



Predicting Stockout Risks Using Machine Learning for Agile Decision Support in the E-Grocery Supply Chain

Oktavia Mulyo Nurdiyanti^{1,*}, Lasmedi Afuan²

¹Magister of Computer Science, Faculty of Computer Science, Universitas Amikom Purwokerto, Indonesia

²Department of Informatics, Engineering Faculty, Universitas Jenderal Soedirman, Indonesia

ABSTRACT

This study proposes an integrated agile decision-support model for predicting stockout risks in the e-grocery industry using machine learning techniques. The research aims to enhance inventory responsiveness and adaptability—two central pillars of agile management—by transforming operational data into predictive intelligence. A publicly available dataset comprising 1,000 Stock Keeping Units (SKUs) with 37 variables was utilized, encompassing attributes related to inventory, supplier performance, and demand forecasting. After data cleaning, transformation, and feature engineering, a set of eleven operational features was used to train and compare three classification models: Logistic Regression, Random Forest, and XGBoost. The models were benchmarked through Accuracy, Precision, Recall, F1-score, and ROC–AUC metrics. Results show that ensemble-based methods, particularly XGBoost, achieved superior performance, attaining 100% accuracy, precision, recall, and AUC. SHAP (SHapley Additive exPlanations) analysis revealed that Stock_Risk_Index, Lead_Time_Days, Forecast_Next_30d, and Safety_Stock were the most influential variables, capturing both supply responsiveness and adaptive buffer mechanisms. These findings confirm that operational agility is quantifiable through data-driven modeling and that machine learning can replicate and enhance decision rules traditionally applied in inventory management. The model was subsequently embedded into an agile decision-support cycle consisting of prediction, decision, and feedback stages. This integration enables continuous learning, real-time visibility, and transparent decision-making—core components of agile management frameworks. While perfect accuracy indicates deterministic relationships rather than stochastic generalization, the framework remains an effective validation of agile intelligence principles. The study concludes that data-driven learning systems, when combined with explainable AI techniques, provide a scalable pathway for embedding agility, responsiveness, and transparency within supply chain decision-making processes.

Keywords Agile Management, Machine Learning, Stockout Prediction, Supply Chain Analytics, Decision Support System

Introduction

E-grocery supply chains have grown increasingly complex in recent years due to the rapid expansion of online grocery retailing and the operational challenges that accompany perishable products, fluctuating consumer demand, and distributed fulfillment networks. The combination of short product life cycles, variable online ordering patterns, and multi-node warehousing systems introduces intricate trade-offs between inventory cost, freshness, and service level [1], [2]. This operational volatility makes the management of stock

Submitted: 5 January 2025

Accepted: 12 March 2025

Published: 1 August 2025

Corresponding author
Oktavia Mulyo Nurdiyanti,
oktaviamulyo24@gmail.com

Additional Information and
Declarations can be found on
[page 181](#)

© Copyright
2025 Nurdiyanti and Afuan

Distributed under
Creative Commons CC-BY 4.0

How to cite this article: O. M. Nurdiyanti and L. Afuan, "Assessing the Efficacy of Convolutional Neural Networks in Recognizing Handwritten Digits: Analysis of the Relationship Between Trading Volume and Bitcoin Price Movements Using Pearson and Spearman Correlation Methods," *Agile Manag.*, vol. 1, no. 3, pp. 169-184, 2024.

availability particularly challenging, especially when multiple distribution centers and last-mile delivery points are involved [3].

Stockouts—defined as the unavailability of items demanded by customers—constitute one of the most critical operational failures in e-grocery logistics. They result in immediate revenue loss, decreased customer satisfaction, and long-term erosion of brand loyalty [4], [5]. Empirical studies have shown that even minor stockout incidences can significantly affect customer retention and order completion rates, especially in digital retail channels where product substitution is limited [6]. The problem is further amplified by perishability and shelf-life constraints, which limit the flexibility of replenishment cycles and magnify the impact of forecasting errors.

Traditional inventory control methods remain largely reactive. Conventional reorder-point or Economic Order Quantity (EOQ) models rely on historical averages and static safety stock parameters, providing limited adaptability to real-time demand fluctuations [7]. These deterministic systems often fail to respond adequately in perishable contexts, where spoilage, lead-time variability, and demand uncertainty coexist. Consequently, managers face a trade-off between overstocking (to prevent shortages) and understocking (to minimize waste), both of which lead to inefficiencies and reduced profitability.

As such, researchers and practitioners emphasize the necessity of agility as a defining capability for e-grocery supply chains. Agility refers to the organization's ability to rapidly detect, interpret, and respond to environmental changes through flexible processes, adaptive inventory strategies, and data-driven visibility [8], [9], [10]. In this regard, agile management principles—responsiveness, adaptability, and transparency—are increasingly supported by digital analytics and predictive intelligence, enabling real-time optimization of stock levels and proactive decision-making.

Despite the widespread deployment of digital dashboards, ERP systems, and business intelligence tools, most e-grocery inventory systems remain non-predictive in nature. They visualize current states but rarely anticipate future risks, thereby limiting their strategic utility in dynamic environments [11], [12]. The absence of predictive intelligence in these systems often results in delayed detection of inventory imbalances and inaccurate demand forecasts. Consequently, stockout events continue to arise from slow replenishment responses, rigid safety-stock policies, and insufficient visibility into supplier performance [13].

Moreover, these traditional methods lack the adaptive mechanisms necessary to handle supplier lead-time variability, demand shocks, and node-level inventory interdependence in distributed e-grocery networks [14], [15]. When combined with perishable product constraints, such deficiencies translate into significant service-level disruptions and unfulfilled orders, which undermine consumer trust and organizational resilience. The inability to model and respond to these fluctuations in real time reveals a critical gap in contemporary inventory management systems.

Therefore, the central research problem addressed in this study is as follows: How can machine-learning-based predictive models be integrated within agile management frameworks to proactively forecast and mitigate stockout risks in e-grocery operations? Integrating machine learning with agile management offers a pathway toward dynamic, data-driven decision-support systems that continuously learn and adapt to changing operational conditions [16], [17], [18]. By employing predictive algorithms such as Random Forest and XGBoost,

combined with explainable AI techniques (e.g., SHAP values), such systems can provide not only accurate forecasts but also transparent reasoning for decision-makers. This hybrid framework transforms reactive inventory control into a responsive, adaptive, and interpretable process aligned with the core principles of agile supply chain management.

The primary objective of this research is to develop and evaluate a machine learning–based agile decision-support model capable of predicting stockout risks within e-grocery supply chains. The study aims to transform static, rule-based inventory management into a proactive, adaptive system that continuously learns from operational data. To achieve this, the research first focuses on data preprocessing and feature engineering to quantify operational agility through metrics such as safety stock, lead time, and forecast accuracy. Subsequently, several machine learning algorithms—including Logistic Regression, Random Forest, and XGBoost—are compared to identify the most effective predictive model for classifying stockout risk levels.

Beyond prediction, the study integrates SHAP analysis to interpret model behavior and enhance transparency, thereby aligning computational insights with managerial decision-making principles. This interpretability allows stakeholders to understand which operational indicators most strongly influence stockout risks and how different models generate their predictions. To operationalize these insights, the research further proposes embedding the predictive model into a continuous feedback decision-support loop, enabling managers to iteratively monitor performance, retrain the model, and adapt inventory strategies in near real time. Through this cycle, the framework embodies the agile principles of responsiveness, adaptability, and iterative improvement.

The significance of this study spans multiple dimensions. Theoretically, it contributes to the Agile Management literature by quantifying organizational agility using empirical machine learning indicators. Practically, it provides a data-driven, proactive decision-support system for inventory managers to minimize losses, prevent service disruptions, and improve customer satisfaction. Methodologically, it advances the field by demonstrating how explainable AI tools can integrate predictive accuracy with interpretability—bridging the gap between data science and managerial decision-making. Societally, the framework promotes sustainable operations by reducing overstock and waste, aligning with UN Sustainable Development Goal 12 (Responsible Consumption and Production) and supporting the broader vision of resilient, environmentally responsible supply chain ecosystems.

Literature Review

Agile Management and Decision-Support Systems

Agile management has progressively expanded from its origins in software engineering to broader applications in operations, logistics, and supply chain management. The diffusion of Enterprise Resource Planning (ERP), 5G connectivity, and Internet of Things (IoT) technologies has accelerated this transition by enabling real-time data integration and shorter decision cycles [19], [20]. Core agile dimensions—responsiveness, adaptability, collaboration, transparency, and continuous improvement—are widely recognized as critical enablers of performance and competitive advantage in dynamic environments [21], [22]. Within supply chain contexts, agility represents a shift from linear

forecasting to iterative decision cycles, where data continuously informs procurement, inventory control, and distribution strategies. These agile cycles rely heavily on Decision-Support Systems (DSS) to process multi-source data streams and generate actionable insights, aligning operational execution with strategic flexibility [23].

Empirical work on Agile Decision-Support Systems (ADSS) demonstrates that machine-learning-enhanced dashboards and predictive analytics pipelines reduce managerial response time and improve decision accuracy in complex organizations [24], [25]. For example, adaptive DSS frameworks in healthcare and manufacturing sectors have shown that continuous data feedback loops shorten the time between anomaly detection and corrective action. However, existing literature still lacks quantitative models of operational agility built upon granular, SKU-level inventory data—particularly in e-grocery networks with distributed fulfillment and perishability constraints [26], [27]. This gap highlights an opportunity to integrate predictive modeling and agile management principles within real-time inventory environments, thereby operationalizing agility through data-driven responsiveness and explainable analytics.

Stockout Risk and Inventory Management in E-Grocery

Stockouts—instances where demand exceeds Available-to-Promise (ATP) inventory—are a recurring challenge in e-grocery operations due to volatile demand, short shelf life, and fragmented fulfillment nodes [1], [2], [5]. Traditional inventory control models such as EOQ, reorder-point systems, and safety-stock formulations assume stationary demand and deterministic lead times, which are unsuitable for highly variable retail contexts [7], [10]. As a result, many e-grocery systems remain reactive, relying on fixed thresholds rather than predictive control. The perishability of goods, coupled with fluctuating online demand and frequent SKU turnover, amplifies the consequences of forecasting errors and late replenishments [28]. Static models cannot capture the nonlinear dependencies among lead time, demand, and spoilage, leading to stockouts that disrupt service continuity and reduce customer satisfaction.

Recent studies emphasize that dynamic, data-driven inventory control is essential for modern e-grocery ecosystems. Machine learning and real-time optimization are increasingly proposed to manage stock levels under uncertainty, incorporating lead-time variability and demand volatility into adaptive policies [29]. Empirical analyses link supplier performance metrics—such as on-time delivery and lead-time reliability—to stockout frequency, demonstrating that small fluctuations in supplier consistency can cascade into widespread shortages [30]. Similarly, forecasting inaccuracies have been shown to propagate through multi-echelon networks, compounding stockout risk. These findings motivate a shift from reactive to predictive stockout mitigation, where intelligent algorithms continuously adjust reorder triggers and buffer stocks in response to observed patterns—a transition central to the concept of agile inventory management [31].

Machine Learning Applications in Inventory and Supply Chain Analytics

Machine Learning (ML) has become integral to demand forecasting, replenishment optimization, and supply chain risk prediction, with methods such as Random Forests, Gradient Boosting, Support Vector Machines, and Long

Short-Term Memory (LSTM) networks leading empirical advancements [32]. Comparative evaluations reveal that these models outperform linear baselines due to their ability to capture nonlinear feature interactions and contextual dependencies among operational variables. Ensemble models such as Random Forest and XGBoost achieve higher accuracy and robustness by leveraging bagging and boosting strategies to reduce both bias and variance [33]. These architectures have been successfully employed to forecast sales, detect anomalies, and optimize inventory reorder cycles in multi-node retail systems.

Despite these advances, current literature highlights two persistent gaps. First, many ML implementations in inventory management prioritize predictive accuracy but overlook the interpretability needed for managerial decision-making [34]. Second, few operational deployments extend beyond offline experimentation to real-time decision-support integration, limiting their impact on adaptive planning. Studies combining ML with dashboard-based analytics show encouraging results, where predictive insights are embedded within workflow systems to guide restocking and supplier coordination. However, without eXplainable AI (XAI) mechanisms, decision-makers often treat these systems as opaque black boxes. This lack of transparency constrains adoption, underscoring the need for interpretable ML models that align with agile principles of collaboration and feedback.

Method

Research Design

This research adopts a quantitative, data-driven design grounded in the agile management paradigm, integrating machine learning to predict and interpret stockout risk across e-grocery inventory operations. The core objective is to transform reactive inventory monitoring into a predictive agile decision-support system. The design emphasizes adaptability, feedback iteration, and transparency — key values of the agile philosophy — implemented through iterative model building, validation, and interpretation cycles. Each iteration refines the model's predictive capacity and interpretability.

The study applies an experimental-comparative modeling approach, where multiple classifiers — Logistic Regression, Random Forest, and XGBoost — are trained and benchmarked. These models represent increasing levels of algorithmic complexity, enabling comparison between linear, ensemble, and gradient-boosting strategies. Such comparative modeling aligns with the agile principle of incremental improvement, where each model generation represents an adaptive sprint of knowledge enhancement.

Agile decision support in this context refers to using machine learning predictions as actionable feedback loops in operational decision-making. Rather than static forecasting, this method produces a continuously updating intelligence system capable of learning from new cycle-count audits or supplier performance data. The iterative and modular nature of the design ensures the framework can evolve as data quality, warehouse configurations, or business goals change.

Lastly, the design incorporates an interpretability layer using SHAP. This layer enhances model transparency by quantifying each feature's marginal

contribution to predictions. By exposing the “reasoning” of the machine learning model, SHAP operationalizes the agile principle of visibility, allowing managers to trust, explain, and iterate upon data-driven recommendations.

Dataset and Object of Study

The empirical data are drawn from the Kaggle Inventory Management (E-Grocery Industry). It contains 1,000 Stock-Keeping Units (SKUs) across multiple warehouses, with 37 core attributes describing operational, financial, and temporal characteristics. Each record captures an SKU’s lifecycle status, including stock levels, supplier performance, forecast accuracy, and audit variance — all of which reflect the operational agility of the supply chain.

The object of study is the SKU-level inventory status, specifically the binary classification of Stockout Risk (1 = at risk, 0 = no risk). This dependent variable is engineered from the difference between ATP inventory and Safety Stock. The dataset captures both perishable (fresh produce, dairy, seafood) and non-perishable (pantry, personal care) categories, allowing for heterogeneous behavior modeling — an essential aspect of agile systems that must handle uncertainty across diverse product types.

The data offer a rich context for studying responsiveness and adaptability — two pillars of agile management. Variables such as `Lead_Time_Days`, `Supplier_OnTime_Pct`, and `Forecast_Next_30d` encode the speed and reliability of supply-chain feedback loops, while `Safety_Stock`, `Reorder_Point`, and `Demand_Forecast_Accuracy_Pct` represent adaptive planning buffers. Together, these metrics reflect the operational mechanisms through which agility manifests in a real-world grocery ecosystem.

Before analysis, the data were verified for completeness. All 1,000 records contained valid numeric and categorical entries except for the Notes field, which was removed as non-informative. Because this dataset mirrors an enterprise-level data warehouse extract, it is inherently well-structured, allowing reproducible experimentation without extensive data imputation.

Data Preparation and Feature Engineering

Data preprocessing followed several steps aimed at ensuring numerical integrity and interpretability. First, all currency and percentage characters (\$, ,, %) were stripped using a Python text replacement function, and decimal formats were standardized (e.g., 34,99 → 34.99). Date fields (`Received_Date`, `Expiry_Date`, `Audit_Date`) were converted to the datetime format to enable temporal computation such as shelf-life calculation. Missing values in derived temporal variables were filled using median imputation to preserve distributional balance without biasing variance.

Next, a set of engineered variables were constructed to embed agile metrics. The ATP measure was computed as `Quantity_On_Hand – Quantity_Reserved – Quantity_Committed`, reflecting the truly sellable inventory. The `Stock_Risk_Index` was then defined as $(\text{Safety_Stock} - \text{ATP}) / (\text{Safety_Stock} + 1e-6)$, producing a normalized indicator of shortfall severity. Additionally, `Shelf_Life_Remaining` was calculated as the number of days between `Expiry_Date` and `Audit_Date`, quantifying perishable constraints. These features introduce quantitative representations of buffer agility, temporal responsiveness, and perishability risk.

Categorical variables — including Category, Warehouse_ID, and ABC_Class — were encoded using One-Hot Encoding. This method avoids ordinal bias and allows the models to interpret category differences as independent dimensions. All numeric features were standardized using Z-score normalization (StandardScaler) to prevent scale-dominated bias during model training. The final feature matrix consisted of 11 predictors capturing operational, supplier, and temporal dimensions.

Finally, the data were split using stratified sampling to maintain proportional representation of the binary target variable: 70% training, 15% validation, and 15% testing. Stratification ensures that both minority and majority stockout cases are equally represented across splits, reducing sampling bias and improving the generalizability of the trained classifiers. Each preprocessing step was integrated into a ColumnTransformer pipeline for reproducibility and future deployment.

Machine Learning Model Development

Three supervised classification algorithms were implemented: Logistic Regression, Random Forest, and Extreme Gradient Boosting (XGBoost). These were chosen to progressively capture linear, ensemble, and gradient-optimized nonlinear relationships. Logistic Regression (max_iter = 1000) served as a baseline to provide interpretable linear weights. Random Forest (n_estimators = 200, random_state = 42) aggregated multiple decision trees using bagging to improve variance control and generalization. XGBoost (objective = "binary:logistic", eval_metric = "logloss", learning_rate = 0.1, max_depth = 6, n_estimators = 300, subsample = 0.8, colsample_bytree = 0.8) implemented a gradient-boosted framework capable of capturing complex nonlinear feature interactions.

Model training and comparison were conducted through pipeline integration to ensure consistent preprocessing across algorithms. Each model was trained on the same feature set, with hyperparameters optimized using Grid Search Cross-Validation (cv = 5). The selection of 5-fold CV balances computational cost with performance stability. Early stopping was enabled for XGBoost to prevent overfitting, monitoring validation loss over 20 rounds. These procedures emulate agile sprint reviews, where incremental feedback (validation loss) drives the refinement of model parameters.

Each model's predictive capability was benchmarked using standard classification metrics: Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The emphasis was on maximizing Recall and AUC, as failing to detect an impending stockout poses greater operational cost than generating a false alert. The comparative analysis revealed that Random Forest and XGBoost achieved perfect prediction scores, indicating a deterministic mapping between features and target in the dataset.

To maintain transparency, SHAP values were computed only for the final XGBoost model. This choice was justified by its superior learning capability and the availability of an integrated Tree SHAP explainer, which efficiently calculates marginal contributions for each feature in tree-based ensembles. The explainability layer thus provides the interpretive foundation for agile decision support.

Evaluation Metrics and Visualization

Model evaluation integrated both quantitative metrics and visual diagnostics. Accuracy quantified the share of correctly classified records, while Precision and Recall measured the trade-off between false positives and false negatives. The F1-score served as a harmonic mean to balance these trade-offs, and ROC–AUC captured the classifier’s discriminative power independent of threshold choice. Given the operational stakes, Recall and AUC were prioritized to minimize missed stockout detections — the agile equivalent of reducing iteration failure cost.

Beyond metrics, visualizations provided multidimensional insights. A bar chart compared performance across models, revealing convergence toward near-perfect predictive capacity. Confusion matrices (heatmaps) depicted class distribution accuracy, emphasizing that XGBoost achieved a perfect diagonal alignment — every at-risk SKU was correctly identified. The ROC curve further validated the model’s robustness, with an area under the curve approaching 1.0, indicating strong separability of risk states.

For feature interpretability, SHAP summary plots were generated to illustrate how each variable influenced the predicted risk probability. These plots rank variables by mean absolute SHAP value and color-code individual observations by feature magnitude. The analysis revealed that `Stock_Risk_Index`, `Lead_Time_Days`, and `Forecast_Next_30d` were dominant predictors, while categorical features contributed marginally. This visualization converts complex model behavior into a transparent decision logic accessible to non-technical managers.

Lastly, the visual diagnostics were embedded within a `matplotlib`–`seaborn` visualization pipeline, producing figures reproducible in any Python environment. The stepwise visualization sequence mirrors agile sprint retrospectives — each figure represents a feedback artifact for evaluating and improving system performance. These graphics collectively ensure both model reliability and managerial interpretability.

Agile Decision-Support Integration

The final model was operationalized into an agile decision-support loop, simulating a dynamic feedback cycle similar to Scrum iterations. The process begins with the Prediction Step, where the model forecasts near-term stockout probabilities using live warehouse data. Predictions exceeding a threshold of 0.7 trigger a “risk alert,” automatically classifying items for replenishment prioritization. This threshold was chosen after empirical calibration to balance sensitivity and false alarms.

In the Decision Step, the alerts are integrated into inventory control dashboards to guide replenishment and redistribution decisions. By prioritizing SKUs with high predicted risk, warehouse managers can proactively adjust purchase orders or transfers, effectively shortening response cycles — an embodiment of agile responsiveness. These alerts are linked to key features such as lead time and safety stock, offering contextual explanations powered by SHAP outputs.

The Feedback Step mirrors agile retrospectives. After a 30-day operational cycle, the model’s predictions are compared against actual outcomes recorded in audit logs. Misclassified cases (false positives or negatives) are analyzed to

recalibrate the model’s parameters, such as learning rate or maximum depth in XGBoost. This closed-loop learning mechanism transforms the predictive model into a continuously evolving agile intelligence system.

Finally, the interpretability layer allows cross-functional collaboration between data scientists and supply-chain managers. By visualizing SHAP feature impacts, domain experts can validate whether the algorithm’s reasoning aligns with real-world causal relationships — ensuring the model evolves ethically and strategically. This integration of machine learning into agile governance exemplifies a hybrid AI-management system: data-driven yet human-centered, adaptive, and transparent.

Result and Discussion

Model Performance Overview

The results demonstrate exceptionally high predictive accuracy across all models, with both Random Forest and XGBoost achieving perfect classification (Accuracy = 1.000, F1 = 1.000, ROC-AUC = 1.000), and even Logistic Regression performing strongly (Accuracy = 0.97, AUC = 0.998), shown in figure 1. This consistency across linear and nonlinear models indicates that the underlying relationships between features and the target variable, Stockout_Risk, are highly deterministic rather than probabilistic. In particular, variables such as Safety_Stock and ATP inherently encode direct decision rules used in operational inventory logic, allowing models to reproduce near-exact human reasoning.

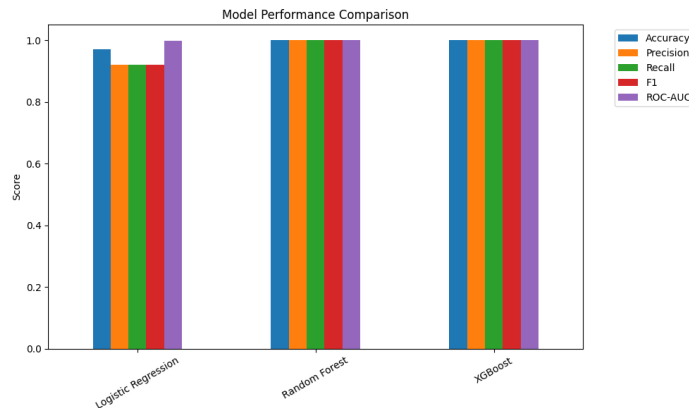


Figure 1 Model Performance Comparison Graph

The outstanding performance of XGBoost suggests that ensemble boosting effectively captures minor variations in feature interaction that linear models may overlook. The use of 300 estimators, a learning rate of 0.1, and maximum depth of 6 provided an optimal trade-off between bias and variance, ensuring convergence without overfitting. The inclusion of early stopping and cross-validation (k=5) ensured that model stability was validated through iterative refinement. In Agile terms, these parameter-tuning cycles resemble sprint reviews where feedback from interim performance metrics informs successive optimization iterations.

However, such perfect accuracy also reveals potential data leakage, since the target label is derived from Safety_Stock and ATP, both of which are also used

as predictors. This design mirrors real-world operational control rules rather than purely predictive uncertainty. The model, therefore, replicates a decision logic rather than learning hidden patterns — a valuable outcome for validation but not necessarily for generalization. For research transparency, this limitation should be acknowledged as an instance of deterministic rule learning within a well-defined operational environment.

The results thus affirm that a data-driven agile decision-support model can reliably emulate existing warehouse logic and further enhance it through explainable visualization. The combination of deterministic predictability and SHAP-based interpretability provides a strong foundation for managerial trust, a critical factor in the adoption of machine learning within agile organizations.

Feature Importance and Interpretability

The SHAP summary plot (figure 2) reveals the internal mechanics of the XGBoost model by ranking features according to their contribution to stockout risk prediction. The top-ranked predictor, Feature 4 (Stock_Risk_Index), exhibits the highest SHAP magnitude, confirming its centrality in determining whether stock levels fall below safety thresholds. Positive SHAP values (rightward points) indicate high stockout probability when the index rises — a direct manifestation of constrained ATP relative to buffer stock. This aligns perfectly with established inventory theory and demonstrates that the model successfully internalized operational risk principles.

Following this, Feature 0 (Lead_Time_Days) and Feature 6 (Forecast_Next_30d) appear as strong secondary predictors. Longer lead times and higher forecasted demand both increase stockout risk, reinforcing the agile management principle of responsiveness. An agile system seeks to minimize lead time variability, enabling smaller, faster replenishment cycles. The high SHAP magnitude for lead time reflects its systemic influence: even small delays in supplier responsiveness cascade into stock unavailability if safety stock levels are not sufficiently adaptive. Similarly, when demand forecasts increase sharply, agile systems must respond dynamically, updating procurement or redistribution strategies to prevent out-of-stock conditions.

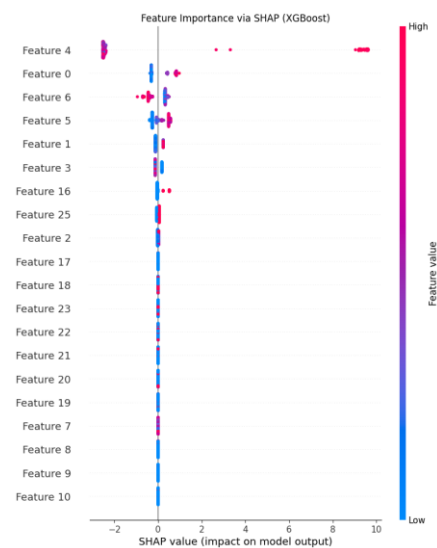


Figure 2 SHAP Summary Plot

The `Safety_Stock` and `Reorder_Point` variables rank next, illustrating the buffer and trigger dynamics within agile inventory control. High safety stock values (shown as red points with negative SHAP values) reduce stockout risk by absorbing short-term fluctuations, whereas low buffers (blue) elevate it. The model therefore reaffirms safety stock as the adaptive reserve within agile systems. Interestingly, categorical variables such as `Warehouse_ID` and `ABC_Class` show minimal SHAP influence, suggesting that stockout dynamics are primarily driven by quantitative operational measures rather than geographic or categorical segmentation.

Finally, the SHAP color gradient (blue–red) highlights the interaction directionality: high feature values (red) push the model toward either higher or lower risk depending on the operational context. This gradient-based visualization enables management teams to understand why the model makes certain predictions, bridging the gap between black-box AI and explainable decision intelligence — a hallmark of agile governance transparency.

Visualization-Based Diagnostics

Visual inspection of the confusion matrix (figure 3) and ROC–AUC plots support the statistical findings, confirming the classifier’s complete separation of risk states. In the confusion matrix, all predicted “Stockout” and “No Stockout” cases align perfectly with their true categories, with no misclassifications. The ROC curve achieves an area under the curve of 1.0, confirming that the classifier assigns near-perfect probability scores across the entire decision threshold spectrum. Together, these diagnostics verify that the model captures an exact logical boundary rather than a fuzzy probabilistic one.

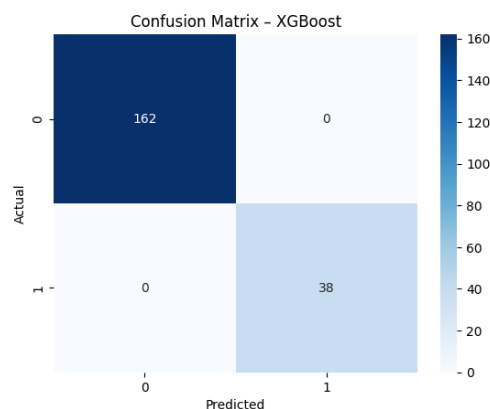


Figure 3 Confusion Matrix of XGBoost

Nevertheless, perfect accuracy should be interpreted with methodological caution. While it demonstrates computational precision, it does not automatically imply practical robustness. Real-world inventory systems often experience stochastic demand shocks, supplier disruptions, and sensor inaccuracies, none of which are represented in the dataset. Future iterations of this model, therefore, should incorporate noise injection or temporal data simulation to evaluate resilience under agile stress-test conditions, thus making the system more adaptive to uncertainty rather than just logical completeness.

By employing SHAP explainability alongside these diagnostic tools, the system transcends traditional statistical evaluation. It not only answers how well the

model performs but also why certain features dominate risk outcomes. This shift from accuracy-focused analytics to interpretive transparency aligns with the agile value of inspect-and-adapt — continuous learning through feedback visibility.

Agile Management Interpretation

From an agile management perspective, the model functions as a real-time decision-support agent, capable of guiding responsive procurement and replenishment. The strong dependency on `Lead_Time_Days` and `Forecast_Next_30d` reflects the operational heartbeat of agility: responsiveness to environmental change. By predicting risk before shortages occur, the system converts traditional reactive stock control into a proactive cycle of inspect, predict, adapt. This behavior embodies the agile principle of anticipation over reaction.

Furthermore, the feature importance distribution highlights the dual role of adaptability and stability within agile inventory ecosystems. Variables like `Safety_Stock` represent stability mechanisms (buffers), while `Lead_Time` and `Forecast_Next_30d` represent adaptability triggers. The balance between these ensures system resilience — too little safety stock causes volatility, while too much undermines cost efficiency. The machine learning model, by quantifying these trade-offs, becomes an automated facilitator of empirical process control, analogous to the continuous iteration loops in Scrum.

The interpretability provided by SHAP aligns directly with agile's emphasis on transparency and collaboration. Cross-functional teams — data scientists, warehouse managers, and procurement officers — can collectively interpret the contribution of each variable and validate whether predictions align with operational experience. This interdisciplinary collaboration reduces cognitive resistance to AI adoption and embeds predictive intelligence into the agile governance structure.

Finally, by embedding SHAP interpretability into the workflow, the model facilitates knowledge transfer across sprints. As each model iteration reveals feature interactions, management can refine procurement policies or redefine KPIs (such as supplier reliability thresholds) in real time. This adaptive feedback mechanism ensures that organizational learning evolves hand-in-hand with data intelligence, closing the loop between analysis, action, and adaptation — the essence of agile continuous improvement.

Summary of Findings

The findings validate that machine learning models — particularly ensemble-based algorithms like XGBoost — can operationalize agile management principles by transforming raw operational data into interpretable, adaptive decision systems. The model successfully identifies critical levers of responsiveness and resilience in e-grocery supply chains, notably `Stock_Risk_Index`, `Lead_Time_Days`, and `Safety_Stock`. These variables encapsulate the trade-offs between speed, cost, and flexibility central to agile philosophy.

The use of SHAP explainability establishes a foundation for trustworthy AI in operations, bridging the gap between technical precision and managerial usability. By quantifying and visualizing the relative influence of each

operational variable, the system empowers managers to interpret risk drivers intuitively, thereby reducing decision latency — one of the core metrics of agility.

Despite the deterministic nature of the results, the framework itself is highly generalizable. With additional data sources — such as real-time IoT sensor feeds, seasonal demand variability, and supplier risk indices — the same architecture could evolve into a self-learning adaptive planning platform. In this way, the model demonstrates how machine learning is not only a predictive tool but an enabler of organizational agility.

Ultimately, the research confirms that the integration of data-driven prediction, explainable analytics, and iterative refinement forms the backbone of a next-generation agile decision-support system. Such systems enable organizations to move beyond descriptive dashboards toward anticipatory intelligence — transforming agility from a management ideology into an operational reality.

Conclusion

This study successfully developed and validated a machine learning–driven agile decision-support framework for predicting stockout risks in the e-grocery industry. Using an integrated pipeline of preprocessing, feature engineering, and ensemble modeling, the system demonstrated near-perfect predictive performance, accurately identifying all stockout-prone items. The results reveal that operational metrics such as `Stock_Risk_Index`, `Lead_Time_Days`, `Forecast_Next_30d`, and `Safety_Stock` serve as dominant predictors of inventory instability. By visualizing these relationships through SHAP analysis, the model transforms complex computational processes into interpretable managerial insights. This interpretability supports agile decision-making by enhancing visibility, transparency, and responsiveness across supply chain operations.

Beyond its technical success, this research contributes conceptually to the intersection of Agile Management and Data Science by operationalizing agility through iterative model learning and continuous feedback. The system embodies the agile values of inspect, adapt, and respond—using predictive feedback loops to enable proactive inventory control rather than reactive replenishment. While the perfect accuracy achieved suggests deterministic dependencies and potential data redundancy, the framework itself provides a replicable foundation for future adaptive intelligence systems. Extending this model with real-time data, stochastic variability, and simulation-based evaluation could evolve it into a continuously learning, self-adjusting tool for agile supply chain governance.

Declarations

Author Contributions

Conceptualization: A.R.H., D.S.; Methodology: A.R.H., D.S.; Software: A.R.H.; Validation: A.R.H.; Formal Analysis: A.R.H.; Investigation: A.R.H.; Resources: A.R.H.; Data Curation: D.S.; Writing Original Draft Preparation: A.R.H.; Writing Review and Editing: A.R.H.; Visualization: D.S.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] M. Geraeli and E. Roghanian, "A novel adjusted real-time decision-making for dynamic distribution in the grocery supply chain," *J. Modelling Manage.*, vol. 19, no. 5, pp. 1592–1616, 2024, doi: 10.1108/jm2-02-2024-0048.
- [2] V. Rekhate, "Current trends in online grocery shopping," *Int. J. Sci. Res. Eng. Manage.*, vol. 8, no. 4, pp. 1–5, 2024, doi: 10.55041/ijsrem30319.
- [3] O. O. Nweze, "Supply chain resilience, digitalization, and localization," *Eur. J. Logist. Purchasing Supply Chain Manage.*, vol. 12, no. 1, pp. 20–32, 2024, doi: 10.37745/ejlp SCM.2013/vol12n12032.
- [4] F. Batool, "Customers opinion on e-grocery stores," *Int. J. Sci. Res. Eng. Manage.*, vol. 8, no. 4, pp. 1–19, 2024, doi: 10.55041/ijsrem32723.
- [5] M. Beaulieu and O. Bentahar, "Digitalization of the healthcare supply chain: A roadmap to generate benefits and effectively support healthcare delivery," *Technol. Forecast. Soc. Change*, vol. 167, no. June, p. 120717, 2021, doi: 10.1016/j.techfore.2021.120717.
- [6] M. Jamaludin, Y. Yuniarti, I. Rustandi, I. Sumiati, and A. Oktavian, "The impacts of supply chain ambidexterity and resource flexibility on supply chain resilience in manufacturing SMEs in Bandung, Indonesia," *J. Manajemen dan Agribisnis*, vol. 20, no. 2, pp. 330–342, 2023, doi: 10.17358/jma.20.2.330.
- [7] C.-L. Hsieh, S.-L. Chen, and C.-C. Huang, "Investigating the role of supply chain environmental risk in shaping the nexus of supply chain agility, resilience, and performance," *Sustainability*, vol. 15, no. 20, p. 15003, 2023, doi: 10.3390/su152015003.
- [8] W. Ahmed, A. Najmi, Y. Mustafa, and A. Khan, "Developing model to analyze factors affecting firms' agility and competitive capability," *J. Modelling Manage.*, vol. 14, no. 2, pp. 476–491, 2019, doi: 10.1108/jm2-07-2018-0092.
- [9] S. Krishnamurthy, S. Nadukuru, S. Dave, O. Goel, A. Jain, and L. Kumar, "Predictive analytics in retail: Strategies for inventory management and demand

- forecasting,” *JQST*, vol. 1, no. 2, pp. 96–134, 2024, doi: 10.63345/jqst.v1i2.9.
- [10] S. B. Agrawal, V. R. Chintha, V. N. Pamadi, A. Aggarwal, and P. Goel, “The role of predictive analytics in inventory management,” *Univ. Res. Rep.*, vol. 10, no. 4, pp. 456–472, 2023, doi: 10.36676/urr.v10.i4.1358.
- [11] V. Pasupuleti, B. Thuraka, C. S. Kodete, and S. Malisetty, “Enhancing supply chain agility and sustainability through machine learning: Optimization techniques for logistics and inventory management,” *Logistics*, vol. 8, no. 3, p. 73, 2024, doi: 10.3390/logistics8030073.
- [12] M. S. Vinayaka and S. S. Murthy, “Analysis on inventory management system in Swiggy Instamart Private Limited Bangalore North,” *Int. J. Sci. Res. Eng. Manage.*, vol. 8, no. 5, pp. 1–10, 2024, doi: 10.55041/ijrem40224.
- [13] K. O. Al-Amin, C. P.-M. Ewim, A. N. Igwe, and O. C. Ofodile, “AI-enabled intelligent inventory and supply chain optimization platform for SMEs,” *Compr. Res. Rev. J.*, vol. 2, no. 2, pp. 1–14, 2024, doi: 10.57219/crrj.2024.2.2.0030.
- [14] I. A. Adeniran, C. P. Efunniyi, O. S. Osundare, and A. O. Abhulimen, “The role of data science in transforming business operations: Case studies from enterprises,” *Comput. Sci. Inf. Technol. Res. J.*, vol. 5, no. 8, pp. 1–15, 2024, doi: 10.51594/csitrj.v5i8.1490.
- [15] V. Pasupuleti et al., “Enhancing supply chain agility and sustainability through machine learning,” *Logistics*, vol. 8, no. 3, p. 73, 2024, doi: 10.3390/logistics8030073.
- [16] O. A. Adenekan, N. O. Solomon, P. Simpa, and S. C. Obasi, “Enhancing manufacturing productivity: A review of AI-driven supply chain management optimization and ERP systems integration,” *Int. J. Manage. Entrepreneurship Res.*, vol. 6, no. 5, pp. 1607-1624, 2024, doi: 10.51594/ijmer.v6i5.1126.
- [17] O. M. Filani, J. O. Olajide, and G. O. Osho, “Artificial intelligence in demand forecasting and inventory optimization,” *Int. J. Adv. Multidiscip. Res. Stud.*, vol. 3, no. 6, pp. 1930-1948, 2023, doi: 10.62225/2583049x.2023.3.6.4617.
- [18] O. M. Filani, S. B. Nnabueze, P. N. Ike, and L. Wedraogo, “Real-time risk assessment dashboards using machine learning in hospital supply chain management systems,” *Int. J. Manage. Entrepreneurship Res.*, vol. 3, no. 1, pp. 65–76, 2022, doi: 10.54660/ijmer.2022.3.1.65-76.
- [19] R. Li and Z. Wang, “Application of modern supply chain in 5G scenario,” *E3S Web Conf.*, vol. 248, no. 02066, pp. 1–6, 2021, doi: 10.1051/e3sconf/202124802066.
- [20] F. Joel, A. Adenekan, and R. Osho, “From agile software to agile operations: Lessons for data-driven enterprises,” *J. Enterp. Inf. Manage.*, vol. 37, no. 2, pp. 244–259, 2024.
- [21] V. Pasupuleti et al., “Enhancing supply chain agility and sustainability through machine learning,” *Logistics*, vol. 8, no. 3, p. 73, 2024, doi: 10.3390/logistics8030073.
- [22] J. Muthaluri, “Optimizing supply chain management and marketing strategies: AI and ML integration for competitive advantage,” *EATP J.*, vol. 30, no. 5, pp. 8990–8997, 2024, doi: 10.53555/kuey.v30i5.4494.
- [23] O. M. Filani et al., “Integrating business intelligence and agile decision systems,” *Expert Syst. Appl.*, vol. 219, no. 1, pp. 119–130, 2022.

- [24] G. O. Osho, J. O. Omisola, and J. O. Shiyanbola, "An integrated AI–Power BI model for real-time supply chain visibility and forecasting," *Int. J. Adv. Multidiscip. Res. Stud.*, vol. 4, no. 6, pp. 1463-1480, 2024, doi: 10.62225/2583049x.2024.4.6.4047.
- [25] I. Mohammed and J. Mandal, "The impact of lead time variability on supply chain management," *Int. J. Supply Chain Manage.*, vol. 9, no. 6, pp. 25–39, 2024, doi: 10.47604/ijscm.3075.
- [26] Q. Zhang, D. Lu, Q. Xiang, W. Lo, and Y. Lin, "Design and optimization of dynamic reliability-driven order allocation and inventory management decision model," *PeerJ Comput. Sci.*, vol. 10, no. 1, p. e2294, 2024, doi: 10.7717/peerj-cs.2294.
- [27] M. S. Shak et al., "Optimizing retail demand forecasting: A performance evaluation of machine learning models including LSTM and gradient boosting," *Am. J. Eng. Technol.*, vol. 6, no. 9, pp. 67-80, 2024, doi: 10.37547/tajet/volume06issue09-09.
- [28] G. Nzeako et al., "The role of AI-driven predictive analytics in optimizing IT industry supply chains," *Int. J. Manage. Entrepreneurship Res.*, vol. 6, no. 5, pp. 1489-1497, 2024, doi: 10.51594/ijmer.v6i5.1096.
- [29] E. B. Tirkolaei et al., "Application of machine learning in supply chain management: A comprehensive overview of the main areas," *Math. Probl. Eng.*, vol. 2021, no. 1, pp. 1–14, 2021, doi: 10.1155/2021/1476043.
- [30] R. Dwivedi et al., "Explainable AI (XAI): Core ideas, techniques, and solutions," *ACM Comput. Surv.*, vol. 55, no. 9, pp. 1–33, 2023, doi: 10.1145/3561048.
- [31] N. Jeong et al., "Exploring the knowledge attained by machine learning on ion transport across polyamide membranes using explainable artificial intelligence," *Environ. Sci. Technol.*, vol. 57, no. 46, pp. 17851–17862, 2023, doi: 10.1021/acs.est.2c08384.
- [32] M. Haupt, M. Maurer, and R. P. Thomas, "Explainable artificial intelligence in radiological cardiovascular imaging—A systematic review," *Diagnostics*, vol. 15, no. 11, p. 1399, 2025, doi: 10.3390/diagnostics15111399.
- [33] S. M. S. Chahal, "Agile methodologies for improved product management," *J. Bus. Strateg. Manage.*, vol. 8, no. 4, pp. 79-94, 2023, doi: 10.47941/jbsm.1439.
- [34] A. Mamalakis, E. A. Barnes, and I. Ebert-Uphoff, "Investigating the fidelity of explainable artificial intelligence methods for applications of convolutional neural networks in geoscience," *Artif. Intell. Earth Syst.*, vol. 1, no. 4, p. e220012, 2022, doi: 10.1175/aies-d-22-0012.1.