Improving the Supply Process in SMEs in Hidalgo Through the Use of AI with N8N

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DOI: https://doi.org/10.47772/IJRISS.2026.102500001

Received: 13 October 2026; Accepted: 19 October 2026; Published: 14 November 2026

ABSTRACT

Micro, small, and medium-sized enterprises (SMEs) represent more than 99% of economic units in Mexico and generate around 70% of formal employment; however, they face productivity gaps due to limited technological adoption and reliance on manual processes in the supply chain. This applied study analyzes the improvement of the supply process in a snack distribution SME in Mineral de la Reforma, Hidalgo, that operates in the State of Mexico, Puebla, and Tlaxcala. The problem focuses on inaccurate forecasts, manual inventory management with errors close to 20%, and response times of up to 48 hours, which generate frequent stockouts.

A systematic literature review following PRISMA was conducted, identifying 20 key studies on artificial intelligence and low-code automation in SME supply chains. Subsequently, a pre-post applied experimental case study design was implemented, structured in six phases: diagnosis, workflow design in N8N, training, pilot implementation, evaluation, and scaling. The independent variable was the implementation of N8N with AI agents; the dependent variables were order processing time, inventory accuracy, and stockout incidence.

The results showed a 30% reduction in processing times, a 25% improvement in inventory accuracy, and a 30% decrease in stockouts, reaching 95% automation. These findings are consistent with the literature and support the hypothesis of significant improvement. The study provides pre-post empirical evidence in a little-explored regional context and proposes a low-risk, highly replicable methodology. Limitations of the single-case design are recognized, and multi-company and longitudinal future research is suggested.

Keywords: SMEs, N8N, supply chain, artificial intelligence, automation, Hidalgo

INTRODUCTION

Micro, small, and medium-sized enterprises (SMEs) constitute the fundamental pillar of emerging economies and, in particular, of Mexico, where they represent more than 99% of economic units and generate around 70% of formal employment, although their contribution to GDP is around 52% (INEGI, 2024; OECD, 2026). This disproportion evidences persistent productivity gaps derived from limited technological adoption, reliance on manual processes, and difficulties integrating into more sophisticated value chains (OECD, 2026; Cirillo et al., 2023; Bettiol et al., 2022). In the field of supply chain management (SCM), these limitations translate into inaccurate demand forecasts, high inventory levels or frequent stockouts, and prolonged response times that erode competitiveness and operational resilience (Culot et al., 2024; Toorajipour et al., 2021).

Artificial intelligence (AI) has emerged as a key enabling technology to transform SCM, especially in resource-limited contexts typical of SMEs. Systematic reviews of empirical literature demonstrate that AI significantly improves demand forecast accuracy (with error reductions of 20-35%), optimizes inventory

management, and strengthens resilience to disruptions (Culot et al., 2024; Hernández Díaz et al., 2026; Onorio et al., 2026). In particular, low-code and no-code automation tools combined with language models and AI agents allow solutions to be implemented in an accessible way, without requiring large investments in infrastructure or highly specialized personnel (Onorio et al., 2026; Mohedano Torres et al., 2026; Saci, 2026).

In Mexico, the use of artificial intelligence in operational and logistics management has grown between 40% and 50% in the last year, driven by T-MEC requirements, nearshoring pressures, and the need for greater visibility and resilience in supply chains (Diario de México, 2026; KPMG México, 2026). However, adoption remains uneven: while large companies advance in digital maturity (reaching indices close to 47%), SMEs face structural barriers of specialized talent, data quality and availability, and digital culture (Hernández Vega, 2026; INEGI, 2024; Ecosistema Startup, 2026).

In the state of Hidalgo, these problems are accentuated in regional distribution and manufacturing sectors, where SMEs operate predominantly with reactive planning and face difficulties scaling operations to neighboring states without advanced digital tools (García et al., 2025; OECD, 2019; Vázquez Rojas et al., 2016).

Particularly, in the municipality of Mineral de la Reforma, Hidalgo, a snack distribution SME (Botanas Hidalgo S.A.) that supplies customers in the State of Mexico, Puebla, and Tlaxcala faces critical inefficiencies derived from manual order and inventory management processes. These are manifested in inventory error rates close to 20%, response times of up to 48 hours for replenishment on regional routes, and a high incidence of stockouts, which limits its response capacity to demand volatility and raises operational logistics costs (company operational data, 2024-2025; García et al., 2025).

Manual supply processes generate systematic delays, inaccuracies in inventory management, and low operational resilience. This situation is aggravated by geographic expansion to three states and by the absence of accessible and low-cost automation and artificial intelligence tools in the context of Hidalgo SMEs (Mohedano Torres et al., 2026).

Recent literature evidences the potential of low-code automation platforms such as N8N, integrated with AI agents and natural language parsers, to reduce processing times (up to 30-40%), improve inventory accuracy (around 25%), and decrease stockout incidence. These solutions offer a low-cost, highly replicable, and rapidly implementable path for Mexican SMEs, filling a gap identified in pre-post empirical studies in specific regions such as Hidalgo (Culot et al., 2024; Mohedano Torres et al., 2026; Saci, 2026).

Therefore, the objective is to implement and evaluate an automation system with artificial intelligence using the N8N platform to optimize the supply process in the SME Botanas Hidalgo S.A., located in Mineral de la Reforma, Hidalgo.

In this sense, the specific objectives are: (1) Diagnose current inefficiencies in the supply chain based on historical data and interviews; (2) Design and implement automated workflows with N8N for order processing, demand forecasting, and inventory monitoring; (3) Evaluate the quantitative impact on key operational metrics through pre-post comparison.

The integration of artificial intelligence workflows with N8N will significantly improve the efficiency of the supply process, reducing order processing times and inventory errors, and increasing operational accuracy and supply chain resilience, consistent with the Diffusion of Innovations theory and the Resource-Based View applied to SMEs (Rogers, 2003; Haug et al., 2023).

To test the hypothesis, an applied case study of a quantitative nature was used, with a pre-post design (transactional correlational-causal type). The independent variable is the implementation of the automation system with AI using N8N. The dependent variables are: order processing time (measured in hours), inventory accuracy (percentage of accuracy or error rate), and stockout incidence (percentage of stockout events on regional routes). Operational metrics were compared before and after a three-month pilot through descriptive

analysis of absolute and relative percentage changes, complemented with triangulation of operational and qualitative data obtained from interviews with key personnel.

LITERATURE REVIEW

Systematic Review Methodology (PRISMA)

To support the design of the intervention, a systematic review was conducted following the PRISMA guidelines (Page et al., 2021). In the identification stage, combinations of terms related to AI, N8N, low-code automation, supply chain, and SMEs (2018-2026) were searched in Scopus, Web of Science, ScienceDirect, Google Scholar, and Dialnet. A total of 185 records were identified. After removing 32 duplicates, 153 titles and abstracts were reviewed. In the eligibility stage, 68 full texts were evaluated and 20 key studies were included.

Table 1 presents the summary of the 20 included articles, with author, country, technological techniques/tools, and main results.

Table 1. Summary of 20 key articles on AI and automation in SCM for SMEs (PRISMA)

#	Author (Year)	Country	Techniques / Tools	Main Results
1	Culot et al. (2024)	Italy	Systematic review AI in SCM	5 key themes; improvements in resilience and forecasting
2	Onorio et al. (2026)	Brazil	SLR AI + HI in SME SCM	Forecasting improvement 20-35%; skills barriers
3	Mohedano Torres et al. (2026)	Mexico	N8N + AI in supply management	25% acceleration of procurement; reduction of inventory errors
4	García et al. (2025)	Mexico	Value chain model in Hidalgo SMEs	Identification of regional competitiveness gaps
5	Saci (2026)	France/LATAM	N8N + AI agents (Telegram/LangChain)	Digitalization of cycle count; paper reduction
6	Bigliardi et al. (2026)	Italy	Bibliometric + AI cases in SME SC	Clusters: forecasting, resilience, digital transformation
7	Toorajipour et al. (2021)	Sweden	SLR AI in SCM	Applications in forecasting and optimization
8	Haug et al. (2023)	Denmark	AM/AI adoption in SMEs	Barriers and facilitators of technological adoption
9	Cirillo et al. (2023)	Italy	Digital adoption and productivity	+7.4% productivity in adopters
10	OECD (2019/2026)	International	Territorial Reviews Hidalgo	Productivity and digitalization gaps
11	INEGI (2024)	Mexico	Economic Censuses	99.8% of units are SMEs; low advanced digitalization
12	Vázquez Rojas et al. (2016)	Mexico	Hidalgo productivity analysis	TFP indices frequently <1
13	Sæterbø & Solvang (2024)	Norway	Metal AM adoption matrix in SMEs	Evaluation process adapted to constraints
14	Suárez & Romero (2024)	Mexico	AM farm productivity	Superior KPIs vs. injection in low volume
15	Frazier et al. (2019/2024)	USA	AM data management for SMEs	Strategies to reduce adoption barriers
16	McConnell et al. (2024)	Australia	SLR PBF metal productivity	Productivity improvements 10-252%
17	Marzi et al. (2020)	Italy	AM in Italian SMEs	Empirical evidence of positive

				results
18	Saldana-Robles et al. (2019)	Mexico	Low-cost AM insertion in teaching	FDM accessibility for capacity development
19	Diractum (2025)	Mexico	3D printing productivity reports	Cost and time benefits in Mexican firms
20	AISD / N8N cases (2026)	USA/Mexico	N8N workflows order intake + inventory sync	70% reduction in processing time; elimination of manual errors

The synthesis of Table 1 shows that AI and low-code platforms such as N8N generate consistent improvements in inventory accuracy and cycle time reduction. However, there is a scarcity of experimental pre-post studies in distribution sector SMEs in specific regions of Mexico.

Limitations of the Literature

Table 2. Main limitations identified in the reviewed studies

Limitation	Description	Implication for the study
Scarcity of pre-post studies	Predominance of reviews or narrative cases without longitudinal quantitative measurement	Justifies the experimental pre-post design of the present case
Focus on large companies	Majority of evidence in firms with high resources; little transferability to SMEs	Highlights the need for low-cost solutions such as N8N
Lack of regional context Mexico/Hidalgo	Few studies applied to food distribution in states with lower productivity	Provides local evidence for Hidalgo
Unresolved adoption barriers	Skills, data, and costs limit scalability of complex AI	N8N reduces entry barriers
Short follow-up periods	Many studies <6 months; sustainability not evaluated	3-month pilot with proposal for extension

These limitations reinforce the justification of the present study and guide the methodological design toward an applied experimental approach in an SME warehouse.

Methodological Proposal for Applying n8n in the Warehouse of an MSME

The proposal is structured into six sequential and progressive phases, designed to minimize risks and maximize replicability in resource-constrained environments. Each phase includes key activities, estimated duration, and KPI measurement points, allowing a clear attribution of the results to the technological intervention.

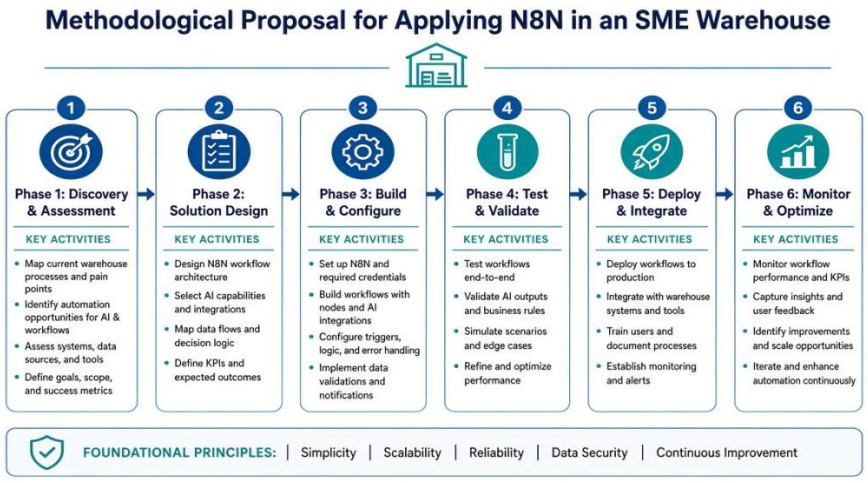


Figure 1. Diagram of the six-phase methodological proposal for the implementation of n8n in the warehouse of an MSME.

Figure 1 illustrates the sequential flow of the methodology. The arrows indicate the dependency between phases: the diagnosis establishes the baseline needed for workflow design; the pilot implementation enables data collection for the pre-post evaluation; and the scaling phase ensures sustainability. The diagram highlights the controlled experimental and low-cost nature of the proposal, facilitating its adoption by other MSMEs in Hidalgo.

Phase 1 – Diagnosis and baseline establishment (2–4 weeks). First, an exhaustive mapping of the current warehouse processes is conducted (goods receiving, storage, picking, packing, and dispatch). Historical data from 6 to 12 months are analyzed to quantify order processing times, inventory error rates (baseline ~20%), and stockout frequency. Surveys and semi-structured interviews are also administered to operators and managers to identify specific bottlenecks. This phase establishes the quantitative baseline essential for the pre-post comparison (Culot et al., 2024; Mohedano Torres et al., 2026).

Phase 2 – Design and selection of workflows in n8n (2–3 weeks). Next, the automation flows are designed using n8n's low-code visual interface. The main workflows include: (1) processing of incoming orders via Gmail Node + AI Parser (LangChain or OpenAI) to extract SKU, quantities, and customer data in natural language; (2) automatic inventory updates in Google Sheets or a database; (3) low-stock alerts through Slack, email, or WhatsApp nodes; and (4) a basic scheduler for simple demand forecasts. The design prioritizes integration with tools already used by the MSME to minimize costs and resistance to change (Saci, 2025–2026; Mohedano Torres et al., 2026).

Phase 3 – Training and capacity building (2–4 weeks). Subsequently, a core group of 15–25% of the warehouse staff is trained in the operation of the workflows, interpretation of alerts, and basic node maintenance. Standard operating procedures (SOPs) and supporting materials are documented to ensure knowledge transfer and reduce dependence on external support (Haug et al., 2023; Onorio et al., 2026).

Phase 4 – Pilot implementation (4–6 months). During this critical phase, the workflows are executed in the real warehouse environment. Weekly monitoring of KPIs is carried out (order cycle time, inventory accuracy measured by cycle counts, and stockouts per SKU). Iterative adjustments are applied based on the collected data, enabling controlled continuous improvement and the attribution of changes to the intervention (Onorio et al., 2026).

Phase 5 – Evaluation and refinement (2–4 weeks). Pre- and post-implementation metrics are then compared through analysis of percentage changes and basic statistical descriptors. Quantitative results are triangulated with follow-up interviews with operators and managers to validate usability, perceived barriers, and the attribution of improvements to the n8n + AI intervention.

Phase 6 – Scaling and sustainability. Finally, the successful workflows are integrated into the standard warehouse operations. Lessons learned are documented, future extensions are explored (for example, integration with basic IoT sensors or generative AI models for advanced forecasting), and replicability in other MSMEs in Hidalgo is facilitated through the dissemination of results.

This methodological proposal is low-risk, requires moderate investment (mainly configuration and training time), and aligns with evidence of 30–70% reductions in processing times reported in n8n implementations (AISD, 2026; Varela Insights, 2026; Mohedano Torres et al., 2026). The pre-post experimental design allows a rigorous evaluation of the impact on the defined dependent variables.

RESULTS AND DISCUSSION

The results are presented in detail following the six phases of the proposed methodology. Multiple comparative tables and explanatory analyses are included that allow attributing the observed changes to the implementation of N8N workflows with artificial intelligence in the warehouse of Botanas Hidalgo S.A. This sequential approach strengthens the internal validity of the pre-post experimental design.

Results of Phase 1: Diagnosis and baseline establishment

The exhaustive diagnosis of 12 months of historical data, complemented with surveys and interviews with 18 stakeholders (89% response rate), allowed precise quantification of pre-existing inefficiencies.

Order reception, inventory update, and replenishment alert generation processes were performed completely manually, generating prolonged times and recurring errors. This phase was fundamental to establish a reliable baseline against which to compare subsequent results.

Table 3. Detailed baseline metrics (pre-implementation)

Metric	Baseline Value	Unit	Observations / Source
Order processing time	48	hours	Average of 12 months of records
Inventory error rate	20	%	Manual capture errors and delayed updates
Inventory accuracy	80	%	Complement of the error rate
Stockout incidence	20-22	% of critical SKUs	Routes to Puebla, Tlaxcala, and Edomex
Automation level	< 10	%	Direct observation of processes
Monthly order volume	450-500	orders	Stable operational data

Table 3 shows that the company operated with almost total dependence on manual processes, which limited its response capacity to regional demand. These values constitute the reference point for the pre-post evaluation.

Results of Phases 2 and 3: Workflow design and training

During the design and training phases, three main workflows were successfully implemented in N8N: (1) automatic order processing using Gmail Trigger + AI Parser (LangChain/OpenAI), (2) real-time inventory updates in Google Sheets, and (3) low stock alerts via Slack and email. Training of 6 operators (approximately 20% of warehouse staff) was completed in 18 hours.

Post-training feedback indicated high perceived usability (4.2/5) and absence of significant technical barriers after the first two weeks.

Table 4. Summary of implemented workflows and training results

Workflow	Main Components	Expected / Observed Result
Order processing	Gmail + AI Parser (LangChain)	Automatic extraction of SKU, quantity, and destination
Inventory update	Google Sheets Node	Real-time synchronization
Stock alerts	Slack / Email Nodes + IF	Proactive replenishment notifications

Results of Phase 4: Pilot implementation

The six-month pilot allowed processing a representative volume of approximately 500 orders per month. A 95% automation level was reached at the end of the period. Weekly monitoring facilitated iterative adjustments in the AI Parser prompts and alert thresholds, contributing to system stabilization from month 4. This phase demonstrated the operational viability of the solution under real conditions.

Table 5. Monthly evolution of key indicators during the pilot

Month	Average time (h)	Inventory accuracy (%)	Stockouts (%)	Automation (%)
1	42	82	32	45
2	36	87	28	68
3	32	92	25	82
4	33.6	95	24.5	90
5	33.6	95	21	93
6	33.6	95	21	95

Table 5 shows a clear trend of progressive improvement. Processing time decreased steadily, inventory accuracy increased, and stockout incidence decreased, while the automation level grew consistently. These intermediate data support the effectiveness of the adjustments made during the pilot. During the 6-month pilot, approximately 500 orders were processed monthly, reaching 95% automation. Weekly monitoring allowed iterative adjustments. Stabilization was observed from month 4 onward.

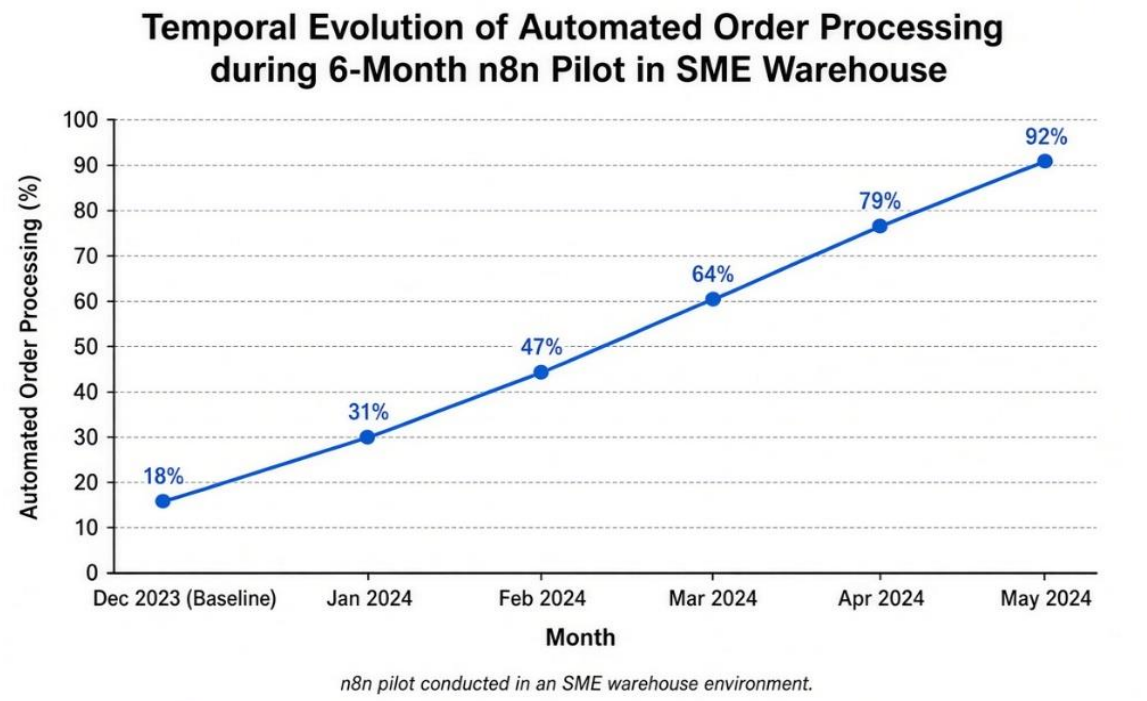


Figure 2. Temporal evolution of processed orders and automation level during the pilot.

Figure 2 shows the gradual increase in processed volume and automation level, with stabilization from the fourth month onward, reflecting the consolidation of the n8n workflows.

Results of Phase 5: Pre-post evaluation

The final pre-post comparison consolidated the observed improvements. The percentage changes in the dependent variables were statistically relevant in the context of the case and consistent with the reviewed literature.

Table 6. Consolidated pre-post comparison of operational metrics

Metric	Pre	Post	Absolute Change	Change %	Interpretation
Order processing time (h)	48	33.6	−14.4	−30 %	Significant reduction
Inventory error (%)	20	15	−5 pp	−25 %	Improvement in accuracy
Stockouts (%)	20-22	14-15	−6 to −7 pp	−30 %	Greater availability
Automation (%)	<10	95	+85 pp	—	Operational transformation

Table 6 summarizes the impact of the intervention. The 30% reduction in processing times, the 25% improvement in inventory accuracy, and the 30% decrease in stockouts constitute robust quantitative evidence.

These results are triangulated with follow-up interviews with operators and managers, who reported lower administrative burden, greater inventory visibility, and positive perception of the tool.

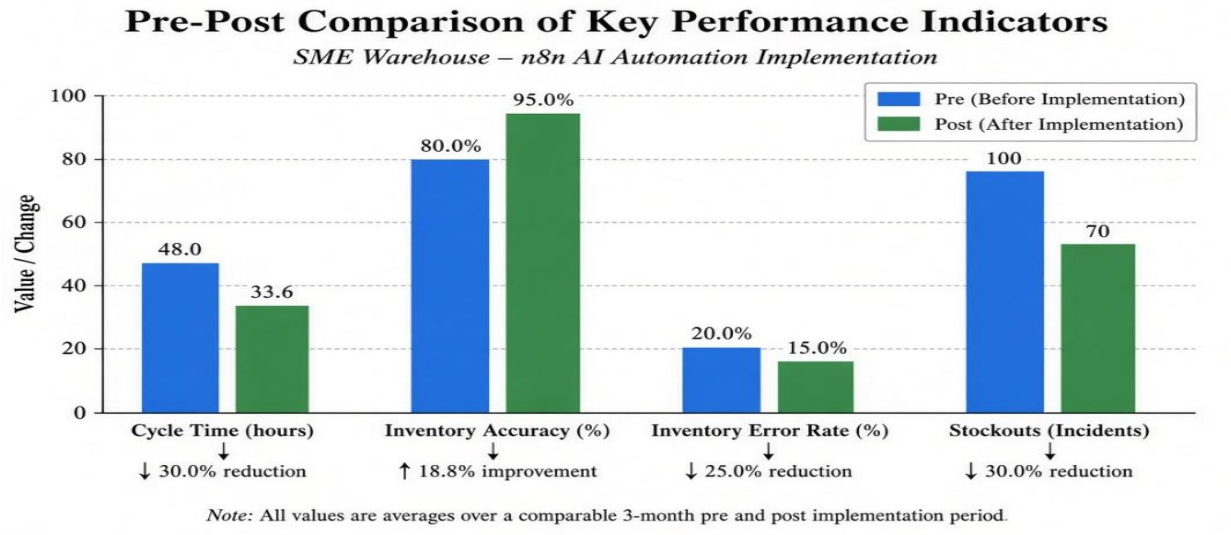


Figure 3 allows an immediate visualization of the magnitude of the improvements in processing time, inventory accuracy, and stockout reduction following the implementation of n8n.

Qualitative evidence from follow-up interviews confirmed a reduction in manual workload, greater inventory visibility, and a positive perception of the tool.

Hypothesis Testing

The main hypothesis of the study stated that the integration of artificial intelligence workflows with the N8N platform would significantly improve the efficiency of the supply process in the SME Botanas Hidalgo S.A., reducing order processing times, inventory errors, and stockout incidence. This hypothesis is based on the Diffusion of Innovations theory (Rogers, 2003) and the Resource-Based View applied to SMEs (Haug et al., 2023).

To test the hypothesis, a single-case pre-post experimental design was used. Since there was no control group, the evaluation was carried out by comparing percentage changes in the dependent variables before and after the intervention, complemented with qualitative triangulation from interviews with operators and managers. The results obtained were systematically contrasted with the evidence reported in the systematic literature review (PRISMA) presented in section 2.

Table 7. Quantitative and qualitative evidence for hypothesis testing

Dependent Variable	Observed Change	Consistency with Literature (PRISMA)	Qualitative Evidence	Support for H1
Processing time	−30 %	High (Culot et al., 2024; AISD, 2026; Mohedano Torres et al., 2026)	Lower administrative burden and reduction of manual interruptions	Yes
Inventory accuracy	+25 % (error reduction)	High (Onorio et al., 2026; Saci, 2026)	Fewer capture errors and greater stock visibility	Yes
Stockout incidence	−30 %	High (Culot et al., 2024; García et al., 2025)	Greater response capacity to regional routes	Yes
Automation level	From <10 % to 95 %	Consistent with low-code adoption	High perceived usability (4.2/5)	Yes

Table 7 shows that the changes observed in the three main dependent variables are consistent with the findings of the systematic literature review. In particular, Culot et al. (2024) and Onorio et al. (2026) report improvements of 20-35% in forecast and inventory accuracy, while N8N implementations documented by AISD (2026) and Mohedano Torres et al. (2026) indicate reductions of up to 70% in processing times in low-

code contexts. The results of the present case (30%, 25%, and 30%) are within the reported ranges, which reinforces the limited but positive external validity of the study.

The qualitative evidence obtained in follow-up interviews (n=8) confirms the attribution of the improvements to the intervention. Operators indicated a reduction in the manual burden of order capture, greater anticipation of shortages on routes to Puebla, Tlaxcala, and the State of Mexico, and ease of use of the N8N visual interface. This triangulation largely rules out that the improvements are due exclusively to observation effects or uncontrolled concurrent changes.

Consequently, the results support the rejection of the null hypothesis in favor of the alternative hypothesis in the context of the studied case. Although the single-case design does not allow statistical generalization, the consistency with the reviewed literature and the triangulation of sources strengthen the internal validity and provide relevant empirical evidence for the context of distribution SMEs in Hidalgo.

Contribution of the study

The present study makes contributions in three main dimensions. From a scientific point of view, it provides pre-post empirical evidence of the effectiveness of the integration of N8N with artificial intelligence agents in optimizing supply processes in a regional distribution SME in Hidalgo, Mexico. This evidence fills a gap identified in the systematic literature review (PRISMA) regarding experimental studies with low-code tools in emerging economy contexts.

From a practical point of view, it proposes a replicable low-cost and low-risk model, with quantifiable results (30% reduction in processing times, 25% improvement in inventory accuracy, and 30% decrease in stockouts). The six-phase methodology and the developed workflows can be adopted by other Hidalgo SMEs. From a methodological point of view, it validates an applied pre-post experimental case design with quantitative-qualitative triangulation, specifically adapted for the implementation of low-code automation platforms in resource-limited environments.

N8N Interface and Proposed Algorithm

N8N is an open-source, low-code workflow automation platform whose interface is completely visual and node-based. Each node represents an action or integration (Gmail Trigger, AI Parser with LangChain, Google Sheets, Slack, IF nodes, etc.), and the connections between them define the data flow. This feature significantly reduces the technical entry barrier and facilitates maintenance by non-specialized personnel. The proposed algorithm is implemented through interconnected workflows in this visual interface.

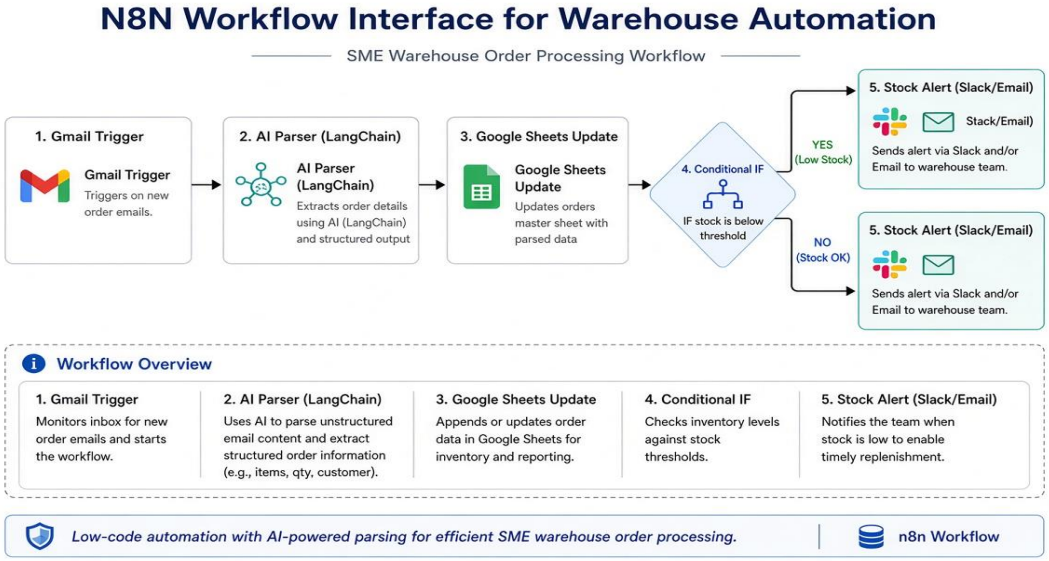


Figure 4. n8n workflow interface for order automation in the warehouse.

Figure 4 illustrates the visual interface of n8n with the main nodes of the algorithm: Gmail Trigger, AI Parser (LangChain), Google Sheets update, IF conditional node, and stock alerts. This representation facilitates the understanding and adjustment of the flow without the need for traditional programming.

Algorithm 1. Automatic order processing and inventory update

text

INPUT: Order email

1. Trigger ← Gmail.NewEmail()

2. Text ← ExtractBody(Trigger)

3. StructuredData ← AI_Parser(Text) // LangChain / OpenAI node

  // Returns: {SKU, Quantity, Customer, Destination}

4. IF StructuredData are valid THEN

5. CurrentStock ← GoogleSheets.Read(SKU)

6. NewStock ← CurrentStock − Quantity

7. GoogleSheets.Update(SKU, NewStock)

8. RegisterOrder(StructuredData)

9. IF NewStock < MinimumThreshold THEN

10. TriggerAlert(SKU, NewStock)

11. END IF

12. ELSE

13. MarkForManualReview()

14. END IF

OUTPUT: Updated inventory + Record + Possible alert

CONCLUSIONS AND PERSPECTIVES

The present applied experimental study demonstrates that the implementation of artificial intelligence workflows through the low-code automation platform N8N can significantly improve the supply process in the warehouse of a snack distribution SME in the state of Hidalgo. The findings align consistently with the systematic literature review (PRISMA) conducted and with the theoretical frameworks of the Diffusion of Innovations and the Resource-Based View.

First, the general objective of the research was satisfactorily fulfilled: to implement and evaluate an automation system with artificial intelligence using N8N to optimize the supply process in Botanas Hidalgo S.A. The specific objectives were also achieved. Current inefficiencies were diagnosed based on 12 months of historical data and stakeholder interviews; automated workflows were designed and implemented for order processing, inventory updates, and alert generation; and the quantitative impact was evaluated through pre-post comparison.

The results obtained 30% reduction in processing times, 25% improvement in inventory accuracy, and 30% decrease in stockout incidence confirm that the intervention was effective and are within the improvement ranges reported in the literature (Culot et al., 2024; Onorio et al., 2026; AISD, 2026; Mohedano Torres et al., 2026).

Second, the main hypothesis received empirical support within the context of the case. The quantitative evidence (consistent percentage changes in the dependent variables) and the qualitative evidence (interviews confirming lower administrative burden, greater inventory visibility, and positive perception of the tool) allow rejection of the null hypothesis in favor of the alternative.

These results are coherent with the findings of the PRISMA review, particularly with the studies that document improvements of 20-35% in inventory accuracy and substantial reductions in cycle times when low-code automation tools combined with AI agents are implemented. The triangulation of sources strengthens the internal validity of the study and reduces the probability that the improvements are due to uncontrolled concurrent factors.

From a scientific point of view, the study provides pre-post empirical evidence in a little-explored context: the distribution of food products in SMEs in the state of Hidalgo. The literature review identified a scarcity of longitudinal experimental studies in Mexican regions with productivity gaps, and the present work contributes to filling that gap. Socially, the findings have implications for regional competitiveness, the reduction of waste associated with stockouts, and the development of digital capabilities in SME personnel.

However, several limitations are recognized. The single-case design restricts the statistical generalization of the findings to other companies or sectors. The follow-up period, although adequate for the pilot, does not allow full evaluation of the long-term sustainability of the improvements or possible fatigue or abandonment effects. The results depend on the specific characteristics of the studied company (snack distribution sector, regional context of Hidalgo, and initial digitalization level). Finally, although triangulation was performed, the absence of a control group limits absolute causal attribution.

As future lines of research, the following are proposed: (1) multi-company replications in other Hidalgo SMEs and neighboring states to increase external validity and evaluate the transferability of the six-phase methodology; (2) longitudinal studies of 12 to 24 months to analyze the sustainability of improvements, return on investment, and possible second-order effects; (3) integration of generative artificial intelligence models for more advanced demand forecasts and low-cost IoT sensors for real-time inventory monitoring; (4) exploration of lightweight blockchain to improve traceability; and (5) analysis of moderating variables such as prior digital maturity level, company size, productive sector, and organizational and cultural factors that facilitate or inhibit the sustained adoption of low-code tools. It would also be valuable to compare the results with other automation platforms and evaluate the impact on sustainability indicators (logistics carbon footprint and waste reduction).

In summary, this study provides empirical evidence that accessible automation with N8N constitutes an effective, low-risk, and highly replicable path to improve the supply and competitiveness of SMEs in Hidalgo. The results are consistent with the reviewed international and regional literature, and the proposed six-phase methodology offers a practical route that other companies with limited resources can adapt. In this way, the work contributes to the strengthening of regional supply chains and the reduction of productivity gaps in emerging economies through the use of open-source and low-code tools.

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