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Original Article

Detailed Analysis of Automating Detention Claim Approval in Shipping with AI Agents and LLMs

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Abstract *- In the $1 trillion shipping industry, approving detention claims where drivers wait additional hours for loading or unloading requires plant and logistics managers to manually match in/out timings from Transportation Management Systems (TMS) with Proofs of Delivery (PODs) and driver tracking details, taking 1–2 days per claim (Transport Topics, 2023). This paper explores how AI agents powered by Large Language Models (LLMs) can automate this process, reducing approval times to 5–30 minutes, a 90–95% efficiency gain. By integrating with TMS, parsing PODs with 90% accuracy (McKinsey, 2024), and analyzing textual data to determine fault (e.g., carrier lateness vs. shipper delays), these agents approve or deny claims like $100 for a 2-hour wait in real-time.*

For 100 monthly claims, this saves 100–200 days of effort annually, cutting labour costs by $7,500–$15,000 at $75/hour (Cass Freight Index, 2023). In this automated landscape, shippers process claims instantly, reducing disputes by 15% (FreightWaves, 2024) and improving carrier relations, though 6–12 month integration timelines and 5–10% data inaccuracies pose challenges (Gartner, 2024). This transformation promises a faster, more consistent detention approval process in a high-stakes logistics ecosystem.

Keywords *- AI agents, LLMs, Detention approval, Shipping logistics, TMS integration, document parsing, Automation efficiency.*

1. Introduction

The global shipping industry plays a critical role in international trade commerce. However, it is burdened by inefficiencies related to detention claims and financial penalties levied when containers are held beyond the allotted free time at terminals [1]. These claims involve substantial manual paperwork, labour-intensive validation, and fragmented communication between the shipper, carrier and logistics provider. The existing workflow is convoluted and prone to errors and disputes, leading to revenue loss, dissatisfied customers and operational gridlock [2].

Although transport infrastructure and digital logistics platforms have evolved significantly since 2023, the processes related to detention are still fragmented and reactive. Regarding detention claims, brokers or logistics coordinators generally stitch together bits of information from disparate systems, including terminal logs, carrier schedules, GPS tracking tools and email threads [3]. Disconnected data sources slow claims processing and lead to differences in claim adjudication, more strained relationships between stakeholders and disagreements over invoices that lead to litigation [4].

Moreover, the nuanced meaning found in service-level agreements (SLAs), contractual clauses and justification documents adds a layer of linguistic complexity that traditional automation is ill-equipped to handle [5]. For example, evaluating whether a delay qualifies as an exception under specific terms such as weather disruptions, port congestion, or force majeure requires a contextual understanding of both structured data (e.g., timestamps, geolocation) and unstructured communication (e.g., emails, notices, contractual terminology) [6]. With instances like this, manual processing of such hybrid datasets is slow and highly prone to subjective judgement, leading to an increased risk of inconsistent or non-compliant decisions [7].

Recent advances in AI technologies, brilliant automation and natural language understanding have paved the way for a more scalable, intelligent, and explainable approach. Detention claim systems can become self-validated by integrating rule-based AI agents for structured data processing with LLMs that can interpret free-text documentation [8]. Such systems can minimize human involvement and provide audit trails. However, they can also create rationales behind approvals or rejections and learn to use more subtle ways to handle outlier exceptions [9].

With supply chains going digital, integrating Artificial Intelligence (AI) agents and Large Language Models (LLMs) offers a transformative solution to streamline detention claim processing. AI agents are responsible for independent mining, verifying and reconciling data from shipment logs, port arrival/departure times, terminal entries and exit notes, and contractual clauses [10]. Furthermore, LLMs improve contextual understanding, streamline document indexing, and enable agile decision-making in ambiguous scenarios [11].

This paper thoroughly analyses how blending automation with AI agents and LLMs can overhaul the detention claim approval process. Further, it explores the role of AI agents LLMs, their benefits, their future for AI automation, and their challenges and constraints.

2. Literature Review

Detention and demurrage (D&D) charges are a big headache from the operational and financial perspectives in maritime trade logistics. Reduced free time and increased fees for D&D create organizational complexities, particularly in intermodal transport, leading to higher risks and costs. Depending on manual processes and disconnected data sources makes the claim process lengthy and imprecise, further straining the system [12].

With increased Maritime operations, AI (Artificial Intelligence) has improved efficiency and decision-making. AI-powered technologies have shown promise across predictive maintenance, risk assessment, and navigation, revolutionizing traditional practices. Specifically, it is the automation of data extraction and validation processes needed for approving detention claims, minimizing human error and processing time, leading to overall efficiency across the ecosystem [13].

Integrating Robotic Process Automation (RPA) with AI capabilities is a powerful combination for advancing business processes in various sectors, including logistics. With RPA, organizations can automate mundane, repeatable tasks like data entry, invoice processing, etc. AI extends the capabilities to make RPA intelligent for decision-making. Such synergy can be harnessed to automate the complex workflows for detention claim approvals [14][15].

Large Language Models (LLMs) have transformed the natural language processing field, enabling sophisticated legal document analysis. The development of datasets such as "MultiEURLEX" allows for the multi-label classification of legal texts, enabling use in legal document understanding and compliance checking. One of the significant benefits of LLMs is their ability to interpret contractual clauses or correspondence regarding detention claims [1].

Autonomous decision-making through AI agents is revolutionizing Supply Chain Management. These agents can interpret real-time input, adapt based on their environment, and autonomously make contextual decisions. AI agents have been employed in supply chain optimization applications to optimize procurement and inventory decision-making [17].

Processing claims of detention requires heterogeneous data such as entering port logs, timestamps, GPS, and contractual frameworks. Integrating structured and unstructured data is critical for comprehensive analysis. Technologies such as knowledge graphs and hybrid AI systems facilitate the fusion of structure reasoning with natural language understanding, thus enabling end-to-end automation of these complex processes [18].

Despite advancements, there is a lack of research focusing on automating a process like detention claim approvals using AI technologies.

Existing AI applications in maritime logistics are based on the process's operational aspect, leaving a gap in the automation of administrative processes. This study attempts to fill this gap by proposing a hybrid model that utilizes AI agents and large language models (LLMs) to automate workflows around detention claims, thereby improving efficiency and compliance.

3. Research Methodology

This research employs a qualitative approach, primarily relying on secondary data sources for its literature review and analysis. The information was sourced from various reliable Internet sources, including industry publications, regulatory agency releases, and market research. Peer-reviewed journals were reviewed to find theoretical foundations and present developments in Automating Detention Claim Approval in Shipping with AI Agents and LLMs [19].

Insights were also gained from trade publications, whitepapers, and case studies from prominent financial institutions, consulting houses, and technology providers. These sources were carefully reviewed to gain a holistic perspective of the current trends, challenges, and best practices in integrating AI into custody services, including enhanced reporting, compliance monitoring, and risk management [20].

4. Research Gap

The supply chain and logistics industry are moving into the digital era. The process of detention claim approval, especially with in-land transportation, is still manually done. Current attempts at automation have mainly concentrated on structured processes such as monitoring the course of giving goods, load planning and fleet routing, and employing rule-oriented systems or legacy ERP/TMS platforms.

However, human analysis is still needed for detention management, requiring someone to sift through check-in/check-out times, investigate contract terms and check supporting communication (e.g. emails, BOLs, driver notes) following agreed terms. Little research discusses

AI's ability to automatically merge data from disparate systems in different formats for precise, instantaneous resolving of claims. Even more important, current studies of AI in logistics say significantly less about how Large Language Models (LLMs) can be integrated with operation workflow for unstructured language data.

This research paper explores addressing that space by creating an LLM-guided framework that can automatically advance the precise acceptance procedures of detention claims while adding contextual language inputs to structured logistic data in a combined intelligent system.

5. Role of AI Agents in Automating Detention Claim Approval

Approving detention claims is complex in the shipping industry as it needs to validate and reconcile large amounts of time-sensitive, multi-source data. Detention charges are applied when containers are held beyond their contracted "free time" at a shipper's or consignee's location [21].

Manually cross-verifying gate-in/gate-out timestamps filled at the container tracking system, port schedules and contract terms are the traditional claim approval process prone to delays and errors. AI agents offer an intelligent automation layer that elevates this manual burden to an autonomous decision-making workflow [22].

5.1. The Definition and Scope of AI Agent

AI agents are autonomous software agents that monitor data, evaluate specific conditions, take actions, and continue to learn and adapt. In detention claim processing, digital operations analysts continuously monitor data streams, apply policy-based rules, and initiate actions such as approving, rejecting or escalating. It seamlessly integrates with the TOS, TMS, and ERP platforms [23].

5.2. Functional Components of AI Agents in Detention Claim Automation

AI agents in this space follow a regimented pipeline, including data ingestion, verification, anomaly detection, and decision-making:

5.2.1. Data Ingestion and Preprocessing

AI agents combine structured data from different systems like:

- Times spent gate-in and gate-out at the port
- Tracking the ID of containers from IoT or GPS devices
- Booking and bill of lading data
- Carrier schedules and voyage data
- Service Level Agreements (SLAs) and Complimentary Time Clauses

The agents then clean, normalize, and enrich the incoming data via APIs and ETL (Extract, Transform, Load) pipelines to build an enriched timeline for when, where, and how containers move [24].

5.2.2. Time-based Rule Application

AI agents are primarily used to apply predefined business rules to determine whether detention charges are valid. For example:

- Compare the actual container return date to the SLA-defined free time window.
- Check whether weekends, holidays or port disruptions should be applied as an Exception.
- Method of calculating the actual chargeable detention days and penalties.

Decision logic is expressed using a combination of the following:

- Deterministic rule engines (e.g., business rule management systems such as Drools)
- Custom evaluators for temporal logic
- Frameworks aligned with regulatory and commercial policies [25].

5.2.3. Anomaly Detection & Pattern Recognition

Supervised learning models (e.g., random forest classifiers or gradient boosting machines) are used to train AI agents that can flag anomalies, such as:

- Repeated claims from specific locations or partners
- Gaps in event logs (missing gate-out entry)
- The discrepancy between Reported timestamps and system-logged timestamps

These models are trained with historical data so agents can validate claims and spot trends that point to systemic issues, fraud, and more [26].

5.2.4. Contextual Exception Handling

Although AI agents mostly deal with structured data, they are also programmed with contextual input:

- Identify and recognize operational Exception (ex. Alerts for port congestion)
- Integrate with external data sources such as marine traffic APIs or weather feeds.
- Auto-exempt events classified under "force majeure" or other conditions

This allows the agents to adjust chargeability logic dynamically based on external context [27].

5.3. Autonomous Decision-Making and Workflow Integration

Post-processing, the AI agent outputs a decision result:

- Approve: If all SLA compliance and data points corroborate the claim
- Blocklist: When the claim does not pass the threshold checks or has invalid data
- Escalate: If the decision confidence is low or if it detects anomalies

The decisions are fed to the workflow automation engine that initiates notifications, ledger updates or manual review tasks based on predefined escalation rules [28].

In more sophisticated deployments, reinforcement learning agents might realize improved decision-making over time by learning from human override behaviour to drive better predictions.

5.4. Benefits of AI Agent-Driven Automation

Table 1. Benefits of Agentic automation

Benefit	Details
Speed	Processes claims in real time or within minutes compared to days with manual processing.
Accuracy	Reduces human error and ensures consistent rule application across different types of cases
Cost Savings	Minimizes labour costs and prevents revenue leakage due to missed or erroneous charges, which occur quite often without AI automation
Scalability	Capable of processing thousands of claims concurrently across multiple regions, helping businesses scale
Auditability	Creates logs and traceable decision paths for compliance and dispute resolution

5.5. Limitations and Design Considerations

While AI agents excel at structured logic and rule-driven workflows, they require structured login and rule-driven workflows; few areas where AI automation needs to be carefully deliberated are-

- Clean datasets for accurate, real-time data streams
- Well-defined business rule configuration
- Train & Adapt, periodic model retraining to evolving shipping policies
- Manual Intervention for complex outlier scenarios

6. How LLM can Help in the Process

Although AI agents excel at processing structured data and rule-based decisions, much of the work involved in processing detention claims is unstructured, ambiguous and language-complex, including email communications, scanned contracts, handwritten delivery notes, and justification texts provided by shippers [29]. Moreover, this is where the Large Language Models (LLMs) come very much in support. LLMs can deal with advanced linguistic complexity that static AI systems of the past could not, thanks to their exceptional natural language understanding, context awareness, and semantic reasoning [30].

6.1. Understanding Contractual Clauses and Service-Level Agreements (SLAs)

Detention claims often hinge on nuanced terms defined in SLAs, e.g.:

- Free time duration (e.g., "5 working days excluding holidays")
- Exceptional circumstances (e.g., "force majeure due to strikes or weather")
- Penalty thresholds and waiver conditions

LLMs can use their pretrained legal/commercial language knowledge to parse and understand these clauses, even if they come from scanned or digital contracts [31].

The LLM can extract using prompt engineering or fine-tuning:

- The applicable free time window
- Exceptions and conditional rules
- Date/time cutoffs based on context (e.g., "from time of discharge")

This knowledge can automate legal interpretation once a completely human territory is created.

6.2. Analyzing and Interpreting Email Communication

A key point in detention claim disputes is the interpretation of communication between stakeholders:

- Shippers claim prior notice was given for delay
- Deadlines were not respected, carriers argue
- Port operators use system alerts

LLMs can read full email threads, highlight events relevant to the timeline, and pick up sentiments or commitments ("approved extension," "noted delay," "confirmed late return").

This contextual insight helps the AI system determine:

- If the delay had been acknowledged or accepted
- If exceptions were granted or denied in writing
- What commitments were made and by whom

6.3. Natural Language Justification Processing

When a claim is submitted, shippers or freight forwarders routinely offer written justifications as free text, for example:

"Truck was delayed due to congestion at inland terminal due to customs backlog. Email notification was sent to the carrier on April 6 at 9:42 AM,"

LLMs are used to:

- Convert your headings into entities (dates, locations, events)
- Identify cause-effect relationships (e.g., delays due to congestion)
- Rate the plausibility and relevance of the rationale
- Compare with reasoning for known exception classes (e.g., terminal delays)

This allows the claim system to indicate whether a justification qualifies for waiver criteria and if the case can be auto-approved [32].

6.4. Document Summarization and Audit Explanation

Transparency is key because one of the biggest challenges in automating detention claims is that carriers and shippers often need a clear rationale for why a claim was accepted or denied. LLMs can generate:

- Summaries of decisions: "Based on container gate-out on April 3 and a 5-day free period, the return on April 10 exceeded limits by 2 days."
- Explanatory notes: "Claim was denied as supporting documentation was not found in the email record, and the SLA does not allow a waiver for trucker delays."

Such narrative abilities boost trustworthiness and create documentation for auditing and regulatory practices [33].

6.5. Intelligent Case Routing and Escalation

LLMs can also assist in:

- Tagging complicated or ambiguous claims needing human review
- Grouping matching examples for batch processing or pattern recognition
- Extracting urgency or risk cues (e.g., VIP customer, legal threats, repeated disputes)

This smart triaging also allows the system to escalate higher-impact or sensitive claims for review [34].

6.6. Advantages of LLM Integration

Table 2. LLM Integration benefits

Benefit	Description
Contextual Understanding	Goes beyond keyword search, understands intent, ambiguity, and nuance
Language Diversity	Handles multilingual inputs (e.g., global shipping documents and emails)
Flexibility	Can adapt to new contract templates, writing styles, or document formats
Consistency	Eliminates subjective bias and outlier situations in interpreting textual claims
Auditability	Generates clear, human-readable rationales for decisions, helping businesses in audit compliance

6.7. Implementation Considerations

To implement LLMs effectively:

- Convey scanned documents, including PDFs, using the OCR tool to convert them into text before LLM processing.
- Search and fetch relevant documents to feed into models using retrieval-augmented generation (RAG) techniques.
- Deploy and tune open-source LLMs (like LLaMA, Mistral) on domain-specific datasets (e.g., shipping SLAs, claims).
- Use frameworks like LangChain or Haystack for orchestration and document chaining.

6.8. Scope AI agents LLM can help with Truck Loading and Unloading Delays

Delays at pickup and delivery points (called dwell time or detention) are among the most enduring inefficiencies in in-land freight movement. Such delays can happen when a truck comes to the shipper or consignee facility and is detained beyond the usual "free time" waiting to load or unload.

The industry norm allows 2 hours free at pickup or delivery, after which detention charges are applied (ranging from $50 to $100 per hour). However , the validation and approval of these detention claims have been highly manual, subjective, and prone to dispute.

Claims in traditional workflow use static data feeds of information from Bills of Lading (BOLs), Electronic Logging Devices (ELDs), driver notes and manually entered time stamps. These inputs are often inconsistent, lack contextual justification, and require back-and-forth between brokers, carriers, and shippers for approval, leading to delays in reimbursements, revenue leakage, and strained relationships.

This complex, fragmented process can be automated using AI agents and Large Language Models (LLMs)d, which can substantially improve accuracy. AI agents can automatically extract TMS log, GPS records and gate entry systems' check-in and check-out time stamps.

LLMs can interpret delays by capturing the events in supporting documents, driver emails, load instructions, or warehouse notices interpreting unstructured data, e.g., *"Waited 3 hours due to missing BOL, guard signed at 2:30 PM"*. These insights allow the system to almost instantaneously validate detention claims and escalate only the exceptions that need human Intervention.

6.9. Truck Loading and Unloading Delays with AI/LLM Automation

Table 3. Loading/Unloading Delays, reasons and role of agent automation

Location	Common Delay Cause	Data Inputs	AI Agent Role	LLM Role	Automated Outcome
Pickup	Long wait for a dock assignment	ELD timestamps, check-in log, dock availability report	Calculates time from gate-in to dock-in	Interprets warehouse note: "Busy shift change at 2 PM."	Detention claim generated with delay context
Pickup	Missing paperwork or	Driver comments, email thread, BOL	Matches delay with missing	Extracts and summarizes: "Waiting for the	Validated detention time, auto-approved

	BOL	timestamps	document logs	shipper to issue BOL."	fee
Pickup	Loading crew unavailability	Facility communication logs, shift reports	Time-matches idle hours against dock staff logs	Interprets note: "Loader break between 1–3 PM"	Flags for partial SLA violation, partial payment recommendation
Delivery	The dock was not ready upon truck arrival	Gate-in/out from GPS, facility logs	Measures difference between arrival and unloading start	Parses consignee message: "Dock 4 under maintenance until 4 PM"	$100 detention charge auto-approved
Delivery	Unclear instructions causing delay	SMS/chat log from driver, delivery notes	Flags location-based delay with TMS geo-tagging	Interprets message: "Had to wait for gate code; no signage."	Approves delay, recommends updating delivery SOP
Delivery	Lumpers unavailable or working slowly	Driver notes, POD image timestamp	Correlates delay duration with lumper interaction window	Extracts from POD: "Unloaded at 6:45 PM; dock open since 4:30 PM."	Identifies excess dwell and triggers charge claim.
Delivery	Wait for load inspection or approval	QC logs, scanned paperwork, inspection checklist	Logs inspection duration vs. SLA window	Reads message: "QC delayed approval by 90 mins due to pallet issues."	SLA-supported detention with reason logged

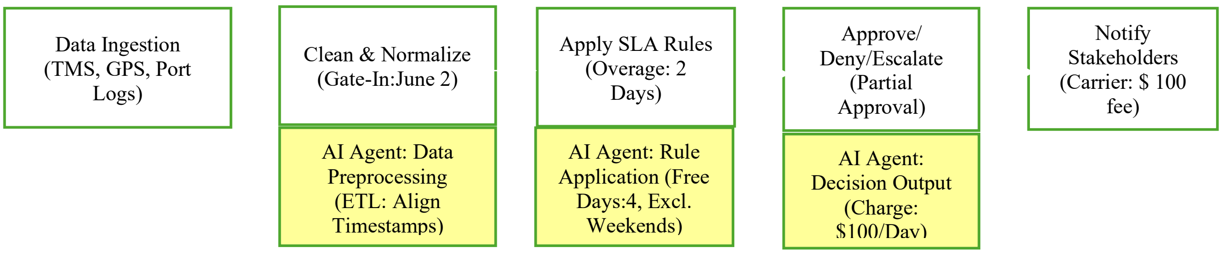

Fig. 1 The step-by-step workflow explains the process and Intervention by AI agents.

AI-Agent-Driven Detention Claim Validation Workflow: This flowchart illustrates how AI agents automate detention claim validation by ingesting data from TMS, GPS, and Port logs, cleaning and normalizing SLA rules (e.g., 4 free days excluding weekends), and outputting decisions like a $ 100/day fee, reducing approval times to minutes, as detailed in the paper.

Automating detention claim approval at pickup and delivery locations offers measurable improvements in operational transparency, payment speed, and carrier satisfaction. It also allows shippers and third-party logistics to identify recurring bottlenecks, quantify the cost of inefficiency and enforce contracts more precisely. As AI systems evolve, it is possible to use the real-time analytics of the dwell time per facility, region or carrier to better plan the network, increase scheduling accuracy and improve the end-to-end customer journey of the inland journey.

7. Future Scope

The increasing volumes of international trade and the sophistication of global supply chain operations will drive the evolution of the automation of detention claim processes (currently based on structured workflows) by AI agents and Large Language Models (LLMs) toward more predictive and autonomous systems [35].

Subsequent innovation will enable detention management processes to be proactive in preventing disputes before they arise rather than reactive to disputes as they are currently. Refined with real port conditions, ship movements, carrier plans, and congestion analytics, AI brokers will identify likely delays ahead of time and initiate preemptive actions including accelerated pickup or dynamic SLA renegotiation.

The ecosystem will witness self-learning adaptive systems in the next wave of innovation. By creating feedback loops, AI agents will produce better decisions over time by analyzing the results of historical claims, patterns of negotiation, and how disputes were resolved. LLMs would get even better at reading more complex documents such as port advisories, legal notices, and international shipping regulations in multiple languages and legal jurisdictions. With multi-modal AI integration, detention claim systems could use text and geospatial, video and sensor data to create a multi-modal situational awareness model for every container.

Using blockchain and innovative contract technologies will probably bolster transparency and trust in detention. Future Artificial Intelligence (AI) agents may automatically implement detention fee waivers, approvals or escalations via smart contracts based on tamper-proof shipment event records. With claim processing being immediate, immutable, and auditable by all stakeholders (including shippers, carriers and terminal operators), disputes over timelines and events would become a thing of the past.

As AI agents and LLMs develop, the automation net widens from detention claims to whole shipment lifecycle compliance and revenue assurance, including claims for demurrage, per diem, chassis fees, and customs holds. Early investment in intelligent, inter-operable and ethically governed AI systems to manage detention will provide companies with a massive competitive edge, turning their logistics networks into an automated, self-regulating ecosystem that drives operational efficiency, customer satisfaction and profitability to new heights.

8. Future Evolution Model for Detention Claim Automation

Table 4. Stages of Detention Claim Automation

Stage	Key Characteristics	Technologies Involved	Human Involvement
Stage 1	Rule-Based Validation	AI agents, basic TOS-TMS-ERP integration	High
Stage 2	Context-Aware Automation	AI agents + LLMs + Workflow engines	Moderate
Stage 3	Predictive & Proactive Management	AI agents + Predictive ML + LLMs + Risk models	Low
Stage 4	Fully Autonomous Detention Ecosystem	AI agents + Blockchain + Smart Contracts + Global LLMs	Minimal/None

8.1. Sample Scenarios

8.1.1. Intelligent Contextual Automation

AI agent handles the structured SLA logic while an LLM interprets unstructured text (emails, advisories)

Table 5. Scenario with Agentic Detention Claim Process

Component	Details
Scenario	AI agent LLM jointly processes a detention claim using TOS, TMS, and ERP data.
Port	Port of Rotterdam
Free Days	4 days post-discharge
Gate-In	June 2, 9:00 AM
Gate-Out	June 9, 3:15 PM
TMS Insight	The pickup was rescheduled from June 5 to June 9 due to driver unavailability.
ERP SLA Clause	Weekends excluded; port strike-related delays are waivable.
LLM Input	Terminal email (June 6): "Delays due to congestion and partial entry closure."
AI Agent Logic	Calculates 2-day overage (excluding the June 8–9 weekend)
LLM Judgment	Validates 1-day exemption based on port disruption context
System Output	Partial approval – 1 day detention charge; explanatory note auto-generated

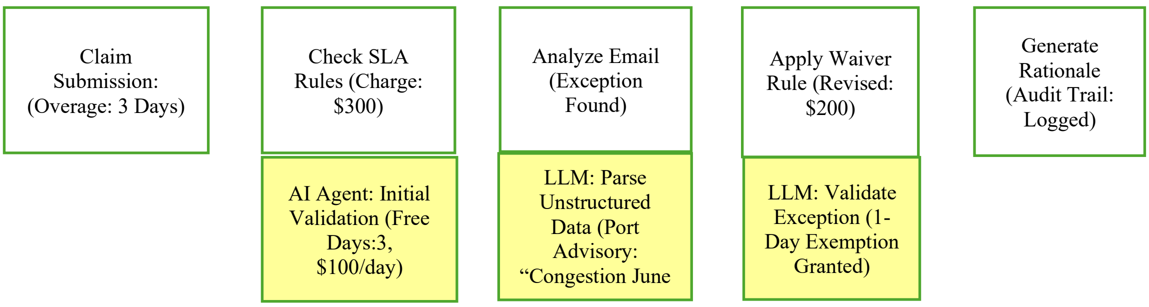

Fig. 2 LLM Enhanced Contextual Exceptional Handling Workflow

LLM-Enhanced Contextual Exception Handling Workflow: This flowchart demonstrated how LLMs assist in detention claim processing by analyzing unstructured data (e.g., port advisory emails) to identify exceptions like congestion, applying for waivers (e.g., 1-day exemption) and generating rationales for transparency, as outlined in the paper.

8.2. Proactive and Predictive Detention Management

In this scenario, AI agents using predictive analytics identify early warning signs of being detained. The LLM reads port advisories and aids in preventive action (early pickup), shifting the detention process from a reactive state to a preventive one, saving money and operations.

Table 6. Preventive detention management scenario

Component	Details
Scenario	AI agent predicts detention risk and intervenes to prevent charges
Port	Port of Los Angeles
Free Days	3 days post-discharge
Scheduled Pickup	Day 3
AI Risk Alert (Day 2)	Forecasted congestion due to vessel bunching and labour slowdowns
TMS Insight	Carrier has a history of delays in similar scenarios.
LLM Input	Terminal advisory + email: "Berths 212–215 severely congested – entry delayed."
AI Agent Action	Recommends rescheduling pickup to Day 2 to avoid risk
LLM Output	Auto-generates justification email for early pickup approval
System Output	The load was picked up early, 0 detention days were incurred, and the decision was logged.

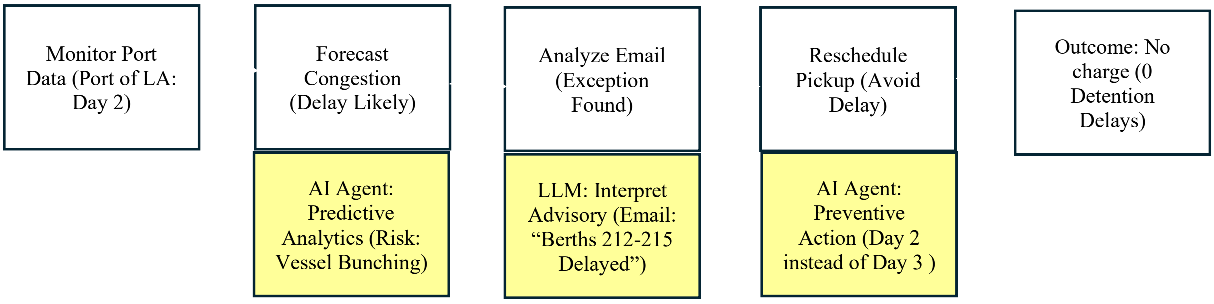

Fig. 3 Step-by-step workflow to avoid detention charges

Predictive and Proactive Detention Management Workflow: This flowchart shows how AI agents and LLMs predict detention risks using port data and terminal advisories (e.g., berth delays), rescheduling pickups to avoid being charged (e.g., 0 detention days), shifting from reactive to proactive management as envisioned in the paper.

8.3. Fully Autonomous, Dispute-Free Logistics Ecosystem

In this more advanced scenario, AI agents operate in a decentralized innovative contract framework, using real-time data combined with LLM-driven document understanding to validate exceptions. When detectors find a claim, the system handles approvals without human Intervention, creating a zero-dispute, transparent, and trustless process for detention claims, an accurate representation of AI logistics automation.

Table 7. Scenario with the agentic process, including blockchain contracts to resolve detention clai

Component	Details
Scenario	AI agents and blockchain smart contracts autonomously resolve a detention claim.
Port	Port of Hamburg
Free Days	5 days post-discharge
Gate-In	August 1, 8:00 AM
Gate-Out	August 7, 9:15 PM
Smart Contract Logic	Charge $250/day post-free-time unless weather event verified on record
Blockchain Input	Immutable timestamps from IoT sensors and port systems
Weather API Validation	Confirms possible flooding delay on August 6
AI Agent Role	Verifies timeline and correlates SLA and external conditions.
LLM Input	Interprets flood notice text from port advisory (multilingual)
System Output	Smart contracts automatically waive detention fees; there is no human involvement.

9. Challenges and Considerations

Despite the promise of automating detention claim AI agents and Large Language Models (LLMs) , several practical and strategic challenges must be addressed to ensure reliability, scalability, and trust in these systems. They range from quality issues with data model explainability to domain generalization, trust issues with stakeholders, and legal issues.

Here are the few challenges businesses must look into before automating the processes-

9.1. Data Quality and Fragmentation

The processing of detention claims depends on the availability of a wide range of data from various sources like port gate logs, ERP systems, GPS trackers and scanned contracts, many of which remain in inconsistent formats or legacy systems. The AI agents can be highly accurate, but any inaccuracies in timestamps, or if the event logs no longer match the environment identifiers (like container IDs), can severely impact the overall accuracy.

Mitigation:

- Establish data standardization protocols using APIs and EDI (Electronic Data Interchange) standards.
- Implement robust data validation pipelines with fallbacks for incomplete or missing data.
- Use entity resolution models to reconcile disparate identifiers across systems.

9.2. Interpretability and Trust in AI Decisions

People involved in decision-making processes, particularly those from legal, finance, and operations, might be reluctant to accept pure AI-generated decisions without being able to trace how they were reached or the rationale behind the decisions. The frequent characterization of LLMs as "black boxes" makes it more challenging to audit their outputs.

Mitigation:

- Employ Explainable AI (XAI) techniques to generate traceable decision logs.
- Use rule-based agents for core calculations and LLMs for contextual understanding, clearly segmenting responsibility.
- Provide natural language rationales and decision summaries to improve transparency.

9.3. Contextual Ambiguity in Language Inputs

LLMs must interpret contract language and free-text justifications that may be vague, contradictory, or legally complex. Even slight misinterpretations could lead to incorrect claim approvals or rejections.

Mitigation:

- Fine-tune LLMs on domain-specific corpora (e.g., shipping SLAs, legal clauses, historical claims).
- Pair LLM outputs with rule-based validation layers.
- Incorporate a human-in-the-loop process for borderline or ambiguous cases.

9.4. Legal and Regulatory Compliance

Countries and ports function differently with their detention policies, labour laws, and individual legal systems, making such a readout difficult. Using one automation logic for all automation can require a fine line and lead to non-compliance or legal issues.

Mitigation:

- Build modular, jurisdiction-aware AI agents that apply location-specific business logic.
- Maintain a rulebase updated with local port holidays, exceptions, and contract types.
- Ensure AI decisions are documented and traceable for audits or legal inquiries.

9.5. Multilingual and Multi-format Inputs

Extracting, classifying, and interpreting such documents requires understanding them in various languages or formats, including PDFs, emails, scanned images, etc.

Mitigation:

- Use OCR tools combined with multilingual LLMs (e.g., XLM-RoBERTa, GPT-4 with language capabilities).
- Preprocess and translate content before passing it to downstream LLM workflows.
- Adopt multi-modal AI pipelines capable of handling mixed data types.

9.6. Handling Exceptions and Escalations

Some detention claims can be expected to follow predictable lines, whilst others may require subjective evaluation or real-time negotiation between parties.

Mitigation:

- Route such claims to human decision-makers with AI-generated summaries and suggested actions.
- Continuously train AI agents on escalated cases to improve exception handling over time.
- Include policy-based escalation workflows in the automation pipeline.

9.7. System Scalability and Integration

Within distributed IT environments, large global logistics networks may process tens of thousands of claims every month. It is not trivial to scale AI solutions without losing performance.

Mitigation:

- Use microservices architecture for modular, scalable deployment.
- Leverage cloud-native solutions (e.g., Azure AI, AWS Bedrock, or Google Vertex AI) for LLM serving.
- Ensure smooth integration with ERP, TMS, CRM, and other enterprise tools.

9.8. Ethical Considerations and Bias

LLMs can potentially carry forward biases and prejudices of the training data. As a result, they can inadvertently harm specific customers or boost interpretations of contract language from market leaders.

Mitigation:

- Continuously audit model outputs for fairness and bias.
- Incorporate ethics-by-design principles into model development and evaluation.
- Allow stakeholder feedback loops to override and correct system behavior.

10. Conclusion

The detention claim approval process in shipping logistics has long been a bottleneck characterized by fragmented data, manual verifications, and interpretive ambiguity. With increasing trade volumes, the urgency to modernize this back-office function has become more critical than ever. This paper presents an approach that leverages the structured efficiency of AI agents and the contextual intelligence of Large Language Models (LLMs) to automate the end-to-end detention claim lifecycle.

AI agents work best on structured data, like timestamps, terminal records, and container tracking data. They are rule-based, so they provide rigour and consistency and can thus easily be validated at speed against an SLA, and violations can be automatically detected.

Unlike previous (not so) AI tools, LLMs come with a layer of interpretive understanding using close-to-human-level language processing skills that can parse and recognize meaning in unstructured data (contracts, emails, justifications, and dispute communications). Together, these technologies make for a strong decision-making ecosystem that can develop with faster turnaround time, high accuracy, and drastically reduced operational costs.

This connected architecture enables detention claim workflows to transform from reactive and manual to predictive, proactive, and mostly autonomous. Besides improving throughput and customer experience, the system maintains an auditable and transparent record that ensures compliance with legal and regulatory standards. The combination of rigid rule engines and a fluid language model allows for adaptive learning, allowing the system to improve with every case.

However, the transition is not without challenges. Data quality, model transparency, contextual ambiguity, and jurisdictional diversity pose significant barriers to adoption. Building a system to handle these challenges requires careful system design, robust data pipelines, and human-in-the-loop oversight to ensure fairness, interpretability, and trust.

In the future, a combination of AI, LLMs, and smart contracts would enable the creation of intelligent, self-learning claim management platforms that prevent them from happening and can resolve disputes quickly with explainability features. The future of detention management is poised to be more automated, intelligent, and resilient, enabling a more efficient global supply chain as logistics providers embrace these technologies at scale.

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