Journal of Artificial Intelligence Practice (2026)
Clausius Scientific Press, Canada

DOI: 10.23977/jaip.2026.090109
ISSN 2371-8412 Vol. 9 Num. 1

A Study on Human–Machine Collaborative Logistics Risk Decision-Making Methods Based on Multi-Source Behavioral Data Fusion

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Keywords: Human-Machine Collaboration; Logistics Risk Management; Behavioral Data Fusion; Decision-Making; Machine Learning; Risk Prediction; Explainable AI

Abstract: This review paper explores the evolving landscape of human-machine collaboration in logistics risk decision-making, focusing on the integration of multi-source behavioral data. The increasing complexity of modern logistics necessitates sophisticated risk management strategies. Traditionally, these decisions relied heavily on human expertise, but the advent of advanced sensors, IoT devices, and data analytics provides opportunities for integrating machine intelligence. By fusing data from various sources, including operational systems, environmental sensors, and human behavioral patterns, decision-making processes can become more informed and robust. This review examines existing methodologies for data acquisition, processing, and integration, with a particular emphasis on behavioral data originating from human operators and intelligent machines alike. We analyze the strengths and weaknesses of various machine learning techniques applied to risk prediction and mitigation within logistics, considering their adaptability to different operational contexts. Furthermore, we address the challenges related to data privacy, security, and the ethical considerations of using behavioral data in automation systems. This paper identifies key research gaps and outlines potential directions for future research, emphasizing the need for explainable AI, robust human-machine interfaces, and adaptive risk management frameworks that can effectively handle the dynamic nature of logistics operations. The ultimate goal is to provide a comprehensive overview of the current state-of-the-art and offer insights for advancing human-machine collaborative solutions for enhanced logistics risk management.

1. Introduction

1.1 Background and Motivation

The modern logistics landscape is characterized by increasing complexity, driven by globalization, e-commerce growth, and intricate supply chain networks. This complexity amplifies potential risks, ranging from disruptions in transportation and warehousing to demand fluctuations and unforeseen events. Effective risk management is therefore crucial for ensuring operational resilience and minimizing financial losses. Human-machine collaboration offers a promising avenue for addressing these challenges, leveraging the complementary strengths of human expertise and machine intelligence to enhance risk identification, assessment, and mitigation strategies. The fusion of multi-source behavioral data further empowers this collaborative approach by providing richer insights into the dynamic risk environment [1].

1.2 Objectives and Scope

This paper aims to review existing human-machine collaborative decision-making methods in logistics, focusing on the fusion of multi-source behavioral data [2]. Specifically, we investigate data fusion techniques applicable to logistics risk assessment, considering data from sources like IoT sensors, GPS tracking, and human operator inputs (x_i). The review encompasses decision-making frameworks that integrate these fused data streams to support or automate risk mitigation strategies. The scope is delimited to transportation, warehousing, and inventory management within the logistics domain, excluding manufacturing and reverse logistics .

2. Historical Overview of Risk Management in Logistics

2.1 Traditional Risk Assessment Approaches

Traditional risk assessment in logistics heavily relies on qualitative methods and human expertise. Techniques like brainstorming, Delphi methods, and expert judgment are commonly employed to identify potential risks across the supply chain, from sourcing to delivery. Risk matrices, often using scales like high, medium, and low for both probability and impact, are then used to prioritize these identified risks [3]. Failure Mode and Effects Analysis (FMEA) is also a prevalent tool, assessing potential failures and their consequences. However, these approaches are often subjective and susceptible to biases. The reliance on historical data and expert opinions can be limiting in dynamic and complex logistics environments characterized by increasing globalization, technological advancements, and unforeseen disruptions. Furthermore, these methods struggle to effectively process and analyze the vast amounts of data (n) generated in modern logistics operations, hindering timely and accurate risk assessments. A comparative overview of these traditional risk assessment techniques is provided in Table 1.

Table 1. Comparison of Traditional Risk Assessment Methods

Method	Description	Advantages	Disadvantages	Limitations
Brainstorming	A group activity where participants generate a wide range of potential risks.	Encourages creative thinking; Identifies a broad spectrum of risks.	Can be dominated by certain personalities; May lack structure and depth.	Subjective; Difficult to quantify risks; Time consuming; Depends on the experience of the participants; Not suitable for large datasets (n).
Delphi Method	A structured communication technique relying on expert panels to reach consensus on risk identification.	Minimizes group biases; Allows for anonymous contributions; Iterative process for refinement.	Time-consuming; Requires careful selection of experts; May not be suitable for urgent situations.	Subjective; Difficult to quantify risks; Relies heavily on expert opinion and historical data; Limited view of dynamic risks.
Expert Judgment	Relies on the knowledge and experience of subject matter experts to identify and assess risks.	Quick and readily available; Provides valuable insights based on experience.	Can be subjective and biased; May overlook less obvious risks; Difficult to replicate.	Subjective; Prone to cognitive biases; Limited by the expert's individual experience; Does not scale well with large and complex datasets (n).
Risk Matrices	A tool for prioritizing risks based on their probability and impact, often using scales like high, medium, and low.	Simple to understand and use; Provides a visual representation of risk priorities.	Subjective assessment of probability and impact; Limited granularity; Does not account for interdependencies between risks.	Difficulty quantifying probability and impact; Oversimplifies risk assessment; Susceptible to biases; Limited capability to handle complex systems and large datasets (n).
Failure Mode and Effects Analysis (FMEA)	A systematic approach to identify potential failures in a process and their effects.	Comprehensive; Identifies potential weaknesses in a system; Proactive risk management.	Time-consuming; Requires detailed knowledge of the process; Can be difficult to quantify risk.	Time consuming and labor intensive; Typically requires deep understanding of the system; Struggles with dynamic changes, and effectively processing large data in modern logistics (n).

2.2 Evolution towards Data-Driven Methods

Traditional logistics risk management heavily relied on qualitative assessments, expert opinions, and historical loss data. These methods, while valuable, often suffered from subjectivity and limited scope [4]. The evolution towards data-driven approaches was spurred by advancements in technology and the increasing availability of data. The proliferation of sensors, Radio-Frequency Identification (RFID), and Internet of Things (IoT) devices enabled real-time tracking of goods, vehicles, and environmental conditions. This influx of data allowed for the development of quantitative models and algorithms capable of identifying patterns and predicting potential risks. Consequently, risk assessment shifted from reactive to proactive, enabling timely interventions and improved decision-making. The ability to analyze large datasets and extract meaningful insights marked a significant turning point in logistics risk management, paving the way for more sophisticated and accurate risk mitigation strategies.

3. Core Theme A: Multi-Source Behavioral Data Acquisition and Fusion

3.1 Sources of Behavioral Data

Behavioral data in logistics originates from both human and machine sources, offering a comprehensive view of operational activities [5]. Human operators, such as truck drivers and warehouse personnel, generate data through driving behavior (v, a, t representing velocity, acceleration, and time), order picking accuracy, and adherence to safety protocols. Machine behavior, conversely, provides data via sensors embedded in autonomous vehicles (e.g., lidar point clouds, GPS coordinates), robotic systems (e.g., joint angles, motor currents), and automated storage and retrieval systems (AS/RS) (e.g., throughput rates, error logs). Integrating these diverse data streams, characterized by variables like x_i, y_i, and z_i for spatial coordinates, is crucial for understanding and mitigating risks in collaborative logistics environments. The main sources and characteristics of behavioral data in logistics are summarized in Table 2.

Table 2. Sources of Behavioral Data in Logistics

Source	Data Examples	Variables
Human Operators (Truck Drivers)	Driving behavior (speeding, harsh braking), Order picking accuracy, Adherence to safety protocols	v(velocity),a(acceleration),t (time)
Human Operators (Warehouse Personnel)	Order picking accuracy, Adherence to safety protocols, Loading/unloading times	Accuracy rate, Time per task
Autonomous Vehicles	Lidar point clouds, GPS coordinates, Vehicle speed, Steering angle	Lidar data, GPS (x_i, y_i, z_i), Vehicle speed, Steering angle
Robotic Systems	Joint angles, Motor currents, Position data	Joint angles, Motor currents, End-effector position (x_i, y_i, z_i)
Automated Storage and Retrieval Systems (AS/RS)	Throughput rates, Error logs, Storage location data	Throughput rate, Error codes, Storage location (x_i, y_i, z_i)

3.2 Data Fusion Techniques

Data fusion is crucial for integrating heterogeneous behavioral data from diverse sources in logistics risk assessment. Kalman filters, effective for linear systems with Gaussian noise, can estimate risk states by fusing sensor data and historical records. Bayesian networks offer a probabilistic framework to model dependencies between risk factors and observed behaviors, updating beliefs as new evidence arrives [6]. Deep learning models, particularly recurrent neural networks (RNNs) and transformers, can capture complex temporal patterns in behavioral sequences, predicting potential risks. The applicability of each technique depends on the data characteristics and the complexity of the risk landscape. Kalman filters are computationally efficient but limited by linearity assumptions. Bayesian networks require careful structure learning. Deep learning models demand substantial training data but can achieve superior accuracy in complex, non-linear scenarios where the risk R is a function of multiple behavioral variables B_i, i.e., $R=f(B_1,B_2,\dots,B_n)$.

3.3 Data Preprocessing and Feature Engineering

Effective data fusion requires rigorous preprocessing. Initially, data cleaning addresses inconsistencies, missing values, and outliers. Normalization, such as Min-Max scaling or Z-score standardization, ensures all behavioral features (x_i) contribute equally, mitigating bias from differing scales. Feature engineering then extracts relevant information. This includes creating interaction features (e.g., $x_i x_j$) to capture combined effects and time-windowed aggregations (e.g., average response time over the last 5 minutes) to represent temporal dynamics. These steps are crucial for accurate risk assessment [7].

4. Core Theme B: Risk Decision-Making Methods

4.1 Machine Learning for Risk Prediction

Machine learning offers powerful tools for predicting risks inherent in complex logistics operations. Algorithms such as logistic regression can estimate the probability of a risk event occurring based on various input features, providing a readily interpretable model. Support Vector Machines (SVMs) excel in handling high-dimensional data and identifying non-linear relationships, potentially uncovering subtle risk patterns [8]. However, SVMs can be computationally expensive for large datasets. Neural networks, particularly deep learning architectures, can capture intricate dependencies and achieve high prediction accuracy. The complexity of neural networks, however, makes them less transparent and requires substantial training data. The choice of algorithm depends on the specific characteristics of the logistics operation and the available data, balancing predictive power with interpretability and computational cost. The predicted risk p can be modeled as a function of input features x_i, i.e., $p=f(x_1,x_2,\dots,x_n)$.

Table 3. Machine Learning Algorithms for Risk Prediction

Algorithm	Advantages	Disadvantages	Mathematical Representation
Logistic Regression	Interpretable model; Estimates probability directly.	May not capture complex relationships.	$p=f(x_1,x_2,\dots,x_n)$ where f is the logistic function.
Support Vector Machines (SVMs)	Handles high-dimensional data; Identifies non-linear relationships.	Computationally expensive for large datasets.	Finds optimal hyperplane to separate classes, maximizing margin.
Neural Networks (Deep Learning)	Captures intricate dependencies; High prediction accuracy.	Less transparent; Requires substantial training data.	Complex layered function approximation: $p=f(W_n \dots f(W_1 X+b_1)\dots+b_n)$.

While Table 3 summarizes general characteristics, the choice of algorithm in logistics must account for temporal dependencies. Logistic Regression and SVMs are effective for static risk profiles, such as supplier credit scoring. However, behavioral data in logistics-such as driver steering patterns or AGV trajectories-are inherently time-series. Our analysis suggests that

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks outperform traditional methods by 15-20% in predicting fatigue-related risks due to their ability to capture long-term temporal correlations. Furthermore, while Transformers offer superior modeling of complex interactions, their high computational latency remains a challenge for real-time safety interventions compared to lightweight statistical filters [9].

4.2 Human-Machine Collaboration Frameworks

Effective human-machine collaboration in risk decision-making necessitates frameworks that integrate human expertise with machine capabilities. These frameworks often involve techniques for presenting risk information, such as visualizations displaying probabilities and potential consequences. One approach is to use interfaces that allow operators to adjust parameters, like the weight w assigned to different risk factors, and observe the resulting changes in the system’s risk assessment. Another involves shared mental models, where both human and machine understand the goals, constraints, and potential risks. Furthermore, frameworks should incorporate feedback mechanisms, enabling human operators to provide input on the machine’s decisions and refine its algorithms, improving the overall accuracy and reliability of the risk assessment process.

4.3 Real-time Risk Mitigation Strategies

Real-time risk mitigation hinges on continuously updated data streams from various sources. Proactive alerts, triggered by exceeding predefined risk thresholds (e.g., cargo temperature deviating by x ℃), enable preemptive action. Dynamic routing, adapting to real-time traffic conditions or weather forecasts, minimizes exposure to potential disruptions [10]. Furthermore, autonomous interventions, such as automated speed adjustments based on road conditions or rerouting instructions triggered by sensor data indicating package damage exceeding y, provide immediate corrective measures. These strategies collectively enhance resilience against unforeseen events in logistics operations.

4.4 Application Scenario: Risk Mitigation in Intelligent Warehousing

In a smart warehouse environment, risk decision-making involves fusing data from human pickers (via wearable heart-rate sensors) and Autonomous Mobile Robots (AMRs, via LiDAR). When the fusion model detects human fatigue (e.g., decreased reaction speed) combined with an AMR’s blind-spot entry, the collaborative framework triggers a tiered response: the AMR automatically reduces speed, while the human interface provides an augmented reality (AR) alert explaining the 'High Collision Risk.' This synergy utilizes machine precision for immediate sensing and human judgment for complex environment navigation, effectively reducing incident rates by an estimated 30% compared to non-collaborative systems [11].

5. Comparison of Approaches and Challenges

5.1 Comparative Analysis of Existing Methods

Existing data fusion and decision-making methods for logistics risk assessment exhibit varying strengths and weaknesses. Rule-based systems, while interpretable, often lack accuracy in complex scenarios due to their reliance on predefined thresholds and limited adaptability. Statistical methods, such as Bayesian networks, offer improved accuracy and can handle uncertainty, but their scalability is constrained by computational complexity, particularly with high-dimensional data (n).

Machine learning approaches, including deep learning, demonstrate high accuracy and scalability, effectively capturing non-linear relationships in large datasets. However, they often suffer from a lack of interpretability, making it difficult to understand the reasoning behind decisions. Furthermore, the computational cost associated with training complex models can be significant, requiring substantial resources and time (t). The choice of method depends on the specific requirements of the application, balancing accuracy, interpretability, scalability, and computational cost（Table 4）.

Table 4. Comprehensive Comparison of Data Fusion and Decision-Making Methods

Method	**Strengths**	**Weaknesses**	**Data Modality Support**	**Interpretability**	**Human-AI Synergy**	**Comp. Cost**
Rule-Based Systems	Easy to implement; High transparency	Low accuracy; Limited adaptability	Single Modality (Text/Logical)	High	Low (Output only)	Low
Statistical Methods	Handles uncertainty; Improved accuracy	Scalability issues with high-dim data	Low-dimensional (Sensors/Numerical)	Medium	Medium (Parameter tuning)	Medium
Deep Learning	High accuracy; Excellent scalability	Lack of transparency; Overfitting risk	Multi-modal (Video/Time-series)	Low (Black-box)	Low (Passive execution)	High
Hybrid (XAI-enabled)	High accuracy; Balanced trust & safety	Complex system architecture	Full-modal Fusion	High	High (Bidirectional feedback)	Medium

5.2 Challenges and Limitations

Data acquisition presents significant hurdles, particularly in obtaining comprehensive and reliable multi-source behavioral data. Variations in data formats, collection frequencies, and inherent biases across different systems necessitate robust fusion techniques. Analyzing this fused data to extract meaningful insights for risk prediction is computationally intensive and requires sophisticated algorithms capable of handling high dimensionality and noise. Current human-machine collaboration frameworks often struggle with effectively integrating human intuition and machine learning outputs, leading to potential decision biases if the human operator overly relies on or distrusts the machine's suggestions. Furthermore, data security and privacy are paramount concerns, especially when dealing with sensitive logistics information. Ensuring compliance with regulations and addressing ethical considerations surrounding data usage and algorithmic transparency are crucial for responsible implementation. The potential for algorithmic bias, leading to unfair or discriminatory outcomes, also requires careful mitigation strategies.

6. Future Perspectives

6.1 Explainable AI in Risk Management

Explainable AI (XAI) is crucial for building trust and facilitating effective human-machine collaboration in logistics risk management. While complex machine learning models can achieve high accuracy in risk prediction, their “black box” nature hinders understanding and acceptance by human decision-makers. XAI methods aim to make these models more transparent and interpretable, allowing users to understand *why* a particular risk is predicted. Techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can provide insights into the feature importance and decision-making processes of the models. Furthermore, rule-based systems and decision trees, while potentially less accurate than deep learning models, offer inherent interpretability. Combining these approaches, perhaps using simpler, explainable models to validate or refine the outputs of more complex ones, is a promising direction. Ultimately, XAI empowers human experts to critically evaluate machine-generated risk assessments, leading to more informed and reliable decisions in complex logistics operations.

6.2 Adaptive Risk Management Frameworks

The increasing complexity and dynamism of logistics environments necessitate adaptive risk management frameworks. Traditional static approaches struggle to cope with unforeseen disruptions and the evolving nature of human-machine collaboration. Future research should focus on developing frameworks capable of dynamically adjusting risk assessments and mitigation strategies based on real-time data streams from diverse sources, including human behavioral data, sensor data, and market trends. This requires exploring novel algorithms for anomaly detection, predictive modeling, and automated decision-making. Furthermore, research should investigate methods for quantifying the uncertainty associated with each data source and incorporating this uncertainty into the overall risk assessment. The goal is to create frameworks that can learn from past experiences, adapt to new information, and proactively mitigate risks in a constantly changing logistics landscape, ultimately minimizing disruptions and optimizing performance. Such frameworks should consider the trade-off between exploration and exploitation, balancing the need to learn from new data with the need to maintain stable operations. The parameter λ could be used to control this trade-off.

7. Conclusion

7.1 Summary of Key Findings

This study reveals that human-machine collaboration in logistics risk decision-making offers enhanced accuracy and efficiency by fusing multi-source behavioral data. Benefits include reduced t for risk assessment and improved resource allocation. Challenges involve data integration complexities, algorithm bias mitigation, and ensuring human trust in machine recommendations, impacting overall system R (reliability).

7.2 Concluding Remarks

Human-machine collaboration represents the next frontier in logistics resilience. This study emphasizes that the future of risk management lies not in replacing human intuition, but in augmenting it through multi-source behavioral data fusion. The transition from 'black-box' automation to transparent, collaborative intelligence is essential. Future efforts should prioritize the calibration of human-machine trust, ensuring that operators can critically evaluate AI-generated insights in high-pressure logistics environments to achieve a balance between operational efficiency and safety.

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