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INTELLIGENT AGENTS AND LEAN LOGISTICS FOR THE IMPROVEMENT OF MANAGEMENT PROCESSES IN TRANSPORTATION COMPANIES

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ABSTRACT

Transportation companies face significant operational challenges including delivery delays, prolonged waiting times, inefficient resource utilization, and low process standardization, which negatively impact service quality and competitiveness. This research proposes the integration of intelligent agents with Lean Logistics principles to improve management processes in transportation firms, with a focus on small and medium-sized enterprises in Hidalgo, Mexico. A mixed-methods approach was employed, combining a systematic literature review following the PRISMA 2020 protocol (20 key articles from 2016-2026), a diagnostic survey of 100 users using a 5-point Likert scale, Value Stream Mapping (VSM), and the design of an intelligent operational management agent implemented in n8n with OpenAI language models. Survey results revealed that 26% of users identified delays as the main problem and 20% highlighted high waiting times, with only 42% reporting satisfaction or high satisfaction. The proposed agent automates data validation, Lean waste detection (waiting, unnecessary transport, overprocessing, etc.), resource optimization, route analysis, risk monitoring, KPI calculation, and automatic generation of actionable recommendations and HTML reports. Complementary standardized control formats (F-01 to F-08) support process standardization under the PDCA cycle. Expected outcomes include reduced planning times, lower operational waste, optimized resource allocation, and improved service consistency. The study provides a practical, scalable methodological framework for digital transformation in regional transportation companies.

KEY WORDS: Intelligent Agents, Lean Logistics, Transportation Management, Process Improvement.

INTRODUCTION

Transport is one of the fundamental pillars for economic and social development worldwide, as it enables the exchange of goods, services and people between regions and countries. In an environment marked by globalization, the growth of e-commerce, the expansion of industrial parks, and increased trade, transport companies play a strategic role in supply chains and market competitiveness (World Bank, 2023; OECD, 2023).

The competitiveness of the sector increasingly depends on the ability of organizations to efficiently manage their resources, respond quickly to market demands and adopt technologies that optimize their operational and administrative processes. However, the isolated implementation of technological tools does not guarantee better results; it is necessary to understand the specific needs of the business and the factors that limit organizational performance (Christopher, 2016; Davenport & Ronanki, 2018).

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Currently, many transportation companies face challenges related to route planning and optimization, fleet management, document management, merchandise tracking, customer service, and incident handling. These problems generate delays in deliveries, increased operating costs, inefficient use of resources, poor visibility of information, and difficulties in making timely decisions (CSCMP, 2023; TraxTech, 2026).

In the state of Hidalgo, due to its strategic location and proximity to important economic and industrial corridors in the country, there is significant potential to strengthen the logistics and transport sector. However, a considerable proportion of companies continue to operate through traditional administrative processes, with a low level of automation, limited digitalization, and insufficient integration of information (INEGI, 2024).

Against this backdrop, digital transformation represents an opportunity through the incorporation of intelligent agents (agentic AI), capable of analyzing large volumes of information, identifying patterns, automating processes, and supporting real-time decision-making (Google Cloud, 2026; AllThingsSupplyChain, 2026). For these solutions to generate sustainable results, it is essential to complement them with continuous improvement methodologies. Lean Logistics is aimed at optimizing logistics processes by identifying and eliminating waste (mudas), improving flow, and standardizing processes (Gomes et al., 2025).

The results of the diagnosis carried out in a transport company in San Agustín Tlaxiaca, Hidalgo (MJ Transport Truck), show that 26% of users consider delays to be the main problem of the service, while 20% identify waiting times as a relevant deficiency. Only 42% of users were satisfied or very satisfied. These data show the need for a solution that optimizes operational management. Therefore, the incorporation of an intelligent agent based on Lean Logistics represents a viable alternative to automate information analysis, identify waste and generate recommendations for continuous improvement, especially adaptable to SMEs in the region.

In this context, the following general hypothesis is proposed: The implementation of an intelligent agent based on Lean Logistics significantly improves operational management processes in transport companies, by increasing operational efficiency, reducing waste and improving service quality. Specifically, it is argued that the use of the intelligent agent reduces the analysis and planning times of transport services by automating information processing; and that the joint application of the intelligent agent and Lean Logistics tools makes it possible to identify operational waste and propose improvement actions that reduce waiting times and delays in the operation.

This research proposes a methodological strategy and implements a prototype of an intelligent agent (using n8n and language models) supported by Lean principles and standardized control formats, with the aim of generating a practical reference for organizations in the sector in Hidalgo and similar regions.,8

RESEARCH ELABORATIONS

The present research was developed under a mixed approach, descriptive and propositional, with an experimental design that includes elements of pre-post comparison through an implementation pilot (Cerchione et al., 2025; Hernández-Sampieri & Mendoza, 2018). This design made it possible to diagnose the current state of the management processes, design and implement a proposal based on intelligent agents and Lean Logistics principles, and establish the indicators to evaluate their impact.

Systematic review of the literature (PRISMA 2020)

The theoretical foundation was based on a systematic review in accordance with the PRISMA 2020 protocol. The Scopus, Web of Science, ScienceDirect, Google Scholar and industry reports databases were consulted, covering the period 2016-2026. Combinations of terms such as "agentic AI", "multi-agent systems", "intelligent agents", "Lean Logistics", "Lean transportation" and "supply chain optimization" were used.

The selection process was carried out in strict phases:

1. Identification: 1,180 records were retrieved from academic databases and industry reports.
2. Duplicate removal: 295 duplicate records were removed, leaving 885 unique records.
3. Screening of titles and abstracts: the 885 records were evaluated; 156 were considered potentially relevant.
4. Full-text evaluation: 72 full-text articles were retrieved and evaluated.
5. Exclusion: 52 articles were excluded because they did not meet the eligibility criteria (year, thematic relevance, empirical evidence, or availability).
6. Final inclusion: 20 key articles that formed the basis of the state of the art were included.

Table 1. Study selection flow according to the PRISMA 2020 protoc ol

PRISMA Process Stage	Number of records
Records identified in databases and industry reports	1,180
Records after deleting duplicates	885
Titles and abstracts screened (screening)	885
Potentially relevant records (full-text retrieved)	156
Full-text evaluated articles	72
Articles excluded after full-text evaluation	52
Articles included in the final review	20

Table 1 presents the study selection process based on the PRISMA 2020 guidelines. The initial search identified 1,180 records from scientific databases and industry reports. After removing duplicate records, 885 studies remained and were screened by reviewing their titles and abstracts. From this process, 156 articles were considered potentially relevant and selected for full-text review.

Next, 72 full-text articles were evaluated using the established inclusion and exclusion criteria. During this stage, 52 studies were excluded because they were not directly related to the research topic, did not meet the required methodological criteria, or did not focus on intelligent agents and logistics process optimization. As a result, 20 studies met all the selection criteria and were included in the final systematic literature review.

Overall, the PRISMA 2020 methodology provided a clear and structured process for selecting the most relevant studies. This approach ensured that the literature review was transparent, consistent, and based on reliable evidence to support the analysis of intelligent agents for logistics process optimization.

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Table 2. Full report of the 20 articles included in the PRISMA systematic review (2016-2026)

#	Author(s)/Year	Title (summarized)	Approach	Key findings	Relevance
1	Page et al. (2021)	PRISMA 2020 statement	Methodological guide	Updated protocol	Basis of the report
2	Rim et al. (2025)	AI, Blockchain & IoT for Sustainable Logistics	Technology integration	444 arts; Clusters Optimization	Multi-level agent + Lean framework
3	Rosić et al. (2025)	Intelligent Agents for Sustainable Maritime Logistics	Maritime AI Agentic	Hybrid architectures, lower emissions	Predictive agent design
4	Gomes et al. (2025)	Lean Transportation Tools in Offshore Industry	Lean + Digitalization	Waste reduction + transformation	Lean Tools for Transportation
5	Liu et al. (2026)	Advances in Truck-Drone Cooperative Delivery	AI Cooperative Routing	VKT reduction and urban times	Multi-agent agents hybrid routes
6	C.H. Robinson (2026)	Lean AI Orchestration	Agentic AI + Lean	+40% productivity, 92% self-employed	Real case agent orchestrator
7	SimpliRoute / Echeverría (2026)	AI Agents in Mexican Logistics	Security agents and routes	-76% cargo theft in 3 months	Applicable directly to Hidalgo
8	Nuvocargo (2026)	Nuvo AI Engine	Agentes cross-border	>70% automated touchpoints	Documentation and exceptions
9	TraxTech (2026)	Agentic AI in Modern Supply Chains	Multi-agent architectures	Autonomous planning and routing	Specialized agents
10	AllThingsSupplyChain (2026)	Agentic AI in Logistics	Think-Decide-Act loop	Production requirements	Think-Decide-Act Architecture
11	Google Cloud (2026)	Agentic AI for Logistics Providers	External Data Orchestration	Proactively reduce disruptions	Real-time integration
12	Christopher (2016)	Logistics & Supply Chain Management	Logistics Fundamentals	Supply Chain Management	Conceptual basis of the sector
13	Davenport & Ronanki (2018)	Artificial Intelligence for the Real World	AI applied to processes	Types of AI and use cases	Intelligent Agent Justification
14	Bhamu & Sangwan	Lean Manufacturing Issues	Lean Review	Waste Disposal	Lean Base Principles for AI
15	AI/ML Revision (2026)	AI/ML for Sustainable Logistics	Revision 71 items	Economic and environmental optimization	Triple impact bottom line
16	CH Robinson / Banker (2026)	Lean AI Engineer & Planner	Agents + continuous improvement	Saving hours and productivity	Modelo closed-loop
17	Mexico AI Logistics (2026)	AI Adoption in Mexico	Agents in fleets	Fuel reduction and safety	Local evidence for Hidalgo
18	Last-Mile Multi-Agent (2025)	Intelligent Multi-Agent for Last-Mile	iMAS Bayesian Q-learning	Improved cooperation, less VKT	Stakeholder coordination
19	Agents Transportation Mexico (2026)	AI in Mexican Motor Transport	Predictive maintenance and routes	Fuel savings 20%+	Case Studies for SMBs
20	Hendriksen (2026)	Agentic AI in Logistics	Education and Prototyping	Agentic tools + workflows	Agent Design Methodology

Table 2 summarizes the 20 studies selected for the systematic literature review and shows the main contributions of each one to this research. Most of the publications focus on the use of intelligent agents, artificial intelligence, and Lean Logistics to improve transportation and supply chain operations.

The reviewed studies show that intelligent agents can support route optimization, predictive maintenance, real-time decision-making, disruption management, and last-mile delivery. In addition, several real-world applications report improvements in productivity, transportation security, fuel consumption, and process automation through the implementation of AI-based solutions.

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The literature also highlights that Lean Logistics continues to be an effective approach for reducing waste and improving operational efficiency. When combined with intelligent agents, Lean principles become more effective by enabling faster data analysis, continuous monitoring, and more accurate operational decisions.
Overall, the selected studies indicate that integrating intelligent agents with Lean Logistics has strong potential to optimize logistics processes, increase operational efficiency, and support continuous improvement. These findings provide a solid foundation for the proposed research and support the development of an intelligent-agent framework for logistics optimization in transportation companies.

The inclusion criteria were: (a) peer-reviewed publications or high-impact technical reports between 2016 and 2026; (b) studies addressing intelligent agents, multi-agent systems or artificial intelligence applied to transport and logistics; (c) research that integrates Lean Logistics principles or continuous improvement in logistics environments; and (d) documents available in full text in English or Spanish. Studies prior to 2016, opinion articles without empirical evidence, and studies not directly related to transportation or supply chains were excluded.

Population, sample and diagnostic instrument

The population was made up of workers and users of the MJ Transport Truck company, located in San Agustín Tlaxiaca, Hidalgo. Non-probabilistic convenience sampling was used. A questionnaire was developed with ten questions on a five-level Likert scale that evaluated: punctuality, waiting time, cleanliness, condition of the units, safety, speed in attending to incidents, general quality of service and level of satisfaction. Additionally, the main perceived problem was asked. A sample of 100 users was obtained.

Value Stream Mapping (VSM)

A Value Stream Mapping of the complete transportation service process was built, from customer request to invoicing. As can be seen in Figure 1, the main waste identified is the waiting time in the client for charging (WT = 5 hours on average), together with high cycle times in administrative stages.

The mapping identified the following main times: Commercial Servi ce (CT = 15 min), Quotation (CT = 30 min), Waiting for customer a pproval (1 to 24 hrs), Planning (CT = 20 min), Route Review (CT = 15 min), Unit Check List (CT = 30 min), Customer Wait for Loadin g (WT = 5 hours average – main move), Documentation (CT = 30 m in), Transportation and GPS monitoring (variable), Unloading (1-3 hrs), Evidence of POD delivery (CT = 15 min) and Invoicing (CT = 20 min). This mapping evidenced significant waste of waiting, admi nistrative overprocessing, and unnecessary movements.

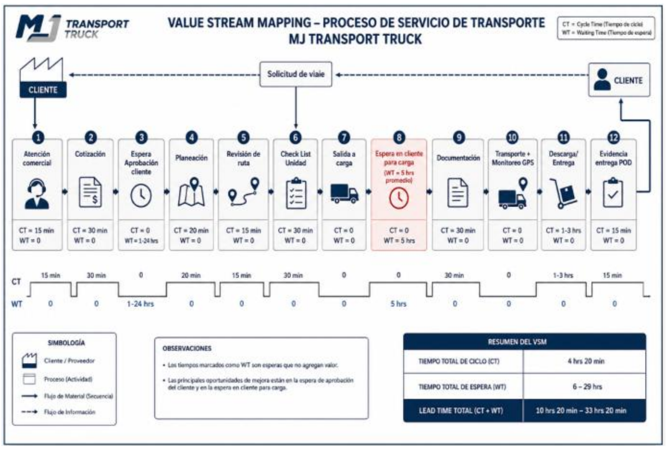

Figure 1. VSM diagram of the MJ Tranport Truck transport service process

Technological proposal: Intelligent Agent of Transport Operational Management-putting agent image

The Intelligent Agent is located as the core of the technological proposal, immediately after the diagnosis and VSM mapping. It is the element that materializes the integration of agentic AI with Lean Logistics and that transforms the diagnostic findings into automated improvement actions.

Based on the findings, a prototype of an Intelligent Operational Man agement Agent was designed and implemented using the n8n (workf low automation) platform integrated with OpenAI language models. Conceptually and in an evolutionary way, a multi-agent architecture is contemplated (route optimization agent, incident management age nt, Lean Auditor agent and central orchestrator); the current prototyp e materializes the core capabilities of Lean analysis, optimization, an d orchestration into a unified agent.

Intelligent Agent pseudocode

ALGORITHM

Agente_Inteligente_Gestion_Operativa_Transporte

ENTRY: archivo_Excel (sheet "Transports") with fields:

customer, origin, destination, date, time, vehicle, operator,

tipo_carga, weight, capacity

========== PHASE 1: Reception and Validation ==========

← Extraer_y_Consolidar(archivo_Excel) data

IF incomplete data THEN

Report campos_faltantes

END YES

========== PHASE 2: Intelligent Analytics ==========

1. Validation ← Verificar_Completitud(data)
2. analisis_operativo ← Evaluar_Disponibilidad_Recursos (units, operators, carga_vs_capacidad, history, restrictions)
3. analisis_lean ← Detectar_Desperdicios (tiempos_muertos, wait, recorridos_innecesarios, duplicity, exceso_movimientos, over-processing)
4. ← Proponer_Mejor_Asignacion (mejor_operador, mejor_vehiculo, mejor_horario, mejor_ruta)

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5. ruta_optima ← Calcular_Ruta (distance, tiempo_estimado, fuel, traffic, costo_total)
6. ← Identificar_Riesgos monitoring (delays, accidents, detours, failures, weather) → alerts
7. Recommendations ← Generar_Recomendaciones_Accionables(...)
8. kpis ← Calcular_Indicadores (efficiency, productivity, utilization%, desperdicios_lean%, cumplimiento_kpi%)
9. plan_mejora ← Elaborar_Plan_de_Accion(...)

SALIDA_ESTRUCTURADA ← JSON { validation, analisis_operativo, analisis_lean, optimization, ruta_optima, monitoring, recommendations, indicators, plan_mejora}

========== PHASE 3: Report ========== reporte_html ← Formatear_Reporte_Profesional(SALIDA_ESTRUCTURADA)

Enviar_Email_Gmail(recipient, asunto_fechado, reporte_html)

END ALGORITHM

General Explanation of Operation

The Intelligent Transport Operational Management Agent works as an intelligent automation system based on workflows (n8n) and integrated with a large language model (OpenAI). Its operation is divided into three main phases:

Phase 1 – Reception and Validation: The user initiates the process manually. An Excel file is uploaded with the transport records (customer, origin, destination, date, time, vehicle, operator, type of load, weight and capacity). The data is consolidated into a single JSON structure.

Phase 2 – Intelligent Analysis and Optimization: The AI agent receives the consolidated data and executes a structured reasoning of 9 steps: (1) validates the completeness of the information, (2) analyzes operational availability and constraints, (3) detects Lean waste (downtime, waiting, unnecessary trips, duplication, excess movements and overprocesses), (4) proposes the best allocation of resources, (5) optimize the route by calculating distance, time, fuel, traffic, and cost, (6) monitor potential risks and generate alerts, (7) write actionable recommendations, (8) calculate key KPIs, and (9) develop an improvement plan. The output is forced into a JSON schema structured using an Output Parser to ensure consistency.

Phase 3 – Report Generation and Delivery: The results are automatically transformed into a professional HTML report (with waste tables, visual KPIs, alerts and recommendations). Finally, the report is sent by email (Gmail) to the operational manager or manager, with a dated subject.

In this way, the agent reduces manual analysis from hours to minutes, systematically applies the Lean methodology and supports real-time decision-making.

CONCLUSION

The present research demonstrated that the integration of intelligent agents with the principles of Lean Logistics constitutes a viable and promising strategy to improve operational management processes in transport companies, particularly in the context of SMEs in the state of Hidalgo.

Based on the diagnosis carried out, the existence of relevant problems was confirmed: 26% of users identified delays as the main problem, 20% high waiting times, and only 42% were satisfied or very satisfied with the service. Value Stream Mapping showed significant waste, especially long waits (up to 5 hours on average at load) and manual administrative processes with high cycle times.

The Intelligent Agent for Transport Operational Management prototype, implemented on the n8n platform and integrated with OpenAI language models, allows automating data validation, Lean waste analysis, optimization of resource and route allocation, calculation of KPIs and the generation of actionable reports and recommendations in real time. Complemented by the eight Lean Logistic control formats (F-01 to F-08) designed for MJ Transport Truck, a standardization system is established that feeds the PDCA cycle and ensures consistent data for the agent.

These elements allow the hypotheses raised to be accepted in a preliminary way: the agent reduces analysis and planning times through automation, and identifies waste to propose improvements that directly impact delays and waits. The expected results (automation of planning, reduction of analysis times, automatic identification of molts, optimized assignment and greater consistency of the service) are consistent with the evidence of the PRISMA systematic review and with industry cases (C.H. Robinson, 2026; SimpliRoute, 2026).

Limitations: The study used non-probabilistic convenience sampling in a single company and was mainly based on user perception; A pre-post experimental pilot with objective operational indicators (real times, costs, productivity) is required to validate the quantitative impact.

Contributions and future work: A practical methodological framework, a functional prototype of an intelligent agent and a set of standardized control formats applicable to other SMEs in the sector are provided. Future research should implement the full pilot, evolve towards a multi-agent system (route optimization, incident management, Lean Auditor and orchestrator), integrate real-time IoT/GPS data and evaluate scalability in a greater number of companies in Hidalgo and similar regions.

In conclusion, the combination of agentic artificial intelligence and Lean Logistics offers a concrete path towards digital transformation and continuous management improvement in the transport sector.

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