# A Physical-agentic AI Enabled, User-centric Machine with an Intuitive Design: Smart Drug Compounding System

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## Abstract

In this study, we developed and integrated a Physical-Agentic AI system using n8n as the communication and orchestration layer between users and the system, enabling Agentic AI to process inputs and issue commands to physical equipment, including a collaborative robot and a compounding machine. In the original implementation, the n8n automated workflows relied on four AI agents to analyse requests and generate control actions; however, each agent accepted API calls from multiple sources, which increased data-handling complexity and raised the risk of errors. To improve the workflow architecture, we introduced a Master Agent as a single-entry point for all incoming API calls. The Master Agent filters and standardises the input data, then routes tasks to the appropriate specialised agents based on their roles. Practical deployment results indicate that the improved workflow achieves higher accuracy and correctness, reduces data ambiguity, and simplifies maintenance and future modifications. Nevertheless, this architecture increases processing time and consumes more AI tokens than the original flow. This trade-off is considered acceptable because chemotherapy compounding is a high-risk process where accuracy and operational safety must be prioritised.

## 1 Introduction

In the preparation of anticancer chemotherapy drugs, routine compounding is typically performed under aseptic conditions within a cleanroom and isolator environment [1]. Pharmacists work in cleanroom garments and carry out solution withdrawal and dose preparation tasks that demand high technical proficiency and sustained concentration, often under strict time constraints. Chemotherapy agents are inherently cytotoxic and may pose serious hazards if personnel are exposed through direct contact or inhalation. These risks are further intensified in large hospitals that must serve a high volume of patients (e.g., specialised cancer centres may manage, on average, more than three hundred outpatient visits per day). Under such workload pressure, the likelihood of compounding errors increases, including mistakes in drug selection and the prepared volume intended for individualized patient administration [2]. Reported incidents of these errors have driven the adoption of automated chemotherapy compounding systems to mitigate occupational exposure risks, reduce human error in pharmacy practice, improve workplace health and safety, stabilize dispensing capacity, and strengthen smart-hospital capabilities through digital data tracking and traceability.

Robotics and automation in pharmaceutical practices, particularly automated compounding devices-have shown rapid growth in adoption and market value [3]. The global market for these systems was valued at USD 2.51 billion in 2025 and is expected to reach USD 3.53 billion by 2030, reflecting a compound annual growth rate (CAGR) of 7% [3]. Demand is especially strong for intravenous chemotherapy preparations, where stakeholders prioritize minimal contamination risk and high dosing accuracy to ensure patient-specific safety and treatment effectiveness.

However, increasing deployment does not automatically translate into positive user attitudes. Evidence from a study on the acceptance of robotic technologies in pharmacy practice in the UAE suggests a pattern of "early use with limited confidence" [4]. Although one in five community pharmacists reported that they were already using robotics-primarily for inventory management and dispensing-many remained unconvinced of clear benefits [4]. This highlights a critical distinction: real-world adoption does not necessarily equal attitudinal acceptance (adoption ≠ acceptance). The study indicates that concerns can suppress acceptance, with key issues including: (1) system failures and downtime (safety and workflow continuity), (2) reduced quality of patient interaction (fear of less "human" service or more difficult communication), (3) challenges for older pharmacists to adapt (digital skill gaps), and (4) high costs and uncertainty regarding investment value [4].

Recent studies also show that agentic-AI workflows, language-model-based robotic reasoning, and multi-agent conversation frameworks can support more flexible healthcare and robotic automation architectures [5], [6], [7].

Nevertheless, the initial workflow architecture relied on multiple specialised agents receiving API calls from several

input sources. Although this distributed arrangement enabled flexible task handling, it also introduced important architectural challenges, including inconsistent payload structures, fragmented workflow context, duplicated routing logic, and difficulty in enforcing safety rules consistently throughout the process [8], [9]. In a high-risk application such as chemotherapy compounding, these issues are not merely technical inconveniences; they directly affect robustness, traceability, and confidence in command execution [2], [10].

To address these limitations, this study introduces a Master Agent as a centralized orchestration layer for the Physical-Agentic AI system. Instead of allowing each specialised agent to receive independent external inputs, the proposed architecture funnels incoming requests through a single-entry point, where the Master Agent normalises input structures, preserves operational context, applies preliminary safety logic, and routes tasks to the appropriate specialised agents [8], [9]. Fig1 to shown overview proposed Physical-Agentic AI workflow, this design is intended to reduce ambiguity in event sequencing, improve maintainability, strengthen auditability, and enable more consistent coordination between AI reasoning and physical execution [8], [10]. Accordingly, this paper presents the design of a Master-Agent-based automated workflow for chemotherapy drug compounding as an initial implementation stage of a Physical-Agentic AI framework. The study emphasizes the architectural rationale for shifting from a distributed multi-agent input scheme to a centrally orchestrated design and establishes a basis for experimental comparison between the two architectures in terms of AI tokens consumption and processing time. Although the centralized approach may introduce additional overhead, the main premise is that, in chemotherapy compounding, improvements in safety, stability, traceability, and workflow governance may justify moderate increases in latency and token usage [2], [10].

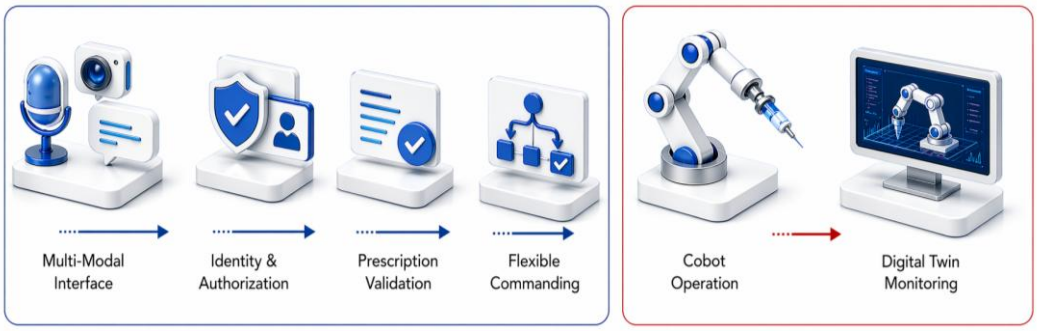


Fig.1 shows the overview proposed Physical-Agentic AI workflow and Digital Twin integration

## 2 Methodology

The proposed system consists of four specialised agents, each responsible for a specific function within the chemotherapy compounding workflow. These functions cover user communication, OCR result verification, authorisation checking, and prescription analysis. The roles, input data, and outputs of each agent are presented in Table 1.

Each agent is trained and configured for a specific domain of expertise. Therefore, the input data, processing logic, and expected outputs are not interchangeable across agents, ensuring that each task is handled by the most appropriate specialised agent with consistent interpretation, minimised errors, and stronger workflow reliability.

Table 1 Shown Roles of the Specialised Agents

| Agent | Agent Role | Sample Input | Sample Output |
|---|---|---|---|
| Agent No.1<br>Communication Agent | Communicate with users, receive commands, and confirm commands | User voice command | AI voice response |
| Agent No.2<br>OCR Agent | Confirms drug name from OCR results | OCR-extracted drug label text | Drug name |
| Agent No.3<br>Authorisation Agent | Verifies user authorisation. | QR-code id, User id | Approval results |
| Agent No.4<br>Prescription Analysis Agent | Analyse physician prescriptions to extract key information and determine the execution order of physical operations | QR-code prescription | Drug, dosage, and task execution order |

This study employed a workflow-comparison methodology to develop and evaluate a Physical-Agentic AI architecture for chemotherapy compounding automation using the n8n platform. The proposed system consisted of one Master Agent and four specialised agents for communication, OCR, authorisation, and prescription analysis. In the initial distributed architecture, each specialised agent could receive API calls directly from multiple external sources. Although this structure enabled flexible integration, it also introduced heterogeneous JSON payloads, fragmented context, duplicated routing logic, and increased complexity in workflow configuration and maintenance. To address these limitations, a centralized Master Agent was introduced as a single-entry orchestration layer to normalize input data, preserve workflow context, and route requests to the appropriate specialised agents. The comparison in this study focused only on internal workflow behaviour within n8n, rather than on downstream physical machine execution. Both architectures were configured to perform equivalent task sequences so that the observed differences would reflect the orchestration model itself. The primary evaluation metric was process time, defined as the elapsed time from workflow input reception to the generation of the corresponding routed response or internal decision result within n8n. Additional qualitative observations were also considered, including workflow continuity, clarity of task routing, consistency of data handling, and ease of process management.

The proposed Master-Agent architecture was expected to introduce slightly higher workflow overhead because of the additional steps required for input normalization and routing. However, this design was intended to improve system stability, traceability, and maintainability, which are critical requirements for safety-sensitive healthcare automation.

For system evaluation, four testing scenarios were defined based on the source of the incoming API request; Scenario 1: voice-based input, Scenario 2: OCR-based input, Scenario 3: personnel QR code scanning, Scenario 4: physician prescription input. Each scenario was tested five times under equivalent workflow conditions to compare the architecture without a Master Agent and the architecture with a Master Agent. For each trial, AI token usage and processing time within the n8n workflow were recorded as the main quantitative metrics. These results were then used to examine how the orchestration structure affected workflow performance, particularly in terms of computational overhead and response time. The comparison also helped assess whether the addition of a centralized Master Agent, responsible for input normalization and task routing, was introduced acceptable overhead in exchange for improved workflow control. Fig 2 shows the comparison of n8n automated workflows with and without the Master Agent

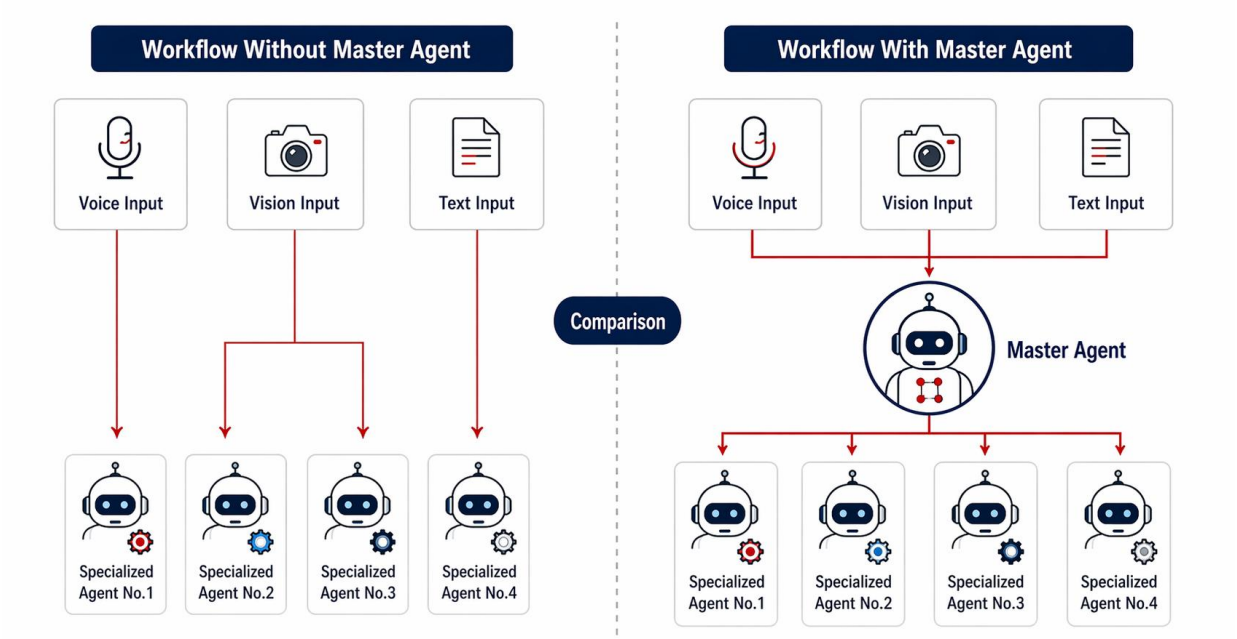


Fig.2 Comparison of n8n automated workflows with and without the Master Agent

These scenarios were selected to cover the major information pathways involved in chemotherapy compounding, including user commands, machine vision outputs, identity verification data, and prescription-related information. By using different input formats, the experiment aimed to assess whether the proposed system could correctly interpret, route, and process heterogeneous data. This setup also helped evaluate the robustness of the workflow when handling noisy, incomplete, or structured inputs that may occur in real operating environments.

Table 2 Experimental Parameters for Each Test Scenario

| Scenario | Experiment Input |
|---|---|
| Scenario 1 | “Start all operations" |
| Scenario 2 | “JMe HYDROCHLORIDE 1% Hc Mial Multidose 1 10 mg Im Dc ENT PHARMACEUTICAL 1 Uon wlv Jonans Fdrochlonde eatalne niv ORGANIZATO lard” |
| Scenario 3 | “6636790\|Mr.\|Pradujthep Maneechay\|FACULTY OF ENGINEERING” |
| Scenario 4 | “Saline 1mg, Gazore 0.5mg, Penicillin 0.25mg” |

As shown in Table 2, the experimental parameters were selected to reflect the main types of input that the proposed system may encounter in practice. All experiments were conducted using the Google Gemini 3 Flash Preview model. Scenario 1 used actual voice commands from real users to represent natural spoken interaction during operation. Scenario 2 was based on genuine OCR outputs obtained from real text recognition results, thereby preserving the formatting noise and text irregularities that typically occur in OCR-based input [11]. Scenario 3 employed authentic QR code data obtained from the WE Mahidol application, representing real personnel identification information used in the workflow. In contrast, Scenario 4 used a mockup prescription-mixing input created solely for experimental purposes. This input was not derived from a real prescription but was designed to imitate the general structure of a medication-related instruction so that the workflow could be evaluated without using actual prescription data.

## 3 Results

Table 3 shows that the introduction of the Master Agent increased both processing time and tokens usage in all four scenarios when using Google Gemini 3 Flash Preview. In Scenario 1, the increase was moderate, indicating that even simple voice-based input required additional orchestration steps. In Scenario 2, the overhead was the highest, mainly because OCR-based input contained noisy and irregular text that required more normalization and routing effort. In Scenario 3, although QR-code input was more structured, the Master Agent still added computational overhead for contextual handling and centralized control. In Scenario 4, the increase was smaller than in the OCR case, suggesting that the mock up prescription input was easier to process due to its more predictable structure. These results suggest that Master-Agent architecture introduces a reasonable trade-off: slightly higher computational cost in exchange for better input standardization, stronger workflow control, and improved suitability for safety-critical medical applications.

Table 3 Experimental Result for Each Scenario Using Google Gemini 3 Flash Preview, with and without the Master Agent

| Scenario | Without Master Agent Processing Time (s) | With Master Agent Processing Time (s) | Time Increase (%) | Without Master Agent Tokens | With Master Agent Tokens | Token Increase (%) |
|---|---|---|---|---|---|---|
| Scenario 1 | 2.385 ± 0.229 [2.152 - 2.610] | 4.311 ± 0.732 [3.466 - 4.738] | 80.7 | 749.00 ± 0 [749 - 749] | 1068.7 ± 0.6 [1068 - 1069] | 42.7 |
| Scenario 2 | 3.472 ± 0.260 [3.180 - 3.679] | 9.781 ± 0.904 [8.747 - 10.421] | 181.7 | 1202.7 ± 0.6 [1202 - 1203] | 1953.0 ± 0.0 [1953 - 1953] | 62.4 |
| Scenario 3 | 4.540 ± 0.918 [3.603 - 5.438] | 8.036 ± 0.780 [7.524 - 8.934] | 77.0 | 436.3 ± 0.6 [436 - 437] | 883.0 ± 1.0 [882 - 884] | 102.4 |
| Scenario 4 | 3.967 ± 0.320 [3.633 - 4.272] | 5.683 ± 0.732 [4.840 - 6.157] | 43.3 | 322.0 ± 0.0 [322 - 322] | 681.0 ± 0.0 [681 - 681] | 111.5 |

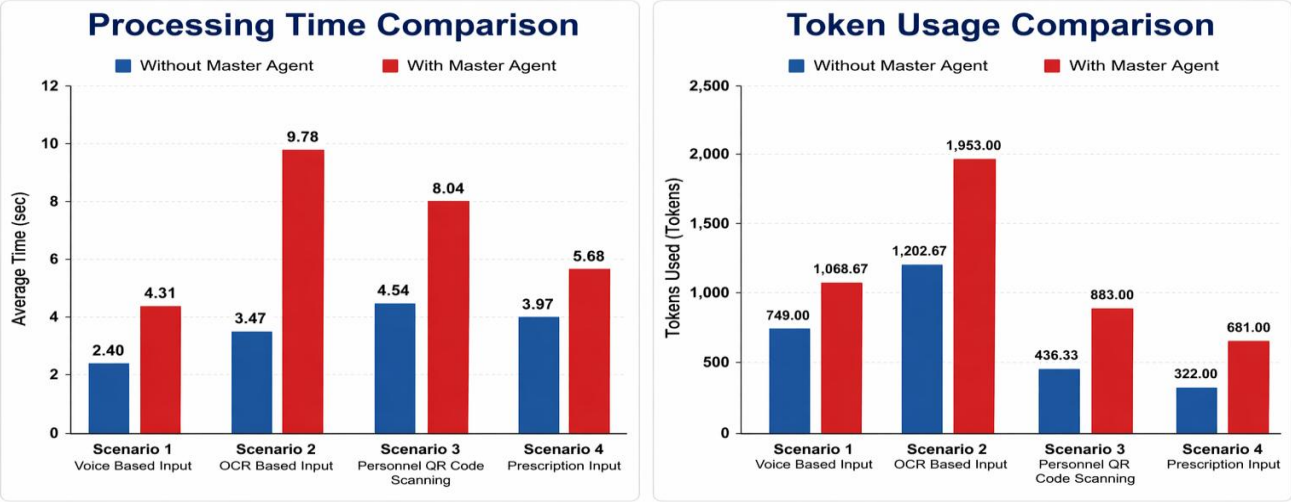


Fig.3 Comparison of processing time and token usage with and without the Master Agent

Fig 3 Shown the experimental results show that the workflow with the Master Agent required higher processing time than the workflow without the Master Agent in all four scenarios. On average, the processing time increased by approximately 95.4%. The OCR-based input scenario showed the highest processing time, reaching 9.78 seconds, because OCR data requires additional interpretation to identify drug-related information and determine the appropriate processing route. Similarly, token usage increased by approximately 79.7% when the Master Agent was added. This increase indicates that the Master Agent introduces computational overhead due to input normalization, context handling, and centralized decision routing. However, this overhead provides a more structured and traceable workflow, which is important for safety-critical chemotherapy compounding tasks where incorrect routing or inconsistent interpretation may affect system reliability. Therefore, the Master Agent represents a trade-off between processing efficiency and improved workflow control, safety, and maintainability.

## 4 Discussion

Nevertheless, while introducing a Master Agent improves workflow structure and governance, a centralized orchestration approach involves important system-level trade-offs. Because the Master Agent becomes a primary dependency, it may introduce a single point of failure and can also act as a bottleneck when many events or user commands arrive concurrently. In addition, complexity is shifted upward to the orchestration layer, including the design of routing rules, priority policies, and the handling of overlapping or concurrent events. If these conditions are not rigorously specified, the workflow may exhibit command-order deviations or agent invocations that are misaligned with the intended context.

Furthermore, although multi-level memory (i.e., Master Memory combined with per-agent Simple Memory) can improve processing flexibility, it also increases the risk of context inconsistency, particularly when tasks are not explicitly bound using a case/session identifier and a clear synchronization mechanism. Finally, multi-stage verification intended to enhance safety may come at the cost of higher latency and increased chatbot token usage. Therefore, practical deployment should carefully balance safety assurance against responsiveness and operational efficiency, consistent with real-world clinical workflow requirements.

## 5 Conclusion

In summary, this study introduces a Master Agent to strengthen the safety and correctness of command execution in the proposed Physical-Agentic AI system, given that chemotherapy compounding is a high-risk process where safety must be treated as the primary priority. Although centralized orchestration can increase processing time and introduce additional latency in certain steps due to multi-stage verification, the resulting benefits lower error likelihood, systematic enforcement of safety constraints, and improved auditability/traceability represent an appropriate and justified trade-off for practical deployment in clinical contexts.

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