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The Role of Explainable AI in Enhancing Trust and Transparency in Supply Chain Risk Mitigation

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Abstract

Increasing complexity of global supply chains along with opacity of the traditional AI models brought out the need for Explainable Artificial Intelligence (XAI) for improving the trust and transparency in risk mitigation. This systematic review investigates the effect that XAI techniques have to the degree of trust and decision-making transparency among stakeholders on supply chain risk Management. Databases such as Scopus, Web of Science, IEEE Xplore, and other databases result in the identification of 21 studies from an earlier 160 records in a rigorous selection process. Inclusion of studies had been done based on the empirical or conceptual application of XAI in supply chain risk contexts. The findings demonstrate that post-hoc explanation methods such as SHAP, LIME, counterfactuals are widely used across transportation, supplier assessment, cyber resilience, fraud detection applications. Consistently, integration of XAI improves interpretability of AI decision outcomes, develops trust in stakeholders, and is useful for complying with regulatory and governance standards. However, there are many applications that remain as concept or prototype, and with little real world longitudinal studies. The synthesised findings while discussing how to improve the XAI methods discuss the need of the industry specific XAI frameworks that are scalable, adaptive and are sensitive to the varied interpretability requirement of supply chain stakeholders. The limitations are the qualitative nature of the synthesis, variation of the study designs and limited empirical validation for the long-term trust impacts. Future research recommends longitudinal case studies, scalability testing across the complex global supply chains, as well as pure scientific work on human AI collaboration dynamics, so as to establish the application of trustworthy and explainable AI systems in the supply chain management.

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Keywords: Explainable Artificial Intelligence (XAI), Supply Chain Risk Management, Trust in AI Systems, Transparency in Decision-Making, Ethical AI in Supply Chains

1. Introduction

1.1 Literature Review

Organisations have recognised the need to utilise Artificial Intelligence (AI) and Machine Learning (ML) in increasing risk management as a result of the increasing complexity and vulnerability of global supply chains, exacerbated by events like the COVID-19 pandemic. AI and ML can significantly enhance the resilience of the supply chain, for instance, by expanding capabilities like interconnectedness, transformability and sharing that are critical for overcoming disturbances, as has been shown by the research (Li *et al*., 2023) [20]. However, advanced deep learning techniques such as recurrent neural networks and temporal convolutional networks have shown very high accuracy in predicting shipment risks and therefore can introduce proactive decision-making during crises (Bassiouni *et al*., 2022). In addition, Zamani *et al*. (2022) state that AI and Big Data analytics can improve different aspects of supply chain resilience, from recovery readiness, helping to manage resources more efficiently. With organisations adjusting to the new post-COVID world, it is expected that these technologies shall integrate with existing supply chain strategies to contribute to an overall increased supply chain agility (Panwar *et al*., 2022) [34].

In high-stakes decision-making environments, black box systems used in traditional AI are less suitable and present serious challenges in light of the opacity of such systems. Often, these models are opaque, and stakeholders have frequently found it difficult to validate AI recommendations created by these models, which often causes trust deficits in the users (Robles & Mallinson, 2023; Rudin, 2019) [39]. The research shows that it is preferable to develop inherently interpretable models that can explain these opaque models (Rudin, 2019) [39]. There are profound moral implications surrounding the use of opaque algorithms as they interfere with an individual's autonomy by preventing them from making informed choices that correspond to their goals (Vaassen, 2022) [41]. In addition, different international bodies have echoed the demand for transparency in AI, which requires that the balance between design and critique reduces more just technological systems (Hollanek, 2020). However, solving these transparency issues is necessary to establish public faith and the responsible governance in the AI. (Robles & Mallinson, 2023; Zerilli, 2022) [45].

As a response to opacity of complex machine learning systems, Explainable Artificial Intelligence (XAI) has recently become a critical tool in being able to make AI decisions more interpretable in a variety of domains including supply chain management. The application of XAI can elucidate the rationale of critical recommendations like supplier substitution and fraud detection, which are increasingly prescribed as an ethical and regulatory demand in alignment with AI governance and ESG standards (Dwivedi *et al*., 2022; McDermid *et al*., 2021; Ridley, 2022) [24, 37] (Ridley, 2022) [37]. However, XAI techniques developed tend to prioritise interpretability over completeness at the cost of its repercussions on completeness, but are indispensable in ensuring that the users understand and trust AI outputs (Zerilli, 2022) [45]. It also emphasizes the need to choose appropriate XAI methods and frameworks for implementing XAI in critical applications against this growing demand for transparent AI systems (Rawal *et al*., 2021) [36].

However, while explainable artificial intelligence (XAI) can provide benefits to the integration in supply chain risk mitigation, much of this work is still to be done. AI used for optimising logistics and inventory still dominates current literature, but lacks interpretability (Hendriksen, 2023; Nimmy *et al*., 2022) [15, 27]. Lack of explainability in AI systems leads to challenges for effective risk management, as operational risk managers might need auditable techniques to learn the rationale of the AI-generated outputs (Nimmy *et al*., 2022) [27]. Additionally, sharing information for effective risk mitigation strategies based on the importance of information sharing and trust in buyer-supplier relationships (Chen *et al*., 2016) [11], it is also necessary to promote trust through forging AI reasoning. Graph neural networks can provide unique approaches for deriving insight and identifying hidden risks in complex supply chains to more accurately make decisions in supply chains (Kosasih *et al*., 2022). Supply chain stakeholders are heterogeneous, and thus supply chain XAI systems should be tailored to their needs separately, with technical analysts and procurement officers having different interpretability needs. However, according to research, current frameworks don't always work with these various requirements; therefore, if AI systems are not transparent and engaging with users, they can become inefficient operations (Balayn *et al*., 2024; Chen & Storchan, 2021) [5, 12]. Balayn *et al*. (2024) [5] conducted a qualitative study with 71 stakeholders to demonstrate the importance of knowing who the user is, what he need information for, and why it matters for designing the AI responsibly. It also suggests that the existence of a stronger needs gap between developers and non-developers is evidence of the need for contextual XAI solutions tailored for particular business applications (Calderon & Reichart, 2024) [8]. While there exists an abundance of learning algorithms in large training datasets, the interpretability of these algorithms is often limited (Prasath & Priya, 2024) [35]. Essentially, without taking the needs of these stakeholders into account, organisations are at risk of adopting technologically sound, but operationally ineffective AI (Chen & Storchan, 2021) [12].

To fill this critical knowledge gap, this systematic review conducts a state-of-the-art review on how Explainable AI can promote the trust and transparency of supply chain risk mitigation research. More specifically, it synthesises prior literature on the types of XAI techniques that exist, the resultant outcomes of using them as tools, and the challenges of doing so in an organisation (Figure 1).

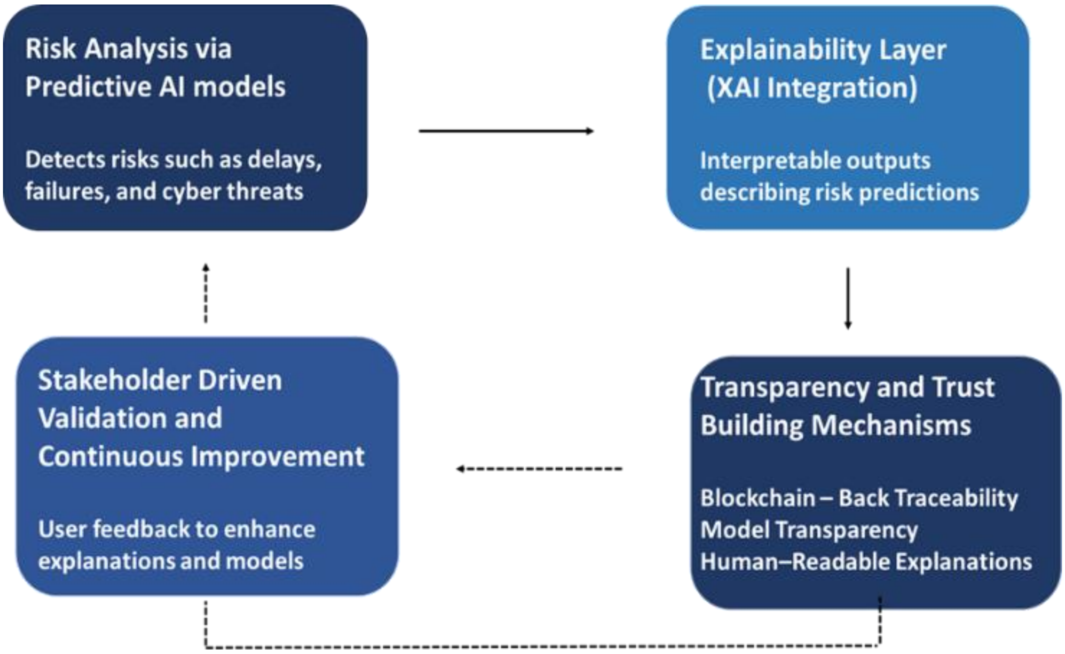

Fig 1: Conceptual framework of the study

1.2 Research Questions

A set of research questions are answered by the review as follows:

- What types of Explainable AI (XAI) techniques have been used in supply chain risk mitigation, and are they effective solutions in increasing supply chain risk decision-making transparency?
- How does the incorporation of XAI influence stakeholder trust in AI-enabled supply chain risk assessment tools?
- What are the significant challenges and limitations in the practicality of implementing XAI in the real-world supply chain system?
- How can the frameworks or best practices be implemented for a combination of XAI to transparent and accountable supply chain operations in terms of ethical governance?

In particular, this review answers some of the questions towards providing the foundation for developing more trustworthy, interpretable and ethically aligned AI systems in supply chain risk management. As such, it also intends to educate practitioners, policymakers, and researchers about how XAI can be used as a technical change, but also as an enabler of reshaping responsible innovation at the global logistics systems level.

2. Methods

2.1 Selection Criteria

Articles were selected based on the carefully defined criteria below, to ensure relevance to the research objectives.

Inclusion criteria focused on studies that:

- Applied the Explainable Artificial Intelligence (XAI) techniques (eg SHAP, LIME, counterfactuals etc) within supply chain risk mitigation focus areas.
- Empirically provided evidence for how XAI has improved trust or transparency of supply chain decisions through (case study) analysis and/or prototype applications.
- Risk mitigation areas were addressed for logistics, supplier management, cyber resilience, operational disruption, customer churn, or fraud detection in supply chain systems.
- Conceptual frameworks or governance models explicitly connecting XAI to more transparent, accountable and trustworthy supply chain decision making.

Exclusion criteria omitted studies that:

- It was based on purely theoretical discussion or lacked empirical, applied, or case-based exploration of XAI (i.e., without real-world application or example).
- Without worrying about interpretability, explainability, transparency, and trust in situations of generic AI or machine learning in supply chain management.
- It did not discuss the supply chain optimisation in the context of risk mitigation or ethical AI governance.
- Discuss regulatory / policy topics other than the context of operational-level supply chain decision making.

From a pool of over 160 records reported across databases and citation chaining, 21 studies were selected from those that went into detail on XAI applications for supply chain risk mitigation, amongst 139 studies that were excluded upon full text review if they fail to cover transparency, trust, or explainability outcomes on supply chain risks.

2.2 Search strategy and string construction

A search strategy that accounted for relevant literature was created. Scopus, IEEE Xplore, Web of Science and Science Direct were utilised in four electronic databases. A search string was formed by combining keywords on "Explainable AI", "supply chain", and "risk" using Boolean operators (AND, OR) (Table 1). The research looked at practical studies published during this time to depict current advancements and to track the development of technology in the field within its timescale, sufficient enough to illustrate the nature of development of technology and the basics on which technologies rely.

Table 1: Search String

Combination of Keywords
("Explainable Artificial Intelligence" OR "Explainable AI" OR "XAI" OR "Interpretable Machine Learning" OR "Transparent AI")
AND
("Supply Chain" OR "Supply Chain Management" OR "SCM" OR "Supply Network" OR "Supply Logistics")
AND
("Risk" OR "Supply Chain Risk" OR "Operational Risk" OR "Supply Chain Disruption" OR "Trust")

2.3 Study Selection Process
A two-phase screening approach of the study selection was implemented according to the PRISMA guidelines. Titles and abstracts were initially screened to select papers that were not related to our objective. Consequently, eligible full text articles were then assessed against the predefined criteria for inclusion. It documented reasons for exclusion, especially if a study had been excluded on the grounds that it discussed AI applications without an XAI component, did not refer to an XAI issue in a supply chain context (or assessed an issue in non supply chain context) and had focused on an outcome that was not some kind of trust, transparency and risk mitigation issue. A detailed study selection process will be illustrated by a PRISMA flow diagram (Figure 2).

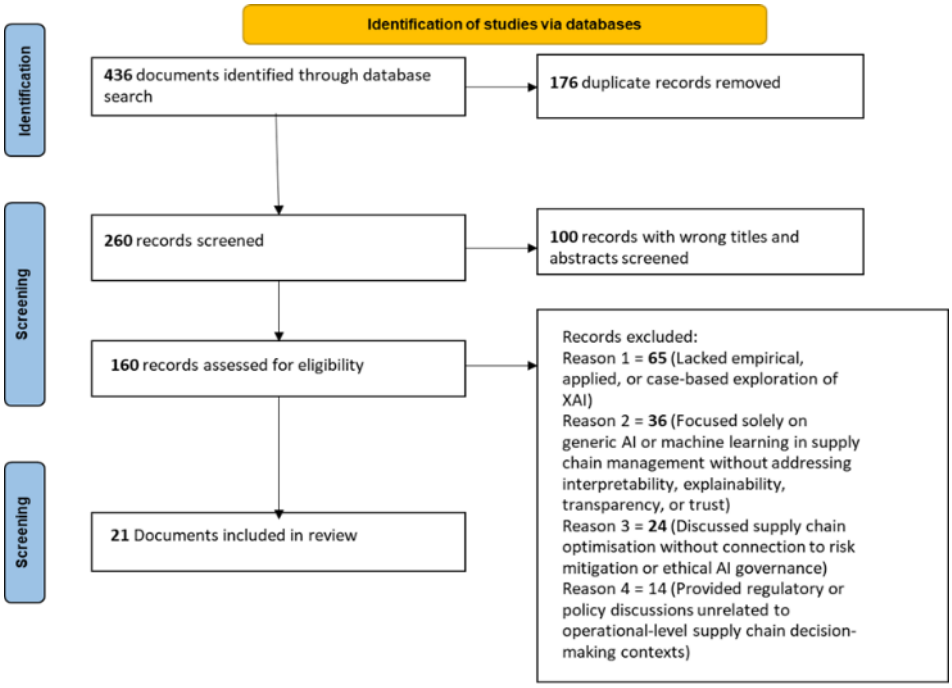

Fig 2: Study selection process

2.4 Data extraction process
Data from the included studies were extracted systematically using a structured data extraction form. Fields captured were Author (s), Year of Publication, Geographical Region, Industrial Sector, Specific AI Technique Used, XAI Method Used, Type of Supply Chain Risk Targeted, Transparency Outcome, Trust Outcome, Evaluation Metrics Used, and Implementation Level (concept, prototype, real-world use). In this way, the consistency across diverse studies was assured, and this then allowed for the thematic synthesis.

2.5 Data synthesis approach
Due to the diversity present in studies, sectors and opioid pain XAI applications, a narrative synthesis was appropriate. The themes for this were identified employing thematic analysis, first, but recurring patterns of how XAI promotes trust, transparency and risk mitigation. Key characteristics and findings of the included studies were summarized in a tabular format to compare easily. The relationships between each XAI method and risk type and outcome were also visualized through concept maps and charts so that the interpretation of the synthesis better represents the results in this area.

3. Results and discussion
Table 2 lists the 21 relevant studies found in this systematic review. The results were synthesized to show strong thematic alignment in the form of the type of XAI techniques applied, the transparency outcomes delivered, the trust dynamics shaped, the decision-making context, and the gaps that need to be filled. According to the results, they are organized in five key thematic areas that directly address research questions that try to fill research gaps characterized.

3.1 Application of XAI techniques in supply chain risk mitigation
Different categories of supply chain risks were addressed

with different types of XAI techniques used within across the selected studies. Most of these were employed as post-hoc explanation methods like SHAP and LIME which help in building interpretability of machine learning predictions in critical domains like transportation accident risks (Abdulrashid *et al*., 2024) [1], supplier segmentation (Arantes, 2024) [4], and cybersecurity resilience (Sadeghi *et al*., 2024) [40]. They also showed how counterfactual explanations could be successfully integrated into transportation scheduling systems (Ordibazar *et al*., 2021) [32] to help in more robust and interpretable logistics planning. Matthew & Ebiniyi (2025) [23], Ogunyankinnu *et al*. (2022) [28] also proposed Blockchain-XAI hybrid models as novel methods for solving traceability and transparency problems throughout distributed supply chain systems. According to Caruana *et al*. (2015) [9], building inherently interpretable models such as Explanable Boosting Machines (EBMs) or Generalised Additive Models (GAMs) usually results in a better trade-off of transparency versus accuracy than seeking out post hock explanations on models that are inherently black box.

3.2 Transparency outcomes across supply chain domains

Integrating XAI methods lead to a consistent outcome across the studies in terms of the enhancement of transparency in the supply chain decision-making processes (Figure 3). As an example, Abdulrashid *et al*. (2024) [1] showed that post hoc explanations will help improve the stakeholders' understanding of their risk predictions, thus resulting in safer logistics systems. Arantes (2024) [4] also demonstrated that transparent model outputs helped to clarify supplier segmentation results and increase sourcing confidence of procurement teams in the area of supplier management. In blockchain-integrated supply chains, product traceability also became more transparent in real time, resulting in increased operational efficiencies and increased but more importantly, more consumer trust in the food and pharmaceutical sectors (Bhatia & Albarrak, 2023; Oluwagbade *et al*., 2023) [7, 31]. Also, governance-oriented works like Olateju *et al*. (2024) [30] and Varošanec (2022) [42] indicate increasing demand for explainability in regulatory compliance and developing algorithmic transparency frameworks for shaping the future supply chain governance practices. In terms of the broader logistics and digital ledger literature, in this work, Casino *et al*. (2019) [10] indicate that blockchain alone is not sufficient to ensure transparency, but it is necessary to complement it with human-readable explanations for all the recorded transactions processed by the blockchain.

3.3 Trust outcomes through explainable decision-making

An important result of the XAI implementation was that building and maintaining stakeholders' trust was a key outcome. While several studies had shown that increasing trust in AI-generated decisions occurred when users could validate and interpret those decisions. For instance, Abdulrashid *et al*. (2024) [1] found that models with better interpretability had higher trust in risk management models of accidents. Arantes (2024) [4] also found that transparent segmentation models improved more reliable procurement decision-making in supplier evaluation contexts. Sadeghi *et al*. (2024) [40] showed that explainable outputs enabled quick and confident responses to the cybersecurity threat in several works. In addition to technical trust, blockchain-backed XAI models promoted organisational trust at a systemic level because of data immutability and traceable verification mechanisms (Matthew & Ebiniyi, 2025; Bhatia & Albarrak, 2023) [23, 7]. This was supported by real-world case studies that included the Volvo AB implementation looked at by Hiljemark and Nika (2024) [16], which offered evidence that explainable AI-supported resilience strategies might be more likely to garner managerial acceptance in high-stakes disruptions. Cheng *et al*. (2023) [13] have recently conducted longitudinal research that demonstrates temporal fluctuations in trust in AI systems according to how performance, perceived fairness and practice in feedback adapt to the system. Amershi *et al*. (2019) [3] showed that explanations need to be adapted dynamically to be effective, and that they can only be effective if explanations match the technical expertise and accomplishing goals of end users.

Table 2: The Role of Explainable AI in Enhancing Trust and Transparency in Supply Chain Risk Mitigation

Citation	Study Methodology	XAI Technique Used	Supply Chain Risk Type	Transparency Outcome	Trust Outcome	Decision-Making Context	Domain/Industry	Implementation Level
Abdulrashid *et al.* (2024) [1]	Empirical modeling and simulation	SHAP, LIME	Transportation/Logistics (road accidents)	Increased interpretability of accident predictions	Enhanced stakeholder confidence in safety recommendations	Accident risk management	Transport Logistics	Applied in simulation case study
Allaparthi (2024) [2]	Conceptual & applied AI models	Not specified (implies post-hoc XAI)	Fraud detection, authenticity	Improved anomaly detection clarity	Reinforced data trustworthiness	Detection of counterfeit products	General Supply Chains	Early conceptual
Arantes (2024) [4]	Mixed-method doctoral research	LIME, SHAP	Supplier risk (quality/financial)	Enhanced model explainability for supplier segmentati	More reliable supplier classification	Supplier assessment/segmentation	Manufacturing	Implemented in real case study

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Table 3: The Role of Explainable AI in Enhancing Trust and Transparency in Supply Chain Risk Mitigation Cont'd.

Citation	Study Methodology	XAI Technique Used	Supply Chain Risk Type	Transparency Outcome	Trust Outcome	Decision-Making Context	Domain/Industry	Implementation Level
Bhatia & Albarrak (2023) [7]	Technical implementation using blockchain + Faster RCNN	Custom visual XAI overlays	Food supply security, traceability	Real-time traceability of items	High customer trust through transparency	Food logistics	Food Supply Chain	Prototype development
Hiljemark & Nika (2024) [16]	Case study (Volvo AB)	Not explicitly stated	Disruption/ resilience risk	Improved risk visualization	Strengthened supply continuity strategies	Enterprise risk planning	Automotive	Real-world application
Jauhar *et al.* (2024) [18]	Simulation + customer behavior modeling	XGBoost + XAI explanation layers	Perishables demand risk	Transparent matching of demand signals	Better alignment with customer needs	Demand responsiveness	Perishable goods supply chain	Tested in model scenario
Li *et al.* (2025) [21]	Deep learning + survival analysis	SHAP, Integrated Gradients	General resilience, disruption	Model interpretability for risk timing	Increased trust in survival forecasts	Long-term risk mitigation	Cross-sector supply chain	Full-stack implementation

Table 4: The Role of Explainable AI in Enhancing Trust and Transparency in Supply Chain Risk Mitigation Cont'd.

Citation	Study Methodology	XAI Technique Used	Supply Chain Risk Type	Transparency Outcome	Trust Outcome	Decision-Making Context	Domain/Industry	Implementation Level
Liu & Chan (2024) [22]	Conceptual framework	XAI integrated into AI-CRM model	Customer compatibility risk	Enhances customer understanding of AI decisions	Supports loyalty through AI trust	CRM and fulfillment	Retail	Conceptual proposal
Matthew & Ebiniyi (2025) [23]	Blockchain-XAI hybrid framework	Model-agnostic explanations	Transparency/traceability risks	Full data visibility	Trust enhanced through data immutability	Secure data sharing	Cross-sector	Applied framework
Mittal (2023) [25]	Prototype development	Not explicitly stated	Multi-risk (delay, disruption)	Visual dashboards for decision aid	User confidence in automated suggestions	Early warning systems	General SCM	Prototype stage
Nimmy (2024) [26]	Systematic review	Various (focus on interpretability)	Operational risks	Evaluation of model explainability	Emphasizes need for trustworthy outputs	Operational decision support	General SCM	Review-level insights

Table 5: The Role of Explainable AI in Enhancing Trust and Transparency in Supply Chain Risk Mitigation Cont'd.

Citation	Study Methodology	XAI Technique Used	Supply Chain Risk Type	Transparency Outcome	Trust Outcome	Decision-Making Context	Domain/Industry	Implementation Level
Ogunyankinnu *et al.* (2022) [28]	Conceptual framework	Not specified	General supply chain risks	Blockchain + AI supports traceability	Reinforces integrity of decisions	Cross-supply data verification	General	Theoretical
Olan *et al.* (2025) [29]	Conceptual + model proposal	Model-agnostic XAI methods	Decision-making risk	Enhances auditability of decisions	Establishes accountable AI support	Strategic SCM decisions	Logistics & planning	Conceptual level
Olateju *et al.* (2024) [30]	Governance framework paper	XAI for data usage clarity	Customer data handling risk	Promotes clear data use policies	Bolsters trust in data systems	Info governance	Data-intensive industries	Policy-level proposal

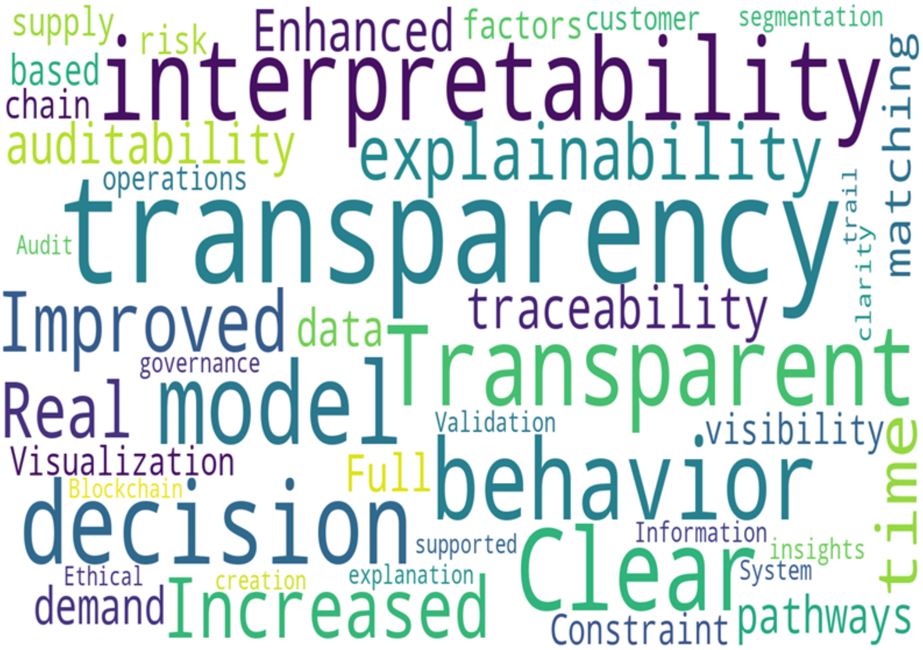
Oluwagbade *et al.* (2023) [31]	Governance lifecycle model	Post-hoc explainability in drug SCM	Bias, validation, equity risks	Ensures validation transparency	Supports fair AI in health SCM	Pharma validation processes	Pharmaceutical	Framework development
Oubelaid *et al.* (2023)	ML model for churn	SHAP	Customer churn	Clear factors behind churn risk	Greater user trust in predictions	Churn prediction & retention	Retail/customer SCM	Model testing phase

Table 6: The Role of Explainable AI in Enhancing Trust and Transparency in Supply Chain Risk Mitigation Cont'd.

Citation	Study Methodology	XAI Technique Used	Supply Chain Risk Type	Transparency Outcome	Trust Outcome	Decision-Making Context	Domain/Industry	Implementation Level
Ordibazar *et al.* (2021) [32]	Recommender system + optimization	Counterfactual Explanation	Transportation delay risk	Constraint-based interpretability	More reliable scheduling	Transport planning	Transport logistics	Tested on real case
Pal (2023) [33]	Theoretical discussion	Not specified	Sustainability & visibility	Framework to improve transparency	Trust as sustainability enabler	Circular SCM	Sustainable SCM	Conceptual stage
Sadeghi *et al.* (2024) [40]	Model development	SHAP, LIME	Cybersecurity threats	Better understanding of cyber attack pathways	Trust in AI responses to breaches	Cyber risk planning	Cyber-physical systems	Operational model
Varošanec (2022) [42]	Regulatory analysis	N/A (policy-level)	AI transparency regulation	Defines standards for explainability	Trust via regulatory compliance	Legal/policy context	EU Regulatory	Policy-level paper
Zolanvari *et al.* (2021) [46]	Case study on IIoT	TRUST XAI (model-agnostic)	Security risk in IIoT	Detailed post-hoc model output	Improves human-AI trust	IIoT anomaly detection	Industrial IoT	Real-world demo

3.4 Decision-making contexts and industry adoption

On the decision making levels, as well as industry sectors, there were many explainable AI applications. XAI has early field implementations in the transport logistics and cyber physical supply chain sectors because live testing was feasible and critical (Abdulrashid *et al.*, 2024; Zolanvari *et al.*, 2021) [1, 46]. However, most of the XAI applications in other areas, e.g., supplier risk evaluation, fraud detection, demand responsiveness in perishables, remained stuck in the prototype, simulation or conceptual framework stage. However, there is a trend in data governance studies that considered the desire for transparent AI practices in sectors where sensitive customer or compliance data is being explored (Olateju, *et al*., 2024; Oluwagbade *et al*., 2023) [24, 31]. In addition, research by Varošanec (2022) [42] on regulatory driven research showed that policy frameworks have increasingly become incorporated into provisions for transparency regarding AI that are required across European and global supply chains. However, the maturity of XAI implementation was clearly not of the same level, as many cases such as the Volvo case study indeed reported on operational deployments. According to Wamba *et al.* (2021), there are additional challenges to digital adoption, even in the AI and XAI, in emerging economies including infrastructure limitations, regulatory fragmentation and workers skill shortage.



Note: The size of the words reflects the frequency of Transparency outcomes reported in studies

Fig 3: Word cloud representing the Transparency outcomes identified across the included studies.

4. Proposed framework and future directions

4.1 A synthesised framework for xai-enabled risk mitigation

Based on the ideas from reviewed studies, a synthesised framework for XAI-supported supply chain risk mitigation can be suggested. It is organised in four pillars, integrated: Risk Identification using AI Models, XAI layer for Interpretability and Trust and Transparency, Stakeholder-driven Validation and Feedback. AI models first predict problems in a supply chain with predictive analytics and then detect anomalies. The second layer is using XAI techniques, like SHAP, LIME or counterfactual explanations, to provide interpretable outputs about what predicts to generate justification for predictions (Abdulrashid *et al*., 2024; Arantes, 2024; Sadeghi *et al*., 2024) [1]. After which, trust and transparency mechanisms, for instance, blockchain-XAI hybrids are embedded, to provide visibility of data and decision pathway (Matthew & Ebiniyi, 2025; Bhatia, 2023) [23, 7]. Next, there exist stakeholder feedback loops that are supported by governance structures, which in turn allow for continuous model refinement based on user trust perceptions and transparency audits (Olateju *et al*., 2024; Oluwagbade *et al*., 2023) [30, 31]. The dynamic, iterative model of this model makes XAI not only detect risk, but also one that continues to evolve to address the needs of trust and transparency within the myriad ecosystems of supply chains.

4.2 Guidelines for implementation (industry and research)

Structured approaches to implement XAI-enabled risk mitigation strategies are particularly important for successful implementation in the industry as well as academic settings. Organisations should start by requiring explainability within AI procurement and development policies, which will then cascade down to the industry. Interpretable models should be broadly included in decision support systems for supply chains, using SHAP, LIME, and more generally model-agnostic frameworks at key points of risk decision (Li *et al*., 2025; Olan *et al*., 2025) [21, 29]. Companies in highly regulated sectors, including the pharmaceuticals and food supply chains, are encouraged to put XAI systems based on blockchain to use as they could provide enhanced traceability and data immutability (Oluwagbade *et al*. 2023; Matthew and Ebiniyi 2025) [31, 23].

Training of supply chain managers and risk officers needs to focus on the building of AI literacy such that they can learn to interpret XAI outputs and use them for making risk-sensitive decisions. Furthermore, firms should adopt continuous auditability through the setting of governance protocols like those proposed by Olateju *et al*. (2024) [30] to ensure that explainability standards are maintained for the AI model's lifecycle. Future experiments, however, should bring together stakeholder-centred evaluation designs to measure the change and user trust and decision confidence when explainable systems are used. Additionally, computer scientists will need to collaborate with supply chain experts and behavioural scientists to create technically sound, organizationally adoptable XAI systems that are not only human-centred but scalable as well (Nimmy, 2024 and Liu & Chan, 2024) [26, 22].

4.3 Recommendations for future empirical and applied research

Much progress has, however, been made, but several avenues remain unrealised. Secondly, more investigations are required in terms of how trust in XAI evolves in the consecutive periods of XAI corporation in actual supply chain operations. Existing studies most frequently evaluate trust immediately after interaction with the model, but fail to evaluate sustained development and decay of trust. Research on the scalability challenges should also include focusing on how XAI models can be adapted for scaling with large-scale, global supply chains that have complex, multi-tier supply networks. In addition, it encompasses how the tradeoffs in terms of a model's complexity, transparency, and real-time performance in operational settings.

Cross-sectoral studies that study XAI adoption across different industries, including manufacturing, healthcare logistics, food distribution, and high-tech electronics, can be done to study how domain-specific barriers and enablers play. Additionally, research must look to XAI for its applications in the development of emerging economies where transparency acts as an antidote for high-risk vulnerabilities due to political instability, unattractive and weak regulatory frameworks, and logistical fragility. Future work should then concentrate on the dynamics of human-AI collaboration in risk mitigation tasks regarding how various types of explanations (for example, visual, verbal, counterfactual) alter decision maker trust, speed, and accuracy. Addressing these research directions can lead the field towards building XAI systems by supply chain stakeholders by predicting risks and earning their global trust in the long term.

5. Conclusion

The findings of this review offer compelling evidence of Explainable Artificial Intelligence (XAI) as having an important role in reducing distrust, enhancing transparency and rising to increase resilience in supply chain risk management. SHAP, LIME, counterfactual explanations, and models that combine blockchain with others have been used across various industries, including transportation logistics, manufacturing, food supply chain, and pharmaceuticals, to deal with operational risks. Results show that stakeholders trust supply chain risk assessment tools greatly, and increase trust when they are given interpretable, transparent insights into AI-driven decision-making processes, allowing informed, timely, and ethical decisions. In addition, the review evidences that transparency is not a technical feature but the central enabler of regulatory compliance, ethical governance, and stakeholder confidence, especially in the context of the sensitive supply chain domain.

However, huge gaps remain even though there have been these advances. Research was carried out describing the proof of concept or early-stage applications of this technology, with very few showing longitudinal impact on trust or scalability across global, complex supply chains. XAI has not been fully integrated into the operational environment, often in the form of pilot deployments or conceptual frameworks, rather than large-scale enterprise deployment. Moreover, while there are still few research results in emerging economies, the measures undertaken to increase transparency and trust within supply chains can curb these systemic vulnerabilities in the economy. However, there is an urgent need for more longitudinal, empirical studies about the evolution of trust in XAI systems and studies that explain how explainability frameworks can cover more without losing operational efficiency as well as interpretability.

5.1 Limitations of the study

The review is largely qualitative, and thematic synthesis is used because the applications of XAI and supply chain contexts vary. Lack of quantitative meta-analysis prevents researchers from generalising statistically across sectors. Inconsistencies were introduced from variations in study maturity, from conceptual frameworks to operational deployments, and potential publication bias affected the results towards positive case reports. Furthermore, the search was limited to English language sources from major databases, which may have resulted in missing other non-English or grey literature. At the same time, the review failed to recognise explainability practices in other supply chain operations areas, which could also provide complementary insights into how XAI can be leveraged within the supply chain. The majority of included studies were in early conceptual or prototype stages and thus made it uncertain any long-term impacts from XAI adoption. Finally, changes in XAI and supply chain technology occur at such a rapid pace that some findings may quickly become dated, and yet more dynamic review approaches are required to capture this emerging development.

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