*International Journal of Innovation and Modern Applied Science*

*Vol. 12 Issue 01 , July 2026*

*Doi : https://doi.org/10.57109/8304*

**ISSN No.: 665-8984**

# Integrating explainable AI into logistics information systems to enhance confidence in decision-making

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**ABSTRACT: Logistics Information Systems (LIS) are increasingly leveraging Artificial Intelligence (AI) to enhance forecasting accuracy, scheduling efficiency, routing optimization, and inventory control. Yet, the opaque or "black box" nature of many AI models often limits their acceptance by decision-makers who demand transparency and accountability. This paper introduces a conceptual and experimental framework for embedding Explainable Artificial Intelligence (XAI) within LIS. The objective is to make algorithmic decisions more interpretable, foster user trust, and support system auditability.**

**A prototype focusing on demand forecasting was developed and tested through a comparative evaluation between traditional black-box models and explainable models. The findings highlight a balanced improvement between predictive accuracy, user understanding, and satisfaction. The paper concludes with user feedback and recommendations for advancing transparent, trustworthy, and human-centered AI applications in logistics.**

**Keywords:** Explainable Artificial Intelligence (XAI), Logistics Information Systems (LIS), transparency, trust, supply chain management, demand forecasting.

## 1. INTRODUCTION

Over the past decade, logistics has undergone a dramatic transformation driven by the combined effects of digitalisation and artificial intelligence (AI). Supply chains, once seen as rigid and linear structures, are now becoming intelligent, interconnected and predictive.

Logistics information systems (LIS) play a vital role in this transformation: they coordinate physical and information flows, facilitate traceability, and support large-scale operational decisions. Thanks to advances in AI, these systems no longer merely describe or record events; they anticipate needs, identify anomalies and propose optimal scenarios in real time (Sadeghi et al., 2024).

However, this growing intelligence comes with a paradox: the more effective the models are, the less comprehensible their decisions become. Complex algorithms — such as deep neural networks or hybrid 'Deep Forecasting' models — offer remarkable accuracy, but their internal logic often remains inaccessible to users.

In a context where logistics decisions have significant economic and social consequences, this opacity poses a real problem. Planners, managers and quality control officers are sometimes faced with recommendations that they can neither explain nor justify (Olan et al., 2024). This is the phenomenon that the literature refers to as the 'black box of artificial intelligence'.

However, in the logistics sector, transparency is a fundamental requirement: it underpins trust, accountability and regulatory compliance. New European policies, notably the AI Act and the ISO/IEC 23894:2023 guidelines, also emphasise the need for AI that is "reliable, traceable and explainable".

In other words, it is no longer enough for AI simply to work: it must also be understood (Van Hoek, 2023).

To address this challenge, researchers and engineers have developed an emerging approach: explainable artificial intelligence (XAI). Its aim is not to simplify models, but to make their reasoning transparent.

XAI provides, for example, indicators of the variables influencing a prediction, or local explanations for each decision: why did the model predict an increase in demand on that day? Which factors (price, weather, delivery time, volume) had the greatest influence on the result?

Recent research shows that explainability is a key driver of trust and acceptance. When an AI system is able to justify its recommendations, users tend to regard it as more credible and rely on it in their day-to-day decision-making (Ghosh et al., 2024).

In logistics, this can lead to better collaboration between humans and machines: the planner becomes an active participant, able to interpret, correct or validate the decision rather than simply accepting it (Zhu et al., 2025). However, despite this growing interest, XAI remains understudied in real-world logistics environments. Most research focuses on algorithmic performance, without examining the user experience or the impact of explainability on decision-making. It is precisely this gap that this article seeks to address.

Our work aims to examine how the integration of explainable AI into a logistics information system can boost user confidence whilst maintaining predictive performance.

To this end, we draw on an experimental framework applied to demand forecasting, combining a machine learning model (LightGBM) with an explanation module based on the SHAP method.

The study aims to measure not only the technical quality of the model, but also user perception and satisfaction, through a human- and decision-centred approach. From a scientific perspective, this research aims to contribute to our understanding of the conditions necessary for the adoption of trustworthy AI in logistics. From a practical perspective, it offers concrete recommendations for companies seeking to balance technological innovation with transparency in decision-making.

## 2. LITERATURE REVIEW

### *2.1. The rise of AI in logistics systems*

Artificial intelligence has established itself as an indispensable tool in modern logistics. It helps to forecast demand, plan delivery routes, manage warehouses and improve traceability. However, the more powerful the models become, the harder it is for users to understand their decisions.

In logistics information systems (LIS), this loss of transparency creates a trust issue: operational managers are reluctant to implement recommendations they cannot explain (Olan et al., 2024). Previously, supply chains operated according to hierarchical and often rigid models, based on pre-established rules. The advent of machine learning, big data and the Internet of Things (IoT) has radically transformed this approach.

Modern supply chain information systems now continuously collect data from multiple sources — sensors, ERP systems, carriers, e-commerce platforms — and analyse it to produce a unified view of the entire chain (Sadeghi et al., 2024).

*a- Artificial intelligence as a driver of predictive logistics*

One of the most significant changes concerns demand forecasting, an area that has historically been prone to uncertainty. Traditional methods, based on linear statistical models, have long shown their limitations in the face of market volatility.

Deep learning algorithms, such as recurrent neural networks (RNNs) or LSTM (Long Short-Term Memory) models, now offer more accurate forecasts, as they simultaneously incorporate external factors (weather, economic trends, customer behaviour) and internal variables (past sales, stock levels, delivery times) (Zhu et al., 2025).

These models also enable the identification of correlations that are invisible to the human eye, thereby transforming data into genuine decision-making tools. In warehouse management, for example, intelligent systems can anticipate labour or equipment requirements based on expected volumes, whilst in transport, AI suggests optimised routes taking into account traffic, energy consumption and contractual deadlines (Olan, Spanaki, Ahmed & Zhao, 2024).

*b- Artificial intelligence: towards autonomous and interconnected logistics information systems*

The integration of AI into LIS is not limited to planning; indeed, it also facilitates the creation of autonomous systems capable of learning and adjusting their actions without direct human intervention.

As a result, smart warehouses tend to utilise computer vision and robotics to automate picking or sorting, whilst smart transport systems, according to Van Hoek (2023), use connected sensors to adjust vehicle routes in real time and avoid delays.

This interconnection between people, machines and data now forms the foundation of Logistics 4.0, in which physical and digital flows operate in sustainable synchronisation.

However, according to studies carried out by several researchers, notably that by Van Hoek (2023), AI delivers significant added value in four main areas:

- Operational performance: reduced lead times and logistics costs;
- Forecast reliability: greater accuracy in inventory and transport planning;
- Supply chain resilience: ability to respond quickly to disruptions (strikes, health crises, component shortages);
- Sustainability: integration of environmental objectives into decision-making models, such as reducing $CO_2$ emissions (Sadeghi et al., 2024).

*c- Artificial intelligence: a challenge of understanding and trust*

Decision-makers are often faced with systems whose decisions are difficult to interpret. This situation creates a tension between performance and transparency.

As Olan et al. (2024) point out, the adoption of AI models in LIS depends as much on their accuracy as on users' ability to understand and trust their results. The literature refers to this as the 'black box paradox': in other words, the more effective a model becomes, the more opaque it becomes.

This issue has led to the emergence of a new field of research: explainable artificial intelligence (XAI). It aims to design systems capable not only of producing reliable results, but also of justifying their decisions to human users.

In the field of logistics, XAI represents a logical extension of this development, as it enables information systems to be made more transparent, auditable and accountable, without sacrificing predictive performance (Ghosh et al., 2024).

The development of AI in logistics systems has thus ushered in a new era: that of smart, interpretable logistics, where technology and people must learn to work together to build supply chains that are more agile, sustainable and trustworthy.

### *2.2. Explainable Artificial Intelligence (XAI): principles and approaches*

In fact, researchers have developed XAI (Explainable Artificial Intelligence), which is a form of artificial intelligence capable of explaining its own decisions.

However, the idea is simple: it is not enough for a model to be accurate; it must also be understandable and justifiable.

Furthermore, two main approaches stem from this:

- Post-hoc methods, which add an explanation after the fact (for example, SHAP or LIME techniques).
- Models that are explainable by design, which incorporate transparency from the outset (decision trees, logical rules).

*a- The lack of transparency in artificial intelligence:*

Explainable artificial intelligence is an approach that seeks to make the decisions of AI models understandable to humans.

Today, in logistics as in other fields, algorithms are capable of analysing millions of data points and proposing highly accurate solutions. However, most of these systems are perceived as 'black boxes', as they produce a result without revealing or demonstrating the reasoning behind it.

According to (Ghosh, Chatterjee & Sarkar, 2024), this situation poses a major problem for logistics managers, who need to understand and justify the decisions generated by these models.

To take an example, when an AI system recommends increasing stock levels or changing a transport route, the decision-maker needs to know the reason:

Is it due to a spike in demand, a supplier delay, or a weather forecast? Without this information, confidence remains limited, even if the decision is correct (Olan, Spanaki, Ahmed & Zhao, 2024).

It is precisely to meet this need that XAI was developed. It does not seek to make models simpler, but to explain their choices in an accessible way.

*b- The fundamental principles of explainable artificial intelligence*

XAI is based on three key principles, which set it apart from traditional approaches to AI:

- Transparency: the model's operation must be visible and understandable. The user must be able to follow the system's reasoning, at least in broad terms.
- Interpretability: the factors influencing a decision must be identifiable. In other words, we must be able to determine which variables (price, lead time, volume, weather, etc.) have the greatest impact on the result.
- Traceability: every prediction or recommendation must be able to be justified retrospectively, in a clear and documented manner (Sadeghi et al., 2024).

These principles therefore meet the new requirements regarding trust and ethics set out in the European AI Regulation and the ISO/IEC 23894:2023 standard, which emphasise the accountability, transparency and security of artificial intelligence systems.

*c- Approaches based on explainable artificial intelligence:*

- *Post-hoc approaches*

These methods are applied after the model has been trained. They do not alter how the algorithm works, but add an “explanatory layer” to it. Among the best-known methods are:

• LIME (Local Interpretable Model-Agnostic Explanations) is a model that creates simplified local models to explain a specific case;

• SHAP (Shapley Additive Explanations) is a method that assigns a weight to each variable in order to show its influence on the final prediction.

Furthermore, these various techniques are extremely useful in logistics information systems. Indeed, they help to explain why a demand forecast is rising, and why a shipment is delayed or an order has been prioritised (Zhu et al., 2025).

- *Explainable models*

Transparency is built into the model from the design stage.The algorithms used are simpler: decision trees, linear models or association rules. The advantage of the latter is that they are immediately comprehensible: we can follow every step of the decision-making process.

However, their limitation is that they are slightly less accurate when dealing with large volumes of data; yet their clarity makes them valuable in logistics environments where decisions need to be understood by multiple stakeholders (Van Hoek, 2023).

*d- The contribution of explainable artificial intelligence to logistics*

Explainable artificial intelligence offers numerous benefits for logistics information systems; we summarise them as follows:

• Increased confidence: users have a better understanding of the model’s decisions and are less hesitant to implement them.

• Decision support: explanations enable the consistency of a forecast or operational decision to be verified.

• Error reduction: by identifying the most influential variables, it becomes possible to detect anomalies well before they occur.

- Better human-machine collaboration: the planner is no longer merely subject to the AI's recommendations but actively participates in the process (Olan et al., 2024; Sadeghi et al., 2024).

Thus, explainable artificial intelligence transforms the way in which businesses perceive artificial intelligence: while it certainly does not replace humans, it does provide them with the means to understand and control the technology.

### *2.3. Methodology for explainable artificial intelligence in logistics*

Recent publications demonstrate a growing interest in explainability within the supply chain:

- Olan et al. (2024) showed that decision-making systems incorporating explainable artificial intelligence increase transparency and collaboration between humans and machines.
- Sadeghi et al. (2024) studied explainable artificial intelligence in logistics crisis management and demonstrated that it helps to respond more quickly in situations of uncertainty.
- Zhu et al. (2025) propose a user-centred approach: in their view, a useful explanation must be simple, visual and linked to business metrics, such as lead times or costs.
- Finally, Van Hoek (2023) points out that explainability fosters trust in AI tools and facilitates their adoption within organisations.

These studies show that XAI is no longer merely a technical matter, but is instead becoming a human and strategic factor for the logistics of the future.

### *2.4. The identified benefits of explainable artificial intelligence*

Among the studies reviewed, there are those that agree on several benefits of explainable artificial intelligence, including:

- Greater trust: users have a better understanding of decisions, which promotes acceptance.
- Effective traceability: explanations facilitate auditing and regulatory compliance (AI Act, ISO 23894:2023) .
- Faster decision-making: when a planner understands the reasons behind a prediction, they can act without delay.
- Continuous learning: user feedback can be used to improve the model.

In summary, explainable artificial intelligence enables a dialogue between humans and machines, rather than a simple execution report.

### *2.5. The current limitations and challenges of explainable artificial intelligence*

Despite significant progress in this field, there are still many limitations, including the following:

- Few studies have been tested in real-world conditions (warehouses, transport, physical flows).
- The explanations are sometimes too technical for non-expert users.
- There are as yet no standardised metrics for assessing the quality of an explanation.
- Furthermore, certain methods of explainable artificial intelligence remain computationally expensive and difficult to integrate into large-scale logistics systems.

It should be noted that the potential of explainable artificial intelligence is immense; however, its limitations show that explainable artificial intelligence is still in its infancy within the field of logistics.

### *2.6. A review of recent literature (2023–2025)*

Based on a contextual analysis of the topics covered in this study, it should be noted that this table summarises the various contributions made by all the authors cited previously.

**Table 1: Analysis of different contributions made by authors concerning XAI**

| Author | Context | Key results | Contributions |
|---|---|---|---|
| Olan et al. (2024) | Supply chain decision-making | SHAP, explainable model | Greater transparency and user confidence |
| Sadeghi et al. (2024) | Agile logistics and resilience | Empirical approach | Reduced response time to risks |
| Zhu et al. (2025) | Demand forecasting | User-centred XAI | Simplification of explanatory interfaces |
| Van Hoek (2023) | Gestion logistique | Approche managériale | Adoption accrue de l'IA grâce à la XAI |
| Ghosh et al. (2024) | Logistics management | Systematic review | The importance of human connection in decision-making |

## 3. CONCLUSION

In conclusion, the development of Artificial Intelligence (AI) in Logistics Information Systems (LIS) has enabled the achievement of respectable levels of performance in forecasting, scheduling and management. Furthermore, this modest study highlights the 'black box paradox', a concept that addresses the growing opacity of complex models, which hinders trust and acceptance among human decision-makers who demand transparency and auditability (Olan et al., 2024; Van Hoek, 2023).

This study meets its objectives by proposing a conceptual and experimental framework for the integration of Explainable Artificial Intelligence (XAI) into Information Systems, specifically for use in demand forecasting.

Thus, a comparative evaluation of a prototype (using LightGBM and SHAP) confirmed that XAI strikes a beneficial balance by maintaining high predictive performance whilst making algorithmic decisions interpretable.

Furthermore, the results highlight explainability, which has become a strategic lever for improving user satisfaction and understanding the factors influencing forecasts (Zhu et al., 2025).

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