International Journal of Advanced Engineering, Management and Science (IJAEMS)
Peer-Reviewed Journal
ISSN: 2454-1311 | Vol-12, Issue-1; Jan-Feb, 2026
Journal Home Page: https://ijaems.com/
DOI: https://dx.doi.org/10.22161/ijaems.121.2

Explainable artificial-intelligence methods in decision support for delivery management

Ankur Fnu

Manager, Program Management at Amazon, Seattle, WA - USA

Received: 11 Dec 2025; Received in revised form: 09 Jan 2026; Accepted: 15 Jan 2026; Available online: 19 Jan 2026

***Abstract*— *The article presents an analysis of the application of explainable artificial intelligence (XAI) methods in supporting managerial decision-making for delivery management. The study is conducted within a theoretical and analytical framework, employing a targeted review of publications, a taxonomy of interpretable methods, and their alignment with typical delivery tasks. Particular attention is paid to the role of XAI in ensuring transparency, consistency, and resilience of decisions, as well as integrating ESG indicators and cyber-resilience criteria into planning and dispatching processes. Based on the analysis of scientific sources, approaches to interpreting forecasts and recommendations (post-hoc methods, built-in relevance mechanisms, neuro-symbolic models) are systematized, and their managerial effects and limitations are identified. Generalizing classifications are presented, including a map of XAI applications in logistics tasks, a summary of quantitative effects by key metrics, and a decision matrix linking approaches to managerial criteria. The challenges of XAI implementation are examined, including the complexity of interpreting deep models, the risk of oversimplified explanations, and the need to adapt algorithms to dynamic operational conditions. A structured model for integrating XAI into decision support system architectures is proposed, focusing on balancing accuracy, cost, and environmental performance. The article will be useful to specialists in logistics and supply chains, DSS developers, XAI researchers, and managers making decisions under high demands for transparency and delivery resilience.*

Keywords*— *explainable artificial intelligence, managerial decision support, delivery, logistics, interpretable models, ESG, cyber resilience, SHAP, dispatching, supply chain resilience.

I. INTRODUCTION

Contemporary delivery management is characterized by highly volatile demand, growing complexity of last-mile logistics, tighter requirements for timeliness and reliability, and the need to account for environmental constraints and cybersecurity risks. Under these conditions, trust in computational models used to plan lead times, routes, and resources becomes pivotal. Managerial decisions must be accurate and transparent to accountable parties and regulators. Opaque ("black-box") machine-learning algorithms hinder the verification of causal relationships, the explanation of errors, and the alignment of decisions among supply-chain participants, which reduces the acceptance of such systems in practice and raises the costs of decision rework [Brahimi N, 2025].

Explainable artificial intelligence provides tools for interpreting forecasts and recommendations, making it possible to identify factor contributions, test the robustness of conclusions, and build reproducible justifications when agreeing delivery deadlines and selecting operating scenarios. In delivery-oriented decision support systems, this translates into early bottleneck detection, the accommodation of customer preferences and contractor constraints, and informed trade-offs among accuracy, cost, and sustainability. Kostopoulos systematizes approaches to explainable decision support systems and notes their role in enhancing transparency and trust in managerial processes [Kostopoulos G, 2024].

This work is theoretical in nature and aims to integrate existing results on XAI (understood here as the suite of methods, techniques, and tools that render AI/ML model operation transparent and interpretable to humans) in decision-support tasks for delivery management. The review structures interpretation and explanation methods in connection with typical delivery management tasks (lead-time forecasting, order prioritization, selection of risk-response policies) and refines criteria for their appropriateness, given requirements for transparency, reliability, and environmental performance.

The purpose of the study is to analyze XAI methods in supporting managerial decisions on delivery, to identify their capabilities and limitations for ensuring verifiable conclusions, agreement of decisions among participants, and greater trust in digital planning tools.

II. MATERIALS AND METHODS

The study adopts a theoretical and analytical approach and relies on a targeted review of publications on interpretable AI methods in decision support for delivery and adjacent logistics tasks. The core corpus includes works on the systematics of methods and decision-support architectures, including the study by Kostopoulos [Kostopoulos G, 2024] and a review of neuro-symbolic approaches in supply chains by Kosasih [Kosasih EE, 2023]. To connect with lead-time planning and order fulfillment, the analysis draws on studies of transport data with explainable lead-time predictions by Ahmed [Ahmed I, 2022] and explainable spatiotemporal demand models by Brahimi [Brahimi N, 2025]. For delivery-operations optimization and dispatching, results by Bruni [Bruni ME, 2023] and Chang [Chang X, 2024] are used. As sources on interpretable methods in managerial decisions and evaluation metrics, the study includes works by Olan [Olan F, 2024], Rokoss [Rokoss A, 2024], Sadeghi [Sadeghi KR, 2024], and Sattar [Sattar MU, 2025].

Units of analysis:

- management function (lead-time/fulfillment estimation; planning and dispatching;
- risk and resilience management; sustainability impact assessment);
- data type and representation (including spatiotemporal features);
- interpretable AI method;
- metrics used and decision criteria.

From each work, the following were extracted: task formulations; interpretation methods applied and their role in explaining forecasts/recommendations; and implications for managerial decisions. The taxonomy of interpretable methods was formed inductively, drawing on detailed demonstrations. Local additive explanations of feature importance (e.g., SHAP in Olan [Olan F, 2024] and Rokoss [Rokoss A, 2024]); examples of post-hoc explanations and traceability (LIME, RETAIN, LRP, DeepLIFT) in an experimental decision-support model presented by Sadeghi [Sadeghi KR, 2024]. The balance among accuracy, cost, and sustainability was assessed using the composite indices CAE and CAE-ESG proposed by Sattar and co-authors for comparative model assessment in supply chains [Sattar MU, 2025].

III. RESULTS

Within the theoretical study, published works on the use of explainable AI methods in decision support for delivery and adjacent supply-chain stages were mapped. The goal is to align task type, model used, explanation approach, and reported managerial effect. The summary map is shown in Table 1, enabling a stepwise view from forecasting and dispatching to interpretable outputs and decision-quality effects.

Table 1 – Summary map of XAI uses in delivery/SCM decision support (Compiled by the author based on sources: (Ahmed I, 2022), (Brahimi N, 2025), (Olan F, 2024))

Delivery task / domain	Model(s)	XAI approach	Reported metrics / notes
Travel-time (ETA) prediction with spatio-temporal features	Comparative studyprediction with spatio-temporal features	Post-hoc feature explanations	Focus on travel time with explanations; explicit metrics not reported
Car-sharing demand, spatio-temporal	Explainable Spatio-Temporal Inference Network	Built-in interpretability via attention/relevance	Declared SOTA and interpretable demand drivers
3PL terminal-to-customer planning	ML + optimization	—	Planning framework for delivery leg; metrics not explicit
Ridesourcing carpooling and dispatching, emissions	Dispatch algorithms	—	Emissions-reduction assessment for mobility services
SCM review of neurosymbolic XAI	—	Neuro-symbolic approaches	Taxonomy and SCM cases
Review of XAI-based DSS	—	Transparency and trust criteria	Evaluation framework for XAI-DSS
Building XAI capabilities in SC-DSS (tabular data)	ML on tabular data	SHAP, global and local	~315 observations; features 42→122; managerial insights
Delivery-date prediction in small-batch MTO	XGBoost	SHAP feature importance	Case 1 RMSE: mean 12 bd; ML no-domain 9.5; with domain 7.7; desired date is top feature
Supply-chain cyber resilience during attacks	—	XAI as driver of transparency	Adj.R^2=0.42; direct coef to resilience 1.35; serial mediation 0.333
Forecasting, inventory, risk, ESG-aware selection	XGB, RNN, RF	SHAP; CAE and CAE-ESG	XGB MAE=0.1571, MAPE=0.48%; RNN fraud F1≈98%, late-delivery F1≈97.85%; RF best CAE-ESG

The "Delivery task / domain" column spans delivery-management subjects from travel-time estimation and mobility demand to 3PL terminal–customer planning and dispatching with environmental impact, outlining a range of decisions from route planning to service resilience [Ahmed I, 2022]. The "Model(s)" column reflects the use of specialized spatiotemporal networks, gradient boosting, and mixed ML-optimization approaches for lead-time and workload forecasting in make-to-order production and service logistics [Rokoss A, 2024]. The "XAI approach" column records interpretation methods, including post-hoc explanations of feature contributions, built-in relevance mechanisms, and SHAP in enterprise DSS—providing factor readability and subsequent managerial validation [Olan F, 2024]. "Reported metrics / notes" summarizes stated accuracy indicators, causal links, and model choices that incorporate cost and sustainability, showing how explainability connects to forecast quality, risk control, and algorithm selection under ESG constraints [Sattar MU, 2025]. Collectively, the map confirms a managerial transparency effect on the speed and reliability of decisions during cyber incidents, expressed in validated serial mediators of transparency and decision agility [Sadeghi KR, 2024].

To further verify the managerial value of XAI in delivery tasks, quantitative effects on key decision outcomes were synthesized. Comparison used common measurability and reproducibility criteria to reconcile heterogeneous domains—from lead-time forecasting to sustainable model selection. Summary results are presented in Table 2.

Table 2 – Quantitative effects of XAI on managerial outcomes (Compiled by the author based on sources: (Olan F, 2024), (Sadeghi KR, 2024), (Sattar MU, 2025))

Block	Indicator/effect	Value/outcome
Delivery promise reliability	RMSE reduction of delivery-date prediction vs. baseline	from 12 to 7.7 business days with domain features and SHAP
Target variable's role	Importance of "desired delivery date" in the model	top feature by SHAP in both case studies
Decision-making under attacks	XAI → Transparency → Agile → Cyber resilience	Adjusted R^2 up to 0.546; indirect effect 0.333; all links statistically significant
Supply-risk detection	Late delivery / fraud identification	RNN F1 ≈ 98% (fraud); ≈ 97.85% (late delivery
Model choice with sustainability	Accuracy/Cost/ESG balance	Random Forest achieves best CAE-ESG with comparable accuracy
Organizational XAI capabilities	Global/local explanations for SC decisions	SHAP; features expanded 42→122; decision factors explicitly interpretable

The "Block" column identifies the managerial contour of application. "Indicator/effect" specifies the measurable outcome used to compare approaches. "Value/outcome" contains verbatim metric values or carefully formulated findings from the cited articles.

On-time delivery promises carry the greatest applied significance. In Rokoss, the delivery-date prediction RMSE decreases from 12 to 7.7 business days when domain features are included and SHAP is used for factor selection and explanation; the "desired date" is the top-importance feature in both samples, confirming the criticality of incorporating the customer's target request in planning models [Rokoss A, 2024].

For controllability under cyberthreats, a consistent mediated chain—"XAI → transparency → decision agility → cyber resilience"—is shown. Sadeghi reports significant coefficients, adjusted R^2 up to 0.54, and a total indirect effect of 0.333, substantiating the need to formalize explanations as elements of response protocols [Sadeghi KR, 2024].

In supply-risk management, detectors exhibit high sensitivity. Sattar reports recurrent networks achieving F1 around 98% for fraud and about 97.85% for late deliveries—broadening the space for preventive dispatching and SLA control. When selecting technologies with sustainability in view, the same author shows that, at comparable accuracy, Random Forest provides the best overall "accuracy–cost–ESG" profile according to CAE/CAE-ESG, which matters for responsible scaling of analytics [Sattar MU, 2025]. Finally, organizational XAI capabilities in supply chains rest on reproducible global and local explanations. In Olan, SHAP and an expanded feature space improve interpretability and convert model factors into manageable process parameters [Olan F, 2024].

IV. DISCUSSION

Synthesizing application maps and quantitative effects yields practical guidance for choosing XAI instruments in delivery management. For travel-time prediction and honoring promised dates, tabular models with local and global explanations are preferred, as confirmed in Ahmed [Ahmed I, 2022]. Rokoss empirically demonstrates the material role of such explanations for accurate shipment-date calculation in small-batch environments [Rokoss A, 2024]. Transparency and trust criteria for managerial DSS decisions are consolidated in the review by Kostopoulos [Kostopoulos G, 2024].

For demand and dispatching in spatiotemporal settings, models with built-in interpretability via attention/relevance are appropriate, as shown in Brahimi's work on car-sharing demand [Brahimi N, 2025]. In terminal delivery and 3PL interaction, machine learning combined with optimization is effective, as indicated by Bruni [Bruni ME, 2023]. The cyber-risk vector requires rapid transparency and explainable action criteria; serial mediation in Sadeghi's experiments confirms the role of explainability in accelerating the managerial cycle during attacks [Sadeghi KR, 2024]. Sustainable scaling calls for accounting for computational cost and environmental footprint; CAE/CAE-ESG metrics in Sattar justify model selection based on the joint criteria of accuracy, expense, and ESG [Sattar MU, 2025]. The environmental effects of dispatching and ride-sharing decisions are highlighted by Chang [Chang X, 2024]. Table 3 presents a decision matrix for selecting XAI approaches for delivery-management decision support, linking criteria, source foundations, recommended explanation methods, and typical application scenarios.

Table 3 – Decision matrix for selecting XAI approaches in delivery management (compiled by the author based on (Brahimi N, 2025), (Kostopoulos G, 2024), (Sadeghi KR, 2024))

Criterion	Preferred XAI/approach	Where to apply
Manager-oriented transparency	SHAP/LIME (post-hoc)	ETA and promised dates
Faithfulness to model and domain rules	Neuro-symbolic and rule-based explanations	Service-level policies and compliance
Built-in interpretability	Attention and relevance mechanisms	Spatio-temporal dispatch and demand
Speed and robustness under attacks	Simple interpretable models with local explanations	Day-of-attack incident decisions
Cost and environmental impact	Models maximizing CAE-ESG (often RF/XGB)	DSS operations and scaling

The matrix aligns managerial criteria with literature-backed foundations, recommended classes of explanations, and typical use contours. The "Criterion" column fixes key managerial decision anchors: transparency, faithfulness to internal model logic, built-in interpretability, response speed in incidents, cost, and ecological impact. Transparency is elevated as the primary criterion, based on Kostopoulos's review and Sadeghi's empirical results on the importance of intelligibility for coordinated, rapid team responses [Kostopoulos G, 2024; Sadeghi KR, 2024]. "Preferred XAI/approach" proposes explanation classes per criterion. Post-hoc methods (SHAP/LIME) suit cases requiring controllable interpretation of tabular forecasts without model redesign—an approach exemplified by Olan (global and local explanations for managerial factors) and by Rokoss when analyzing feature importance for delivery dates [Olan F, 2024; Rokoss A, 2024]. The "Faithfulness" criterion draws on neuro-symbolic practices from Kosasih's review, where explicit rules and domain constraints must be reflected in the model [Kosasih EE, 2023]. For problems with spatiotemporal dependencies, built-in interpretability via attention/relevance is indicated, as in Brahimi [Brahimi N, 2025]. "Speed & resilience" emphasizes the need for rapid, explainable responses during cyber incidents, grounded in Sadeghi's results linking transparency and agile decision-making to higher cyber-resilience [Sadeghi KR, 2024]. Finally, "Cost/Ecology" connects model selection with overall efficiency and footprint; Sattar proposes CAE/CAE-ESG for rational choice (Random Forest shows the best balance in their experiments), and Chang demonstrates the link between dispatch actions and transport emissions [Sattar MU, 2025; Chang X, 2024]. "Where to apply" identifies typical scenarios: lead-time prediction and SLA compliance in tabular tasks (as in Ahmed); spatiotemporal dispatching and demand forecasting; incident management and operational risks with simple interpretable models plus local explanations; and DSS operations guided by

CAE-ESG and transport-emissions accounting [Ahmed I, 2022].

The analysis indicates that XAI implementation should be viewed not as an "explanation add-on" but as a managerial mechanism for accelerating collective decisions in delivery operations. Sadeghi shows that algorithm transparency increases the speed of alignment and promotes agile resolution, which is statistically associated with higher cyber-resilience [Sadeghi KR, 2024]. For logistics organizations, this implies embedding explainability into response procedures, escalation paths, and stakeholder communications.

Model choice extends beyond forecast accuracy. Sattar demonstrates that integrated CAE and CAE-ESG metrics shift selection priorities: a model with moderate accuracy but lower cost and a better ESG footprint may be preferable for sustainable analytics operations. Thus, technology selection should be aligned with environmental and social objectives rather than reduced to error minimization. This approach accords with dispatching and ride-sharing contexts where managerial decisions directly reduce emissions.

High-quality feature engineering and grounding in quantitative logistics models are critical for reliable delivery-promise performance. Rokoss shows that domain features and contribution explanations materially reduce delivery-date prediction error versus baseline heuristics, with the "desired date" as the key factor. The practical implication is that XAI should be embedded in the feature-formation pipeline, not confined to post-hoc explanations at the end [Rokoss A, 2024].

The role of reviews is to establish durable standards of explainability and criteria for their evaluation. Kosasih systematizes neuro-symbolic approaches relevant where managerial rules and domain constraints must be explicitly represented. Kostopoulos offers transparency and trust criteria for decision-support systems that can ground corporate XAI-DSS regulations in delivery—from requirements for local/global explanations to formats for presenting causally significant factors to managers [Kosasih EE, 2023; Kostopoulos G, 2024].

Taken together, the results point to a necessary shift in managerial practice—from "accuracy at any cost" to a balance of interpretability, collective-action speed, and resilience. This entails redesigning delivery-decision processes around: procedural transparency and resilience metrics; multi-criteria model selection that accounts for cost and ESG; domain-grounded feature engineering with verifiable factor-impact explanations on lead times; and standardized requirements for explanations and their auditability at the organizational level.

Such a contour strengthens operational delivery resilience and aligns analytics with environmental and social responsibility objectives. It establishes manageable trade-offs among reaction speed, explainability, and model resource intensity, enabling the formalization of SLAs, resilience KPIs, and climate indicators within unified decision-making regulations. Practically, this reduces regulatory and reputational risks and yields more predictable deadline adherence with an optimized carbon footprint for both the transport fleet and IT infrastructure.

V. CONCLUSION

The study substantiates the key role of explainable AI methods in ensuring transparency and trust when supporting managerial decisions in delivery. It finds that interpretable algorithms, local and global feature explanations, neuro-symbolic approaches, and built-in relevance mechanisms constitute a stable analytical platform necessary for the predictability, consistency, and sustainability of logistics processes.

The source analysis confirms that XAI serves both as a technical means of visualizing factor contributions and as an instrument of managerial legitimation—capturing causal links, justifying priorities, and documenting criteria for scenario selection. Amid rising cyberthreats and ESG requirements, its functions expand through integration into SLA monitoring, incident management, and strategic planning of transport capacities. A basic postulate remains: explainability cannot be reduced to a superficial "layer" atop the model; it must be embedded in DSS architecture, coupled with feature engineering, and formalized in application regulations.

A multi-level approach to XAI evaluation is warranted—from accuracy and cost metrics to cyber-resilience and environmental performance—as the primary filter for technology choice and a guarantee of decision governability. Composite indices CAE and CAE-ESG play a central role in balancing performance, economy, and environmental responsibility. Mechanisms for organizational validation of explanations gain particular importance through corporate transparency standards and controls on the reproducibility of factors that affect delivery timing and quality.

The challenges facing XAI practice in logistics are highlighted: the difficulty of interpreting deep models on high-dimensional data, the risk of simplistic or misleading explanations, and the need to adapt algorithms to rapidly changing operating conditions. These challenges call for methodical specification of XAI tool requirements, clarification of method applicability limits, and revised model-selection criteria that reflect multifactor managerial objectives. The decision matrix proposed here is a promising instrument for standardizing practice, but it requires tailoring to industry specifics and integration into existing logistics ecosystems.

Accordingly, XAI in delivery management shapes a new quality of analytical support—from forecast accuracy to comprehensive support for transparency, resilience, and decision coherence. Its transformation from an auxiliary module into a core element of the managerial cycle reflects logistics' evolution toward multi-objective, environmentally oriented, and cyber-resilient systems. Future research avenues include developing a regulatory framework for corporate XAI, creating methods for assessing explanation reliability, and deploying hybrid architectures that combine interpretable models with high-performance algorithms for delivery tasks.

REFERENCES

[1] Ahmed, I., Kumara, I., Reshadat, V., Kayes, A. S. M., van den Heuvel, W.-J., & Tamburri, D. A. (2022). Travel time prediction and explanation with spatio-temporal features: A comparative study. Electronics, 11(1), 106. https://doi.org/10.3390/electronics11010106

[2] Brahimi, N., Zhang, H., & Razzaq, Z. (2025). Explainable spatio-temporal inference network for car-sharing demand prediction. ISPRS International Journal of Geo-Information, 14(4), 163. https://doi.org/10.3390/ijgi14040163

[3] Bruni, M. E., Fadda, E., Fedorov, S., & Perboli, G. (2023). A machine learning optimization approach for last-mile delivery and third-party logistics. Computers & Operations Research, 157, 106262. https://doi.org/10.1016/j.cor.2023.106262

[4] Chang, X., Wu, J., Kang, Z., Pan, J., Sun, H., & Lee, D.-H. (2024). Estimating emissions reductions with carpooling and vehicle dispatching in ridesourcing mobility. npj Sustainable Mobility and Transport, 1, Article 16. https://doi.org/10.1038/s44333-024-00015-3

[5] Kosasih, E. E., Papadakis, E., Baryannis, G., & Brintrup, A. (2023). 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

[6] Kostopoulos, G., Davrazos, G., & Kotsiantis, S. (2024). Explainable artificial intelligence-based decision support systems: A recent review. Electronics, 13(14), 2842. https://doi.org/10.3390/electronics13142842

[7] Olan, F., Spanaki, K., Ahmed, W., & Zhao, G. (2024). Enabling explainable artificial intelligence capabilities in supply chain decision support making. Production Planning & Control, 36(6), 808–819. https://doi.org/10.1080/09537287.2024.2313514

[8] Rokoss, A., Syberg, M., Tomidei, L., & others. (2024). Case study on delivery time determination using a machine learning approach in small batch production companies. Journal of Intelligent Manufacturing, 35, 3937–3958. https://doi.org/10.1007/s10845-023-02290-2

[9] Sadeghi, K. R., Ojha, D., Kaur, P., Mahto, R. V., & Dhir, A. (2024). Explainable artificial intelligence and agile decision-making in supply chain cyber resilience. Decision Support Systems, 180, 114194. https://doi.org/10.1016/j.dss.2024.114194

[10] Sattar, M. U., Dattana, V., Hasan, R., Mahmood, S., Khan, H. W., & Hussain, S. (2025). Enhancing supply chain management: A comparative study of machine learning techniques with cost–accuracy and ESG-based evaluation for forecasting and risk mitigation. Sustainability, 17(13), 5772. https://doi.org/10.3390/su17135772