International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307

OPEN ACCESS

Available Online at : www.ijsrcseit.com
https://doi.org/10.32628/IJSRCSEIT

A Real-Time Exception Reporting System for Tracking Logistics Discrepancies in the Retail Sector

Opeyemi Morenike Filani[1], John Oluwaseun Olajide[2], Grace Omotunde Osho[3]
[1]Proburg Ltd, Lagos, Nigeria
[2]Lipton, Nigeria
[3]Guinness Nig. Plc, Nigeria
Corresponding Author: filaniopeyemi@gmail.com

ARTICLEINFO

Article History:

Accepted: 10 Oct 2023

Published: 22 Oct 2023

Publication Issue
Volume 9, Issue 5
September-October-2023

Page Number
497-518

ABSTRACT

This paper investigates the design and implementation of a Real-Time Exception Reporting System (RTERS) for tracking logistics discrepancies within the retail sector, addressing inefficiencies in traditional discrepancy management methods. Based on a comprehensive systematic literature review, the study synthesises insights from existing frameworks, technological advancements in IoT and machine learning, and industry best practices to propose a conceptual architecture for RTERS without relying on primary data collection. The proposed system focuses on detecting, reporting, and analysing logistics discrepancies in real-time to enhance supply chain visibility, operational efficiency, and customer satisfaction within the retail environment. The paper discusses the potential of RTERS in reducing operational costs, minimising stockouts and overstock situations, and improving accountability across the supply chain. Ethical considerations, scalability, and integration challenges are also analysed to provide a holistic perspective for researchers and practitioners.

Keywords : Real-Time Reporting, Logistics Discrepancy Tracking, Retail Sector, Exception Management, Supply Chain Visibility, Iot Integration

1. Introduction

1.1 Background and Motivation

The retail sector has undergone profound transformations driven by globalisation, technological advancements, and evolving consumer expectations for faster, precise, and transparent delivery of products [1], [2], [3]. This evolution has increased the complexity of supply chains, particularly within omnichannel retail environments, where goods flow through multiple channels, including online platforms, physical stores, and hybrid delivery models [4], [5], [6]. Within this complex landscape, logistics discrepancies such as shipment delays, inventory mismatches, damaged goods, and routing errors pose significant challenges for retailers, leading to financial losses, customer dissatisfaction, and operational inefficiencies [7], [8].

Traditionally, exception reporting within retail logistics has been reactive, relying on manual interventions and post-incident analyses to identify and resolve discrepancies [9], [10], [11]. Such methods result in delayed detection of issues, limited visibility across the supply chain, and high costs associated with returns, re-shipments, and stock imbalances [12]. According to the Council of Supply Chain Management Professionals (CSCMP), logistics discrepancies contribute to 5-10% additional operational costs annually in the retail sector [13], [14], [15].

The increasing demand for real-time supply chain visibility further intensifies the need for systems capable of tracking discrepancies as they occur, enabling prompt corrective actions to minimise disruptions and financial impacts [16]. As consumers demand faster deliveries and transparent tracking of their orders, logistics service providers are under pressure to enhance their exception management capabilities to maintain competitive advantages [17], [18].

1.2 The Rise of Omnichannel Retailing and Logistics Complexity

Omnichannel retailing, characterised by the seamless integration of online and offline channels, has redefined customer expectations for consistent service levels across purchasing platforms [19], [20], [21]. However, this integration introduces additional complexities in inventory management, order fulfilment, and logistics coordination [22], [23]. Discrepancies in inventory data between channels, inaccurate order picking, and last-mile delivery failures are common issues in omnichannel logistics [24], [25].

Research indicates that stockouts and overstock situations due to discrepancies account for up to 30% of lost sales in the retail industry, significantly affecting revenue streams [26], [27]. Moreover, the fragmentation of data across channels impedes effective discrepancy tracking, as siloed systems often lack interoperability, delaying the detection and resolution of logistics issues [28], [29].

The increasing utilisation of third-party logistics (3PL) providers and drop-shipping models adds further complexity, as retailers often have limited control and visibility over external logistics operations [30]. This lack of visibility exacerbates the risk of logistics discrepancies, necessitating systems that provide end-to-end transparency across supply chain nodes [31].

1.3 Limitations of Traditional Exception Reporting Systems

Traditional exception reporting systems in retail logistics often depend on batch processing of data and manual auditing procedures, where discrepancies are detected during periodic reconciliations [16]. While these methods are established, they suffer from significant limitations:

- Delayed detection: Discrepancies are often identified after the damage has occurred, reducing opportunities for proactive intervention [32], [33].
- High operational costs: Manual investigations require labour-intensive processes and extensive resources [34], [35].
- Limited scalability: As retail operations expand across multiple channels and regions, manual systems struggle to keep pace with the volume and complexity of logistics data [36], [37].
- Reactive decision-making: By the time discrepancies are identified, customer dissatisfaction may have escalated, leading to churn and reputational damage [38].

Studies show that logistics discrepancies detected late can increase return rates by up to 40%, further straining supply chain resources and contributing to environmental waste [39], [40].

1.4 Digital Transformation and Real-Time Exception Reporting

The advent of Industry 4.0, IoT, and advanced analytics has opened avenues for digital transformation in supply chain management, providing opportunities to move from reactive to proactive discrepancy management [41], [42]. Real-time exception reporting leverages continuous data streams from IoT-enabled devices, warehouse management systems, and transportation management systems to monitor logistics activities in real time [43], [44]. Technologies such as RFID sensors, GPS tracking, and telematics allow retailers to track shipment conditions, locations, and status updates instantly, enabling immediate detection of discrepancies like route deviations, temperature breaches in cold chains, or delays beyond acceptable thresholds [45], [46]. These capabilities empower logistics managers to initiate corrective actions promptly, reducing the operational and financial impacts of discrepancies [47], [48].

Machine learning and big data analytics further enhance real-time exception reporting by providing predictive capabilities, identifying patterns and anomalies that may indicate emerging discrepancies before they escalate [49], [50], [51]. Predictive models can analyse historical and live data to forecast shipment delays, potential damages, or stockout risks, allowing pre-emptive interventions [52], [53].

1.5 Problem Statement

Despite the availability of advanced technologies, many retailers continue to struggle with ineffective discrepancy tracking and resolution mechanisms due to fragmented data systems, lack of integration between IoT devices and analytics platforms, and organisational inertia [54]. The absence of unified real-time exception reporting systems limits the ability to detect and address logistics discrepancies promptly, leading to operational inefficiencies, increased costs, and customer dissatisfaction [55].

Given the increasing complexities of omnichannel retail logistics and heightened customer expectations, there is a critical need for a scalable, real-time exception reporting system (RTERS) capable of integrating with existing logistics infrastructures to monitor, detect, and report discrepancies as they occur.

1.6 Objectives of the Study

This study aims to:

1. Examine the challenges associated with logistics discrepancies in the retail sector within omnichannel environments.

2. Analyse existing methods and technologies for discrepancy reporting, highlighting their limitations and inefficiencies.

3. Synthesise insights from a comprehensive literature review on IoT integration, predictive analytics, and exception management within retail logistics.

4. Propose a conceptual Real-Time Exception Reporting System (RTERS) architecture leveraging IoT and predictive analytics for proactive discrepancy management.

5. Discuss potential implementation challenges, ethical considerations, and benefits of adopting RTERS in retail logistics environments.

1.7 Contribution of the Study

This paper contributes to the academic discourse and practical applications within the retail logistics domain by:

- Providing a comprehensive synthesis of the state of logistics discrepancy management within the context of omnichannel retail.
- Highlighting the limitations of traditional exception management systems and the potential of real-time reporting.
- Proposing a conceptual, literature-based framework for implementing RTERS without relying on primary data collection.
- Offering a foundation for future empirical research and pilot implementations of RTERS in retail supply chains.
- Addressing ethical, privacy, and scalability considerations associated with real-time discrepancy tracking.

1.8 Structure of the Paper

The paper is structured as follows:

- Section 2: Literature Review systematically reviews the state of logistics discrepancy reporting in the retail sector, challenges of traditional systems, and the role of IoT, predictive analytics, and machine learning in exception management.
- Section 3: Methodology outlines the systematic literature review approach, including data sources, selection criteria, and thematic analysis processes.
- Section 4: Proposed Framework presents the conceptual architecture for RTERS, detailing its layers, functionalities, and integration strategies.
- Section 5: Discussion analyses the practical, operational, ethical, and sustainability implications of implementing RTERS within retail environments.
- Section 6: Conclusion summarises key findings, contributions, and future research directions.

1.9 Significance of Real-Time Exception Reporting in the Retail Sector

In an era where customer loyalty is closely tied to fulfilment reliability, the ability to monitor and resolve discrepancies in real-time is no longer optional but essential for retailers aiming to remain competitive [56]. Studies indicate that real-time visibility and exception management can reduce logistics costs by 10-20%, improve customer satisfaction scores by up to 30%, and significantly reduce return rates due to delivery failures [57].

Furthermore, with increasing pressures to enhance supply chain sustainability, reducing waste associated with logistics discrepancies aligns with broader environmental and corporate social responsibility objectives [58], [59]. Real-time systems facilitate proactive waste reduction by preventing redundant shipments, reducing fuel consumption due to re-deliveries, and minimising product spoilage in sensitive supply chains [60], [61].

2. Literature Review

2.1 Introduction to Logistics Discrepancy Reporting

The retail sector's supply chain is a complex network of interconnected nodes involving suppliers, distributors, warehouses, and retailers, each contributing to the seamless flow of goods [1]. Within this network, discrepancies such as delivery delays, inventory mismatches, routing errors, and damaged goods can disrupt operations, erode profit margins, and diminish customer satisfaction [2]. Traditionally, discrepancy reporting relied on periodic reconciliations and manual checks that often failed to detect problems until substantial losses had already occurred [3]. Given the rise of omnichannel retailing and customer demands for near-perfect fulfilment, legacy systems are increasingly inadequate for timely exception management [4].

2.2 Traditional Discrepancy Management Approaches

Classic approaches to discrepancy tracking typically involve batch processing and manual exception handling, where discrepancies are reconciled during regular audits [5]. As noted by Lee et al. [6], manual exception management is laborious, error-prone, and highly reactive. According to the Association for Supply Chain Management (ASCM), companies relying solely on manual methods report discrepancies only after significant delays, which can lead to excess inventory, redundant shipments, and escalated returns [7]. In the retail context, the cost of handling discrepancies reactively can account for up to 7% of total supply chain operating costs [8].

While Enterprise Resource Planning (ERP) and Warehouse Management Systems (WMS) offer modules for exception tracking, many traditional systems lack real-time data capabilities and interoperability with external logistics partners [9]. This disconnect leads to data silos and incomplete visibility of shipment conditions, causing delays in detecting critical discrepancies [10].

2.3 The Omnichannel Challenge

The rapid adoption of omnichannel strategies adds further complexity to logistics discrepancy tracking. Omnichannel retail integrates online and offline channels, creating multiple touchpoints and fulfilment pathways that increase the likelihood of discrepancies [11]. For example, the same stock may be allocated for online orders, in-store purchases, and click-and-collect options, heightening the risk of stockouts, double allocation, or inaccurate picking [12].

Hübner et al. [13] highlight that 40% of retailers struggle to synchronise inventory data across channels, leading to inconsistencies that complicate exception tracking. These challenges are exacerbated by fragmented legacy systems that cannot communicate seamlessly across warehouses, stores, and last-mile delivery services [14]. Without integrated real-time monitoring, retailers lack the operational agility needed to address discrepancies proactively [15].

2.4 Emergence of Real-Time Visibility in Logistics

In response to the limitations of traditional systems, supply chain visibility has become a major focus area for researchers and practitioners alike [16]. Real-time visibility refers to the continuous tracking of goods, conditions, and events across the supply chain using IoT devices, cloud platforms, and data analytics [17]. According to Christopher [18], real-time visibility transforms supply chains from reactive to proactive systems by providing stakeholders with timely, actionable insights to prevent or resolve disruptions.

IoT sensors, RFID tags, GPS trackers, and telematics are among the most widely used technologies to enable real-time monitoring of goods in transit [19]. In retail logistics, these technologies allow continuous data collection on shipment location, environmental conditions (e.g., temperature for perishables), and delivery status [20]. By integrating these data streams into exception management systems, discrepancies such as delays, route deviations, and damages can be identified instantaneously [21].

2.5 Machine Learning and Predictive Exception Management

Beyond real-time tracking, predictive analytics and machine learning (ML) provide advanced capabilities for forecasting potential discrepancies before they occur [22]. ML models trained on historical shipment data can detect patterns that indicate a high likelihood of delivery failures, inventory inaccuracies, or transit damages [23].

As Zhang et al. [24] demonstrated, ML-based anomaly detection systems can identify subtle data deviations that human operators may overlook. For example, a predictive model may flag a shipment as likely to be delayed if traffic conditions, driver behaviour, or weather data align with patterns associated with past delays [25]. Integrating such predictions into exception reporting frameworks enables proactive measures such as rerouting, customer notifications, or dynamic rescheduling [26].

Several studies have explored the integration of ML into logistics operations. For example, Waller and Fawcett [27] highlight that predictive analytics reduces supply chain disruption costs by 20% when embedded into real-time monitoring systems. Despite these promising findings, the literature reveals gaps in applying ML specifically to real-time exception tracking tailored for retail discrepancy scenarios [28].

2.6 IoT and Big Data Integration

IoT devices generate vast amounts of structured and unstructured data, presenting opportunities and challenges for logistics exception management [29]. Big data platforms enable the processing and analysis of these high-volume data streams to extract actionable insights in real time [30].

According to Kamble et al. [31], IoT-enabled big data analytics enhance supply chain responsiveness by combining sensor data with external datasets such as weather forecasts, traffic updates, and geopolitical events. This integration strengthens anomaly detection and exception management capabilities by correlating multiple factors influencing logistics discrepancies [32].

However, operationalising these capabilities requires robust infrastructure, interoperability standards, and skilled personnel to manage data governance and analytics workflows [33]. Data silos, security concerns, and inconsistent data quality remain significant barriers to the widespread adoption of IoT-driven discrepancy management systems [34].

2.7 Cloud-Based Exception Reporting Systems

Cloud computing has emerged as a key enabler for scalable, real-time exception reporting [62], [63]. Cloud-based platforms provide the computational power and storage capacity required to handle massive IoT data streams while enabling collaboration across geographically dispersed supply chain partners [64], [65], [66].

Cloud-enabled exception reporting systems allow retailers to deploy analytics dashboards, real-time alerts, and performance monitoring tools accessible through web interfaces or mobile applications [67], [68]. As noted by Jaswal [69], cloud infrastructure supports rapid deployment of updates, API integrations with ERP and WMS systems, and centralised data governance, all essential for effective real-time discrepancy tracking.

2.8 Comparative Analysis of Existing Frameworks

Multiple frameworks for logistics exception management have been proposed in the literature. For example, Tawalbeh et al. [70] developed a conceptual model integrating predictive analytics with real-time visibility tools for supply chain risk management. Similarly, Al-Hujran et al. [71] outlined an IoT-based supply chain monitoring architecture for perishable goods, highlighting the benefits of environmental condition tracking.

However, most existing frameworks are sector-specific or focus on broader supply chain risk management rather than the unique requirements of discrepancy reporting within retail logistics [72], [73]. Furthermore, limited research has addressed the integration of IoT, ML, and cloud technologies into a cohesive, real-time exception reporting system tailored for omnichannel retail operations [74], [75].

2.9 Gaps in Current Literature

Despite growing interest in supply chain visibility and predictive analytics, notable gaps persist in the research on real-time discrepancy tracking for retail logistics:

- Sector-specific solutions: Many frameworks do not address the complexities of omnichannel retailing, including synchronising inventory data across online and offline channels [76], [77].
- Integration challenges: Few studies examine how to seamlessly integrate IoT devices, predictive models, and cloud infrastructure into existing retail logistics systems [78], [79].
- Scalability and adaptability: Research on scalable architectures that can handle the dynamic, high-volume data environments typical of retail supply chains remains limited [80], [81], [82].
- Ethical and privacy concerns: While real-time monitoring improves operational efficiency, it raises questions about data privacy, algorithmic fairness, and workforce implications [83], [84].

Addressing these gaps is critical for developing practical, deployable solutions that enhance discrepancy detection and resolution in complex retail environments.

2.10 The Rationale for Real-Time Exception Reporting in Retail

Given the limitations of traditional reporting systems and the potential of digital technologies, there is strong justification for developing a Real-Time Exception Reporting System (RTERS) for the retail sector. Such a system would:

- Continuously ingest IoT sensor data to monitor shipment location, condition, and status.
- Apply machine learning algorithms for anomaly detection and predictive alerts.
- Generate real-time notifications for stakeholders to enable prompt corrective actions.
- Integrate with cloud platforms for scalability and seamless access across supply chain partners.
- Address privacy and security concerns through encryption, access controls, and compliance with regulations such as GDPR.

2.11 Summary of Literature Review

In summary, the literature demonstrates a clear evolution from manual, reactive discrepancy management approaches to data-driven, predictive frameworks leveraging IoT, big data analytics, and cloud computing. However, specific solutions targeting the unique challenges of logistics discrepancy reporting in the retail sector remain underdeveloped.

This gap underscores the need for a conceptual RTERS architecture that synthesises existing best practices and technological enablers while addressing practical implementation, ethical, and scalability considerations. The next section presents the methodology for this study, followed by the proposed framework to guide retailers and researchers in deploying real-time exception reporting systems to enhance operational resilience and customer satisfaction.

3. Methodology

3.1 Research Design

Given that this study is literature-based with no primary data collection, a Systematic Literature Review (SLR) approach was employed to gather, analyse, and synthesise current knowledge on logistics discrepancy reporting and real-time exception tracking within the retail sector. The SLR method ensures transparency, replicability, and comprehensive coverage of relevant scholarly contributions while enabling the identification of research gaps and industry trends.

The SLR aligns with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, ensuring that the review process is systematic, structured, and rigorous. This approach allows for a robust conceptual foundation for proposing the Real-Time Exception Reporting System (RTERS) without relying on empirical data collection.

3.2 Data Sources and Search Strategy

Multiple academic databases were utilised to collect relevant literature, including:

- IEEE Xplore
- Scopus
- Web of Science
- ScienceDirect
- SpringerLink

Keywords used for searches included:

- "logistics discrepancy reporting"
- "exception management in retail"
- "IoT in supply chain"
- "real-time logistics monitoring"
- "machine learning for logistics"
- "predictive analytics in retail supply chain"

Boolean operators (AND, OR) were applied to refine searches, and citation chaining was used to identify additional relevant studies.

3.3 Inclusion and Exclusion Criteria

To ensure relevance, the following inclusion criteria were applied:

- Peer-reviewed journal articles and conference papers published between 2013 and 2023.
- Studies focusing on logistics discrepancy management, exception tracking, and IoT integration within the retail supply chain.
- Papers discussing predictive analytics, machine learning, and cloud-based frameworks in logistics.

Exclusion criteria included:

- Articles not in English.
- Studies focusing exclusively on sectors outside retail unless they contributed directly to frameworks applicable to retail logistics.
- Opinion pieces and non-peer-reviewed sources.

3.4 Screening and Selection Process

The initial search retrieved 632 articles across the selected databases. After removing duplicates, 498 articles remained. Titles and abstracts were screened, leading to 120 articles for full-text review. Following a detailed evaluation based on relevance to retail logistics discrepancy reporting and technological frameworks for exception management, 97 articles were selected for inclusion in the thematic analysis.

3.5 Data Extraction and Coding

A structured data extraction sheet was used to record:

- Author(s) and publication year.
- Research objectives.
- Methodologies applied.
- Technologies utilised (e.g., IoT, ML, cloud computing).
- Sector focus.
- Key findings related to discrepancy reporting and exception management.

Each paper was coded based on:

- Technological enablers (IoT, big data, ML, cloud frameworks).
- Operational challenges (data silos, system integration, real-time processing limitations).
- Ethical considerations (privacy, transparency, algorithmic bias).
- Frameworks and models proposed.

3.6 Thematic Analysis

The extracted data were analysed thematically to identify common patterns, technological trends, operational barriers, and gaps in the current literature. Themes identified included:

1. The inadequacy of traditional discrepancy reporting systems.
2. The rise of IoT-enabled supply chain visibility.
3. The role of predictive analytics in exception management.
4. The need for integrated, scalable frameworks in retail logistics.
5. Ethical and privacy challenges in real-time monitoring systems.

This thematic analysis informed the design of the proposed RTERS framework by grounding it in state-of-the-art practices while aligning it with the unique challenges identified within retail logistics environments.

3.7 Validation through Triangulation

To enhance the reliability of the SLR findings, methodological triangulation was employed:

- Cross-referencing insights across multiple high-impact journals and conferences.
- Comparing findings with industry reports from CSCMP, ASCM, and McKinsey on retail logistics trends.
- Analysing case studies on IoT and predictive analytics deployment in supply chains to validate theoretical frameworks against industry practices.

3.8 Ethical Considerations

Although primary data collection was not conducted, ethical considerations were integrated into the review by:

- Critically analysing papers for their discussions on privacy-preserving practices in IoT-enabled tracking.
- Highlighting algorithmic transparency and bias concerns as key dimensions in real-time exception reporting frameworks.
- Emphasising compliance with regulations such as GDPR in designing system architectures for RTERS.

3.9 Methodological Limitations

While the SLR provides a comprehensive synthesis of current knowledge, certain limitations are acknowledged:

- The exclusion of non-English studies may have omitted relevant regional research.
- The absence of primary data means practical, contextual challenges of RTERS deployment can only be hypothesised based on literature.
- Technological advancements after 2023 are not captured, which may impact the framework's adaptability in future contexts.

3.10 Transition to Proposed Framework

The SLR findings, thematic analysis, and triangulated validation informed the conceptualisation of the Real-Time Exception Reporting System (RTERS) proposed in the next section. The framework leverages IoT, predictive analytics, and cloud-based infrastructures while addressing identified operational, ethical, and scalability challenges, positioning it as a practical solution for real-time logistics discrepancy management in the retail sector.

4. Proposed Framework

4.1 Framework Overview

Based on the systematic literature review and identified gaps, this study proposes a Real-Time Exception Reporting System (RTERS) conceptual architecture designed to detect, report, and manage logistics discrepancies within retail supply chains proactively. The framework integrates IoT-enabled data collection, machine learning-based anomaly detection, real-time alert generation, and dashboard visualisation, enabling actionable insights for logistics managers.

4.2 Framework Components

The RTERS consists of the following interconnected layers:

4.2.1 IoT Data Ingestion Layer

- Function: Continuously captures shipment conditions, location, and transit status using RFID tags, GPS sensors, and environmental sensors (e.g., temperature, humidity).
- Role: Enables granular, real-time visibility across transit points and distribution nodes in the supply chain.
- Justification: Studies [85], [86] show IoT data enhances detection of discrepancies such as route deviations and environmental violations (e.g., cold chain failures).

4.2.2 Data Processing and Storage Layer

- Utilises cloud-based infrastructure for scalability, allowing ingestion of high-volume sensor data with minimal latency [87], [88].

- Supports API-based integration with ERP, WMS, and TMS platforms for seamless data exchange and contextual alignment.
- Employs stream processing frameworks (e.g., Apache Kafka, Spark Streaming) to handle real-time data processing [3].

4.2.3 Anomaly Detection and Predictive Analytics Layer

- Implements machine learning models (e.g., Isolation Forests, LSTM models) to detect deviations from normal shipment patterns and predict potential discrepancies.
- Models are trained using historical shipment, traffic, and environmental data to forecast risks such as delays, damages, and stockout conditions [89], [90].
- Outputs include risk scores and anomaly flags for shipments requiring attention.

4.2.4 Real-Time Alert and Notification Layer

- Generates automated alerts when discrepancies are detected or predicted, sending notifications to relevant stakeholders via SMS, email, or in-app dashboards.
- Supports rule-based prioritisation of alerts based on severity, shipment value, and customer priority, ensuring timely interventions [5].

4.2.5 Visualisation and Decision Support Layer

- Provides an interactive dashboard for logistics managers, visualising shipment statuses, discrepancy trends, and predicted risks.
- Includes drill-down capabilities to analyse discrepancy root causes and facilitate data-driven decision-making.
- Enables monitoring of key performance indicators (KPIs) such as on-time delivery rates and discrepancy resolution times.

4.3 Key Features of the RTERS

- Real-Time Monitoring: Immediate detection and reporting of discrepancies to minimise financial and operational impacts.
- Predictive Capability: Anticipates discrepancies before they escalate, enabling pre-emptive mitigation.
- Scalability: Cloud-based infrastructure supports high data volumes across multiple geographic regions.
- Interoperability: Integrates seamlessly with existing retail logistics infrastructures.
- User-Centric Design: Provides actionable insights through intuitive dashboards for diverse stakeholders.

4.4 Addressing Ethical and Privacy Concerns

The framework incorporates:

- Data Encryption and Access Controls to ensure data security and privacy [91], [92].
- Compliance with GDPR and local data protection laws [93].

- Inclusion of explainable AI components to enhance transparency of ML-driven predictions, building trust among stakeholders [94].

4.5 Implementation Considerations

- Data Quality: Successful deployment depends on the reliability and accuracy of IoT sensor data and historical records.
- Change Management: Employee training and stakeholder engagement are essential for system adoption.
- Continuous Model Updates: Predictive models require retraining with updated data to maintain accuracy in dynamic logistics environments.

4.6 Expected Benefits

The RTERS framework, when implemented, is expected to:

- Reduce operational costs associated with manual discrepancy handling.
- Minimise shipment delays, damages, and inventory mismatches.
- Enhance customer satisfaction through improved delivery reliability and transparency.
- Support sustainability objectives by reducing redundant shipments and returns, lowering carbon footprints.

5. Discussion

5.1 Practical Implications of Implementing RTERS

Implementing the proposed Real-Time Exception Reporting System (RTERS) in retail logistics can transform operational practices by shifting from reactive to proactive discrepancy management. Retailers can detect shipment delays, damages, inventory mismatches, and routing deviations in real time, allowing them to initiate corrective actions promptly, thus reducing customer dissatisfaction and financial losses [1]. This system also enables dynamic rerouting, reallocation of inventory, and customer notification systems to mitigate the impacts of discrepancies before they escalate [2].

Studies have demonstrated that real-time visibility solutions can reduce supply chain disruption costs by up to 20% while enhancing customer service metrics [3]. The RTERS, with its predictive analytics layer, further extends these benefits by anticipating potential discrepancies using machine learning, allowing interventions such as dispatch rescheduling or alternate carrier allocation, ultimately improving delivery reliability and customer trust [4].

5.2 Comparative Advantages over Traditional Systems

Unlike traditional exception reporting methods that rely on periodic reconciliations and manual inspections, the RTERS offers:

- Immediate alerts for anomalies, reducing detection latency.
- Predictive discrepancy management, lowering risk exposure.
- Integrated dashboards for decision support, enhancing transparency.
- Automated notifications, improving communication across stakeholders.

These features enable agility and responsiveness within logistics operations, aligning with the increasing complexities of omnichannel retail where discrepancies can arise from varied fulfilment methods [5].

5.3 Operational and Technical Challenges

Despite its advantages, implementing RTERS in retail environments involves several challenges:

- Data Quality and Integrity: The system's accuracy depends on the quality of data from IoT sensors and historical records. Inconsistent or missing data can lead to false positives or undetected discrepancies [6].
- Integration with Legacy Systems: Many retailers operate on diverse ERP, WMS, and TMS platforms, making seamless integration a significant technical hurdle requiring middleware solutions and API development [7].
- Cost of Deployment: Although cloud-based infrastructure reduces upfront capital expenditures, investments in IoT devices, system integration, and employee training can be substantial for mid-sized retailers [8].
- Scalability: Managing real-time data streams across geographically distributed operations necessitates robust cloud architecture capable of handling high throughput while maintaining low latency [9].

5.4 Ethical and Privacy Considerations

Deploying RTERS involves continuous monitoring of shipment and operational data, raising privacy and ethical concerns:

- Data Privacy: The collection of granular shipment data must comply with data protection laws (e.g., GDPR), necessitating robust data governance and user consent frameworks [95], [96].
- Algorithmic Transparency: ML-based anomaly detection systems may operate as 'black boxes'. Ensuring explainability is crucial for stakeholders to understand and trust the system's decisions [97], [98], [99].
- Workforce Implications: Automation of discrepancy reporting may reduce manual monitoring tasks, potentially affecting employment in certain logistics roles. Retailers should adopt workforce reskilling strategies to mitigate adverse impacts [100], [101].

5.5 Sustainability Impacts

RTERS can contribute to sustainability goals in retail logistics by reducing:

- Redundant shipments due to undetected discrepancies.
- Returns and associated emissions.
- Waste from damaged or spoiled goods by enabling timely interventions [102].

These improvements align with corporate sustainability initiatives, enhancing both operational efficiency and environmental responsibility.

5.6 Research and Pilot Testing Opportunities

The conceptual framework of RTERS developed from literature review sets the foundation for future empirical studies and pilot testing within retail logistics environments. Pilot implementations can evaluate:

- The accuracy of ML-based discrepancy predictions across diverse product categories [103], [104].
- The cost-benefit analysis of IoT-enabled real-time monitoring systems [105].
- User acceptance and adaptation to automated exception reporting tools.

Such pilot studies will further refine the framework and provide practical insights for scalability across varied retail contexts.

5.7 Summary

The discussion has highlighted the practical potential, comparative advantages, and challenges of implementing a Real-Time Exception Reporting System in retail logistics. While promising in enhancing operational efficiency and customer satisfaction, successful deployment requires careful attention to data quality, integration strategies, ethical practices, and stakeholder engagement.

The next section presents the conclusion, summarising the study's contributions and outlining future research directions for advancing real-time logistics discrepancy management in the retail sector.

6. Conclusion

This paper explored the critical challenge of logistics discrepancies in the retail sector and proposed a Real-Time Exception Reporting System (RTERS) grounded entirely on a systematic literature review. The paper demonstrated that while traditional exception management systems in retail logistics are primarily reactive, manual, and fragmented, the integration of IoT, machine learning, and cloud-based infrastructures provides opportunities to transition towards proactive, data-driven discrepancy management.

The literature review highlighted:

- The limitations of legacy exception reporting systems in detecting discrepancies such as shipment delays, damages, and inventory mismatches in a timely manner.
- The transformative potential of IoT devices in enabling continuous monitoring across supply chain nodes.
- The predictive capabilities of machine learning models to forecast potential discrepancies before escalation.
- The importance of cloud-based frameworks for ensuring scalability and interoperability in omnichannel retail environments.

Based on these insights, the proposed RTERS framework was detailed, outlining a layered architecture that includes IoT data ingestion, predictive anomaly detection, real-time alerting, and dashboard-based decision support. The framework aims to enhance operational efficiency, customer satisfaction, and sustainability while addressing challenges related to data quality, integration complexities, and ethical considerations such as privacy and algorithmic transparency.

While the conceptual framework sets a foundation, empirical validation through pilot implementations in live retail environments is essential to assess the framework's practicality, cost-benefit ratio, and adaptability across different retail contexts. Future research should focus on:

- Developing explainable AI models for transparency in discrepancy detection.
- Evaluating the socio-economic and workforce impacts of deploying real-time monitoring systems.
- Exploring cybersecurity measures to protect sensitive shipment data.

In conclusion, implementing a Real-Time Exception Reporting System has the potential to significantly reduce logistics discrepancies, minimise operational costs, and improve customer experiences within the increasingly complex retail logistics landscape. By leveraging digital technologies effectively, retailers can build resilient, agile, and customer-centric supply chains necessary for maintaining competitiveness in today's market.

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