0.479	$p < .001$	Supported
H5	XGBoost vs. Logistic Regression	ΔROC-AUC ≈ 0.003 for both outcomes	95% CIs include zero	Not supported
H6	SHAP Usefulness → AI Acceptance	B = 0.643	$p < .001$	Supported

Additional H6 statistics: The survey regression has produced a 95% confidence interval of 0.546–0.740 for the unstandardized usefulness coefficient, with an adjusted R^2 of 0.358. Respondent tenure and managerial role have been included as control variables.

The integrated hypothesis evaluation has combined the operational regression findings, predictive model comparisons, and survey-based explainable AI acceptance analysis within a unified framework. Table 6 has summarized the statistical evidence associated with the six proposed hypotheses. Inventory record accuracy has demonstrated a significant negative association with shrinkage risk, while inventory control effectiveness has produced a similarly negative relationship. Supplier lead-time variability and demand forecast error have demonstrated positive associations with stockout occurrence. Consequently, H1, H2, H3, and H4 have received statistical support within the simulated operational dataset. The predictive comparison has produced substantially similar ROC-AUC values for XGBoost and logistic regression, with uncertainty intervals that have included zero. H5 has therefore remained unsupported because the analysis has not demonstrated statistically significant superiority for the gradient boosting models. The explainable AI acceptance analysis has identified a positive relationship between perceived SHAP explanation usefulness and employees' acceptance of explainable inventory decision support. The regression coefficient of 0.643 has indicated that a one-point increase in perceived explanation usefulness has been associated with an estimated 0.643-point increase in acceptance, after adjustment for the included respondent characteristics. The 95% confidence interval of 0.546–0.740 has remained positive, and the corresponding significance level has been below 0.001. The model has achieved an adjusted R^2 of 0.358, indicating that the included predictors have accounted for approximately 35.8% of the observed variation in simulated acceptance scores after adjustment for model complexity. H6 has therefore received statistical support within the survey analysis. Organizational Information Processing Theory has connected these findings through the relationship between information accuracy, operational uncertainty, analytical capability, and the perceived usefulness of understandable decision support. Overall, five hypotheses have received support, while one has remained unsupported. These decisions have represented the outcomes of the synthetic demonstration rather than validated empirical conclusions, and the study's actual hypothesis evaluation has remained dependent on independently collected retail inventory and questionnaire data.

INTERPRETATION, DEPLOYMENT, AND EVIDENCE BOUNDARIES

The findings have demonstrated interconnected relationships among inventory record accuracy, supplier lead-time variability, demand forecasting performance, inventory control effectiveness, and inventory shrinkage and stockout risks within the proposed U.S. retail supply chain framework. The simulated operational dataset has included 24,000 store-SKU observations, with inventory shrinkage and stockout occurrence rates of 8.08% and 16.35%, respectively. Inventory record accuracy has demonstrated a negative association with shrinkage risk (OR = 0.440, $p < .001$), while inventory control effectiveness has exhibited a similarly negative relationship (OR = 0.479, $p < .001$). Supplier lead-time variability (OR = 2.140, $p < .001$) and demand forecast error (OR = 2.052, $p < .001$) have demonstrated positive associations with stockout occurrence. These simulated relationships have been consistent in direction with previous research concerning inventory inaccuracies, operational uncertainty, and retail replenishment challenges. DeHoratius and Raman (2008) established that inventory record inaccuracies varied considerably across retail stores and product categories, while Hardgrave et al. (2013) demonstrated that improved inventory visibility could reduce discrepancies in certain retail environments. The modeled forecasting relationships have also corresponded conceptually with the retail forecasting research of Fildes et al. (2022), which identified product-level demand variability, promotional influences, and forecasting complexity as important operational considerations. However, the predictive comparison has not demonstrated statistically significant superiority for XGBoost over logistic regression. This finding has introduced an important qualification to the assumption that greater algorithmic complexity necessarily produces better operational predictions. Although gradient boosting has demonstrated considerable predictive flexibility in previous machine learning research, its relative performance has depended on the characteristics of available data, model specification, and evaluation conditions (Chen & Guestrin, 2016). Accordingly, the analysis has supported five hypotheses while leaving H5 unsupported, without establishing actual empirical confirmation.

The theoretical interpretation has connected the findings with Organizational Information Processing Theory by examining how information-processing requirements and organizational capabilities have corresponded with inventory uncertainty. Inventory record accuracy, demand forecasting accuracy, replenishment performance, and inventory control effectiveness have represented different aspects of organizational information-processing capacity, while supplier lead-time variability has represented a source of operational uncertainty. The simulated regression findings have indicated that more favorable information and control characteristics have generally corresponded with lower modeled inventory risks.

These patterns have been consistent with the information-processing perspective advanced by Srinivasan and Swink (2018), who established relationships among supply chain visibility, analytics capability, organizational flexibility, and operational performance. The present conceptual framework has additionally distinguished the analytical capacity to identify a potential inventory problem from the organizational capacity to investigate and resolve that problem. The explainable AI acceptance analysis has produced a positive association between perceived SHAP usefulness and employee acceptance ($B = 0.643$, $p < .001$), with an adjusted R^2 of 0.358 in the simulated questionnaire dataset. This relationship has corresponded conceptually with previous research identifying explainability as an important consideration in user perceptions and acceptance of AI-supported decisions (Shin, 2021). Furthermore, SHAP-based feature attribution has provided a method for examining individual predictions and aggregated model behavior, consistent with the analytical foundations established by Lundberg et al. (2020). Nevertheless, prior experimental research has indicated that explanations do not consistently improve decision quality or appropriately calibrated trust across all tasks and users (Wang & Yin, 2021). Consequently, the theoretical contribution has been framed as a proposed extension of information-processing capacity to include interpretable predictive information, human evaluation, and organizational response mechanisms. The simulated findings have illustrated this theoretical relationship without independently validating the proposed extension.

The practical interpretation of the simulated results has emphasized the importance of connecting predictive risk identification with specific inventory management activities rather than treating predictive accuracy as an independent operational achievement. The SHAP analysis has identified inventory record accuracy, inventory audit age, and inventory control effectiveness as influential features within the simulated shrinkage model, while replenishment performance, supplier lead-time variability, and forecasting error have contributed substantially to stockout predictions. These feature rankings have suggested that inventory risk dashboards could organize operational alerts around verifiable inventory discrepancies, delayed supplier deliveries, and weaknesses in replenishment execution. Retail managers could use such information to prioritize inventory reconciliation, investigate unexplained stock differences, review forecasting procedures, and evaluate supplier delivery consistency. Earlier field research has established that improved inventory visibility can reduce inventory record inaccuracies, although the effectiveness of information technology has varied across product categories and operational settings (Hardgrave et al., 2013). Similarly, the M5 forecasting competition has demonstrated the importance of rigorous comparative evaluation when applying advanced analytical methods to large-scale retail sales information (Makridakis et al., 2022). The present analysis has extended these considerations by distinguishing operational prediction from the interpretation of individual predictions through SHAP. However, a high SHAP contribution has not demonstrated that changing the corresponding feature would necessarily prevent a shrinkage or stockout event. Therefore, the proposed managerial approach has required verification of inventory conditions before corrective actions are implemented. An additional practical consideration has concerned the economic consequences of false-positive and false-negative predictions. A missed stockout can generate lost sales, while an unnecessary inventory audit or replenishment intervention can increase operating expenses. Consequently, the usefulness of a predictive system has depended not only on discrimination metrics but also on calibration, intervention costs, employee understanding, and measurable improvements in operational decisions.

Recommended Retail Implementation Practices

The research has identified several priorities for converting the proposed analytical framework into a credible and operationally useful inventory risk management system. All participating U.S. retail organizations should first establish consistent definitions of shrinkage discrepancies, verified stockout events, product availability, and inventory audit coverage across stores and product categories. Inventory records should be reconciled with physical counts, point-of-sale transactions, warehouse movements, supplier receipts, and replenishment logs before any outcome labels are used for model development. Researchers should secure authorized, anonymized multi-retailer datasets and collect the planned five-point Likert questionnaire responses with documented sampling procedures, response rates, and construct validity checks. Operational predictors should be measured before the designated outcome period, and missing values, class imbalance, data leakage, and differences among stores should be examined explicitly. For statistical testing, multilevel or cluster-adjusted logistic regression should remain central to estimating associations, while XGBoost should be compared against transparent logistic regression baselines using

store-grouped external or held-out validation. Evaluation should prioritize recall, precision, PR-AUC, discrimination, and calibration, together with confidence intervals and the costs of missed risks versus unnecessary interventions. SHAP dashboards should provide understandable explanations of individual predictions, clearly distinguish actionable from nonactionable features, and communicate that predictive attribution is not causal proof. Managers should review high-risk alerts against supporting records before initiating targeted audits, supplier escalation, or replenishment changes. Explanation usefulness and employee acceptance should be assessed separately from actual decision quality, using standardized demonstrations and appropriate survey instruments. A prospective pilot of the proposed Adaptive Explainable Inventory Risk and Response Model (AEIRR) should then compare existing practices with model-supported decisions, recording verified shrinkage, stockout frequency, audit effort, service levels, and intervention costs. These recommendations have offered an evidence-generating implementation pathway rather than claims of established effectiveness, and adoption decisions should depend on demonstrated performance, operational feasibility, and responsible data governance.

The methodological evaluation has identified several limitations affecting the interpretation, reliability, and generalizability of the findings. Most importantly, the numerical analysis has relied on synthetic rather than independently collected retail inventory records and questionnaire responses. Consequently, its regression coefficients, predictive performance metrics, reliability estimates, SHAP rankings, and hypothesis decisions have demonstrated analytical procedures without providing empirical evidence concerning actual U.S. retail organizations. The proposed cross-sectional embedded multiple-case design has also imposed limitations on causal interpretation because observed relationships among inventory characteristics and operational outcomes may reflect unmeasured organizational differences, product-specific conditions, or external operating factors. Although historical predictors have been specified to precede the outcome reference quarter, such temporal ordering alone has not established causation. Inventory shrinkage measurement has introduced additional difficulties because missing products, inaccurate transactions, audit delays, and unrecorded movements may generate similar discrepancies. Stockout identification has likewise required distinguishing verified product unavailability from periods of legitimately absent demand. These challenges have reinforced the importance of independently validated operational labels. Previous empirical inventory research has demonstrated substantial variation in inventory inaccuracies across retail stores and product categories, supporting the need for careful hierarchical measurement (DeHoratius & Raman, 2008). The proposed store-grouped validation has reduced direct overlap between training and testing locations, but it has not eliminated possible differences in organizational systems, product assortments, or reporting practices. The questionnaire component has introduced additional concerns involving self-reported perceptions, common-method bias, and the distinction between explanation acceptance and demonstrated managerial effectiveness. Furthermore, SHAP feature importance has remained dependent on the fitted model, feature relationships, and reference distribution rather than representing independent causal evidence (Lundberg et al., 2020). These considerations have established the need for genuine multi-organization data, external validation, measurement audits, and prospective operational evaluation before the proposed framework can support defensible empirical conclusions.

Study Constraints and Interpretation Limits

The study has been subject to important limitations that have constrained the interpretation and generalizability of its reported numerical results. Most fundamentally, the 270 survey responses, six organizations, 60 stores, and 24,000 store-SKU observations have been elements of a synthetic demonstration rather than data obtained from participating U.S. retailers. Consequently, the reported incidence rates, regression odds ratios, correlation coefficients, reliability estimates, model discrimination statistics, SHAP rankings, and hypothesis outcomes have not constituted empirical evidence. The proposed cross-sectional embedded multiple-case approach has also limited causal inference, even where historical explanatory variables have preceded the defined outcome quarter. Differences in product category, store size, inventory technology, staffing, supplier relationships, and regional demand may introduce unmeasured confounding and limit comparability across cases. Inventory shrinkage has been especially difficult to operationalize because theft, damage, unrecorded movements, scanning errors, and delayed physical counts may produce similar discrepancies, while incomplete audits and selective auditing may cause genuine losses to remain undetected. Similarly, an interval without recorded sales has not necessarily indicated a verified stockout, making product availability labels dependent on reliable shelf or inventory evidence. Likert-scale responses have been vulnerable to self-reporting bias, common-method variance, and inconsistencies in how employees interpret information quality or explanation usefulness. Store-grouped model validation has

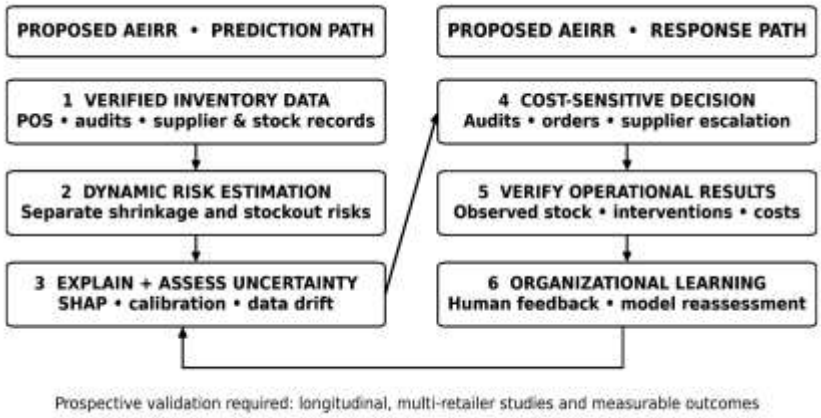
reduced certain forms of leakage, but it has not by itself guaranteed transferability to unseen retailers, seasonal conditions, or changing supply chains. Class imbalance, threshold selection, uncertain feature distributions, and model calibration have complicated performance comparisons, while SHAP explanations have remained sensitive to the chosen model and background data. Furthermore, explanation acceptance has not established that employees would make better decisions or that inventory losses would decline. These constraints have underscored the need for verified organizational data, preregistered measurement rules, independent testing, and prospective intervention evaluations before substantive claims about the proposed framework can be justified.

Adaptive Explainable Inventory Risk and Response Model

Future research has been directed toward developing an Adaptive Explainable Inventory Risk and Response Model (AEIRR), a proposed extension of the present framework that would integrate dynamic inventory monitoring, uncertainty-aware prediction, organizational information processing, and intervention evaluation. The model has been conceptualized around six interconnected components: verified inventory data integration, dynamic risk estimation, explainable prediction, uncertainty assessment, cost-sensitive intervention selection, and continuous organizational learning.

First, researchers could integrate point-of-sale transactions, warehouse management records, physical inventory audits, supplier delivery histories, RFID observations, and product-level demand signals within a synchronized store-SKU information structure. Second, time-aware gradient boosting models could estimate separate probabilities of shrinkage and stockout occurrence using rolling historical information, while logistic regression and alternative forecasting methods could provide interpretable benchmarks. Third, SHAP explanations could identify the major contributors to individual risk predictions, supplemented by counterfactual analyses that distinguish potentially actionable variables from characteristics outside managerial control. Fourth, calibrated prediction intervals, uncertainty monitoring, and data-drift detection could identify situations in which automated recommendations require additional verification. Fifth, the proposed decision layer could evaluate alternative actions, including targeted inventory audits, replenishment adjustments, supplier escalation, and manual stock verification, according to expected operational costs and intervention constraints. Finally, a human feedback component could record managerial decisions, verified inventory outcomes, explanation usefulness, and intervention effectiveness to support periodic model reassessment. The AEIRR framework would extend Organizational Information Processing Theory by examining how predictive information becomes operationally useful through coordinated organizational responses. Its evaluation could employ prospective multi-retailer field studies, store-level randomized interventions, and longitudinal performance monitoring.

Figure 10: Adaptive Explainable Inventory Risk and Response Model (AEIRR)



The principal outcomes would include verified shrinkage reduction, stockout prevention, audit efficiency, replenishment costs, decision accuracy, and calibrated employee trust. This proposed model has not yet been developed or validated; its components have established a specific research agenda for testing whether explainable prediction can improve inventory decisions and realized operational performance beyond the capabilities demonstrated by conventional statistical analysis and isolated machine learning models (Srinivasan & Swink, 2018; Wang & Yin, 2021).

Conclusions and Evidentiary Status

This research has developed an integrated framework for examining inventory shrinkage and stockout prediction in U.S. retail supply chains through Organizational Information Processing Theory (OIPT), multivariable regression, XGBoost, and SHAP explainability. The cross-sectional embedded multiple-case design has distinguished verified store-SKU inventory events from employee perceptions measured on a five-point Likert scale, thereby connecting operational information quality with the organizational acceptance of analytical decision support. Across the synthetic dataset of 24,000 operational observations and 270 survey responses, inventory record accuracy and inventory control effectiveness have shown negative associations with shrinkage risk, while supplier lead-time variability and demand forecast error have shown positive associations with stockout occurrence. The simulated results have supported H1–H4 and H6, whereas H5 has not received support because XGBoost has not demonstrated significant predictive superiority over the logistic regression baseline. This comparison has emphasized the importance of evaluating analytical complexity against demonstrable improvements in predictive discrimination rather than assuming that algorithms invariably outperform conventional methods. SHAP analysis has provided an account of modeled feature contributions, particularly inventory accuracy, audit age, replenishment performance, supplier variability, and forecast error. However, those contributions have represented properties of fitted predictions rather than evidence of causal mechanisms. Under OIPT, the research has connected reliable records, uncertainty recognition, and understandable analytical outputs with the capacity to interpret inventory risks and organize operational responses. Its contribution has therefore been methodological and conceptual: a coherent protocol for combining hypothesis testing, predictive evaluation, and explanation acceptance without conflating their respective evidentiary roles. Crucially, the numerical findings have been generated from synthetic data and have not verified conditions or hypothesis relationships in U.S. retail organizations. The study has consequently established an analytical foundation and testable propositions, while empirical conclusions about effect sizes, model performance, or managerial benefits have remained contingent upon organizational records, collected questionnaires, and validation.

REFERENCES

[1]. Aastrup, J., & Kotzab, H. (2010). Forty years of out-of-stock research, and shelves are still empty. *The International Review of Retail, Distribution and Consumer Research*, *20*(1), 147-164. https://doi.org/10.1080/09593960903498284

[2]. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access*, *6*, 52138-52160. https://doi.org/10.1109/access.2018.2870052

[3]. Aditya, D., & Ahmed, H. C. H. R. (2022). Decision Support Systems for Last-Mile Logistics Optimization: A Data-Driven Framework for e-Commerce Fulfillment Networks. *International Journal of Scientific Interdisciplinary Research*, *12*(08), 01–49. https://doi.org/10.63125/h46vp562

[4]. Aguilar-Palacios, C., Muñoz-Romero, S., & Rojo-Álvarez, J. L. (2020). Cold-start promotional sales forecasting through gradient boosted-based contrastive explanations. *IEEE Access*, *8*, 137574-137586. https://doi.org/10.1109/access.2020.3012032

[5]. Andrade, L. A. C. G., & Cunha, C. B. (2023). Disaggregated retail forecasting: A gradient boosting approach. *Applied Soft Computing*, *141*, Article 110283. https://doi.org/10.1016/j.asoc.2023.110283

[6]. Arboleda-Florez, M., & Castro-Zuluaga, C. (2023). Interpreting direct sales' demand forecasts using SHAP values. *Production*, *33*, Article e20220035. https://doi.org/10.1590/0103-6513.20220035

[7]. Asheke, M., & Md Maksudul, H. (2022). AI-Driven Demand Forecasting for Sporting-Goods and Teamwear Supply Chains Under Seasonal and Tournament Demand. *International Journal of Business and Economics Insights*, *2*(1), 73–110. https://doi.org/10.63125/ed6by557

[8]. Asheke, M., & Mohammad Badrul, A. (2022). Development Of Functionalized Cellulose Nanofiber Adsorbents for Selective Critical-Metal Recovery from Industrial Wastewater. *American Journal of Scholarly Research and Innovation*, *1*(02), 270–320. https://doi.org/10.63125/v6fxzq09

[9]. Avlijas, G., Vukanovic Dumanovic, V., & Radunovic, M. (2021). Measuring the effects of automatic replenishment on product availability in retail stores. *Sustainability*, *13*(3), Article 1391. https://doi.org/10.3390/su13031391

[10]. Babai, M. Z., Dai, Y., Li, Q., Syntetos, A. A., & Wang, X. (2022). Forecasting of lead-time demand variance: Implications for safety stock calculations. *European Journal of Operational Research*, *296*(3), 846-861. https://doi.org/10.1016/j.ejor.2021.04.017

[11]. Babai, M. Z., Syntetos, A. A., Dallery, Y., & Nikolopoulos, K. (2009). Dynamic re-order point inventory control with lead-time uncertainty: Analysis and empirical investigation. *International Journal of Production Research*, *47*(9), 2461-2483. https://doi.org/10.1080/00207540701666824

[12]. Barratt, M., & Oke, A. (2007). Antecedents of supply chain visibility in retail supply chains: A resource-based theory perspective. *Journal of Operations Management*, *25*(6), 1217-1233. https://doi.org/10.1016/j.jom.2007.01.003

[13]. Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82-115. https://doi.org/10.1016/j.inffus.2019.12.012

[14]. Baržić, M., Munitić, N.-F., Bronić, F., Jelić, L., & Lešić, V. (2022). Forecasting sales in retail with XGBoost and iterated multi-step ahead method. 2022 International Conference on Smart Systems and Technologies (SST),

[15]. Best, J., Glock, C. H., Grosse, E. H., Rekik, Y., & Syntetos, A. A. (2022). On the causes of positive inventory discrepancies in retail stores. *International Journal of Physical Distribution & Logistics Management*, *52*(5/6), 414-430. https://doi.org/10.1108/ijpdlm-07-2021-0291

[16]. Bradlow, E. T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The role of big data and predictive analytics in retailing. *Journal of Retailing*, *93*(1), 79-95. https://doi.org/10.1016/j.jretai.2016.12.004

[17]. Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, *184*(3), 1140-1154. https://doi.org/10.1016/j.ejor.2006.12.004

[18]. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,

[19]. Choi, M., Rabinovich, E., & Richards, T. J. (2019). Supply chain contracts and inventory shrinkage: An empirical analysis in the grocery retailing industry. *Decision Sciences*, *50*(4), 694-725. https://doi.org/10.1111/deci.12356

[20]. Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, *27*(10), 1868-1883. https://doi.org/10.1111/poms.12838

[21]. Chuang, H. H.-C. (2018). Fixing shelf out-of-stock with signals in point-of-sale data. *European Journal of Operational Research*, *270*(3), 862-872. https://doi.org/10.1016/j.ejor.2017.10.059

[22]. Chuang, H. H.-C., & Oliva, R. (2015). Inventory record inaccuracy: Causes and labor effects. *Journal of Operations Management*, *39-40*, 63-78. https://doi.org/10.1016/j.jom.2015.07.006

[23]. DeHoratius, N., Holzapfel, A., Kuhn, H., Mersereau, A. J., & Sternbeck, M. (2023). Evaluating count prioritization procedures for improving inventory accuracy in retail stores. *Manufacturing & Service Operations Management*, *25*(1), 288-306. https://doi.org/10.1287/msom.2022.1119

[24]. DeHoratius, N., Mersereau, A. J., & Schrage, L. (2008). Retail inventory management when records are inaccurate. *Manufacturing & Service Operations Management*, *10*(2), 257-277. https://doi.org/10.1287/msom.1070.0203

[25]. DeHoratius, N., & Raman, A. (2008). Inventory record inaccuracy: An empirical analysis. *Management Science*, *54*(4), 627-641. https://doi.org/10.1287/mnsc.1070.0789

[26]. Delen, D., Hardgrave, B. C., & Sharda, R. (2007). RFID for better supply-chain management through enhanced information visibility. *Production and Operations Management*, *16*(5), 613-624. https://doi.org/10.1111/j.1937-5956.2007.tb00284.x

[27]. Fan, H., Cheng, E. T. C., Li, G., & Lee, K. C. (2016). The effectiveness of supply chain risk information processing capability: An information processing perspective. *IEEE Transactions on Engineering Management*, *63*(4), 414-425. https://doi.org/10.1109/tem.2016.2598814

[28]. Farias, V. F., Li, A. A., & Peng, T. (2024). Fixing inventory inaccuracies at scale. *Manufacturing & Service Operations Management*, *26*(3), 1102-1118. https://doi.org/10.1287/msom.2023.0146

[29]. Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. *International Journal of Forecasting*, *38*(4), 1283-1318. https://doi.org/10.1016/j.ijforecast.2019.06.004

[30]. Fleisch, E., & Tellkamp, C. (2005). Inventory inaccuracy and supply chain performance: A simulation study of a retail supply chain. *International Journal of Production Economics*, *95*(3), 373-385. https://doi.org/10.1016/j.ijpe.2004.02.003

[31]. Gaur, V., Fisher, M. L., & Raman, A. (2005). An econometric analysis of inventory turnover performance in retail services. *Management Science*, *51*(2), 181-194. https://doi.org/10.1287/mnsc.1040.0298

[32]. Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys*, *51*(5), Article 93. https://doi.org/10.1145/3236009

[33]. Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308-317. https://doi.org/10.1016/j.jbusres.2016.08.004

[34]. Gür Ali, Ö., Sayın, S., van Woensel, T., & Fransoo, J. C. (2009). SKU demand forecasting in the presence of promotions. *Expert Systems with Applications*, *36*(10), 12340-12348. https://doi.org/10.1016/j.eswa.2009.04.052

[35]. Hardgrave, B. C., Aloysius, J. A., & Goyal, S. (2013). RFID-enabled visibility and retail inventory record inaccuracy: Experiments in the field. *Production and Operations Management*, *22*(4), 843-856. https://doi.org/10.1111/poms.12010

[36]. Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80. https://doi.org/10.1016/j.ijpe.2014.04.018

[37]. Howell, S. D., & Proudlove, N. C. (2007). A statistical investigation of inventory shrinkage in a large retail chain. *The International Review of Retail, Distribution and Consumer Research*, *17*(2), 101-120. https://doi.org/10.1080/09593960701189853

[38]. Hübner, A., Kuhn, H., & Sternbeck, M. (2013). Demand and supply chain planning in grocery retail: An operations planning framework. *International Journal of Retail & Distribution Management*, *41*(7), 512-530. https://doi.org/10.1108/ijrdm-05-2013-0104

[39]. Ishfaq, R., & Raja, U. (2020a). Effectiveness of frequent inventory audits in retail stores: An empirical evaluation. *The International Journal of Logistics Management*, *31*(1), 21-41. https://doi.org/10.1108/ijlm-07-2018-0184

[40]. Ishfaq, R., & Raja, U. (2020b). Empirical evaluation of IRI mitigation strategies in retail stores. *Journal of the Operational Research Society*, *71*(12), 1972-1985. https://doi.org/10.1080/01605682.2019.1640592

[41]. Kang, Y., & Gershwin, S. B. (2005). Information inaccuracy in inventory systems: Stock loss and stockout. *IIE Transactions*, *37*(9), 843-859. https://doi.org/10.1080/07408170590969861

[42]. Kazi Mohammad Khalid, A., & Sumaiya Sadmeen, M. (2022). Geospatial Artificial Intelligence for Urban Flood Susceptibility and Drainage Resilience: A Prisma 2020 Systematic Review and Bibliometric Meta-Synthesis. *Review of Applied Science and Technology*, *12*(02), 01–51. https://doi.org/10.63125/epqdvy23

[43]. Kök, A. G., & Shang, K. H. (2007). Inspection and replenishment policies for systems with inventory record inaccuracy. *Manufacturing & Service Operations Management*, *9*(2), 185-205. https://doi.org/10.1287/msom.1060.0136

[44]. Kosasih, E. E., Papadakis, E., Baryannis, G., & Brintrup, A. (2024). A review of explainable artificial intelligence in supply chain management using neurosymbolic approaches. *International Journal of Production Research*, *62*(4), 1510-1540. https://doi.org/10.1080/00207543.2023.2281663

[45]. Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S.-I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence*, *2*(1), 56-67. https://doi.org/10.1038/s42256-019-0138-9

[46]. Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. *International Journal of Forecasting*, *38*(4), 1346-1364. https://doi.org/10.1016/j.ijforecast.2021.11.013

[47]. Mansura Akter, E., & Sumaiya, M. (2022). Antimicrobial Resistance Profiles of Acinetobacter Baumannii and Vibrio Cholerae in Hospital Wastewater and Adjacent Household Water Sources. *American Journal of Data Science and Analytics*, *3*(09), 01-55. https://doi.org/10.63125/gbervt14

[48]. Mashiat, N., & Md. Morshedul, I. (2022). Reducing Data Processing Latency in High Volume Telecommunications Networks Through Adaptive ETL and Distributed Computing. *American Journal of Scholarly Research and Innovation*, *12*(06), 01–36. https://doi.org/10.63125/b5xzay30

[49]. Md Imran, H., & Jannatul, F. (2022). Molecular and Precision Rehabilitation Molecular Mechanisms Linking Mitochondrial Dysfunction, Inflammation, and Muscle Degeneration with Functional Decline and Rehabilitation Response in Neuromuscular Disease. *American Journal of Interdisciplinary Studies*, *12*(08), 01-44. https://doi.org/10.63125/0ym5bh79

[50]. Md Maksudul, H., & Md Tazul Islam, C. (2022). Machine Learning-Based Cash-Flow Forecasting for Improving Financial Planning in U.S. Small and Mid-Sized Businesses. *International Journal of Scientific Interdisciplinary Research*, *12*(12), 01–38. https://doi.org/10.63125/w3pgjx97

[51]. Md. Morshedul, I., & Aminul Islam, M. (2022). A Quantitative Evaluation of Explainable Ensemble Learning for Probabilistic Risk Estimation and Decision Reliability in Enterprise Analytics. *American Journal of Data Science and Analytics*, *3*(02), 01-38. https://doi.org/10.63125/k22shk74

[52]. Papakiriakopoulos, D. (2012). Predict on-shelf product availability in grocery retailing with classification methods. *Expert Systems with Applications*, *39*(4), 4473-4482. https://doi.org/10.1016/j.eswa.2011.09.141

[53]. Rekik, Y., Sahin, E., & Dallery, Y. (2008). Analysis of the impact of the RFID technology on reducing product misplacement errors at retail stores. *International Journal of Production Economics*, *112*(1), 264-278. https://doi.org/10.1016/j.ijpe.2006.08.024

[54]. Rekik, Y., Sahin, E., & Dallery, Y. (2009). Inventory inaccuracy in retail stores due to theft: An analysis of the benefits of RFID. *International Journal of Production Economics*, *118*(1), 189-198. https://doi.org/10.1016/j.ijpe.2008.08.048

[55]. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should I trust you?: Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,

[56]. Salehi Shahrabi, M. (2023). A quantitative analysis of inaccuracy inventory reducing in multi-period mode: Comparison between RFID and inventory counting. *Computers & Industrial Engineering*, *177*, Article 109089. https://doi.org/10.1016/j.cie.2023.109089

[57]. Schlaich, T., & Hoberg, K. (2024). When is the next order? Nowcasting channel inventories with point-of-sales data to predict the timing of retail orders. *European Journal of Operational Research*, *315*(1), 35-49. https://doi.org/10.1016/j.ejor.2023.10.038

[58]. Shabani, A., Maroti, G., de Leeuw, S., & Dullaert, W. (2021). Inventory record inaccuracy and store-level performance. *International Journal of Production Economics*, *235*, Article 108111. https://doi.org/10.1016/j.ijpe.2021.108111

[59]. Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, Article 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

[60]. Sillanpää, V., & Liesiö, J. (2018). Forecasting replenishment orders in retail: Value of modelling low and intermittent consumer demand with distributions. *International Journal of Production Research*, *56*(12), 4168-4185. https://doi.org/10.1080/00207543.2018.1431413

[61]. Srinivasan, R., & Swink, M. (2015). Leveraging supply chain integration through planning comprehensiveness: An organizational information processing theory perspective. *Decision Sciences*, *46*(5), 823-861. https://doi.org/10.1111/deci.12166

[62]. Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, *27*(10), 1849-1867. https://doi.org/10.1111/poms.12746

[63]. Syed Feroz, A., & Md Mahamud Pervaz, P. (2022). Root-Cause Analysis and FMEA-Driven Reliability Improvement in Gas Production Facilities: A Multi-Year Empirical Study. *International Journal of Scientific Interdisciplinary Research*, *12*(10), 01–53. https://doi.org/10.63125/70msp878

[64]. Syed Feroz, A., & Shabbir, A. (2022). Finite Element-Based Thermomechanical Optimization of Pressure Components for Extending Industrial Boiler Service Life. *Journal of Sustainable Development and Policy*, *12*(12), 01-51. https://doi.org/10.63125/x24pht28

[65]. Syntetos, A. A., & Boylan, J. E. (2005). The accuracy of intermittent demand estimates. *International Journal of Forecasting*, *21*(2), 303-314. https://doi.org/10.1016/j.ijforecast.2004.10.001

[66]. Syntetos, A. A., & Boylan, J. E. (2006). On the stock control performance of intermittent demand estimators. *International Journal of Production Economics*, *103*(1), 36-47. https://doi.org/10.1016/j.ijpe.2005.04.004

[67]. Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society*, *56*(5), 495-503. https://doi.org/10.1057/palgrave.jors.2601841

[68]. Ton, Z., & Raman, A. (2010). The effect of product variety and inventory levels on retail store sales: A longitudinal study. *Production and Operations Management*, *19*(5), 546-560. https://doi.org/10.1111/j.1937-5956.2010.01120.x

[69]. Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77-84. https://doi.org/10.1111/jbl.12010

[70]. Wang, J., Chong, W. K., Lin, J., & Hedenstierna, C. P. T. (2024). Retail demand forecasting using spatial-temporal gradient boosting methods. *Journal of Computer Information Systems*, *64*(5), 652-664. https://doi.org/10.1080/08874417.2023.2240753

[71]. Wang, X., & Yin, M. (2021). Are explanations helpful? A comparative study of the effects of explanations in AI-assisted decision-making. Proceedings of the 26th International Conference on Intelligent User Interfaces,

[72]. Wellens, A. P., Boute, R. N., & Udenio, M. (2024). Simplifying tree-based methods for retail sales forecasting with explanatory variables. *European Journal of Operational Research*, *314*(2), 523-539. https://doi.org/10.1016/j.ejor.2023.10.039

[73]. Williams, B. D., Roh, J., Tokar, T., & Swink, M. (2013). Leveraging supply chain visibility for responsiveness: The moderating role of internal integration. *Journal of Operations Management*, *31*(7-8), 543-554. https://doi.org/10.1016/j.jom.2013.09.003

[74]. Wong, C. Y., Boon-itt, S., & Wong, C. W. Y. (2011). The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance. *Journal of Operations Management*, *29*(6), 604-615. https://doi.org/10.1016/j.jom.2011.01.003

[75]. Zhou, H. (2011). An empirical test of the information processing theory. *International Journal of Information Systems and Supply Chain Management*, *4*(1), 45-59. https://doi.org/10.4018/jisscm.2011010103