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Agentic AI System for PTA on the n8n Workflow Automation Platform in Small Business Environments

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Abstract

There is an increasing need for research on agentic AI to understand how autonomous decision-making systems can safely and effectively execute complex tasks with minimal human intervention. It also helps address challenges such as reliability, ethical responsibility, and real-world deployment, enabling the development of intelligent systems that enhance productivity and innovation across diverse domains. Agentic Artificial Intelligence systems facilitate the automation of intricate administrative tasks by integrating reasoning, decision-making, and tool execution. The present study proposes a design and evaluation of an Agentic AI system for personalized task automation using reasoning-and-action workflows implemented on the n8n workflow automation platform. The system integrates multiple APIs, including Gmail, Google Calendar, and contact management services, to automate email processing, scheduling, and customer data management in small business environments. The system's evaluation is conducted through API scalability testing across a range of configurations, including 2, 4, 8, and 16 APIs. The findings indicate that task completion improves from 68% to 92% as system complexity increases, while execution time rises from 4.2 seconds to 10.9 seconds. The eight-API configuration offers an optimal balance between performance and reliability. Extant literature has demonstrated that agentic AI systems require careful integration of tool-usage training, human-AI collaboration, alignment methods, explainability, safety, and governance. The findings demonstrate that open-source workflow platforms such as n8n effectively support agentic AI systems with low cost, high flexibility, and strong integration capabilities. This research makes a significant contribution to the field by providing a practical framework and empirical evaluation of workflow-based agentic AI for small business automation.

Keywords: Agentic AI, PTA (Personalized Task Automation), n8n workflow, Reasoning-and-Action Framework, Workflow Automation

Introduction

Artificial Intelligence (AI) has evolved from predictive models into autonomous systems capable of reasoning, planning, and executing tasks in real-world environments (Acharya, 2025). Advances in large language models, API integration, and workflow automation have enabled the development of Agentic AI systems that can manage communication, scheduling, and information processing tasks (Hamon, 2020). However, while large enterprises have widely adopted these technologies, many small businesses continue to rely on manual processes due to cost, complexity, and lack of accessible solutions (Yang, 2023). This research addressed this gap by designing an Agentic AI system for automating daily administrative tasks, including email management, appointment scheduling, and customer data updates. Communications motivated by observed workflow inefficiencies in a small cleaning business, where manual handling of

customer communication and scheduling led to time consumption, reduced productivity, and increased risk of human error. These challenges highlighted the need for affordable and practical automation solutions tailored to small business environments. Tasks such as checking availability, replying to customers, updating contact information, and scheduling appointments required significant time and introduced opportunities for human error. These challenges highlighted a practical need for affordable intelligent automation solutions. The importance of this research lies in demonstrating that agentic AI systems are not limited to large organizations with significant technical resources. The proposed system demonstrated that open-source workflow automation platforms such as n8n can enable small organizations to implement intelligent assistants capable of reasoning and acting through API integrations. By combining reasoning-and-action architectures with workflow automation, the system provided a practical approach to applying agentic AI in real-world scenarios. This study contributed to the field by emphasizing implementation, integration challenges, and operational considerations, rather than focusing solely on theoretical models. The choice of the name Echo had also symbolized the way the system interacted with user input. Just as an echo reflects and returns sound, the Agentic AI system is designed to receive user requests, process them through reasoning and action workflows, and return meaningful results. This analogy helped capture the idea of a responsive and intelligent system that not only reacts but also interprets and executes tasks based on context. This personal naming decision has also helped define the system's identity and scope. Instead of treating the project as only a workflow engine or automation tool, it had been developed as a recognizable AI assistant with a central role in communication, scheduling, and customer management. This perspective influenced both the system architecture and user interaction design, emphasizing usability, clarity, and real-world applicability.

Related Research

The emergence of machine learning shifted AI development toward data-driven approaches, where models learned patterns from datasets rather than relying entirely on predefined rules. This transition enabled improvements in prediction, classification, and optimization problems. The development of deep learning further accelerated AI capabilities by introducing neural networks capable of learning hierarchical representations of data. Advances in computing power, particularly the use of GPUs, enabled large-scale training of these models (Park, 2023).

At the same time, the growth of cloud computing allowed organizations to deploy AI solutions without requiring specialized hardware. More recently, the emergence of large language models represented a major advancement in AI capability. These models demonstrated the ability to perform reasoning, generate text, and interact with tools through natural language instructions. This technological shift enabled the development of agentic AI systems capable of autonomous decision-making and task execution. This had not only provided background knowledge on artificial intelligence and agentic systems but had also directly supported the Technica design l and conceptual design of the project. Research on tool-using language models, such as GPT4Tools and Agent Tuning, had supported the idea that AI agents could move beyond text generation and actively interact with external systems to complete tasks (Shavit, 2023). This was directly related to the project because Echo had depended on external APIs for Gmail, Google Calendar, and contact management rather than functioning as a stand-alone conversational model. Research in agentic AI has demonstrated that large language models could learn to use tools and execute workflows. GPT4Tools had shown that models could be trained to call external tools through instruction-based datasets, enabling multimodal and API-based automation (Yang et al., 2023). Agent Tuning research had demonstrated that structured interaction trajectories could improve general agent abilities and allow open-source models to perform complex tasks (Zeng et al., 2023). Generative AI studies emphasized that AI systems should be treated as socio-technical systems involving infrastructure, interfaces, and human

collaboration rather than isolated algorithms (Feuerriegel et al., 2023). Alignment research has also influenced agent design. Training language models with human feedback had shown that reinforcement learning with human preferences improved safety and usefulness (Ouyang et al., 2022). Human-compatible AI research had argued that AI systems should remain uncertain about human objectives and continuously learn from feedback to avoid harmful outcomes (Russell, 2019).

Bias and governance studies had highlighted risks related to unfair decisions, transparency, and global coordination of AI systems (Ferrara, 2023; Cihon, 2019). Human-AI collaboration research had emphasized that AI systems should function as partners rather than replacements. Theory-of-Mind AI research had shown that modeling user intent improved interaction quality (Çelikok et al., 2019). AI delegation studies had demonstrated that intelligent task allocation improved performance and satisfaction (Hemmer et al., 2023). Human-AI interaction frameworks had identified challenges related to explainability, interface design, fairness, and agency (Abedin et al., 2022). Trust and evaluation research has also influenced this project. Studies on robustness and explainability had emphasized transparency and accountability in AI systems (Hamon et al., 2020). Guardrail frameworks had proposed modular safety layers to prevent misuse and data leaks (Biswas & Talukdar, 2023). Research on agent evaluation had shown that cost efficiency and reproducibility were as important as accuracy (Kapoor et al., 2024). Insights about large language models had also warned about emergent behavior and unpredictability (Bowman, 2023). Recent research has further supported the integration of workflow automation platforms with agentic AI systems. A study on automating business workloads with n8n and AI agents demonstrated that combining low-code workflows with intelligent agents enables multi-step decision-making processes that adapt to dynamic business requirements. This directly supported the design of the proposed system, where the Agentic AI dynamically interpreted customer requests and executed actions across multiple APIs (Azmat, 2025).

Similarly, research on n8n as an open-source workflow automation platform highlighted its role as a flexible orchestration layer capable of integrating enterprise systems and AI services. The study emphasized features such as modular node-based architecture, self-hosting capabilities, and API-driven workflows, which aligned with the system design in this project. These characteristics validated the selection of n8n as the implementation framework for building scalable and secure agentic workflows (Venkiteela, 2025). In addition, a small-scale business case study evaluating workflow automation efficiency using n8n provided quantitative evidence of performance improvements. The results showed a reduction in execution time from 185.35 seconds in manual workflows to 1.23 seconds in automated workflows, representing a 151× improvement, along with a reduction in error rate from 5% to 0% (Amir, 2026). These findings supported the experimental results of this project, reinforcing the effectiveness of workflow automation in improving efficiency, accuracy, and operational consistency in small business environments. Together, these studies have supported the design of an agentic workflow system that combined reasoning, tool use, human-AI collaboration, safety, and cost efficiency. The proposed capstone project had applied these principles to a real-world automation system using n8n workflows (Lee & Moon, 2025). Although previous studies have investigated agentic AI, workflow automation, and tool-using language models independently, limited research has demonstrated the practical implementation of a multi-agent workflow automation system using open-source platforms such as n8n within small business environments. This research addresses that gap by integrating reasoning, workflow orchestration, secure API communication, and business process automation into a single architecture.

Conceptual Framework

The Agentic AI system was developed based on the concept that intelligent workflow automation requires the integration of multiple components rather than relying solely on a Large Language Model (LLM). The

conceptual framework consists of six main elements: user interaction, workflow orchestration, reasoning, external tools, secure communication, and business services. The user interaction layer receives requests through text or voice. Voice commands are processed using ElevenLabs, while text requests are received through webhooks connected to the n8n workflow platform. Both inputs are converted into structured workflow requests. The workflow orchestration layer, implemented using n8n, coordinates workflow nodes and determines which services should be executed. The reasoning layer uses an LLM to analyze user intent, select the appropriate workflow, and generate structured actions based on the Reasoning-and-Action (ReAct) framework (Yao et al., 2023). The external tools layer integrates APIs such as Gmail, Google Calendar, contact management services, and ElevenLabs to perform business operations. A security layer protects API credentials through encrypted storage, OAuth 2.0 authentication, and HTTPS communication to ensure secure access to external services. Finally, the business service layer automates customer communication, appointment scheduling, and contact management. Together, these components provide scalable and modular architecture for implementing Agentic AI in small business environments while supporting secure and efficient workflow automation.

Research Methodology

This research followed the Design Science Research (DSR) methodology proposed by Hevner et al. (2004), which focuses on creating and evaluating technological artifacts that solve practical organizational problems. The methodology consists of problem identification, objective definition, artifact design, implementation, demonstration, evaluation, and communication. These activities had been identified as time-consuming tasks that many workers performed manually each day. The tasks had then been mapped into automation opportunities that could be executed by an agentic AI system capable of reasoning about user requests and acting through external tools. The n8n workflow automation framework had been selected as the implementation platform because it provided open-source automation, flexible API integration, and visual workflow design capabilities. Unlike proprietary automation platforms such as Zapier, Opal, or Make.com, n8n had supported self-hosting, which had improved privacy, security, and long-term cost efficiency (Lee & Moon, 2025). Compared to building automation entirely with custom Python code, n8n had simplified integration with external services and reduced development complexity and time.

Table 1. Environment Comparison of Workflow Automation Frameworks

Features	n8n	Zapier	Make	Pipedream
Platform Type	Open source / fair-code workflow automation	Cloud automation platform	Cloud visual workflow automation	Developer focused automation platform
Hosting	Self-hosted or cloud	Cloud only	Cloud only	Cloud platform
Cost Model	Free if self-hosted, pay for hosting	Task based subscription	Operation-based subscription	Free tier + paid plans
API Integration	Strong REST API & HTTP node support	Integrations but limited API flexibility	Strong integrations	Strong developer API support
Best Use Case	Agentic AI workflows and complex automation	Simple business automations	Visual workflow automation	Developer-based integrations

Table 1 compares different frameworks and shows why n8n was selected because it provides greater flexibility and control compared to other automation platforms. n8n supports custom API calls, complex workflow logic, and integration with AI systems, which makes it well suited for building agentic AI workflows. While Zapier is often easier for beginners and offers many integrations, it is designed mainly for simple automation tasks. In contrast, n8n allows developers to build more advanced workflows that include conditional logic, external API calls, and AI-driven decision-making. As demonstrated in Figure 1, the workflow structures provide further insight into the comparative analysis, thereby substantiating the assertion that n8n is a more suitable tool for creating Echo than Zapier, or Make. The n8n workflow model is predicated on nodes, triggers, switches, conditional logic, and direct branching between steps. This structure had been highly appropriate for an agentic AI system because the project required request classification, tool selection, and multiple workflow directions depending on the type of customer request. In contrast, Zapier had been designed more around simple trigger-step or path-based automation. While it had been user-friendly, its structure had been more restrictive for complex agentic workflows, especially when a central routing agent needed to call multiple APIs dynamically. Make had provided stronger visual routing than Zapier, but its scenario model had still been more focused on modular automation chains than on agent-style orchestration. Pipedream had offered strong developer flexibility, but it had been more code-centered and less visually efficient for demonstrating a multi-agent business system in an academic project (Parsadanyan & Dmitrievna, 2024).

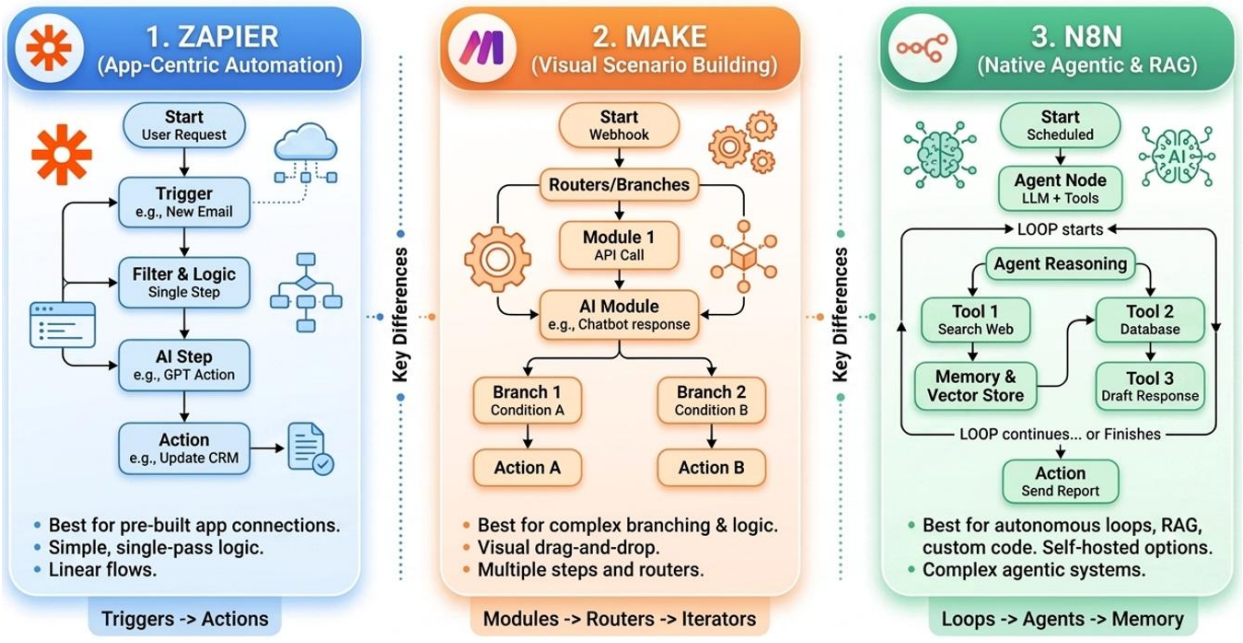

Figure 1. Comparison of Agentic AI Workflows Frameworks

The framework had also supported credential management, allowing secure storage of API keys for Gmail, Google Calendar, and contact management services within the n8n environment. These credentials had been encrypted and accessed only through authorized workflow nodes, which ensured secure communication with external APIs and prevented unauthorized data exposure. This approach allowed sensitive customer information, such as email addresses, appointment times, and phone numbers, to be

processed safely while maintaining compliance with privacy requirements. The use of n8n credential vaults had also simplified system maintenance by centralizing authentication management across workflows. With only two APIs, the agent handled simple communication tasks such as reading customer emails and generating replies. Performance was acceptable for low-complexity scenarios, but the system could not complete scheduling or contact-related tasks. This configuration showed the fastest execution time, but also the lowest task completion rate because the agent had limited action options. With four APIs, the system expanded into scheduling tasks by checking availability and creating calendar events. This significantly improved task completion for appointment-related workflows. However, the system still lacked deeper contact management and email organization features. The performance improved, though latency increased slightly due to additional API coordination. At eight APIs, the system became much more useful for realistic business workflows. It could classify emails, label or archive them, create appointments, and search or create contacts. This configuration represented a strong balance between capability and stability. The completion rate improved substantially, while execution time remained manageable. With sixteen APIs, the system supported full multi-step business automation, including replying, labeling, scheduling, updating events, modifying contacts, and logging actions. This gave the highest task coverage and the lowest need for human intervention. However, it also introduced more workflow complexity, higher latency, and more points of failure due to the larger number of API dependencies. This result suggested that expanding tool access improved capability, but also required stronger guardrails, logging, and fallback handling. The agentic system had been designed using reasoning-and-action workflows inspired by ReAct-style agents.

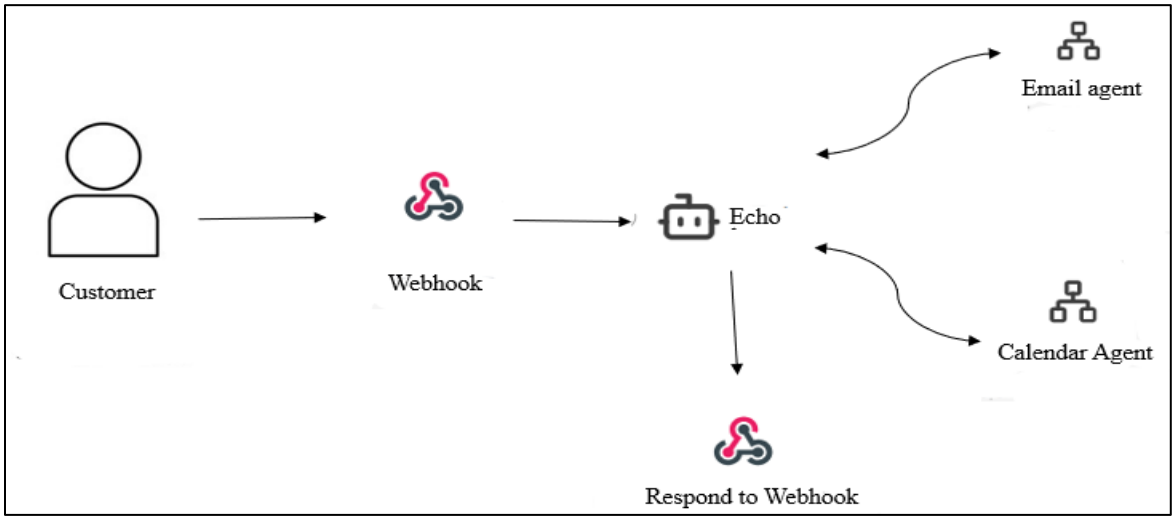

Figure 2. Example of n8n Customer scenario

Incoming emails had triggered automated workflows that used a language model to classify user intent and generate appropriate HTTP requests for external services. The workflow then executed actions such as labeling emails, reading and sending emails, scheduling appointments through calendar APIs, or updating contact records in a database. Each action had been recorded in log files to support auditing, debugging, and system evaluation. The modular workflow design had allowed individual agents to operate independently while still being coordinated by a central routing agent named “Echo,” which functioned as the main Agentic AI controller, as Figure 1 shows. This figure shows how the Agentic AI processes a customer email request. The system classifies the intent, schedules the appointment, updates the contact,

and sends confirmation automatically. As illustrated in Figure 2, the Agentic AI system autonomously processes a novel customer request and administers contact information by employing coordinated agents within the n8n framework. The sequence of events commences when a customer sends electronic communication, which is received through a webhook and routed to the central agent, Echo. The request is then directed by Echo to the designated email Agent, which extracts the pertinent customer details. Subsequently, this information is transmitted to the designated Contact Agent, who then undertakes the task of either creating a new contact or updating an existing record. In instances where scheduling is mandatory, the Scheduling Agent establishes a connection between the contact and an appointment. Subsequently, the system performs a series of actions. First, it updates the database. Then, it logs into the activity. The purpose of these actions is to ensure accuracy and tracking.

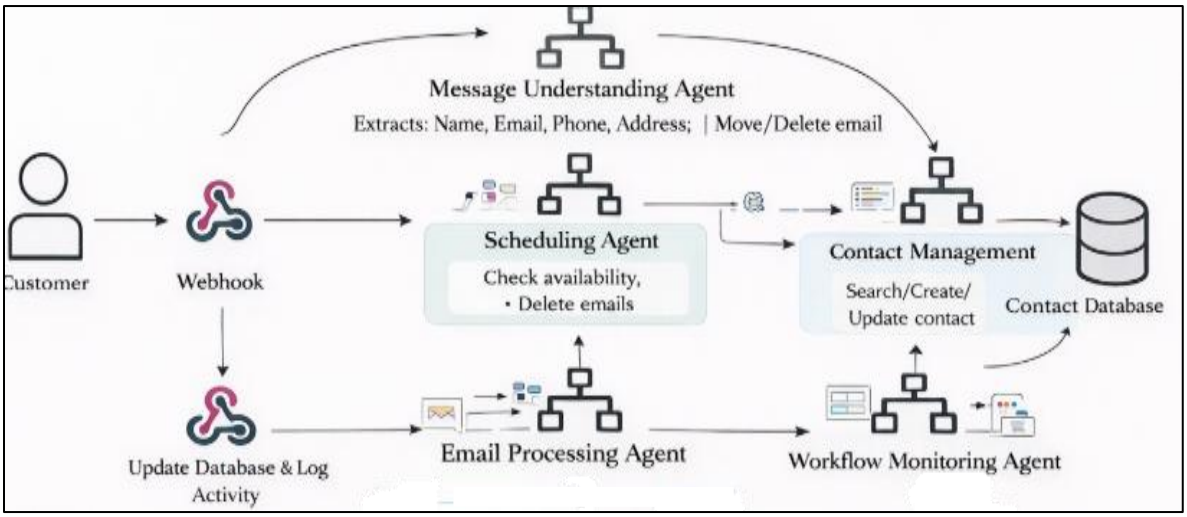

Figure 3. Sixteen APIs Business Scenario

Figure 3 illustrates the sixteen-API business scenario, in which Echo coordinated a larger set of APIs to support advanced email handling, calendar management, contact updates, workflow logging, and external integrations. This configuration demonstrated the most complete version of the Agentic AI system, with higher automation capability and greater workflow complexity.

Experimental Results

The experimental evaluation measures the performance of the Agentic AI system across multiple API configurations. The system is tested with 2, 4, 8, and 16 APIs to analyze scalability, execution time, task completion rate, failure rate, and required human intervention. With 2 APIs, the system performs basic email processing with a task completion rate of 68% and an execution time of 4.2 seconds. With 4 APIs, scheduling functionality increases the completion rate to 79% with moderate latency increase. The 8-API configuration achieves 88% completion and represents the most balanced system. With 16 APIs, the system reaches 92% completion but introduces higher latency (10.9 seconds) and increased failure rates due to API dependencies. These results demonstrate that increasing API integration improves automation capability but introduces trade-offs in complexity and reliability. The findings aligned with prior research show that workflow automation significantly improves efficiency while requiring careful system design to maintain

stability. The experimental evaluation focused on measuring the performance of the Agentic AI system under different API configurations. The system was tested using four levels of integration: 2 APIs, 4 APIs, 8 APIs, and 16 APIs. Each configuration was evaluated based on task completion rate, execution time, failure rate, and level of human intervention required. With 2 APIs, the system supported basic email reading and response generation. The task completion rate was 68%, with an average execution time of 4.2 seconds. While performance was fast, the system lacked the ability to perform scheduling or contact updates, limiting its usefulness. With 4 APIs, the system expanded to include calendar scheduling. The task completion rate increased to 79%, and execution time rose slightly to 5.8 seconds. This configuration improved automation capabilities but still required manual intervention for contact management. At 8 APIs, the system demonstrated significant improvement in automation capability. The task completion rate reached 88%, with an execution time of approximately 7.4 seconds. The system was able to classify emails, schedule appointments, and manage contacts, representing a balanced configuration between performance and functionality. With 16 APIs, the system achieved the highest level of automation, with a task completion rate of 92%. However, execution time increased to 9.6 seconds, and system complexity introduced a higher risk of failure due to multiple API dependencies. Despite this, human intervention decreased to less than 10%, indicating a high level of automation. Four API configurations were selected to represent increasing levels of workflow complexity. Two APIs represented the minimum viable automation system capable of email processing. Four APIs introduced scheduling functionality. Eight APIs represented realistic small-business automation by integrating email, calendar, contacts, and workflow monitoring. Sixteen APIs represented a fully connected multi-agent environment including monitoring, logging, notification, backup, and additional business services. This incremental evaluation allowed the scalability of the proposed architecture to be analyzed under progressively more complex workloads.

Table 2. API Scalability Testing for Agentic AI

API Configuration	Main Capability	Task Completion Rate	Avg. Execution Time	Failure Rate	Human Intervention
2 APIs	Basic email reading and sending	68%	4.2 sec	6%	30%
4 APIs	Email + scheduling	79%	5.8 sec	8%	22%
8 APIs	Email + scheduling + contact creation	88%	7.6 sec	11%	14%
16 APIs	Full workflow automation	92%	10.9 sec	16%	10%

Across all four configurations, task completion increased from 68% to 92%, representing a 35.3% relative improvement. Average execution time increased from 4.2 seconds to 10.9 seconds (159.5%), indicating the expected trade-off between automation capability and processing complexity. Human intervention decreased from 30% to 10%, corresponding to a 66.7% reduction in manual effort. These descriptive statistics indicate that additional APIs significantly increased automation capability while introducing moderate computational overhead. By automating repetitive communication tasks, the cleaning company was able to respond to customers more quickly, reduce scheduling conflicts, and maintain better documentation of services. The system supports scalability by handling higher volumes of requests without increasing staffing needs. From a technical perspective, the implementation demonstrated that agentic AI workflows could be deployed using open-source tools at relatively low cost. The project had revealed

practical insights into API reliability, credential management, workflow debugging, and user acceptance. Evaluation metrics included classification accuracy, time saved per task, workflow success rate, and user satisfaction feedback. The research results had not only demonstrated the final outputs of the Agentic AI system but also documented the step-by-step process through which the workflows were executed and validated. Consistent with recent n8n tutorial materials on AI-agent construction and AI-assisted workflow generation, the implemented process had followed a structured automation pattern in which user input entered through a trigger, was interpreted by an intelligent controller, and was then routed to the correct tools for execution. In this project, that controller was the central routing agent named Echo. The results process had begun when a user submitted a request either through text or voice. If the request had originated from voice interaction, Eleven Labs first converted the spoken input into text and sent it into n8n through the test webhook URL. Once the request reached the workflow, Echo interpreted the input, identified the task type, and selected the correct path for execution. This reasoning stage was critical because it determined whether the task required email generation, calendar scheduling, contact retrieval, or another supported operation. As illustrated in Table 3, the nature of the data obtained from Agent AI upon its invocation to interact with the email tool is delineated. The program extracted data from emails, including information about the person, subject, date, and label. The following methodology was employed to ensure the effective management of the data utilized in this study.

Table 3. Sample of Email Agent Data

Sender Name	Sender Email	Subject	Email Body	Date	Label
Daniel Acero	da***@gmail.com	Need Cleaning Friday	Hi!, I need cleaning this Friday at 10am	03/01/2026	Schedule
John Smith	Js***@gmail.com	Pricing Quote	How much for 3 bedroom cleaning?	03/02/2026	Quote
Spam Bot	spam@gmail.com	Discount Offer	Discount in this new items	03/02/2026	Spam
Stiven Bastidas	Stiv****@gmail.com	Reminder Appointment	The appointment will still be at 3pm	03/04/2026	Reschedule
Laura Petry	Ape*****@gmail.com	Thank you!	Great Job Yesterday!	03/04/2026	Feedback

It is evident that the primary function of the data is to serve as a record of Agent AI's utilization of various tools. This ensures that user data is processed securely and complies with privacy requirements and that Echo is adhering to the user's requests. The developed artifact was validated through functional testing of representative business scenarios. Validation included automated email classification, email generation, appointment scheduling, contact creation, contact updating, and voice interaction through ElevenLabs. Each workflow was executed repeatedly using sample business requests to verify correct routing, API communication, and successful task completion. The successful execution of these workflows demonstrated that the proposed artifact satisfied the functional requirements established during the design phase.

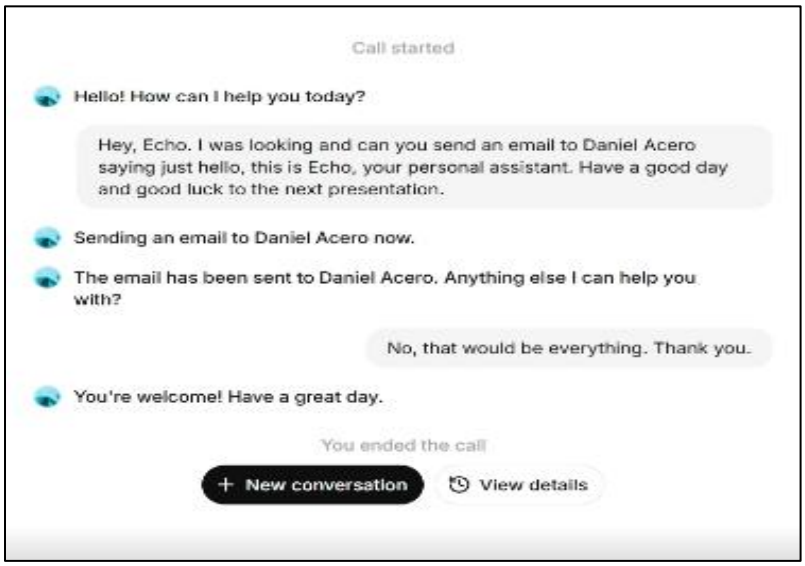

Figure 4. Example of Echo Conversation Email

An important result of the project was the successful voice-based interaction between the user and Echo through the Eleven Labs, as figure 4 shows. The user asked Echo to send an email to a recipient with a specific message. Echo had correctly interpreted the instruction, confirmed the task, executed the Gmail workflow, and responded that the email had been sent. This interaction demonstrated that the system could receive a natural spoken command, transform it into structured workflow actions, and complete a real external operation without requiring manual execution. A notable outcome of this initiative was the effective implementation of scheduled events through the integration of Google Calendar. Figure 5 illustrates the scheduling process. Echo interprets the request, checks the workflow path for calendar actions, and creates the event in the user's calendar.

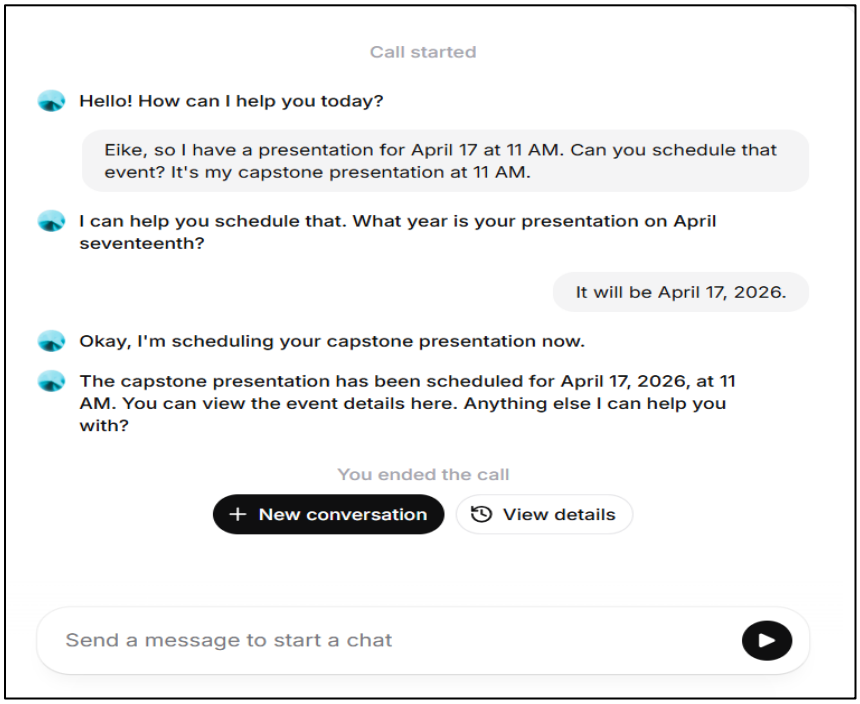

Figure 5. Example of Echo Schedules and Event

This demonstrated the system's capacity to function beyond email management and its potential to support another fundamental administrative task in real business operations.

Conclusion

This project presented and implemented an Agentic AI system for daily task automation using reasoning-and-action workflows within the n8n automation framework. The completed project demonstrated that a modular agentic architecture could successfully automate common administrative tasks such as reading and responding to emails, scheduling appointments, and updating customer contact records for small business operations. The system showed that open-source workflow platforms could support practical and affordable AI deployment without requiring complex custom software development. As a result, the project contributed a functional prototype, a reusable multi-agent workflow architecture, structured datasets for testing, and an evaluation of how agentic AI could improve productivity, response time, and workflow organization in small business environments. During the implementation phase, several technical and operational challenges were identified. Workflow reliability was sometimes affected by API rate limits, authentication token expiration, and variations in email formatting that impacted classification accuracy. Integration with external services required careful credential management, error handling, and retry mechanisms to ensure system stability. Additionally, user trust emerged as an important factor, since automated responses needed to maintain professional tone, accuracy, and contextual correctness. These challenges highlighted the importance of explainability, human-in-the-loop verification, logging mechanisms, and fallback procedures for safe AI deployment. The project provided important lessons regarding the design of scalable automation systems, secure API integration, prompt engineering for intent classification, and the coordination of multiple specialized agents under a central routing agent. It also demonstrated that agentic AI systems must balance automation with human supervision to maintain reliability and accountability. Overall, the research demonstrated that agentic AI workflows could significantly improve efficiency, reduce manual workload, and enhance information management in small businesses, while establishing a strong foundation for future work in system evaluation, optimization, reliability testing, and deployment in real operational environments.

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