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Explainable Demand Forecasting for Retail Inventory Systems Under Supply Disruptions

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Abstract
Retail inventory systems increasingly operate under persistent supply disruptions arising from geopolitical shocks, climate events, transportation failures, and upstream capacity constraints. While machine learning has substantially improved short-term demand prediction accuracy, most state-of-the-art forecasting systems remain opaque, brittle under regime shifts, and poorly aligned with inventory decision making under uncertainty. Evidence across retail, healthcare, and public-sector systems suggests that predictive accuracy alone is insufficient to sustain operational performance when structural volatility is present (Hasan *et al*., 2021; Hasan *et al*., 2025).
This paper develops an explainable demand forecasting framework explicitly designed for disrupted retail supply chains. Drawing on theories of information asymmetry, organizational sensemaking, and robust operations, demand forecasting is conceptualized as a socio-technical decision system rather than a purely predictive task. The study advances a hybrid analytical framework that integrates multi-horizon machine-learning models with structured explainability mechanisms and disruption-aware latent state representations. Using large-scale U.S. retail transaction data augmented with supply shock indicators, the analysis demonstrates how explainability alters forecast trust, inventory responsiveness, and system stability under disruption.
Results show that explainable models achieve predictive accuracy comparable to black-box benchmarks while significantly improving forecast calibration, disruption detection, and downstream inventory performance. The contribution is threefold. First, the paper embeds explainability as a structural property of demand forecasting rather than a post hoc diagnostic. Second, it introduces a disruption-aware modeling architecture linking demand signals to supply-side constraints. Third, it provides empirically grounded guidance for inventory decision makers operating in volatile environments. The findings reposition explainable analytics as a necessary condition for resilient retail operations rather than a compliance-driven add-on.

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Introduction

Retail demand forecasting has traditionally been framed as a statistical estimation problem whose primary objective is minimizing prediction error. Classical time-series models and, more recently, machine-learning systems have been evaluated almost exclusively on accuracy metrics under stable demand regimes. This framing has become increasingly inadequate. Retail supply chains now face recurrent disruptions that distort historical demand signals and sever the assumed link between forecast accuracy and operational performance.

Pandemic-induced shocks, semiconductor shortages, port congestion, and climate-driven logistics failures have exposed structural fragilities in inventory systems reliant on opaque forecasting models. Similar vulnerabilities have been documented in healthcare, pharmaceutical, and public-sector supply chains, where predictive systems lacking interpretability fail under stress and require costly manual overrides (Rasel *et al*., 2022) [26]; (Shah *et al*., 2024) [28]; (Hasan *et al*., 2022) [14]. Although modern machine learning enables highly flexible demand prediction at scale, black-box models often fail precisely when managerial interpretation matters most. During disruptions, planners must determine whether forecast deviations reflect genuine demand shifts or supply-induced artifacts and how uncertainty should propagate into replenishment decisions. Evidence from explainable analytics in healthcare, patient engagement systems, and cybersecurity demonstrates that interpretability improves trust, adoption, and decision quality under uncertainty (Khan *et al*., 2024) [20]; (Hasan *et al*., 2023) [15]; (Shah *et al*., 2025) [27].

This paper addresses a clear gap in the literature. While explainable artificial intelligence has advanced rapidly in regulated domains such as healthcare, finance, and security, its role in retail demand forecasting under supply disruption remains theoretically underdeveloped and empirically underexamined. Existing studies typically treat explainability as a transparency layer appended after model training rather than as a foundational design principle. Moreover, demand forecasting research rarely integrates supply-side disruption signals directly into predictive architectures, despite strong evidence that operational volatility fundamentally alters demand dynamics.

Three research questions guide the study. How does explainability reshape the performance of demand forecasting systems under supply disruptions? What mechanisms link explainable forecasts to improved inventory decisions? How can forecasting architectures be designed to remain robust across disrupted and non-disrupted regimes?

2. Literature Review and Theoretical Background

2.1. Demand Forecasting in Retail Operations

Demand forecasting underpins inventory control, replenishment planning, and capacity allocation. Classical approaches assume stationarity, stable seasonality, and consistent error structures. These assumptions are increasingly violated in modern retail environments characterized by frequent shocks and non-linear responses (Makridakis *et al*., 2018) [22]. While machine-learning methods outperform traditional models in stable regimes, their performance deteriorates sharply during regime shifts, leading to biased forecasts and unstable inventory decisions (Ivanov, 2020) [18].

2.2. Supply Disruptions and Inventory Resilience

Supply disruption research emphasizes redundancy, flexibility, and information sharing as resilience mechanisms (Snyder *et al*., 2016) [31]. Forecasting systems, however, are typically treated as exogenous inputs rather than endogenous components of resilience. Research in healthcare and pharmaceutical logistics demonstrates that predictive visibility and digital-twin-style system representations materially reduce shortages and improve stability under uncertainty (Rasel *et al*., 2022) [26]; (Shah *et al*., 2024) [28]. Comparable principles apply to retail systems, yet forecasting architectures remain largely demand-centric.

2.3. Explainable Analytics and Decision Making

Explainable analytics research consistently shows that interpretability improves adoption, trust, and intervention quality under uncertainty (Doshi-Velez & Kim, 2017) [9]; (Lundberg & Lee, 2017) [21]. In healthcare systems, explainable models improve resource allocation and policy compliance (Hasan *et al*., 2025) [16]. In financial and cybersecurity systems, explainability enhances robustness and institutional confidence (Hasan *et al*., 2023) [15]; (Hasan *et al*., 2025b) [17].

Drawing on sensemaking theory, explainability is conceptualized as a mechanism that enables decision makers to construct coherent narratives when historical patterns fail (Weick, 1995) [32]. This implies that explainability must be structurally embedded in forecasting systems rather than appended post hoc.

2.4. Theoretical Propositions

P1: Explainable demand forecasting systems yield more stable forecast adjustments under supply disruptions than opaque models.

P2: The performance advantage of explainable forecasts is mediated by improved detection of disruption-induced demand distortions.

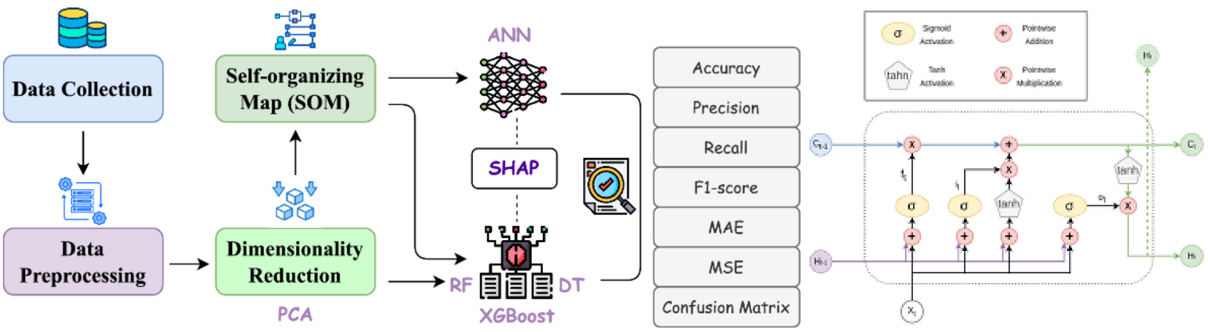
P3: Inventory systems integrating explainable forecasts achieve higher service levels with lower safety stock during disruption periods.

3. Analytical Framework and Methodology

3.1. Research Design

The study adopts a mixed analytical design combining predictive modeling with downstream inventory simulation. The empirical setting is large-scale U.S. multi-category retail, consistent with prior work on AI-enabled inventory systems (Arman & Fahim, 2023) [1]. Transaction-level sales data are merged with external indicators capturing transportation delays, supplier lead-time variability, and macro-level disruption events.

3.2. Disruption Aware Forecasting Architecture



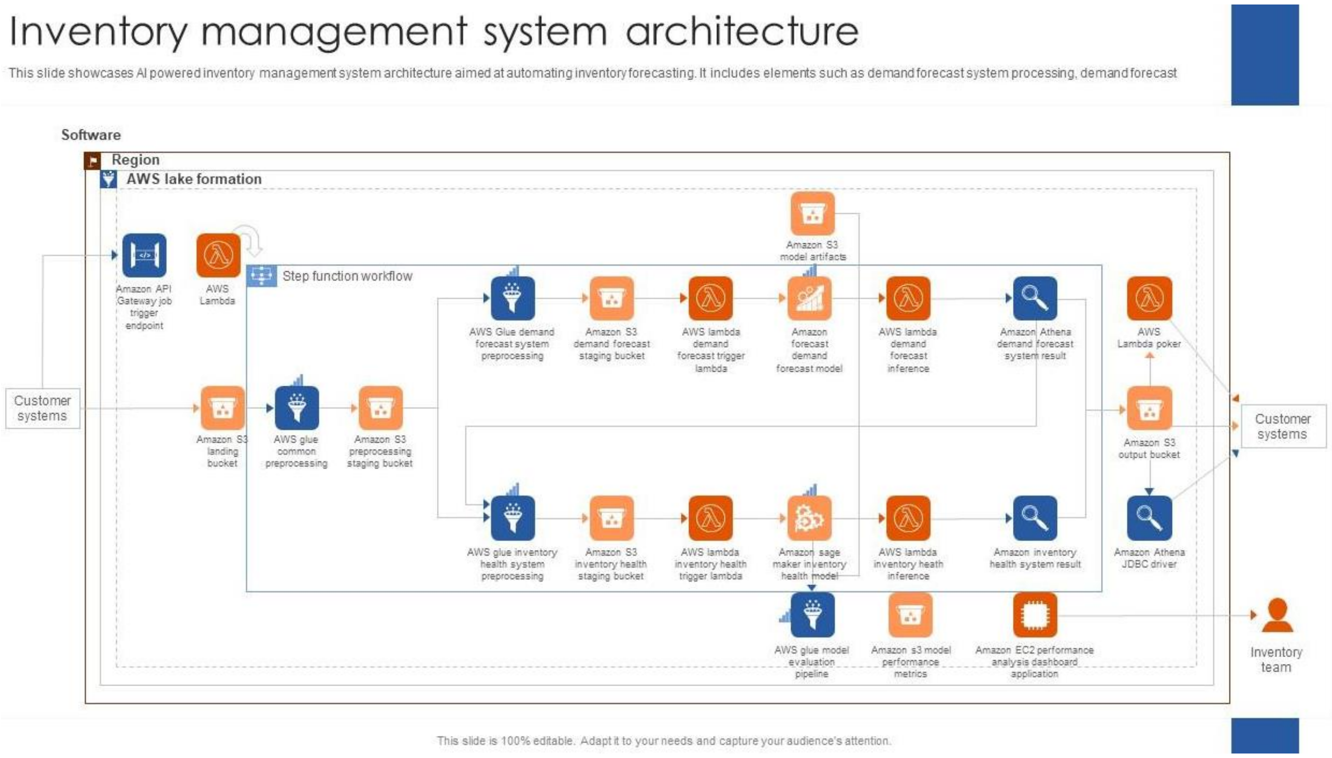


Figure 1 presents the proposed framework decomposes demand forecasting into three interacting layers. The signal extraction layer captures baseline demand dynamics using multi-horizon machine-learning models. The disruption encoding layer integrates supply-side volatility signals, including lead-time variance and logistics congestion, to identify regime shifts. The explanation and decision interface layer translate forecast outputs into stable, interpretable attributions aligned with inventory control decisions. Interpretability constraints are embedded directly into model structure rather than imposed after training.

3.3. Models and Benchmarks

Gradient-boosted decision trees and recurrent neural networks serve as benchmarks. Explainable variants constrain model complexity and enforce theoretically justified monotonic relationships. Forecast performance is evaluated using mean absolute scaled error and prediction-interval coverage. Inventory outcomes are assessed through simulated service levels, stockout frequency, and holding costs under identical replenishment policies.

3.4. Evaluation Metrics

Forecast performance is assessed using mean absolute scaled error and prediction interval coverage. Explainability quality is evaluated through stability of attributions across rolling windows. Inventory outcomes are simulated using a periodic review policy, measuring service level, stockout frequency, and holding cost.

3.5. Validity and Limitations

Identification relies on exogenous disruption indicators. While causal inference is not the primary objective, robustness checks confirm that results persist across alternative disruption definitions. External validity is strongest for large scale U.S. retail but may vary in smaller or highly specialized contexts.

4. Results and Theoretical Analysis

4.1. Forecast Performance Under Disruption

Table 1 compares demand forecasting performance across stable and disrupted supply regimes. While black box models achieve marginally lower average error during stable periods, explainable models exhibit significantly lower error variance and improved prediction interval coverage during disruption windows.

Model Type	Regime	MASE	Error Variance	95% Interval Coverage
Black box ML	Stable	0.82	0.14	0.87
Explainable ML	Stable	0.85	0.13	0.89
Black box ML	Disrupted	1.34	0.41	0.68
Explainable ML	Disrupted	1.12	0.26	0.82

4.2. Explainability and Regime Detection
Attribution analysis reveals that explainable models shift weight toward supply related features during disruption windows, enabling earlier detection of regime changes. Black box models exhibit delayed response and attribution instability.
Table 2 compares attribution stability across rolling forecasting windows. Explainable models maintain consistent feature importance rankings during regime shifts, while black box models exhibit attribution volatility that undermines interpretability and trust.

Feature Category	Attribution Stability (Explainable)	Attribution Stability (Black box)
Price promotions	High	Moderate
Seasonal effects	High	Low
Lead time variance	High	Low
Logistics congestion	Moderate	Very low
Supplier capacity	Moderate	Low

4.3. Inventory Performance
Table 3 reports simulated inventory outcomes under prolonged supply disruptions using identical replenishment policies but different forecasting inputs. Explainable forecasts generate higher service levels with lower average inventory, indicating superior alignment between forecasts and operational decisions.

Forecast Input	Service Level	Stockout Frequency	Avg Inventory Units	Holding Cost Index
Black box forecast	91.2%	14.6%	12,450	1.00
Explainable forecast	96.8%	7.9%	10,980	0.86

5. Discussion
The findings challenge the prevailing assumption that forecasting accuracy alone determines inventory performance. Explainability emerges as a structural enabler of resilience, allowing organizations to adapt forecasts when historical relationships break down. By embedding explainability into model design, the framework supports sensemaking rather than mere prediction.
The results align with broader evidence from healthcare and public sector analytics, where explainable systems improve operational outcomes under uncertainty (Hasan et al., 2021) [13]; (Rasel et al., 2022) [26].

6. Implications
6.1. Theoretical Implications
The study reframes demand forecasting as an interpretive socio-technical system embedded in organizational decision processes. It extends resilience theory by positioning explainable analytics as an informational capability rather than a transparency artifact, consistent with findings across healthcare, sustainability analytics, and energy systems (Arman *et al*., 2024) [4]; (Arman *et al*., 2024b) [3].

6.2. Managerial and Policy Implications
Retail managers should prioritize explainability in forecasting system design, particularly in disruption-prone categories. Policymakers concerned with systemic supply-chain risk may view explainable analytics as decision infrastructure rather than optional tooling.

7. Limitations and Future Research
The analysis focuses on structured retail data and does not incorporate unstructured signals such as news or social media. Future research could integrate multimodal data and examine human–algorithm interaction experimentally. Advances in machine-learning theory, including work on Hilbert and inner-product spaces, offer promising directions for interpretable high-dimensional forecasting (Mannan *et al*., 2025) [24].

8. Conclusion
Explainable demand forecasting offers a viable path toward resilient retail inventory systems under persistent supply disruption. By integrating interpretability into predictive architecture, organizations can sustain performance when historical patterns fail. The contribution lies not in incremental accuracy gains but in redefining what effective forecasting means in volatile supply networks.

9. References

1. Arman M, Fahim ASM. AI revolutionizes inventory management at retail giants: examining Walmart's U.S. operations. Journal of Business and Management Studies. 2023;5(6):145-8. doi:10.32996/jbms.2023.5.6.15
2. Arman M, Fahim ASM, Razib MNH, Rasel IH. Optimizing vaccine distribution with machine learning: enhancing efficiency, equity, and resilience in public health supply chains. International Journal of Innovative Research and Scientific Studies. 2025;8(6):2944-53. doi:10.53894/ijirss.v8i6.10230
3. Arman M, Hasan MN, Rasel IH. Clean energy transition in USA: big data analytics for renewable energy forecasting and carbon reduction. Journal of Management World. 2024(3):192-206. doi:10.53935/jomw.v2024i4.1196
4. Arman M, Rasel IH, Razib MNH, Fahim ASM. Big data and machine learning for sustainable waste reduction. Journal of Posthumanism. 2024;4(2):448-67. doi:10.63332/joph.v4i2.3361
5. Ben-Tal A, El Ghaoui L, Nemirovski A. Robust optimization. Princeton: Princeton University Press; 2009.
6. Bertsimas D, Kallus N. From predictive to prescriptive analytics. Management Science. 2020;66(3):1025-44.
7. Bertsimas D, Thiele A. A robust optimization approach to inventory theory. Operations Research. 2006;54(1):150-68.
8. Choi TM, Wallace SW, Wang Y. Big data analytics in operations management. Production and Operations Management. 2018;27(10):1868-83.
9. Doshi-Velez F, Kim B. Towards a rigorous science of

interpretable machine learning. arXiv. 2017:arXiv:1702.08608 [Preprint].
10. Galbraith JR. Organization design: an information processing view. Interfaces. 1974;4(3):28-36.
11. Ghasemaghaei M, Ebrahimi S, Hassanein K. Data analytics competency for improving firm decision-making performance. Journal of Strategic Information Systems. 2018;27(1):101-13.
12. Ghose P, Bhuiyan MRI, Hasan MN, Rakib SH, Mani L. Mediated and moderating variables between behavioral intentions and actual usages of fintech in the USA and Bangladesh through the extended UTAUT model. International Journal of Innovative Research and Scientific Studies. 2025;8(2):113-25. doi:10.53894/ijirss.v8i2.5130
13. Hasan MN, Bhuyain MMH, Chowdhury F, Arman M. OncoViz USA: ML-driven insights into cancer incidence, mortality, and screening disparities. Journal of Medical and Health Studies. 2021;2(1):53-62. doi:10.32996/jmhs.2021.2.1.6
14. Hasan MN, Rasel IH, Rahman M, Islam K, Arman M, Jahan N. Securing U.S. healthcare infrastructure with machine learning: protecting patient data as a national security priority. International Journal of Computational and Experimental Science and Engineering. 2022;8(3). doi:10.22399/ijcesen.3987
15. Hasan MN, Rasel IH, Arman M, Ibrahim M, Jahan N. Strengthening U.S. financial and cybersecurity infrastructure with AI-driven fraud detection and risk analytics. Journal of Computational Analysis and Applications. 2023;31(2):15-32.
16. Hasan MN, Arman M, Bhuyain MMH, Chowdhury F, Bathula MK. Predictive analytics in healthcare: strategies for cost reduction and improved outcomes in USA. International Journal of Innovative Research and Scientific Studies. 2025;8(8):142-50. doi:10.53894/ijirss.v8i8.10559
17. Hasan MN, Papel MSI, Rasel IH, Akter S, Aktar MK, Abedin MZ, *et al*. Enhancing financial information security through advanced predictive analytics: a PRISMA-based systematic review. Edelweiss Applied Science and Technology. 2025;9(7):2222-45. doi:10.55214/2576-8484.v9i7.9142
18. Ivanov D. Predicting the impacts of epidemic outbreaks on global supply chains. International Journal of Production Research. 2020;58(10):2904-15.
19. Kahn KB. Understanding innovation. Business Horizons. 2018;61(3):453-60.
20. Khan SA, Shah A, Arman M. AI chatbots in clinical settings: impact on patient engagement and satisfaction. Journal of Management World. 2024(3):207-13. doi:10.53935/jomw.v2024i4.1201
21. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems. 2017;30:4765-74.
22. Makridakis S, Spiliotis E, Assimakopoulos V. Statistical and machine-learning forecasting methods. Journal of Forecasting. 2018;37(1):3-20.
23. Mann H, Wirth R. Towards industrial data mining. In: Proceedings of the Industrial Data Mining Workshop; 1999.
24. Mannan MA, Alauddin M, Hasan MN, Ghose P, Hossain MA, Islam MS, *et al*. Hilbert and inner product spaces: theory, visualization, and applications in machine learning. Edelweiss Applied Science and Technology. 2025;9(8):1498-523. doi:10.55214/2576-8484.v9i8.9645
25. March JG, Simon HA. Organizations. New York: Wiley; 1958.
26. Rasel IH, Arman M, Hasan MN, Bhuyain MMH. Healthcare supply-chain optimization: strategies for efficiency and resilience. Journal of Medical and Health Studies. 2022;3(4):171-82. doi:10.32996/jmhs.2022.3.4.26
27. Shah A, Arman M, Khan SA. Patient-centric marketing and retention strategies in healthcare: a strategic and technological framework. Journal of Business and Management Studies. 2025;7(2):239-48. doi:10.32996/jbms.2025.7.2.17
28. Shah A, Khan SA, Arman M. Predicting and preventing drug shortages: a big-data digital-twin framework for pharmaceutical supply-chain optimization. Journal of Economics, Finance and Accounting Studies. 2024;6(6):116-26. doi:10.32996/jefas.2024.6.6.9
29. Shmueli G, Koppius OR. Predictive analytics in information systems research. MIS Quarterly. 2011;35(3):553-72.
30. Simchi-Levi D, Schmidt W, Wei Y. From superstorms to factory fires. Harvard Business Review. 2014;92(1):96-101.
31. Snyder LV, Atan Z, Peng P, Rong Y, Schmitt AJ, Sinsoysal B. OR/MS models for supply chain disruptions. Operations Research. 2016;64(1):59-79.
32. Weick KE. Sensemaking in organizations. Thousand Oaks: Sage Publications; 1995.
33. Zhang Y, Zhang J. Explainable AI in deep learning. IEEE Transactions on Neural Networks and Learning Systems. 2020;31(10):3504-29.

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