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RESEARCH ARTICLE

Platform Architecture Approach for Managing Traceability, Visibility, and Risk Management in Freight Transportation

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ABSTRACT Freight transportation is one of the largest and fastest-growing industries in the world. The movement of goods is a complex process that involves a wide variety of factors, including environmental factors and transportation routes. This paper proposes a comprehensive platform architecture that integrates real-time tracking, data collection, AI-based analytics, risk management, and liability-based decision making. The proposed platform consists of six interconnected components designed to improve traceability, visibility, and risk management in freight transport. The core components of the proposed platform are real-time tracking, geolocation tracking, user interfaces, liability considerations, and telemetry data collection. The model consists of six components that enable dynamic monitoring and management of freight movement throughout the supply chain. The first component is tracking, and the second focuses on the risk assessment algorithm to evaluate the impact of environmental factors on transportation routes. The third component is liability, providing a robust framework for aligning logistics operations with legal, ethical, and safety standards. Finally, the proposed model offers a vision for a more efficient, secure, and compliant logistics industry. This research lays the foundation for the continued evolution of modern freight transportation systems by integrating advanced technologies and addressing the complexities of the field.

INDEX TERMS Freight transport, traceability, risk management, visibility.

I. INTRODUCTION

Digital Transformation (DT) has substantially changed how organisations operate, make decisions, and interact with their environments. In the logistics sector, this transformation involves adopting enabling technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and real-time monitoring systems to improve operational visibility, automate processes, and enable faster responses under uncertainty [1]. In freight transportation, these technologies are increasingly associated with smarter, more connected, and more sustainable operations. Consequently, DT is no longer only a technological option but a strategic requirement for improving service reliability, responsiveness, and competitiveness.

Freight transportation serves as a backbone of global commerce by connecting production, distribution, and consumption across geographically dispersed supply chains [2], [3]. However, as supply chains become more interconnected and time-sensitive, the operational demands placed on freight systems have increased considerably. In Latin America, these pressures are intensified by uneven digital maturity,

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fragmented information systems, and continued reliance on manual or semi-digital processes. Recent evidence indicates that more than 35% of logistics companies in the region still lack real-time visibility of their operations, which contributes to delays, economic losses, and limited responsiveness to unexpected disruptions [4]. In practice, this gap is not explained only by the absence of advanced technologies, but also by constraints such as heterogeneous fleets, limited budgets for large-scale IoT deployment, intermittent connectivity along rural corridors, and difficulties in integrating modern analytics tools with legacy enterprise systems.

Under these conditions, traceability, visibility, and risk management have become critical requirements for freight transportation systems. These dimensions directly affect operational efficiency, cost-effectiveness, regulatory compliance, and stakeholder trust. Nevertheless, despite the progress reported in recent years, these challenges persist because many transportation processes remain distributed across disconnected platforms, outdated workflows, and isolated decision-support mechanisms [5]. As a result, many freight operators still lack a unified and timely view of cargo conditions, route status, environmental exposure, and decision risks throughout the transportation lifecycle.

The potential reduction in fuel consumption is directly enabled by the AI-driven route optimization component, which leverages real-time data from the tracking and data collection layers to dynamically adjust routes based on traffic conditions, delays, and operational constraints. By continuously updating routing decisions and minimizing unnecessary detours or idle time, the architecture contributes to more efficient fuel usage, particularly in dynamic and uncertain transportation environments.

Traceability is fundamental for ensuring accountability, quality assurance, and compliance from origin to destination [6]. However, many companies still depend on paper-based controls or disparate digital tools, which increases the probability of delays, errors, information asymmetries, and even fraud [6], [7]. Prior studies have shown that better tracking and monitoring mechanisms can improve the use of operational resources. For instance, [8] reported that real-time monitoring and evaluation can reduce fuel consumption by up to 20%, which illustrates the operational relevance of continuous visibility in transportation processes. Although obtained in a specific transport-monitoring context, this result illustrates the operational value of integrating tracking data with decision-support systems. Likewise, tracking capabilities are increasingly recognised as an important component of efficient freight-forwarding practices across the supply chain [9].

Beyond traceability, real-time visibility has become a core expectation in modern freight transportation [10]. Customers and supply-chain partners increasingly demand accurate and timely updates to reduce downtime, improve inventory control, and strengthen service reliability. In this sense, [11] argue that real-time access to freight-related information positively influences customer loyalty and service relationships. Even so, many transportation networks still present significant blind spots, especially in cross-border and multimodal operations. For example, [12] report that although 32.66% of respondents use shipment tracking to achieve real-time visibility, important limitations remain due to technical issues and data security concerns. These findings reinforce the need for integrated digital platforms rather than isolated tracking tools. This suggests that IoT- and GPS-based tracking technologies, while promising, require integration with broader data-processing and decision-support platforms in order to deliver effective operational value [13], [14], [15].

At the same time, risk management in freight transportation has become more complex due to the interaction of operational, environmental, and security-related threats. Cargo movements are exposed to accidents, equipment failures, route deviations, weather events, criminal activity, and geopolitical disruptions. In maritime and intermodal contexts, these risks may affect people, goods, and the environment, requiring systematic mitigation strategies [16]. For example, [17] report that the probability of an accident with significant consequences in a port environment reaches 59.8%, with human and management factors as major contributors. Similarly, [18] suggest that many random factors affecting cargo transportation can be better controlled through structured risk-management approaches. These findings support the need for architectures capable not only of monitoring freight movements but also of identifying anomalies, prioritising risks, and supporting timely intervention.

Security threats further reinforce this need. Cargo theft remains a major challenge for the transportation sector. Freight systems are increasingly exposed to criminal attacks, underscoring the need for greater visibility and better coordination among supply-chain actors [19]. In Europe alone, cargo crime represents a multibillion-dollar problem [20]. Moreover, TAPA EMEA recorded more than 15,000 cargo-loss incidents between 2019 and 2020, with total losses above 373 million dollars [21]. These figures underline the practical relevance of incorporating security monitoring and rapid-response capabilities into modern freight transportation platforms. From a legal and institutional perspective, [22] note that criminal-law mechanisms can help protect cargo transportation, but their effectiveness remains underdeveloped. Taken together, these studies show that freight transportation challenges are not limited to visibility or optimisation alone; they also involve legal accountability, safety, and compliance dimensions that must be considered within operational decision-making.

The literature has made important advances in tracking technologies, AI-based analytics, and logistics optimisation. However, existing approaches still exhibit critical limitations. Many solutions address traceability, visibility, and risk management as separate functionalities, relying on fragmented architectures or loosely coupled systems. In addition, AI is often incorporated only for isolated optimisation tasks, without being integrated into a broader decision-support structure that also considers legal and regulatory constraints. Therefore, although multiple enabling technologies are available, there remains a need for integrated freight transportation architectures that combine real-time monitoring, analytics, risk prioritisation, and compliance-aware decision support within a single operational framework.

Motivated by this gap, this paper proposes a platform architecture for managing traceability, visibility, and risk in freight transportation. The architecture integrates real-time tracking, data collection, AI-driven analysis, user-oriented decision support, risk management, and civil liability considerations into a unified framework. The contribution of this work does not lie in presenting IoT, AI, or GPS as novel technologies in and of themselves, since these are already established in Logistics 4.0 research. Instead, the contribution lies in their coordinated integration within a six-component architecture designed to provide end-to-end operational visibility, support distributed decision-making, and incorporate legal and liability-related criteria into transportation management.

A distinguishing feature of the proposed architecture is the explicit incorporation of civil liability into the decision-making logic. Rather than treating legal and regulatory issues as external compliance checks, the model treats them as constraints that should be integrated into risk assessment, route evaluation, and operational recommendations. This perspective is particularly relevant in freight transportation, where route selection, cargo handling, environmental exposure, delivery conditions, and incident response may all have contractual, legal, and safety implications.

The proposed architecture is also intended to be applicable in operational environments characterised by infrastructure heterogeneity and connectivity limitations. For that reason, the model is conceived as a distributed architecture that can support real-time data acquisition, local preprocessing, and progressive integration with existing digital platforms. This is particularly relevant in regions where uninterrupted high-bandwidth connectivity cannot be assumed throughout the transportation corridor. In this sense, the architecture is designed to support not only monitoring and analytics, but also interoperability, resilience, and scalable deployment in real freight scenarios.

To provide preliminary support for the proposal's viability, this paper also includes a simulation scenario implemented in iFogSim 2. The simulation evaluates latency, processing distribution, and workload allocation in a representative logistics corridor, thus providing an initial assessment of the proposed fog-cloud organisation for freight transportation management. While this evaluation does not replace a full real-world deployment, it provides quantitative evidence of the architecture's operational feasibility under realistic communication and processing conditions.

The main contributions of this paper are as follows:

- the proposal of a unified six-component architecture for freight transportation management that integrates traceability, visibility, risk management, and civil liability;
- the explicit incorporation of legal and liability-related criteria into the decision-support framework;
- the definition of an operational architecture oriented toward heterogeneous freight environments with interoperability and connectivity constraints; and
- a preliminary simulation-based evaluation of the proposed architecture using iFogSim 2.

The remainder of this article is structured as follows. Section II describes the methodology adopted for the development and preliminary evaluation of the proposed platform architecture. Section III presents the literature review, with emphasis on the main advances and remaining gaps in traceability, visibility, risk management, and decision support in freight transportation. Section IV details the proposed architecture and the interaction among its six core components. Section V describes the iFogSim 2 simulation scenario and discusses the obtained performance metrics. Section VI presents the conclusions of the study. Finally, Section VII outlines future research directions for further evaluation and technological extension.

II. METHODOLOGY

This research adopts a design science methodology aimed at proposing an integrated platform architecture for freight transportation systems [23]. The methodology consists of five interconnected phases that guide the construction of the model, focusing on solving the challenges of traceability, visibility and risk management through technology integration. These phases are: Exploratory Literature review, Identification of Functional Gaps, (3) Architectural Design, (4) Component Definition and interrelation, and (5) Evaluation and scalability.

A. EXPLORATORY LITERATURE REVIEW

The first phase consisted of an exploratory and semi-systematic review of the state of the art in the fields of IoT-based logistics, AI, real-time tracking, and risk assessment in multimodal freight transportation. Key sources were identified using Scopus, IEEE Xplore and Web of Science, considering papers published between 2015 and 2024. The selection criteria prioritized articles proposing architectures, decision models or integrated systems. This phase allows synthesizing critical requirements and detecting persistent limitations in current implementations.

B. IDENTIFICATION OF GAPS AND REQUIREMENTS

Based on the literature synthesis, a cross-analysis is performed to detect unmet technological and operational needs, particularly in Latin American transportation contexts. The analysis will provide information on: (i) the lack of unified data models for multi-agent environments, (ii) the absence of real-time risk mitigation strategies in edge processing, and (iii) the limited incorporation of legal liability frameworks in logistics platforms. These findings served as the basis for the functional specification of the proposed model.

C. ARCHITECTURAL DESIGN

In the third phase, it adopts a modular design approach to develop the platform architecture. The architecture integrates six key components: real-time monitoring, data collection, AI-based analytics, user interface, risk management, and liability. Each component is defined based on technological feasibility, functional independence and interoperability. The model is designed to support scalability, cooperation between cloud and edge, and legal compliance, incorporating elements of event-driven design and predictive intelligence.

D. COMPONENT MODELING AND INTEGRATION

Each module of the architecture is specified in terms of its inputs, outputs, processing mechanisms and interaction patterns. Data flow between components is conceptualized using unified tuples and flows, using publish-subscribe logic. AI modules were modelled with supervised machine learning workflows for route optimization, anomaly detection and predictive maintenance. Risk assessment was formulated using a three-step process: anomaly identification, categorization, and prioritization, with a feedback loop to liability filters.

E. EVALUATION AND SCALABILITY PLANNING

In this phase, the proposed architecture is evaluated through simulation to assess its feasibility and performance under realistic operating conditions. The evaluation focuses on key system requirements, including low-latency processing for real-time decision-making, efficient workload distribution between edge and cloud layers, and the ability to operate under constrained connectivity environments.

To this end, a simulation scenario was implemented using iFogSim 2, modeling a representative freight transportation corridor with distributed IoT devices and fog nodes. Performance metrics such as latency, CPU utilization, and tuple processing distribution are analyzed to determine whether the architecture satisfies the defined operational requirements. The results of this evaluation are presented in Section V.

In addition, scalability considerations are addressed by outlining strategies for incremental deployment, horizontal expansion, and modular integration in real-world logistics environments.

This simulation-based evaluation corresponds explicitly to the evaluation phase of the Design Science Methodology. In this context, the proposed architecture is treated as an artifact whose performance is assessed against predefined operational requirements, including latency constraints, distributed processing efficiency, and resilience under intermittent connectivity conditions. The use of iFogSim 2 enables a controlled and reproducible environment to evaluate whether the artifact satisfies these requirements before real-world deployment.

This methodology, shown in Fig. 1 ensures that the model is grounded in both current technological capabilities and the practical demands of modern freight transportation, providing a solid foundation for addressing key industry challenges. The following sections detail the theoretical integration of the identified components and the rationale for their inclusion in the proposed framework.

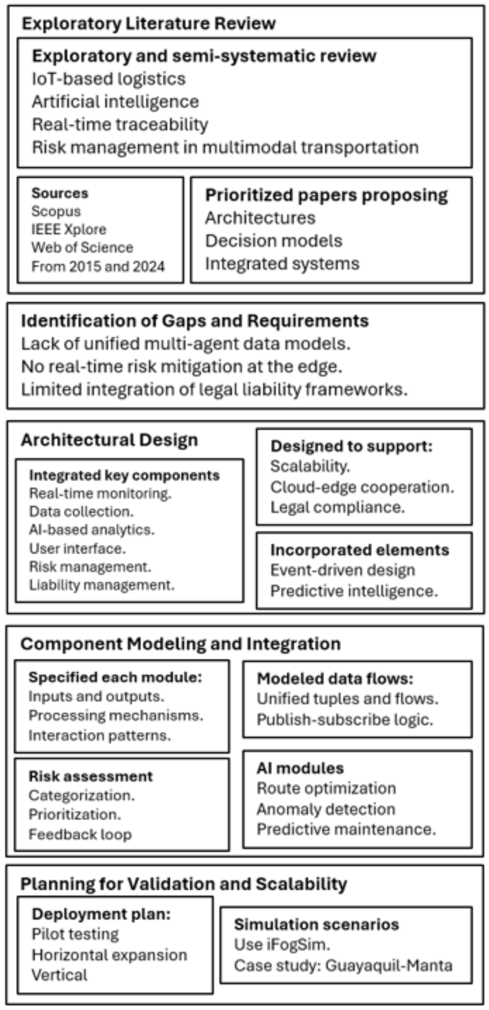

FIGURE 1. Methodological framework.

III. LITERATURE REVIEW

The management of freight transportation has undergone significant transformations in recent years, driven by the need to address complex challenges such as operational inefficiencies, security threats, and dynamic market demands [24], [25]. To tackle these challenges, a robust understanding of the existing tools, frameworks, and technologies is essential. This literature review aims to provide a comprehensive examination of the current state of the art in key areas critical to the proposed platform architecture for managing traceability, visibility, and risk in freight transportation.

The review is structured to explore the most relevant aspects that form the foundation of the proposed platform. These aspects include real-time tracking and data collection, which focus on monitoring and gathering critical operational metrics such as timelines, speeds, and statuses; AI-driven analysis and prediction, which leverage advanced analytics to anticipate logistics disruptions and optimize operations; decision-making systems, which facilitate actionable insights and informed choices; and risk management and optimization, which address strategies for mitigating operational, physical, and environmental risks.

Each of these elements plays a pivotal role in ensuring a cohesive, efficient, and reliable freight transportation management system. The following sections will delve into the existing literature, identifying technological advancements, practical applications, and gaps in research that the proposed platform seeks to address.

A. REAL-TIME TRACKING AND DATA COLLECTION

Real-time tracking and data collection systems have become essential in modern freight transportation, providing tools to optimize logistics, enhance security, and improve the overall efficiency of supply chains [26], [27]. Recent advancements, particularly through IoT, GPS, and blockchain technologies, have substantially improved the capabilities of these systems.

The integration of IoT technology into logistics systems has enabled higher levels of real-time visibility [26], [28]. IoT devices installed in cargo containers and vehicles collect data on location, environmental conditions, and cargo integrity. These devices use sensors for temperature, humidity, and vibration, which are crucial for handling sensitive and perishable goods like pharmaceuticals and food [14], [29]. The collected data must then be transmitted to processing nodes where it can be visualized, stored, and analyzed for operational decision-making.

IoT systems also facilitate predictive maintenance, ensuring vehicles and containers are serviced before failures occur, reducing downtime and optimizing operational schedules [30]. These systems rely heavily on machine learning to analyze data trends, optimizing routes and forecasting risks, thus improving efficiency and security [31].

In this sense, GPS technology remains a key enabling technology for real-time cargo tracking. Modern GPS systems provide accurate location data, enabling logistics managers to monitor fleet movements and ensure timely deliveries. The combination of GPS with IoT enhances the tracking of vehicles and individual shipments, as seen in systems that integrate clustering algorithms to analyze road usage patterns and improve lane usage for freight vehicles [14], [26].

Despite these technological advancements, challenges persist. IoT systems require reliable connectivity, especially in remote or underdeveloped regions. Power consumption of IoT devices, data security, and integration with existing systems are additional hurdles that need to be addressed [31]. Blockchain systems, while highly secure, involve significant computational costs and require coordination among diverse stakeholders [14].

Cold chain logistics particularly benefit from IoT and GPS integration. In cold chains, monitoring the freshness of goods is critical, and IoT systems are deployed to ensure optimal storage conditions throughout the transportation process. Simulations have shown that these systems significantly reduce spoilage by providing real-time alerts for deviations in temperature or humidity [26].

Another relevant application arises in high-mobility environments, where real-time data collection helps manage cargo in transit without continuous network connectivity. Intelligent algorithms ensure data synchronization when connectivity is restored, enhancing system robustness [31].

Overall, real-time tracking technologies have substantially improved shipment visibility and condition monitoring. Nevertheless, many reported solutions remain focused on isolated sensing or tracking functions, while challenges such as interoperability, connectivity resilience, cybersecurity, and scalable data integration remain insufficiently addressed. These limitations support the need for unified architectures capable of combining tracking data with higher-level analytics and operational decision support.

B. AI AND DATA ANALYSIS

The freight transportation industry has increasingly adopted artificial intelligence (AI) and machine learning (ML) to address challenges related to efficiency, sustainability, and operational reliability. These technologies are being used to support more data-driven logistics processes through forecasting, optimization, anomaly detection, and predictive maintenance [32], [33], [34]. Rather than replacing traditional planning methods, AI techniques increasingly complement them by improving responsiveness to dynamic operating conditions. Typical applications include route planning, predictive maintenance, demand forecasting, shipment visibility enhancement, and decision-support functions.

AI-based route optimization has become an increasingly relevant application in freight transport. Algorithms can analyze historical and real-time variables such as traffic conditions, weather, delivery windows, and fuel consumption to identify efficient routing alternatives. Vehicle Routing Optimization (VRO) models frequently combine heuristic methods, metaheuristics, or reinforcement learning approaches to solve complex dispatching problems under operational constraints [35], [36]. Reported benefits in the literature include reductions in travel time, fuel use, and scheduling inefficiencies, although outcomes depend strongly on fleet characteristics, infrastructure conditions, and deployment context.

Predictive maintenance is another important application area. By analysing sensor data, AI models can estimate the probability of equipment failures, enabling preventive maintenance actions and minimizing unplanned downtime. This capability is particularly relevant for trucking fleets and railway operations, where unexpected breakdowns may disrupt supply chains [32], [37]. Commonly reported models include artificial neural networks for demand and delay forecasting, random forests for anomaly classification, support vector machines for condition monitoring, and gradient-boosting methods for estimated time-of-arrival (ETA) prediction.

AI technologies may also support sustainability objectives by improving vehicle utilization, reducing idle time, and enabling lower-emission routing decisions. In combination with IoT data, analytics tools can monitor vehicle performance and cargo conditions to improve resource efficiency [13], [36]. However, environmental benefits depend not only on algorithmic performance, but also on implementation quality, fleet composition, and broader transport transition strategies.

AI also complements the Internet of Things in creating high-traceability logistics systems. IoT devices provide real-time data on cargo location, temperature, and condition, while AI models transform these data streams into operational insights. Such technologies can enhance visibility across supply chains, reduce freight losses, and improve customer service levels. High-traceability systems may also support value-added logistics services and better asset utilization [32].

Despite these benefits, the adoption of AI in freight transportation faces several challenges. Data privacy and cybersecurity concerns are important given the reliance on continuous data exchange. The integration of AI systems with legacy infrastructure presents technical and financial hurdles, particularly for organizations with fragmented information systems. Moreover, ethical issues related to algorithmic bias, accountability, and decision transparency require careful consideration to ensure trustworthy AI applications [13].

As AI and ML technologies continue to evolve, their applications in freight transportation are expected to expand in areas such as multimodal coordination, demand forecasting, autonomous assistance systems, and carbon-aware planning. Future progress will depend not only on predictive accuracy, but also on explainability, interoperability, cybersecurity, scalability, and effective human oversight.

Overall, AI methods show strong potential for route planning, predictive maintenance, forecasting, anomaly detection, and sustainability optimization. However, many studies evaluate algorithms in narrow scenarios or controlled datasets and do not fully address deployment constraints such as data quality, explainability, legacy-system integration, and human oversight. This suggests that practical freight applications require AI modules embedded within broader operational platforms rather than stand-alone predictive tools.

C. DECISION-MAKING

Decision-making in freight transportation requires balancing cost, service level, timing, capacity constraints, regulatory requirements, and environmental objectives. As logistics systems become more dynamic and data-intensive, research has increasingly focused on analytical frameworks capable of supporting operational, tactical, and strategic decisions under uncertainty.

One prominent stream of research applies Operations Research (OR) models, which classify decisions into strategic, tactical, and operational levels—for example, infrastructure investments at the strategic level and dynamic dispatching at the operational level [2]. Mixed-integer linear programming and multi-objective optimization techniques are commonly used to balance trade-offs among cost, time, and environmental impact. For example, heuristic models combined with IoT-enabled real-time data have been applied to rake rescheduling in rail freight operations, reporting improvements in cost efficiency and service performance [12].

Behavioral dimensions of decision-making have also received increasing attention. Cognitive biases, such as status quo bias, may hinder the adoption of environmentally friendly transport modes [38]. Interventions such as behavioral nudges and financial incentives have been proposed to encourage more sustainable logistics choices. Moreover, descriptive freight transportation models have been developed to better predict how logistic decisions impact freight flows, emphasizing the integration of qualitative and quantitative insights for enhanced predictive accuracy [39].

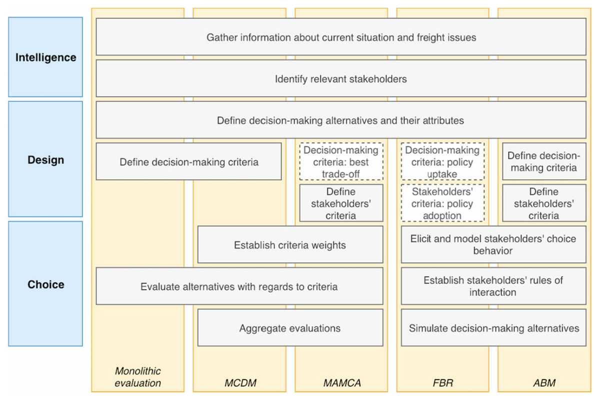

FIGURE 2. Overview of activities according to three stages of decision-making and five types of decision-making procedures from the literature [40].

Integrated frameworks are also crucial in addressing the multidimensional challenges of freight transport. Multi-Criteria Decision Analysis (MCDA) methods like AHP and MAMCA facilitate the evaluation of competing priorities, such as cost efficiency and environmental impact [40]. A brief comparison between some of these models found in the literature is shown in Fig. 2. Additionally, tools like simulation-based analytics and what-if analysis allow stakeholders to anticipate the impact of decisions in dynamic scenarios, enhancing decision reliability [5].

Additional approaches such as Complex Adaptive Systems (CAS) model logistics networks as evolving systems characterized by interdependence and adaptation. Agent-based models are useful in this context because they simulate stakeholder interactions, decentralized decisions, and policy effects [40]. Similarly, rewards-based protocols for transshipment decisions provide flexible, decentralized strategies for optimizing supply chains, balancing shortage and transport costs [41].

International freight transport planning introduces additional complexity related to customs procedures, multimodal coordination, border delays, and regulatory compliance. Decision boards, decision trees, and rule-based tools have been applied to structure these choices and improve planning consistency in cross-border operations [42].

Current decision-making research demonstrates the value of optimization, simulation, and multicriteria methods in freight transport planning. However, these approaches are frequently separated from real-time operational data streams, limiting responsiveness in dynamic environments. This gap highlights the relevance of integrating analytical decision tools with live monitoring and predictive modules.

D. RISK MANAGEMENT AND OPTIMIZATION

Risk management in freight transportation addresses uncertainties that may affect service continuity, safety, cost performance, regulatory compliance, and environmental outcomes. As transportation networks become more interconnected and time-sensitive, structured risk-management approaches have become increasingly important for resilient logistics operations.

Sustainability-related risks—including economic, social, and environmental dimensions—have received growing attention in freight transportation research. Choudhary et al. [43] analyzed risks such as fossil-fuel dependence and resource mismanagement using fuzzy evidential reasoning methods, highlighting the importance of behavioral and managerial factors. Similarly, Dadsena et al. [44] proposed a fuzzy FMEA framework for the trucking sector to prioritize mitigation actions under budget constraints.

Quantitative models are widely used for structured risk assessment. Bondareva et al. [45] discussed hybrid logical-probabilistic models for port logistics environments, while Kaewfak et al. [46] introduced an FAHP-DEA framework to prioritize multimodal freight risks and support resource allocation under uncertainty, as illustrated in Fig. 3. Later work extended this approach through fuzzy FMEA methods to address high-priority risks such as compliance delays and infrastructure limitations [47].

Additional sector-specific studies have examined railway freight stations and container logistics. In railway environments, combinations of AHP and entropy methods have been used to rank operational hazards. In multimodal container transport, BP neural networks have been applied to estimate risk levels and support coordinated mitigation strategies [48].

Long-term strategic resilience has also been studied in cargo motor transport enterprises. Semin et al. [49] applied the IDEF methodology to map risks across multiple planning horizons, while outsourcing and intermodal coordination were identified as potential resilience enablers. Additionally, in [47] the integration of fuzzy methods is emphasized to better manage intermodal dependencies, enhancing overall system robustness.

The integration of diverse methodologies remains central to contemporary literature. Advances in fuzzy set theory, as applied by [44], and hybrid modeling approaches, such as those discussed by [46], demonstrate the potential for improving multimodal transportation networks.

The reviewed literature confirms that freight transportation risks are multidimensional and require structured assessment methods. While existing models provide valuable prioritization and mitigation techniques, they are often domain-specific and not directly connected to continuous monitoring systems. Consequently, more integrated approaches are needed to translate risk analysis into real-time operational action.

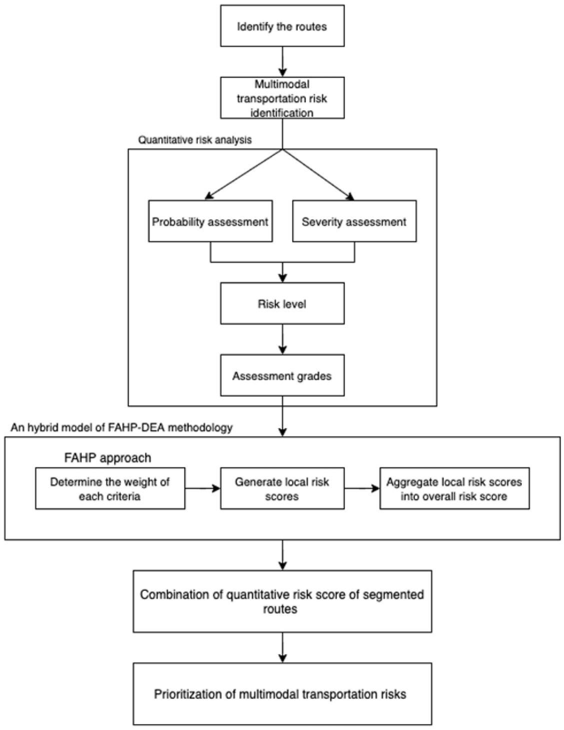

FIGURE 3. The framework of quantitative risk assessment in multimodal transportation [46].

Despite the extensive body of work on IoT, GPS-based tracking, blockchain, and AI-driven optimization in logistics, most existing approaches remain limited by their fragmented nature and lack of end-to-end integration. Many solutions focus on optimizing individual components—such as routing algorithms or tracking systems—without addressing the systemic interaction between data acquisition, real-time processing, risk management, and decision-making. As a result, these platforms often fail to provide consistent real-time visibility, particularly in dynamic and connectivity-constrained environments, leading to delayed responses and suboptimal operational decisions.

In contrast, the proposed architecture addresses these limitations by integrating real-time data collection, distributed processing, predictive analytics, risk management, and civil liability considerations into a unified framework.

This holistic approach enables coordinated decision-making across all system layers, ensuring that operational efficiency, risk awareness, and regulatory compliance are simultaneously considered. By overcoming the fragmentation and contextual limitations identified in existing solutions, the model provides a more robust and adaptable platform for freight transportation management.

E. COMPARATIVE SYNTHESIS OF EXISTING APPROACHES

While the literature on logistics digitalization presents a wide range of technological solutions (including IoT-based tracking systems, GPS monitoring, blockchain-enabled traceability, and AI-driven optimization) most contributions remain focused on specific components rather than providing a fully integrated operational framework. As a result, despite significant advances in individual technologies, many existing solutions fail to deliver consistent real-time visibility and effective decision support in complex, real-world transportation environments.

Table 1 presents a comparative synthesis of the main approaches identified in the literature, highlighting their contributions, limitations, and the gaps that remain unaddressed. The analysis reveals a recurring pattern of fragmentation, where data acquisition, processing, analytics, and decision-making are treated as separate layers without sufficient coordination. In addition, several approaches rely heavily on stable connectivity and centralized processing, which limits their applicability in geographically distributed or infrastructure-constrained contexts.

Another critical limitation identified is the lack of integration between operational optimization and higher-level considerations such as risk management and regulatory compliance. While some studies incorporate predictive analytics or real-time monitoring, they often do not extend these capabilities into actionable, risk-aware, and legally compliant decision-making processes.

In contrast, the proposed architecture is designed to address these limitations through a unified framework that integrates real-time data acquisition, distributed processing (fog–cloud), AI-driven analytics, risk management, and civil liability considerations. By explicitly linking these components within a cohesive decision-support system, the model overcomes the fragmentation observed in existing approaches and provides a more robust and context-aware solution for freight transportation management.

IV. PROPOSAL

What distinguishes this model is its interoperable integration of IoT, AI, and GPS—not as isolated tools, but as components of a synergistic platform architecture. This integration enables the transformation of fragmented operational data into predictive intelligence and coordinated action. By connecting real-time sensor data with AI-driven insights and geolocation tracking, the model empowers logistics operators to anticipate events, adapt in real time, and ensure traceable, efficient, and legally compliant freight movements.

The proposed model aims to address critical challenges in freight transportation by integrating advanced technologies to enhance traceability, visibility, and risk management. This model is presented as a further development of the previous work presented in [50] in which a first approach to an architecture proposal for a freight transportation management system is made. It leverages real-time tracking, intelligent data analysis, and user-centered decision-making to optimize operational efficiency and ensure the safe and legal movement of goods. In Fig. 4 a block-diagram schematic of the operation of the proposed model is shown. By bridging existing gaps identified in the state of the art, the model provides a comprehensive approach that aligns technological advancements with practical requirements in the logistics sector.

At the core of the model lies a seamless integration of real-time data collection and AI-driven analysis. Freight transportation systems produce vast amounts of data related to vehicle locations, operating conditions, and environmental factors. The proposed architecture captures these data streams in real-time through IoT-enabled sensors and GPS platforms, ensuring continuous visibility of goods throughout the supply chain. These data are then processed by advanced machine learning algorithms to extract actionable insights, such as predictive maintenance schedules, anomaly detection, and dynamic risk assessments.

The user interface is a pivotal component of the system, designed to deliver relevant, actionable information to decision-makers in a comprehensible format. It consolidates predictive analytics and custom reports, providing users with an interactive platform to evaluate scenarios, assess potential risks, and optimize routes or operations. The interface further facilitates decision-making by incorporating legal and security criteria, ensuring that all actions comply with civil liability standards and regulatory frameworks.

Risk management and operational optimization are tightly coupled in the model's architecture. Predictive analytics derived from real-time data streams not only enhance risk awareness but also inform proactive measures to mitigate delays, minimize resource waste, and ensure the integrity of transported goods. The system dynamically adjusts to external variables, such as traffic congestion or weather conditions, to optimize logistics performance.

Overall, the proposed model combines innovative technologies with a user-centric framework, offering a robust solution to the complex demands of freight transportation. By integrating components such as IoT, AI, and user-centered decision-making, the model sets a foundation for future advancements in freight logistics.

A. COMPONENTS OF THE MODEL

The proposed model is composed of six interconnected components designed to enhance traceability, visibility, and risk management in freight transportation. These components are: real-time tracking, which ensures continuous monitoring

TABLE 1. Summary of literature review and identified gaps.

Approach / Technology	Main Contribution	Limitations	Identified Gap
IoT-based Tracking Systems	Enable real-time monitoring of vehicles and cargo conditions using sensors and connectivity technologies.	Dependence on continuous connectivity; limited processing capabilities at the device level; lack of integration with decision-making systems.	Absence of edge intelligence and resilience mechanisms for intermittent connectivity environments.
GPS-based Logistics Monitoring	Provide location tracking and route visibility for transportation systems.	Limited to positional data; lack of predictive capabilities and contextual awareness; not integrated with risk management.	Need for integration with predictive analytics and operational decision support.
Blockchain in Logistics	Improve traceability, transparency, and data integrity across stakeholders.	High computational and infrastructure costs; limited real-time processing; weak integration with operational optimization.	Lack of integration with real-time analytics and decision-making layers.
AI-based Optimization Models	Support route optimization, demand forecasting, and anomaly detection using machine learning techniques.	Often evaluated in isolated scenarios; lack of integration with real-time data streams and system-wide architecture.	Need for end-to-end integration with data acquisition and execution layers.
Cloud-based Logistics Platforms	Enable centralized data storage and large-scale analytics.	High latency in real-time scenarios; dependence on stable connectivity; limited responsiveness in dynamic environments.	Need for distributed processing (edge/fog) to reduce latency and improve responsiveness.
Integrated Logistics Platforms (Industry 4.0)	Combine multiple technologies (IoT, AI, cloud) for digital transformation of logistics.	Fragmented implementations; lack of cohesive architecture; insufficient consideration of connectivity constraints and legal factors.	Need for a unified, context-aware architecture that integrates technical, operational, and regulatory dimensions.

of freight movement; data collection, which aggregates and processes information from various sources; AI-driven analysis, which generates actionable insights through predictive and prescriptive analytics; user interface, which delivers intuitive reports and decision-support tools; risk management and optimization, which proactively identifies and mitigates potential disruptions; and civil liability, which ensures compliance with legal, ethical, and safety standards.

Each of these components plays a critical role in the functionality of the model, and their integration creates a seamless system for optimizing logistics operations. The following sections will provide a detailed explanation of each component, highlighting their purpose, design, and contribution to the overall efficiency and resilience of the proposed solution.

1) REAL-TIME TRACKING

The real-time tracking component serves as the basis of the proposed model, enabling dynamic monitoring and management of freight movement across the supply chain. Leveraging IoT-enabled devices and GPS technology, this system facilitates comprehensive data acquisition on critical variables such as location, speed, and operational status of vehicles. By integrating these technologies, freight companies gain real-time visibility into their operations, enhancing decision-making and responsiveness to unforeseen challenges [51]. Fig. 5 shows the main functions of the component: variable acquisition, local processing and buffering and data transmission.

Real-time tracking is particularly critical for ensuring the reliability and safety of high-value or perishable goods [14]. Regarding the measurement of the variables, IoT-enabled sensors embedded in cargo containers can measure variables such as temperature, humidity, and shock levels, ensuring that goods meet quality standards throughout transit [52]. In cold chain logistics, for example, temperature sensors can alert operators to deviations in required conditions, enabling immediate corrective actions to avoid spoilage [53].

In relation to data transmission, the proposed architecture does not assume uninterrupted 5G connectivity along the entire freight route. Although 5G and companion technologies can improve transmission speed and service capacity in areas where coverage is available [54], freight transportation frequently crosses rural, mountainous, cross-border, or low-coverage areas where continuous high-bandwidth communication cannot be guaranteed. Therefore, the device layer is designed to operate under intermittent connectivity conditions.

To address this limitation, the tracking unit incorporates a store-and-forward communication logic. Sensor and GPS records are locally timestamped, compressed, and buffered in the vehicle gateway when network access is unavailable. When connectivity is restored, the buffered data are asynchronously synchronized with the edge or cloud platform. This mechanism allows the system to preserve traceability even when real-time transmission is temporarily unavailable.

The communication layer follows a multi-channel strategy. Depending on availability, cost, and operational criticality, data can be transmitted through 4G/LTE, 5G, Wi-Fi at

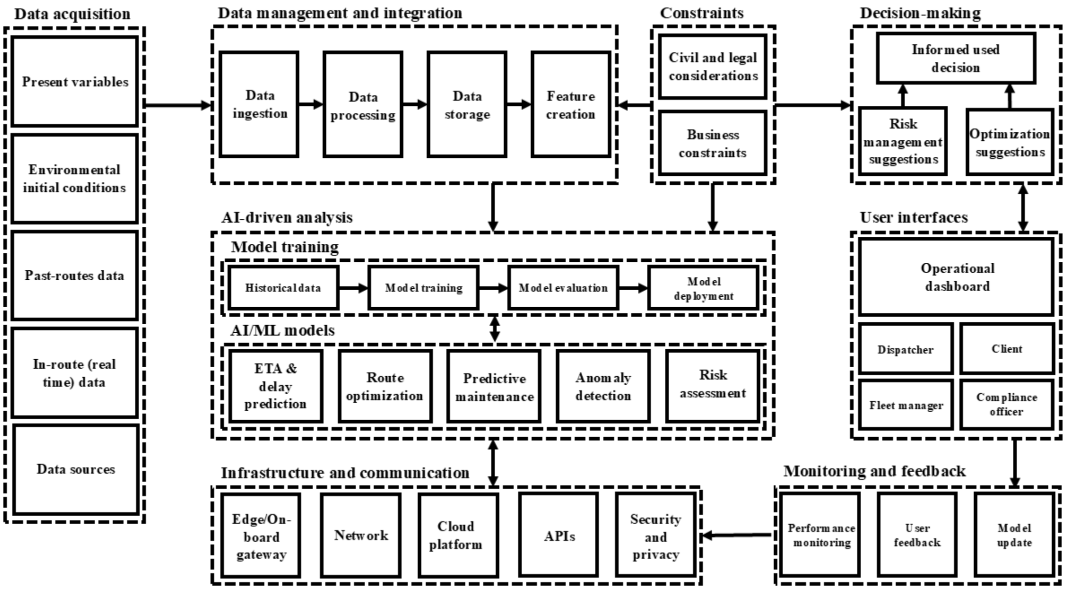

FIGURE 4. Proposed model structure.

logistics nodes, or satellite links for high-value cargo or remote corridors. Critical alerts, such as route deviations, cargo-door openings, or cold-chain temperature excursions, are prioritized over routine telemetry to reduce bandwidth consumption and ensure that high-impact events are transmitted first.

This design improves the robustness of the real-time tracking component by distinguishing between continuous monitoring and continuous transmission. Even when live connectivity is degraded, the system continues collecting operational data locally and synchronizes them once communication is re-established. As a result, the proposed architecture is better suited for freight transportation contexts where connectivity, infrastructure availability, and communication costs vary across routes.

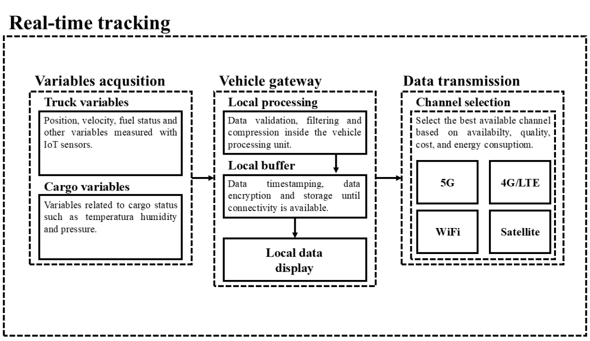

FIGURE 5. Real-time component parts.

2) DATA COLLECTION

The data collection component plays an important role in the proposed model by serving for informed decision-making and system optimisation. This element focuses on acquiring, processing, and structuring vast amounts of real-time and historical data from various transportation and logistics operations. Leveraging IoT devices, sensors, and cloud-based platforms, the data collection system captures critical parameters, including timelines, delivery statuses, vehicle speeds, cargo conditions, and route efficiency. Furthermore, data from past trips can be recorded as a reference for future implementations.

Modern advancements in IoT technologies significantly enhance data collection capabilities, enabling the integration of multiple data sources into a unified system. These datasets contribute to a more comprehensive understanding of transportation efficiency and fleet management [39]. Such practices align with research on the role of IoT-driven analytics in minimizing transportation inefficiencies and enhancing system reliability.

Cloud computing technologies further enhance the efficiency of data collection systems [55]. While cloud platforms centralize large-scale data processing, edge computing allows for local, real-time processing of critical information. This dual approach ensures that urgent decisions, such as rerouting a shipment or addressing a vehicle malfunction, can be made without latency, even in remote areas. For instance, in [56] it is emphasized that the integration of cloud and edge computing is instrumental in achieving low-latency data processing, a critical factor in freight logistics systems. Moreover, advancements in secure data transfer protocols and blockchain technology address concerns about data authenticity and privacy [57].

Fig. 6 briefly explains the operation of this component by showing the input of real-time and historical information and how it should be processed. In the first instance, the information must be filtered and purified to avoid redundancies or inconsistent data. Then, this data must be structured and formatted and its relationships in order to be stored. Finally, this information is stored for later use as AI model training to analyze the data in real time.

3) AI-DRIVEN ANALYSIS

The AI-driven analysis component constitutes the intelligence layer of the proposed architecture, transforming heterogeneous operational data into actionable insights for route planning, predictive maintenance, anomaly detection, and risk mitigation. Rather than relying on a single generic algorithm, the proposed model adopts a modular analytics framework in which different machine-learning methods are assigned according to the characteristics of each operational task. This approach improves scalability, interpretability, and adaptation to diverse freight transportation scenarios.

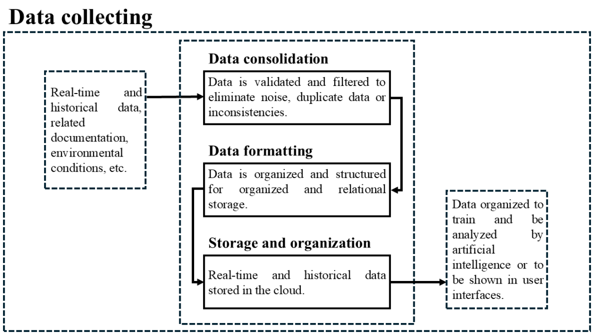

FIGURE 6. Data collection process.

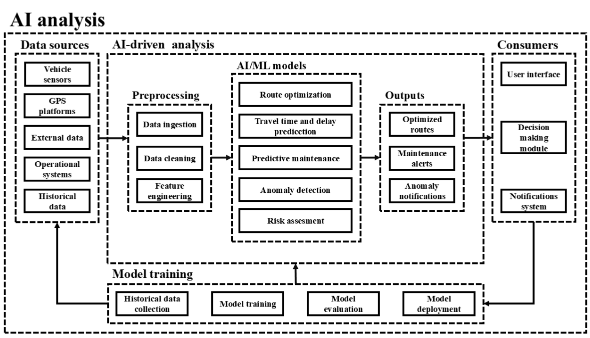

FIGURE 7. AI-Driven analysis functional structure.

The component continuously ingests data from IoT devices, GPS platforms, enterprise systems, and historical operational records. Typical inputs include vehicle position, speed, route progress, delivery windows, traffic conditions, weather variables, fuel consumption, maintenance logs, cargo temperature, vibration levels, and incident reports. After preprocessing and synchronization, these data streams are used for both real-time inference and offline model retraining.

For travel-time estimation and delay prediction, the model proposes supervised-learning approaches such as Gradient Boosting (e.g., XGBoost) and Long Short-Term Memory (LSTM) neural networks. These methods are suitable for capturing nonlinear relationships and temporal traffic patterns, enabling dynamic updates of estimated arrival times and early detection of probable service delays.

For route optimization, predictive outputs are integrated with optimization methods such as Genetic Algorithms, Ant Colony Optimization, or Mixed-Integer Linear Programming (MILP) solvers. This enables route recommendations that simultaneously consider distance, congestion, delivery priorities, fuel consumption, vehicle restrictions, and customer time windows [58].

Another key application is predictive maintenance. Using telemetry signals such as engine temperature, mileage, vibration, battery status, and fault-code histories, supervised models such as Random Forests or Gradient Boosting classifiers can estimate the probability of mechanical failures before they occur. These predictions support preventive interventions, reducing downtime, extending vehicle useful life, and improving fleet reliability [59].

Risk assessment and anomaly detection are also integral functions of the AI component. Unsupervised or semi-supervised techniques such as Isolation Forests, Autoencoders, or clustering-based detectors can identify deviations from expected behavior, including unusual delays, unauthorized route deviations, abnormal fuel consumption, unexpected cargo-door openings, or temperature excursions in sensitive shipments. When anomalies are detected, the system can trigger alerts and recommend corrective actions to safeguard cargo integrity and reduce operational losses.

Similarly, the reduction in accident probability is associated with the integration of real-time monitoring and anomaly detection mechanisms within the proposed architecture. The combination of sensor-based data acquisition, AI-driven anomaly detection, and the risk management module enables the early identification of unsafe conditions, such as route deviations, abnormal vehicle behavior, or adverse environmental factors. This allows for timely interventions, thereby reducing the likelihood of incidents during freight transportation.

For strategic decision support, Bayesian Networks are proposed to estimate composite logistics risks by combining operational, environmental, regulatory, and security variables. Their probabilistic structure facilitates interpretable risk scores and scenario analysis for managerial planning.

Operationally, the AI analysis component is structured in three stages. First, model training is performed using historical trips, maintenance records, traffic patterns, incident databases, and policy constraints. Second, deployed models perform real-time inference on incoming operational data streams. Third, the generated outputs, such as ETA forecasts, rerouting recommendations, maintenance alerts, anomaly notifications, and risk scores, are transmitted to the user interface and decision-making modules for execution and supervision.

To preserve reliability over time, the architecture also considers periodic model recalibration, performance monitoring, and human validation of high-impact recommendations, reducing degradation caused by changing operational conditions or data drift.

4) USER INTERFACE

The user interface (UI) serves as the bridge between the complex technological structure of the proposed model and its human operators. Designed with a focus on usability, accessibility, and efficiency, the UI ensures that decision-makers at all levels of the logistics chain can interact with the system seamlessly. Its primary function is to deliver real-time, actionable insights derived from AI analysis and data collection, enabling stakeholders to monitor operations, evaluate risks, and make informed decisions.

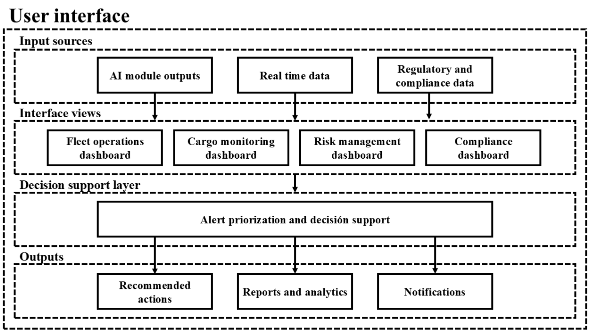

FIGURE 8. User interface structure.

As shown in Fig. 8, the UI is structured around key functionalities that address the diverse needs of logistics operators, fleet managers, and other stakeholders. One of its central features is a dashboard that provides a comprehensive overview of critical metrics, including shipment status, route performance, and risk alerts. This dashboard consolidates data from IoT devices, GPS systems, and AI models into visually intuitive formats, such as graphs, heatmaps, and trend analyses.

The interface should also incorporate advanced features, such as interactive scenario analysis and decision support tools. These features enable users to simulate the impact of various decisions, such as rerouting shipments or adjusting delivery schedules, under different conditions. For example, if a risk alert indicates severe weather along a planned route, the system can present alternative routes, complete with estimated costs and delivery times.

The user interface is a critical enabler of the proposed model, transforming complex analytics into actionable insights and facilitating effective decision-making. By prioritizing usability, customization, and security, the UI ensures that stakeholders at all levels can leverage the full capabilities of the system to enhance efficiency, mitigate risks, and optimize logistics operations.

5) RISK-MANAGEMENT

Risk management is relevant in the proposed model, designed to proactively identify, evaluate, and mitigate risks across the freight transportation ecosystem. This component integrates real-time data, predictive analytics, and decision-support tools to address a wide array of risks, including operational disruptions, security threats, and environmental challenges.

The foundation of the risk management framework lies in its ability to process and analyze data collected from IoT sensors, GPS systems, and operational records. Real-time data streams enable the system to detect anomalies such as route deviations, delays, and equipment malfunctions. In this way, predictive analytics, powered by AI, extends the capabilities of the risk management system by forecasting potential issues before they occur. Machine learning models analyze historical and contextual data to identify patterns and trends that indicate emerging risks. Predictive capabilities are necessary to reduce operational delays and associated costs significantly [60].

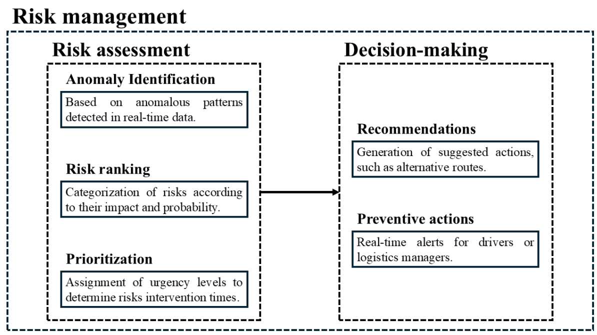

FIGURE 9. Risk management components.

The model also addresses physical and security risks, particularly in regions prone to cargo theft or vandalism. By integrating geofencing technology and real-time tracking, the system might provide alerts when shipments deviate from designated routes or enter high-risk zones. These alerts enable logistics operators to coordinate with local authorities or adjust delivery plans to safeguard goods.

Environmental risks, such as extreme weather events, are another critical focus. The model integrates real-time meteorological data and risk assessment algorithms to evaluate the impact of environmental factors on transportation routes. This capability ensures that goods are transported safely while minimizing exposure to hazardous conditions. Integrating environmental risk management into logistics systems can improve delivery reliability and reduce insurance claims for weather-related damages [61].

Risk management within the model also emphasizes compliance with legal and regulatory frameworks. The system incorporates criteria related to civil liability, ensuring that all risk mitigation strategies adhere to applicable laws and standards. This integration not only reduces legal exposure but also enhances stakeholder confidence in the system's reliability and integrity.

In this sense, the risk management component of the proposed model is composed of two essential parts, as shown in the Fig. 9: risk assessment and decision-making. As can be seen, the first part is also segmented for the characterization of risks, taking as a first step the identification of anomalies, their subsequent categorization and finally a prioritization of these in order of priority.

6) CIVIL LIABILITY

Decision-making in freight transportation involves balancing operational efficiency with compliance to legal, ethical, and safety standards. The proposed model integrates civil liability considerations into its decision-making framework, ensuring that all decisions align with regulatory requirements and minimize legal and financial risks for stakeholders. This component provides a structured approach to evaluate the implications of actions across various dimensions, including legal accountability, public safety, and environmental responsibility.

At the core of this component is the integration of legal and regulatory criteria into the decision-support algorithms. These criteria ensure that operational choices, such as route selection, vehicle utilization, and cargo handling, comply with international, national, and regional transportation laws. For instance, the system considers weight restrictions, environmental regulations, and customs requirements when recommending routes or schedules.

To operationalize this component within the proposed architecture, civil liability is implemented as a decision validation layer that evaluates the outputs generated by the AI-driven analysis and risk management modules before final user recommendation. Specifically, the system applies a set of structured legal and regulatory criteria as rule-based constraints that are mapped to operational variables such as route selection, cargo characteristics, vehicle conditions, and environmental context. These criteria include, but are not limited to, weight restrictions, route permissions, environmental regulations, and compliance with safety standards.

From a functional perspective, each decision generated by the AI module—such as route optimization or risk mitigation actions—is subjected to a filtering process in which potential violations of legal or regulatory conditions are identified. When a conflict is detected, the system either adjusts the recommendation by prioritizing compliant alternatives or flags the decision for user review through the interface. This mechanism ensures that operational efficiency is not achieved at the expense of legal compliance. Furthermore, this component operates in continuous interaction with the risk management module, incorporating legal implications into the prioritization of risks. For example, events such as route deviations, delays, or cargo condition anomalies are not only evaluated in terms of operational impact but also in terms of potential liability exposure. By embedding these constraints into the decision-making flow, the model enables a more comprehensive and accountable approach to freight transportation management, where each action is simultaneously optimized, risk-aware, and legally validated. The model further extends this validation mechanism by integrating civil liability assessments into the risk management and optimization processes. Predictive analytics evaluate the likelihood of legal risks, such as cargo damage, delivery delays, or accidents, allowing operators to take preemptive actions.

The model also supports environmental responsibility as part of civil liability. By incorporating sustainability metrics into decision-making processes, the system ensures compliance with emission regulations and promotes environmentally friendly practices. This is particularly relevant as governments worldwide impose stricter environmental standards on the transportation sector.

As a result, the civil liability-based decision-making component of the proposed model provides a robust framework for aligning logistics operations with legal, ethical, and safety standards. By integrating legal criteria into predictive analytics, risk assessments, and decision-support tools, the model ensures that decisions are not only operationally efficient but also legally sound.

This approach enables the proposed architecture to function not only as an optimization platform but also as a compliance-aware and legally grounded decision-support system.

B. INTEGRATION AND INTERCONNECTION OF MODEL COMPONENTS

The proposed model achieves its objectives of enhancing traceability, visibility, and risk management by ensuring seamless integration and interdependence between its components. Each part of the system—real-time tracking and transportation, data collection, AI-driven analysis, user interface, risk management, and civil liability works in tandem, creating a cohesive and efficient architecture that adapts to the dynamic needs of freight transportation. Fig. 10 shows the interconnection of these six components.

The real-time tracking component serves as the foundation of the system, continuously capturing critical data through IoT devices, GPS systems, and sensors. This data flows directly into the data collection module, where it is aggregated, structured, and processed. The data collection system harmonizes inputs from diverse sources, ensuring that the information is clean, reliable, and readily available for higher-level analysis. For example, data on vehicle location, cargo conditions, and route performance are standardized and stored, providing a consistent stream of information for the subsequent AI analysis.

The AI-driven analysis component then transforms the collected data into actionable insights. Advanced machine learning algorithms process the information to predict potential risks, optimize routes, and detect anomalies. These insights are not only used to improve operational efficiency but also to feed directly into the risk management module, where they are assessed for potential disruptions, physical security concerns, and environmental factors.

The user interface (UI) acts as the central hub where all these components converge, providing decision-makers with an accessible platform to monitor and control operations. The UI integrates outputs from the AI and risk management

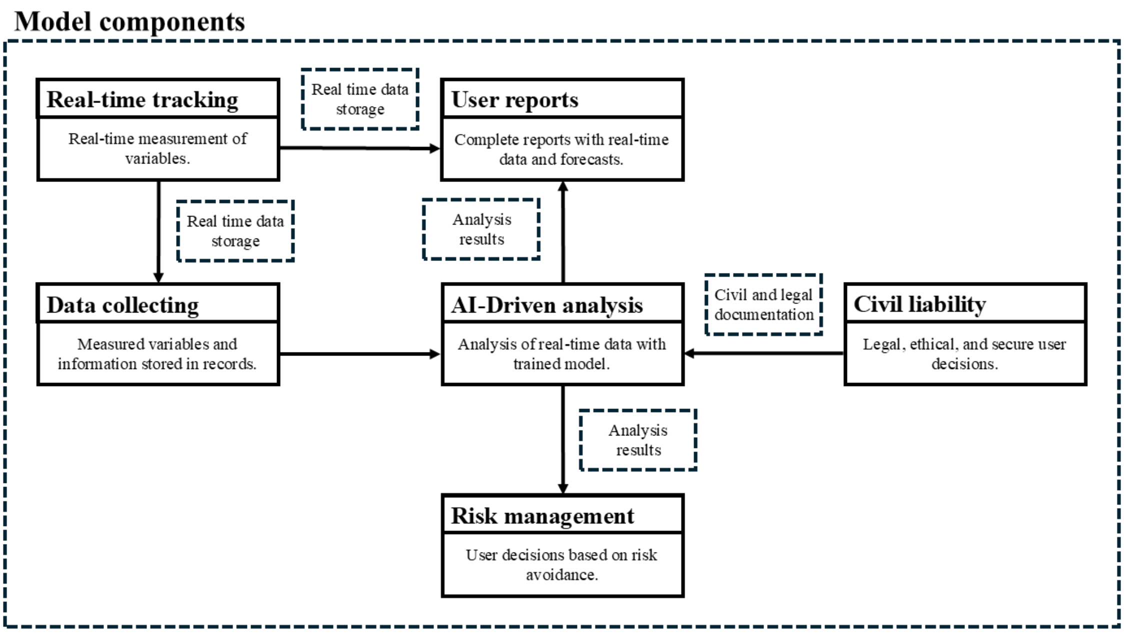

FIGURE 10. **Proposed model components interconnection.**

systems, presenting users with visualized dashboards, predictive alerts, and decision-support tools. For example, a logistics manager using the UI can view real-time shipment updates, analyze risk probabilities, and simulate alternative routes based on changing conditions.

The risk management module is tightly interlinked with both the AI and UI components, facilitating proactive decision-making. Risk assessments generated by the AI feed into the risk management framework, which prioritizes mitigation strategies and communicates them to users through the UI. On the other hand, the civil liability-based decision-making component overlays the entire system, ensuring that all decisions comply with legal and ethical standards. Insights generated by AI and risk assessments are evaluated against regulatory requirements and civil liability criteria. The UI incorporates these legal considerations, allowing users to weigh operational efficiency against potential legal risks.

In operational terms, the civil liability component acts as a validation stage within the decision-making flow, positioned after the AI-driven analysis and risk assessment modules and before the final recommendation is presented to the user. Once the AI module generates optimization or mitigation actions and the risk management component prioritizes potential disruptions, these outputs are evaluated against a set of legal and regulatory constraints. This evaluation functions as a filtering mechanism that verifies compliance with applicable rules and identifies potential violations related to route selection, cargo conditions, or operational parameters.

If a conflict is detected, the system either refines the proposed action by selecting compliant alternatives or flags the recommendation for user intervention through the interface. In this way, the civil liability layer does not operate as an isolated module, but as a cross-cutting control mechanism embedded in the data and decision flow, ensuring that all system outputs are consistent with legal constraints and regulatory frameworks without compromising operational performance.

The interconnection between these components creates a feedback loop that continuously enhances the system's performance. Real-time data collected during operations not only informs immediate decisions but also feeds back into the AI for future predictive analysis, improving the system's ability to anticipate and address challenges. Similarly, lessons learned from risk events and legal considerations are incorporated into the system, refining its decision-making framework and ensuring adaptability to evolving conditions.

As a result, the proposed model's components are deeply interdependent, with each part reinforcing and complementing the others. This integration ensures a seamless flow of information and decision-making, enabling the model to deliver a comprehensive and adaptive solution to the complex challenges of freight transportation.

C. JUSTIFICATION OF PROPOSED MODEL

The proposed model addresses critical gaps in freight transportation by integrating cutting-edge technologies and a holistic approach to traceability, visibility, and risk management. Its design not only aligns with the pressing needs of the logistics industry but also sets a foundation for future advancements. By combining real-time tracking, AI-driven analysis, user-friendly interfaces, and civil liability considerations, the model provides a comprehensive framework that improves operational efficiency, enhances stakeholder trust, and ensures compliance with legal and environmental standards.

The fragmented nature of existing systems often leads to inefficiencies, security vulnerabilities, and limited visibility across supply chains. Current solutions frequently address these issues in isolation, neglecting their interconnected nature. Similarly, many risk management systems lack the predictive capabilities necessary for proactive interventions. The proposed model bridges these gaps by integrating all critical components into a unified platform, enabling seamless data flow and coordinated decision-making.

A key differentiator of this model is its emphasis on adaptability and scalability. Designed to accommodate diverse operational contexts, the system can be tailored to suit various transportation modes, geographic regions, and industry-specific requirements. This flexibility ensures the model remains relevant in a rapidly evolving logistics landscape.

The integration of AI analytics enhances the model's capacity for predictive insights, enabling proactive responses to potential disruptions. Unlike traditional reactive approaches, the proposed system leverages machine learning to forecast risks, optimize routes, and identify operational inefficiencies.

Furthermore, the model's incorporation of civil liability considerations represents a critical advancement in aligning logistics operations with legal and ethical standards. By embedding regulatory compliance into its decision-making framework, the system not only minimizes legal risks but also fosters transparency and accountability across supply chains. This aspect is particularly important as transportation networks face increasing scrutiny from governments and consumers regarding safety, sustainability, and ethical practices. Thus, the proposed model stands out for its holistic design, technological integration, and alignment with industry trends. By addressing the limitations of existing systems and offering a scalable, adaptable framework, it provides a transformative solution to the challenges facing modern freight transportation.

D. LIMITATIONS, SCALABILITY, AND FUTURE EXTENSIONS

The successful implementation of the proposed model requires a phased and systematic approach to ensure effective integration and adaptability across diverse logistics environments. While the model offers significant potential for improving freight transportation systems, it faces some limitations, including high initial implementation costs, the need for reliable connectivity in remote regions, and concerns about data security and privacy.

From an implementation perspective, deploying the proposed architecture in real-world logistics environments presents several practical challenges beyond technical design. These challenges include the integration with heterogeneous legacy systems such as ERP and TMS platforms, which often lack standardized interfaces and require customized data transformation layers. Additionally, ensuring reliable data acquisition from IoT devices in geographically dispersed or connectivity-constrained regions remains a significant operational constraint, particularly in multimodal and cross-border transportation scenarios.

Another relevant challenge lies in data governance and security, as the system relies on continuous data exchange across multiple stakeholders, including transport operators, regulatory entities, and clients. This requires robust mechanisms for access control, data validation, and compliance with data protection regulations. Furthermore, organizational adoption represents a non-technical barrier, as the successful implementation of the platform depends on user training, process alignment, and the willingness of stakeholders to transition from fragmented or manual systems to integrated digital environments.

These considerations demonstrate that, although the proposed architecture is technically feasible, its real-world deployment depends on effectively addressing interoperability constraints, infrastructure limitations, and organizational readiness.

To enable practical and scalable deployment of the platform, the following strategies are proposed:

- **Objective: Validate core functionalities in controlled environments**
  - Deploy pilot tests with selected high-volume clients and routes.
  - Focus on monitoring data capture, risk detection accuracy, and user interface usability.
  - Use SQL and WIDETECH platforms for real-time operational data collection and integration.
- **Objective: Expand the system horizontally across new regions or clients**
  - Extend the database structure and dashboard modules to additional geographic areas.
  - Incorporate new clients with similar operational profiles to those tested.
  - Adjust operational parameters to accommodate regulatory and logistic differences.
- **Objective: Enhance functionality vertically through modular additions**
  - Integrate new modules for route optimization, scheduling, and automated billing.
  - Add features for cross-platform API connections with client and partner systems.
  - Implement predictive analytics dashboards using historical and operational data.
- **Objective: Ensure infrastructure adaptability and performance**
  - Use scalable database architecture and cloud-based services (e.g., SQL + cloud hybrid).
  - Employ low-code integration layers to ensure rapid adaptation to business logic changes.
  - Design system components to function in offline mode when connectivity is low.

- **Objective: Facilitate stakeholder adoption and inter-organizational interoperability**
  - Provide customized user training based on role and decision-making needs.
  - Generate web-based reports and notifications aligned with client-specific KPIs.
  - Enable data exchange through secure, standardized formats with regulatory and logistics partners.

These strategies also need to consider potential integration barriers, as discussed below.

A further practical challenge lies in the integration with existing proprietary systems used by logistics operators, such as ERPs, legacy TMS platforms, or custom-developed software. These systems often lack standardized APIs, have restricted data access, or rely on legacy formats that are incompatible with modern cloud-based or AI-driven tools. In many cases, full integration requires significant customization or middleware development, which can delay implementation or increase costs. To address these challenges, the proposed model advocates the use of flexible data ingestion layers, low-code integration frameworks, and interoperability standards such as RESTful APIs and JSON/XML data exchange formats. These measures aim to reduce friction and facilitate progressive adoption in heterogeneous digital environments.

Future work will include full-scale implementation across multiple clients and regions, with performance indicators to measure return on investment, system responsiveness, and user satisfaction. Additionally, research into blockchain integration, carbon tracking features, and AI-driven compliance validation may further enhance the robustness and reach of the platform.

E. STRATEGIC AND MANAGERIAL IMPLICATIONS

Beyond its technical functionality, the proposed model carries significant implications for engineering management. By enabling real-time visibility and predictive analytics across the transportation workflow, the platform empowers logistics managers and decision-makers to transition from reactive to proactive strategies. This shift allows organizations to optimize asset utilization (e.g., tractor-trailer rotation), reduce lead times, and manage exceptions more efficiently—contributing directly to improved return on assets (ROA) and return on investment (ROI).

Moreover, the model supports key managerial functions such as risk monitoring, compliance oversight, and customer performance reporting. The integration of AI-driven dashboards and traceability tools creates a data governance structure that enhances accountability and strategic alignment with corporate objectives. As such, the platform exemplifies the role of digital technologies in enabling intelligent operations and continuous improvement in engineering-driven organizations.

V. SIMULATION-BASED VALIDATION USING IFOGSIM

This section presents the evaluation phase of the proposed Design Science Methodology, in which the architecture artifact is validated through simulation. The objective of this phase is to assess whether the proposed model satisfies the operational requirements defined in the design stages, particularly in terms of latency, workload distribution, and performance under constrained connectivity environments.

To complement the conceptual design and validate the viability of the proposed architecture, a simulation scenario was developed using iFogSim 2 [62]. This simulation aims to evaluate the system behaviour under realistic network constraints and application workloads in a logistics context.

- Simulation objective: It focuses on replicating a freight corridor between Guayaquil and Manta (Ecuador), which serves as a representative case study of high-density logistics routes. The objective is to model the flow of telemetry data from moving freight vehicles and evaluate system performance in terms of Latency reduction through fog layer processing, utilization of edge node and cloud resources, scalability and workload distribution, and the efficiency of AI-based analytics in the cloud.
- Infrastructure Configuration:
  The topology to be simulated consists of:
  - Four fog devices: a central node in the cloud, and three edge nodes deployed in Guayaquil, Puerto Cayo (mid-route), and Manta, 100 vehicle sensors, each of which sends GPS data every 5 seconds to the nearest fog node. A hierarchical latency model based on estimates from the Ecuadorian backbone:
    - Cloud ⇔ Guayaquil: 80 ms
    - Guayaquil ⇔ Puerto Cayo: 40 ms
    - Puerto Cayo ⇔ Manta: 30 ms
    - Sensor ⇔ Edge Node: 5 ms.

  All devices are modelled with parameters as close to reality as possible (MIPS, RAM, bandwidth, power consumption), following previous research in fog computing and logistic simulation.
- Application Model: A two-module application is deployed:
  - Preprocessing module: deployed in the fog layer, responsible for the preprocessing of raw sensor data.
  - Analysis module: executed in the cloud node, it performs predictive analysis and anomaly detection.

  The simulation models the transmission of tuples between sensors, processing modules and actuators, using event-based flow and publish-subscribe patterns. During the simulation window (1 hour simulated) metrics such as tuple latency, network usage and CPU utilization are recorded.
- Output Metrics and Expected Results: Key results obtained from the simulation include:

- Average CPU usage per device: to identify the distribution of processing load.
- Tuple transmission latency: to measure the time from the sensor to the cloud and back to the actuator.
- Cumulative number of tuples processed: to indicate the performance and scalability of the system.
- Workload ratio of fog vs. cloud: to evaluate the efficiency of processing at the edges.

Simulation results, visualized through temporal graphs and summary tables, support the architectural assertion that a distributed fog-based model can significantly reduce latency and central processing overhead in freight environments.

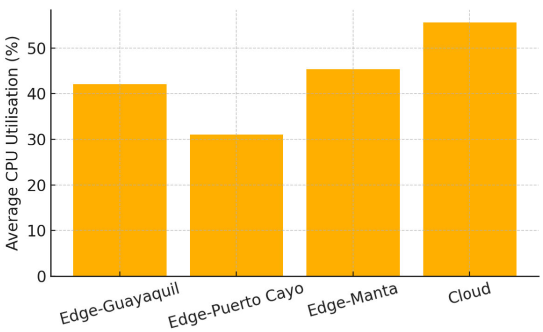

FIGURE 11. Average CPU usage per device.

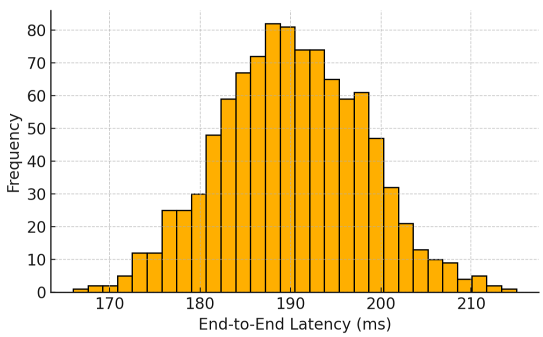

FIGURE 12. End-to-end latency.

A. SIMULATION RESULTS

As described below, the results of the different indications obtained as a result of simulation show that the proposed architecture effectively distributes the computational load among the fog layer.

- Average CPU usage per device: as shown in Fig. 11, the highest processing load fell on the cloud, Cloud registered 55.6% average CPU utilisation, while edge nodes operated with lower loads: Edge-Manta reached 45.3%, Edge-Guayaquil 42.1% and Edge-Puerto Cayo 31.0%.
- End-to-end latency: as shown in Fig. 12, the analysis of 1,000 tuples indicated that the mean sensor-cloud-actuator latency was 189.7 ms, with a median of 189.5 ms and a 95th percentile of 200.4 ms. These times remained below the 250-ms threshold recommended for critical logistics applications, confirming the suitability of the Fog-Cloud hierarchy.
- Cumulative tuples processed: Over 60 min of simulation, the system processed 72000 tuples, with a practically linear slope (1 200 tuples/min). This trend evidenced the absence of bottlenecks and the scalability of the proposed architecture under the representative load of 100 vehicles transmitting every 5s, as shown in Fig. 13.

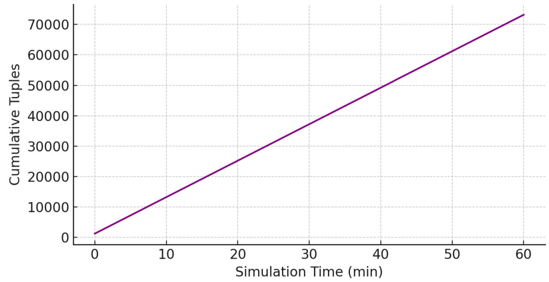

FIGURE 13. Cumulative Tuples Processed.

- Fog vs. Cloud load ratio: as shown in Fig. 14, of the total number of messages, 76.9% were served entirely at the edge layer, while only 23.1% were routed to the cloud for intensive analysis. This proportion corroborates the effectiveness of perimeter processing in reducing upstream traffic and latency, while preserving central computing resources for high-level tasks.

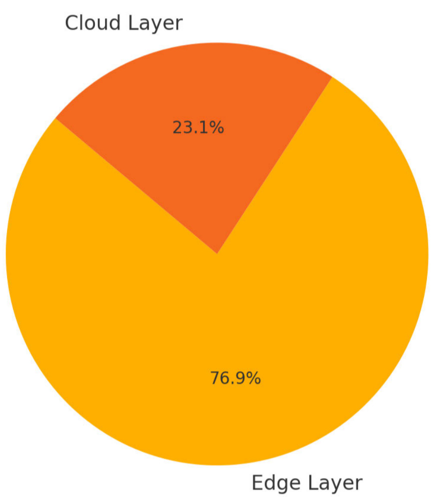

FIGURE 14. Fog vs. Cloud load ratio.

B. LOGICAL VALIDATION OF CORE AI/RISK COMPONENTS

This subsection provides architectural and operational validation of the AI/risk pipeline, rather than model-level predictive validation. Specifically, the simulation in iFogSim 2 primarily measures infrastructure performance, but also evaluates AI-based analytics and risk management. These modules require fast data processing, distributed workloads, and reliable telemetry to enable real-time decision-making.

The simulation reported an average end-to-end latency of 189.7 ms, a median latency of 189.5 ms, and a 95th percentile latency of 200.4 ms. All latency metrics fall below the 250 ms threshold suitable for critical logistics scenarios. These results demonstrate that the architecture enables near-real-time tasks, including anomaly detection, estimated time-of-arrival prediction, route deviation detection, and early alert generation.

Workload allocation corroborates the architecture. Edge nodes process 76.9% of the input data, while only 23.1% is routed to the cloud. This allocation affirms the architecture's ability to execute preprocessing, filtering, and event classification at the edge, delegating the cloud to advanced analytics, model retraining, and strategic risk analysis.

CPU utilisation measurements exhibit no saturation. The cloud averages 55.6% utilization, and edge nodes operate between 31.0% and 45.3%. The system processes 72,000 tuples in 60 minutes (1,200 tuples/minute), exhibiting linear throughput and no bottlenecks. This performance supports telemetry streaming from 100 vehicles, each generating data every five seconds.

The logical viability of the AI and risk management modules underpins the proposed architecture. Fog-cloud integration delivers requisite latency, workload partitioning, and scalability for anomaly detection, risk estimation, alert prioritisation, and decision support under real-time constraints. However, validation relies on simulation. Future research should assess predictive accuracy, false positive rates, and decision efficacy using real operational datasets.

VI. CONCLUSION

This research proposed a comprehensive theoretical model to strengthen traceability, visibility, and risk management in freight transportation systems. Based on a comprehensive review of the state of the art, the model coherently articulates technological advances in the Internet of Things (IoT), AI-driven analytics, real-time monitoring, user interfaces, and liability frameworks. By overcoming the limitations of isolated solutions, the proposal seeks to improve operational efficiency, strengthen risk mitigation mechanisms, and ensure regulatory and legal compliance. One of the model's core aspects is the seamless interconnection between its components, which enables a continuous flow of data and adaptive and contextual decision-making processes. Real-time data acquisition provides the foundation for constant operational visibility, while intelligent analytics modules and responsive interfaces transform data into actionable knowledge. The inclusion of risk assessment and legal liability mechanisms strengthens the system's resilience and legal traceability, aligning it with best practices in the logistics sector. While the model represents a promising solution to current freight transportation challenges, its theoretical nature requires practical validation. As a preliminary step toward such validation, a simulation was run using the iFogSim 2 tool, considering a representative corridor of the Ecuadorian road network (Guayaquil–Manta). The results showed a balanced distribution of the computational load between the fog and cloud levels, an average latency of less than 200 milliseconds, and high efficiency in edge processing, with more than 75% of the tuples managed locally. These metrics support the viability of the architecture in operational contexts with intensive data flows and latency constraints. In summary, this work establishes the conceptual foundations for a next-generation freight transportation management platform. By integrating advanced digital technologies with legal and operational considerations, the proposed model offers a holistic, robust, and scalable approach that drives the digital transformation of the logistics sector toward smarter, more resilient, and legally accountable systems.

VII. FUTURE WORKS

As future work, it is proposed to implement a functional prototype of the architecture in a real freight transportation environment, integrating IoT sensors, fog nodes and cloud services. It is also proposed to evaluate its performance with a larger number of vehicles, variable networks and heterogeneous sensors. Additionally, a blockchain-based legal intelligence module will be developed to ensure legal traceability in case of incidents. Simulators such as iFogSim 2 and YAFS will be used to analyse the resilience of the system against failures or cyberattacks. Finally, the integration of 5G networks will be studied to improve latency and connection capacity, as well as the feasibility of adapting the architecture to emerging technologies such as 6G, with a focus on critical services, distributed intelligence and massive connectivity.

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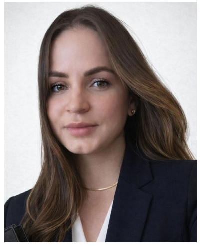

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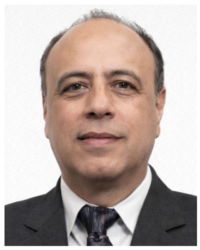

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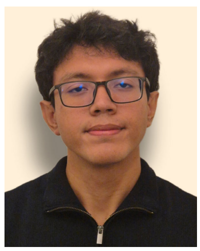

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