AI Agent-Driven Procurement Automation with n8n Integration

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Abstract—**This study proposes a high-level automated procurement agent model by integrating AI Agent technology with the low-code automation platform n8n, aiming to establish an enterprise-grade procurement workflow deployable within a LINE Bot interface. By incorporating multimodal input comprehension, semantic extraction, modular command execution, and reactive workflow generation, the system can autonomously handle procurement requests, data validation, inventory lookup, supplier price comparison, managerial approval, and order notification, minimizing human intervention. Furthermore, a formalized modeling and reasoning architecture is introduced, which leverages mathematical constructs such as state-action representations, cost functions, and policy optimization. This enables the agent to reason over time-dependent procurement states, make cost-effective decisions, and adapt dynamically to varying inputs across modalities.**

Index Terms—AI Agent, Procurement Automation, Low-code Workflow (n8n), Multimodal Semantic Parsing, LINE Bot Integration.

I. Background and Motivation

Recent developments in artificial intelligence and automation technologies have prompted enterprises to rethink their internal operations and workflows, especially in repetitive yet mission-critical domains such as procurement. Traditionally, procurement workflows rely on manual verification, email-based approvals, and fragmented systems that make real-time coordination and responsiveness challenging. In small to medium-sized enterprises, the lack of IT infrastructure further exacerbates these inefficiencies.

The growing accessibility of large language models (LLMs), low-code orchestration platforms like n8n, and communication bots such as LINE Bot offers a unique opportunity to transform procurement from a manual, document-centric process into a responsive, intelligent, and automated pipeline. By leveraging AI Agents equipped with semantic reasoning, multimodal understanding, and process-aware decision-making, businesses can reduce human error, improve speed, and optimize cost across the procurement lifecycle.

This paper aims to formalize and implement a workflow that captures this transformation, highlighting how AI Agents and low-code automation can jointly enable practical and scalable solutions for modern enterprise procurement.

II. INTRODUCTION

In recent years, rapid advancements in artificial intelligence—particularly in language models and agent-based systems—have opened new opportunities for enterprise process automation. Natural language processing (NLP) has evolved from rule-based systems into deep learning-driven semantic models, with large language models (LLMs) such as ChatGPT demonstrating powerful contextual understanding and task execution capabilities. These models have given rise to autonomous AI Agents equipped with memory, task planning, and environmental interaction abilities, transforming them into central elements of automation pipelines.

AI Agents are no longer limited to textual interaction but are increasingly capable of integrating speech and image modalities, while interfacing with heterogeneous systems like enterprise databases, email servers, and ERP modules. In domains such as procurement, these agents can handle end-to-end processes: from multimodal input (e.g., voice or images), information extraction via OCR or speech-to-text, semantic parsing through LLMs, to price comparison, approval routing, and notification dispatch—all completed through automated workflows.

Simultaneously, low-code automation platforms like n8n and Zapier have emerged as crucial enablers for enterprises, especially SMEs without dedicated engineering teams. These tools offer modular and visual process design interfaces that make AI Agent orchestration highly flexible and scalable. n8n in particular provides robust node-based orchestration with support for GPT APIs, Whisper, Google Vision, MySQL, SMTP, and more, making it an ideal platform for implementing this research prototype.

In summary, this study builds a comprehensive AI procurement agent workflow system, integrating ChatGPT-based semantic modeling with multimodal inputs such as OCR and voice recognition, connected through API modules and rendered into a Directed Acyclic Graph (DAG) structure. Formal modeling and decision logic are employed to validate its system feasibility within the LINE Bot ecosystem.

III. Related Work

Several recent studies have explored intelligent automation for procurement and enterprise workflows. Gupta et al. [1] proposed a hybrid ML-based framework for decision support in procurement, focusing on rule extraction and data analytics. Kim et al. [2] implemented conversational agents within smart factories for automating procurement decisions, while Chen et al. [3] presented reinforcement learning strategies tailored for supply chain optimization. These studies indicate growing momentum toward AI-supported operations but often

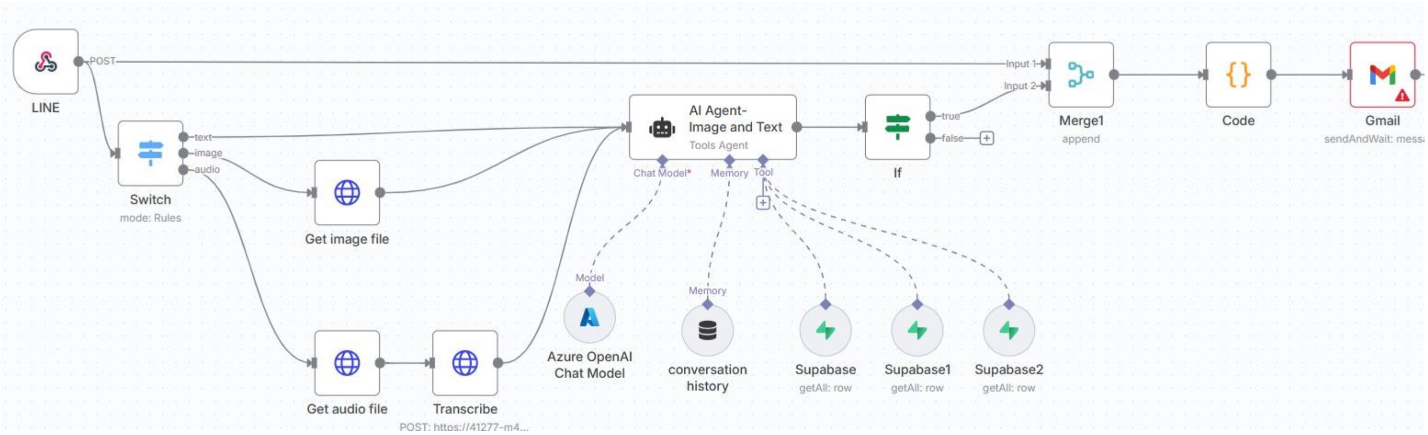

Figure 1. Visual representation of the proposed n8n-based AI procurement workflow. The process begins with a LINE Bot webhook input that captures multimodal content—text, image, or voice. A switch node classifies the input type and routes it to either Google Vision for OCR or Whisper for transcription. The result is passed to an OpenAI GPT-4 module for semantic parsing. Extracted data fields are used to query a Supabase database. A code node then merges the result using custom logic and forwards the output to a Gmail node for final notification dispatch. The entire flow is visually orchestrated in n8n, illustrating a modular and scalable AI-driven procurement pipeline.

To complement Figure 1, Table 1 provides a stepwise mapping of the modules used in the AI procurement workflow. It illustrates the sequence of operations, their respective functionalities, and the corresponding n8n nodes involved in the orchestration.

Table 1. AI Agent Workflow Mapping and Corresponding Modules in Figure 1

Step	Module	Function Description	Corresponding Node in Figure 1
1	LINE Bot Input	Captures user input in text, image, or voice format	LINE Bot Webhook Node
2	MIME Type Classifier	Determines the content type (text/image/audio)	Switch Node
3	OCR / Speech Processor	Converts image to text using Google Vision or audio to text via Whisper	Google Vision API / Whisper Model
4	Semantic Parser	Extracts structured entities such as item, quantity, budget	GPT-4 Parsing Module
5	Database Query Module	Queries inventory and pricing data from back-end database	Supabase SQL Node
6	Logic Controller	Applies business logic: vendor selection, budget check	Code Node (Custom Decision Logic)
7	Notification Dispatcher	Sends formatted procurement request to stakeholders	Gmail Integration Node

lack end-to-end integration across multimodal inputs and low-code platforms.

Complementary to these efforts, Liu et al. [6] evaluated the capabilities of modern low-code systems for business process automation, highlighting n8n as a competitive tool for scalable enterprise integration. Lee et al. [7] explored multimodal conversational agents, and Zhao et al. [8] introduced service orchestration through agent architectures—both aligning with the direction of this paper. Our approach distinguishes itself by combining modular AI Agent design with n8n-based orchestration and integrating it directly into popular user interfaces like LINE Bot.

IV. PROBLEM STATEMENT

To enhance procurement efficiency and automation in enterprises, we conceptualize the procurement process as a time-series decision-making problem characterized by dynamic state transitions and cost minimization. Formally, let S denote the set of possible system states, A the set of permissible actions, $P(s'|s,a)$ the probability distribution over next states given current state s and action a, and $C(s,a)$ the immediate cost associated with taking action a in state s. Each state $s \in S$ may encompass multimodal elements such as image inputs I, an inventory vector v, a supplier price matrix M, and a historical user interaction log H. Actions $a \in A$ correspond to system decisions including querying databases, comparing vendor prices, or initiating purchase execution.

The agent's goal is to learn a policy function $\pi(s)$, which determines the optimal action under each state, so as to minimize the expected cumulative cost across a decision horizon T. The cost objective is defined as:

$$J(\pi) = \mathbb{E}_\pi \left[\sum_{t=0}^{T} \gamma^t C(s_t, a_t) \right] \quad (1)$$

where $\gamma \in [0,1]$ is a discount factor that mediates the trade-off between immediate and future rewards.

In addition to minimizing cost, the system must satisfy two operational constraints. First, the expected response time $\mathbb{E}[T_r]$ must remain within an acceptable threshold to ensure responsiveness in real-world applications. Second, the system must maintain a satisfactory user experience, which we represent as a satisfaction metric U. To formalize this aspect, we define $U \in [0,1]$, where 1 represents maximum user satisfaction and 0 denotes total dissatisfaction. In practice, U may be calculated through post-task user surveys or inferred from behavioral signals, such as interaction latency, task success rate, frequency of corrections, or escalation to human agents. This quantified measure enables the policy to incorporate user-centric considerations into its optimization process, thereby balancing efficiency with usability.

The principal technical challenge arises from the multimodal and asynchronous nature of the input data, the stochastic delays in supplier responses, and the complex interdependencies between successive decisions. Rule-based approaches fall short under these conditions. As a result, this research employs AI Agents empowered by reinforcement-inspired logic and modular orchestration via the n8n platform, offering a robust and scalable solution capable of automating procurement workflows across diverse enterprise environments.

V. METHODOLOGY

To align this framework with practical implementation using n8n, each module defined in the DAG can be directly mapped to a functional node in a workflow configuration. The orchestration begins with the LINE Bot webhook, which captures

user inputs in the form of images, voice, or text. Based on the MIME type of the message, the system dynamically evaluates the input and routes it accordingly. Image inputs are passed to the Google Vision API for optical character recognition (OCR), while audio inputs are processed through the Whisper model for speech-to-text conversion. Once the input is transformed into text, it is sent to a GPT-4-based semantic parsing module. This module extracts key procurement parameters such as item name, quantity, budget, and delivery date.

The extracted information is then structured and forwarded to a Supabase node, which executes SQL queries to retrieve inventory levels or relevant supplier pricing. These results are evaluated by a custom logic module that applies decision rules such as budget thresholds, vendor priority, or product availability. The finalized output is then formatted into an actionable procurement request, which is delivered through a Gmail integration node to the appropriate recipient or supplier. This configuration leverages n8n's modularity to transform high-level agent reasoning into an executable sequence of connected operations. It exemplifies the adaptability of DAG-based orchestration, especially in environments requiring multimodal inputs and contextual decision-making.

The proposed framework employs a multimodal AI Agent pipeline organized through a Directed Acyclic Graph (DAG) structure. Each node in the DAG corresponds to an intelligent module that transforms, routes, or makes decisions based on the input context. The input sample $x \in X$ may originate from voice, image, or textual sources. A preprocessing module $f_0(x)$ converts all incoming inputs into normalized text format x'. This is followed by a semantic parsing function $f_s(x')$ which extracts structured entities $y =$ {item,quantity,budget,delivery_date}.

Each subtask in the procurement process corresponds to a node $v_i \in V$ in the DAG $G = (V, E)$, with edges E representing information or control flow. Modules include speech-to-text conversion (Whisper API), optical character recognition (OCR via Google Vision), semantic analysis using GPT-4, inventory database queries (MySQL API), supplier communication (via Gmail API), pricing analysis using a GPT-based parser, and a final controller node for decision integration.

The optimal procurement path $P^* \subseteq G$ is defined as the one minimizing total execution cost and aggregated error risk:

$$P^* = \arg\min_P \sum_{v_i \in P} C(v_i) + \beta R(v_i), \quad (2)$$

where $C(v_i)$ is the operational cost of module v_i, and $R(v_i)$ denotes its expected error probability. The weighting factor β calibrates the trade-off between cost and reliability.

This formulation not only enables fine-grained control over process routing but also permits dynamic substitution of modules under resource constraints or failure recovery conditions. The use of n8n as the orchestration layer allows all these components to be configured in a scalable, API-based low-code interface, facilitating rapid deployment and ease of maintenance across heterogeneous environments.

To illustrate the practical implementation of our proposed architecture, Figure 1 presents an actual n8n orchestration workflow integrating LINE Bot, multimodal input handling, semantic parsing, and back-end integration with Supabase and Gmail. In this workflow, input from LINE (image, audio, or text) is dynamically routed via a switch node to either an OCR or transcription module. The resulting content is passed to an AI Agent powered by an OpenAI chat model, which also accesses conversation history and performs context-aware analysis.

Semantic understanding and data extraction from user messages enable the agent to query Supabase databases, retrieve pricing or inventory data, and, depending on conditions, merge responses and apply additional logic in a code node. The system then constructs a formal procurement response, which is emailed to the designated supplier or department. This flow demonstrates an effective low-code implementation of an intelligent procurement assistant, automating decision chains and enhancing workflow reliability.

VI. Conclusion and Future Work

This paper proposes an enterprise procurement automation framework led by AI Agents and implemented through n8n, operationalized within the LINE Bot ecosystem. Through formal task modeling and modular orchestration, the system demonstrates robust expandability and adaptability to complex, multimodal procurement workflows.

Looking ahead, several directions offer promising extensions to this research. One potential enhancement involves incorporating few-shot learning and knowledge graphs, which would enable the system to better interpret unstructured or previously unseen inputs. Another direction is the integration of Retrieval-Augmented Generation (RAG) techniques, allowing the agent to fetch relevant external knowledge dynamically and improve its handling of complex or long-tail queries. Furthermore, the framework could be scaled to support multi-agent collaboration across organizational boundaries, enabling shared procurement strategies and real-time negotiation in decentralized supply chains. These advancements are expected to elevate the proposed system into a core infrastructure for intelligent decision support in procurement environments. These developments lay a solid foundation for future deployments of intelligent agents in enterprise resource planning systems.

VII. References

[1] H. Gupta, K. Jain, and A. Shukla, “Intelligent decision support for procurement: A hybrid approach using machine learning,” *Expert Systems with Applications*, vol. 178, p. 114999, 2021.

[2] S. Kim, J. Park, and H. Choi, “Automated procurement workflow using conversational agents in smart factories,” *IEEE Access*, vol. 11, pp. 20242–20255, 2023.

[3] L. Chen, Y. Zhang, and Y. Luo, “Reinforcement learning for supply chain management: A review,” *International Journal of Production Research*, vol. 60, no. 12, pp. 3704–3726, 2022.

[4] X. Wang and H. Lee, “Data-driven supplier selection using deep neural networks,” *Computers & Industrial Engineering*, vol. 147, p. 106676, 2020.

[5] H. Li and J. Wang, “Conversational AI agents in procurement: Bridging automation and flexibility,” *Journal of Intelligent Manufacturing*, vol. 35, no. 1, pp. 111–128, 2024.

[6] Y. Liu, M. Zhang, and X. Yang, “Low-code platforms in enterprise automation: A comparative study,” *Journal of Systems and Software*, vol. 196, p. 111542, 2023.

[7] J. Lee, S. Banerjee, and R. Tiwari, “Multimodal conversational agents for workflow automation,” *Proceedings of the 31st ACM International Conference on Intelligent User Interfaces*, pp. 33–44, 2022.

[8] K. Zhao, H. Sun, and L. Mei, “Agent-based architecture for intelligent service orchestration,” *IEEE Transactions on Services Computing*, vol. 16, no. 2, pp. 285–298, 2023.