An-Najah University Journal for Research – A
Natural Sciences

An Intelligent Over-the-Counter (OTC) Pharmacy System Using Conversational AI and Robot Manipulator

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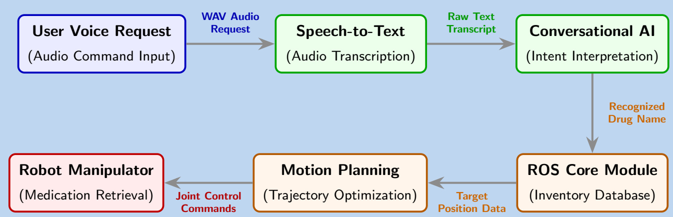
Type: Full Article. Received 6th Jun. 2026, Accepted 6th Jul., 2026.

Accepted Manuscript, In Press
(This article belongs to the Special Issue: Engineering for Palestine Conference 2025)

Abstract: This paper presents an intelligent over-the-counter (OTC) pharmacy system that integrates conversational AI with robotic manipulation for voice-driven medication retrieval. The system employs OpenAI's ChatGPT for natural-language interpretation, a ROS-based control framework, and a Franka Emika Panda robotic arm. User voice requests are transcribed, mapped to a predefined pharmaceutical inventory, and translated into robotic retrieval actions. The platform supports a modular design, real-time human–AI interaction, and coordinated task execution. Experimental evaluations in simulation and real-time settings demonstrated high accuracy in interpreting the tested requests and executing the associated retrieval actions within the predefined inventory. These results indicate repeatable performance under the controlled experimental conditions considered in this study. The proposed architecture provides a framework for integrating conversational interfaces with robotic retrieval in controlled service environments. Future work should extend the evaluation to broader inventory configurations, varied speech conditions, and practical pharmacy-workflow constraints.



Keywords: Natural-Language Request Interpretation, Pharmacy Automation, Voice-Based Human–Robot Interaction, Predefined Inventory Mapping, ROS-Based Motion Planning, OTC Medication Retrieval.

Introduction

The rapid proliferation of artificial intelligence (AI) across service-oriented domains has created new opportunities for automating tasks that previously required continuous human oversight. In healthcare settings—particularly community pharmacies and outpatient clinics—the demand for reliable, accessible, and intelligent dispensing solutions has increased because of staffing constraints, rising patient volumes, and the need for consistent service quality [1, 2]. In the Palestinian context, community-pharmacy practice has also been examined in relation to professional, operational, and regulatory considerations that affect pharmacy services and OTC medicine provision [3]. Robotic automation and conversational AI are complementary technologies that can support these operational requirements.

Large language models (LLMs), exemplified by OpenAI's ChatGPT, have demonstrated the capacity to interpret unstructured natural-language inputs across diverse domains [4]. In parallel, robotic platforms coordinated through middleware frameworks such as the Robot Operating System (ROS) have matured into programmable systems capable of precise manipulation in structured environments [5, 6]. Integrating conversational AI with reliable physical robotic execution remains a challenging research direction. Many robotic systems continue to rely on structured task inputs or predefined command interfaces, whereas natural-language interaction requires an additional layer that maps variable user expressions

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to constrained and executable robotic tasks.

Recent pharmacy-automation research has examined robotic dispensing, automated drug-retrieval systems, automated drug-preparation platforms, and implementation strategies for structured medication workflows. These studies show that automation can support inventory handling, retrieval, preparation, and verification activities in pharmacy settings, while emphasizing reliable workflow design, inventory control, and systematic performance assessment [7–12]. Most reported systems, however, are designed for hospital or outpatient pharmacy environments and commonly depend on predefined procedures, barcode-supported processes, electronic health-system integration, or professional-user interfaces.

Recent research on large language models has also demonstrated their potential for supporting natural-language interaction in health-related applications [13]. At the same time, security and privacy studies have emphasized the need for controlled deployment, data protection, and clear operational boundaries when cloud-based generative-AI services are used in healthcare-oriented environments [14]. Related work in human–robot interaction, robotic task planning, and practical robotic implementation has shown how user interfaces, task information, sensing, and natural-language instructions can be connected to structured robotic actions through modular software architectures [15–19].

Against this background, the present work investigates a controlled OTC retrieval configuration in which conversational language processing is linked to a predefined inventory and a ROS-controlled Franka Emika Panda manipulator. The workflow interprets voice requests, maps them to available inventory items, and executes the corresponding robotic retrieval action. It is distinct from hospital-scale automated dispensing systems and does not provide clinical decision support; rather, it evaluates an end-to-end voice-to-retrieval architecture within a controlled proof-of-concept setting.

The Robot Operating System (ROS) is a widely used middleware framework for integrating heterogeneous hardware and software components in robotic systems [6, 20]. Its node-based publish/subscribe architecture, together with simulation tools such as Gazebo and visualization support through RViz, provides a foundation for developing, testing, and deploying modular robotic applications. The Franka Emika Panda robotic arm, with seven degrees of freedom, joint-torque sensing, and sub-millimetre positional repeatability, is a well-established research platform for precise manipulation tasks [21]. Together, ROS-based control and the Panda manipulator provide the technical basis for the controlled retrieval workflow investigated in this study.

Existing studies in pharmacy automation and language-enabled robotics address complementary aspects of the proposed workflow. Pharmacy-automation systems commonly focus on structured dispensing, drug preparation, or institutional workflow integration, whereas language-enabled robotic systems generally address broader service, assistive, or patient-care tasks. Table 1 summarizes representative studies and places the present work within this landscape.

This system-level integration provides the basis for the contributions summarized below.

The principal contributions of this work are as follows:

- Integration of a conversational AI module (ChatGPT) with a ROS-controlled robotic manipulator into a unified, deployable dispensing system.
- A natural language-to-action mapping pipeline that translates unstructured voice queries into precise robotic waypoint commands without requiring keyword-based or structured input.
- Experimental validation of the complete system through real-time human-subject trials and simulation-based testing, demonstrating high accuracy in query interpretation and task execution.
- A modular and reconfigurable system architecture that supports adaptation to service environments beyond pharmacy dispensing, including smart kiosks and assistive service stations.

The proposed system is developed for controlled OTC dispensing environments, where conversational interaction is used to facilitate access to a predefined medicine inventory. The current implementation focuses on the technical integration of natural-language interaction, inventory selection, and robotic retrieval. Clinical assessment and individualized medication decisions remain outside the scope of the present system.

Accordingly, the proposed platform is positioned as an intelligent OTC retrieval and dispensing system for controlled environments, rather than as a replacement for pharmacists, physicians, or professional medical consultation.

The remainder of this paper is organised as follows. Section 2 outlines the architectural and methodological foundations of the proposed system. Section 3 details the software architecture and control logic. Section 4 presents the implementation and modular com-

Table (1): Comparison of the proposed system with representative pharmacy-automation and language-enabled robotic studies.

Study	Application Context	User Interaction	Automation / AI Approach	Main System Characteristic
Takase et al. [12]	Hospital pharmacy dispensing	Structured pharmacy workflow	Robotic dispensing system	Focuses on the safety and efficiency of structured robotic dispensing.
Lin et al. [10]	Hospital central pharmacy	Professional-user workflow	Automated retrieval cabinet and robotic dispensing	Focuses on high-throughput medication retrieval and institutional pharmacy workflow integration.
Al Nemari and Waterson [7]	Outpatient pharmacy	Pharmacy staff and system interfaces	Robotic dispensing implementation	Addresses the implementation and workflow impact of pharmacy robotics.
Shin et al. [11]	Cytotoxic drug preparation	Structured automated workflow	Robotic compounding systems	Focuses on robotic drug compounding, preparation accuracy, and contamination-related performance.
Kim et al. [16]	Patient-care robotics	Natural-language interaction	LLM-based robotic task planning	Explores language-enabled task execution for patient-care robotics.
Pinto-Bernal et al. [17]	Social and assistive robotics	Natural-language interaction	LLM-enabled social robot design	Focuses on conversational interaction for social and assistive robotic applications.
Proposed system	**Controlled OTC retrieval**	**Voice-based natural-language requests**	**Speech-to-text processing, ChatGPT-based inventory mapping, ROS, and Panda-arm retrieval**	**Integrates voice-based request interpretation, predefined OTC inventory mapping, and physical retrieval using a ROS-controlled Panda manipulator.**

The comparison shows that the present system combines conversational request interpretation with predefined OTC inventory mapping and physical robotic retrieval within one controlled end-to-end workflow. It is therefore distinct from hospital-scale dispensing platforms, robotic compounding systems, and broader language-enabled service robots.

ponents. Section 5 discusses the experimental evaluation, including both simulation-based and real-time performance tests. Finally, Section 6 concludes the paper and outlines directions for future work.

System Architecture and Design Methodology

System interaction begins when a user provides a voice request through a microphone. This audio signal is relayed to an AI controller based on transformer models, which interprets the user's request against a specialized medical data set. The interpreted request is then translated into control signals that guide the robotic manipulator in selecting and retrieving the corresponding item from the predefined inventory.

The main system components include a microphone, a language-processing module, and a robotic arm. The microphone captures the user's speech, serving as the primary interface. The AI controller processes the voice input using natural language processing to extract commands and transform them into robotic instructions. This translation step is essential for mapping human language to machine-level directives.

Subsequently, the robotic controller interprets the AI's outputs and generates precise actuation commands. The robot performs waypoint-based grasping and retrieval of the selected inventory item, requiring accurate kinematic modeling and reliable motion execution.

The system utilizes the Franka Emika Panda robotic arm, chosen for its dexterity, precision, and compatibility with human-like motion. Featuring seven degrees of freedom, torque sensing at each joint, and a positional repeatability of ±0.1 mm, it is well-suited for precise and adaptive tasks. Its control interface supports responsive motion execution. Its ROS compatibility allows modular development and testing. Availability at the Intelligent Research Lab (IRL) at Palestine Polytechnic University facilitated implementation.

The robot follows a Revolute-Revolute-Revolute (RRR) configuration and offers a payload of up to 3 kg with an 855 mm reach. Its kinematic behavior is modeled using Denavit-Hartenberg (DH) parameters, which are essential for computing forward and inverse transformations [22]. This model supports the computation of robot poses required for trajectory planning.

Software integration is implemented through the Robot Operating System (ROS). ROS provides node-based modularity, a publish/subscribe messaging framework, support for tools such as RViz and Gazebo. These features allow for debugging, simulation, and visualization, making ROS central to system coordination [20]. ROS also supports C++ and Python and benefits from a vast community and library ecosystem. Its BSD open-source license supports cost-effective development and hardware adaptability.

To illustrate the component interactions, the system is shown via a block diagram. The microphone captures user input, which is interpreted by the AI. The AI sends processed commands to the robotic control logic via ROS, and the robot performs the corresponding physical action. This voice-controlled AI-robotic system architecture is shown in Figure 1.

Intelligent Control and Software Integration

The system in this work is built for adaptability across various environments, such as pharmacies, libraries, and retail settings. At its core, the integration of ChatGPT and ROS enables a high degree of customization.This can be directly done by modifying prompts or positional data, the same platform can be applied in different domains, such as automated book retrieval or product selection. This reconfigurability underscores the general-purpose nature of the architecture.
The architecture is organised as modular software components that separate speech processing, language-based request interpretation, inventory selection, motion planning, and gripper control. This modularity facilitates monitoring and further extension of the workflow, for example by incorporating additional validation or recovery functions where required by the intended deployment environment.
The software architecture follows a component-based data flow, illustrated in Figure 2. The workflow begins with a user voice request and ends with retrieval of the selected inventory item. The main sequence is summarized as follows:

1. The user initiates a process through the application GUI.
2. The `record\_audio()` function captures audio input via a microphone.
3. The audio is transcribed using `transcribe\_audio()` powered by AssemblyAI.
4. The transcribed text is processed by: `choose\_medicine\_with\_gpt4()` via OpenAI.
5. The `get\_medicine\_waypoint()` function maps the selected medicine to a coordinate.
6. The robotic arm navigates to the coordinate using MoveGroupCommander.
7. The `open\_gripper()` function prepares the gripper for object retrieval.
8. The `close\_gripper()` function secures the medicine.
9. The `move\_to\_home\_position()` resets the robotic arm.
10. The application logs task completion.

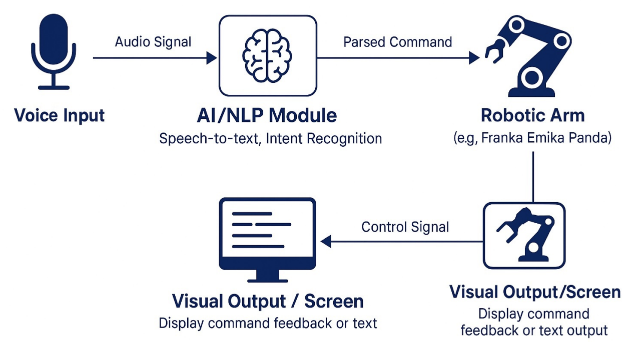

Figure (1): Voice-controlled AI–robotic system architecture illustrating the interaction between the user, AI module, ROS, and the Franka Emika Panda robot.

This workflow integrates speech processing, inventory-item selection, motion planning, and robotic execution through ChatGPT and ROS. ChatGPT, developed by OpenAI [4], serves as the NLP engine for interpreting user commands. It provides a powerful, pre-trained, and ready-to-deploy model capable of understanding and responding to complex instructions. Developing a comparable AI from scratch would be computationally intensive and financially prohibitive. ChatGPT's cloud-based architecture, frequent updates, and rich language model offer a practical and scalable solution for real-world deployment. Its role is important in translating voice-transcribed text into contextual meaning, allowing the robotic system to determine the appropriate response or action. Within the predefined inventory configuration, ChatGPT supports the interpretation of varied user requests and their mapping to corresponding robotic retrieval tasks.
On the other hand, ROS is the primary interfacing layer of the system, providing communication, coordination, and control interfaces. Its node-based architecture and publish-subscribe messaging model are ideal for distributed systems with multiple sensing and actuation modules. ROS includes packages for hardware abstraction, device control, data processing, and simulation support [6].

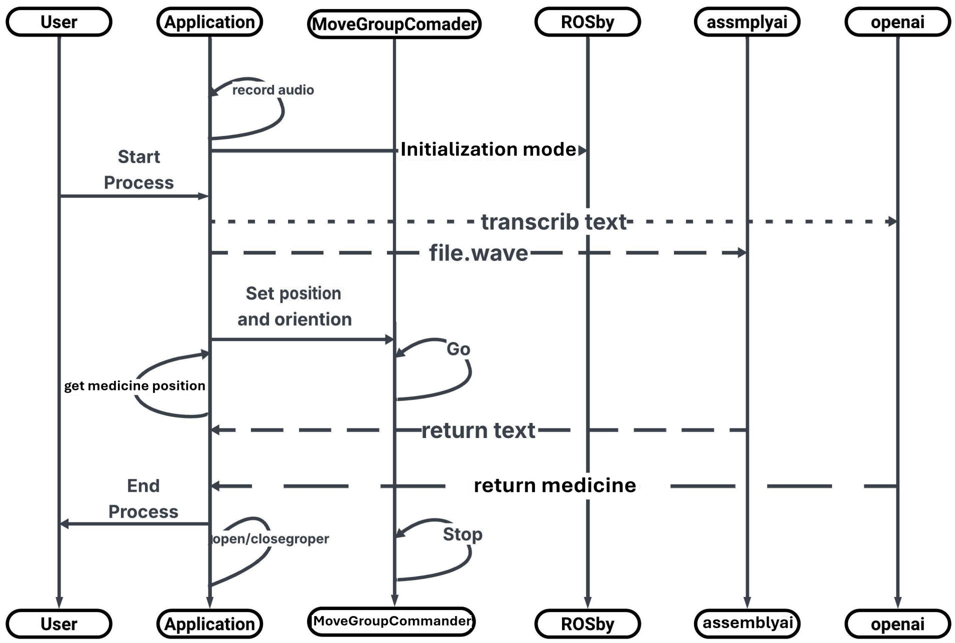

Figure (2): Data flow of the proposed voice-to-retrieval workflow: user speech is recorded and transcribed, processed by the language module to identify an inventory item, mapped to the corresponding waypoint, and executed by the ROS-controlled robotic manipulator.

The platform, with a plug and play structure as well as wide compatibility with C++, Python, and various hardware make it a suitable choice for integrating AI with robotics. The availability of visualization (RViz) and simulation (Gazebo) tools accelerates development and validation. ROS provides the communication and software-integration infrastructure required for coordinating the system modules.

The integration of ChatGPT and ROS under this software framework allows seamless interaction between human inputs, AI-driven logic, and robotic execution, resulting in a flexible, reliable, and intelligent dispensing system.

AI–Robot Software Integration and Execution Workflow

This section presents the implementation workflow that connects speech transcription, language-based inventory selection, waypoint generation, and robotic retrieval. The listed software components and pseudocode describe the functional modules through which user requests are processed and translated into coordinated ROS-based robot actions.

The workflow is implemented through ROS, speech-processing, language-processing, inventory-mapping, motion-planning, and gripper-control modules. Table 2 summarizes the main software libraries supporting these functions.

Table (2): Libraries Used in the System and Their Descriptions

Library	Description
`sys`	Handles system-level tasks like passing arguments to ROS nodes.
`rospy`	Enables communication with ROS for robot control.
`os`	Manages environment variables and file system access.
`moveit_commander`	Provides motion planning tools for controlling the robot arm.
`geometry_msgs.msg`	Defines movement data such as positions and orientations.
`subprocess`	Executes shell commands (e.g., to record audio).
`assemblyai`	Transcribes spoken input to text using a speech API.
`openai`	Uses language models to interpret user commands.
`json`	Parses and writes data in JSON format (e.g., locations).
`math`	Supports mathematical functions used in motion calculations.
`tf_conversions`	Converts between coordinate frames in the robot.
`tkinter`	Builds the GUI for user interaction and monitoring.
`std_msgs.msg`	Sends basic messages like gripper open/close commands.

The main system parameters are defined in a dedicated configuration block. These include API keys, topic names, file paths, and planning group identifiers. See the implementation in Code 1.

Code 1 Initialize ROS Parameters and API Keys

```
GRIPPER_TOPIC ← "gripper/command_topic"
gripper_publisher ← rospy.Publisher(GRIPPER_TOPIC, Float64, queue_size=1)
assemblyai.settings.api_key ← "..."
OPENAI_API_KEY ← "..."
RECORD_SECONDS ← 5
WAVE_OUTPUT_FILENAME ← "file.wav"
GROUP_NAME_ARM ← "panda_arm"
JSON_FILE_PATH ← "medicin.json"
```

Codes 2 through 7 describe the functional modules used in the implementation, including: audio recording and transcription, loading medicine data, selecting medicine using GPT-4, waypoint navigation and robot movement, robot gripper actuation and repositioning, and graphical user interface (GUI) of our system, respectively.

Code 2 Audio Recording and Transcription

```
procedure RECORD_AUDIO
    command ← ``arecord -D plughw:0,0 -f cd -t wav -d {RECORD_SECONDS} -r 16000 {WAVE_OUTPUT_FILENAME}''
    subprocess.run(command, shell=True)
end procedure
procedure TRANSCRIBE_AUDIO
    transcriber ← assemblyai.Transcriber()
    transcript ←
transcriber.transcribe(WAVE_OUTPUT_FILENAME)
    while transcript.status
≠ assemblyai.TranscriptStatus.completed do
        transcript ←
transcriber.get_transcript(transcript.id)
    end while
    return transcript.text if transcript.status == assemblyai.TranscriptStatus.completed else ``No transcription available.''
end procedure
```

Code 3 Load Medicine Data and File Content

```
procedure LOAD_MEDICINES_WITH_POSITIONS
    file ← open(JSON_FILE_PATH, 'r')
    data ← json.load(file)
    return data['medicines']
end procedure
procedure LOAD_FILE_CONTENT(filepath)
    if filepath.endswith(".txt") then
        file ← open(filepath, 'r')
        return file.read().strip()
    else if filepath.endswith(".json") then
        file ← open(filepath, 'r')
        return json.load(file)
    else
        raise ValueError("Unsupported file format: filepath")
    end if
end procedure
```

The language-processing module receives the transcribed request together with the available inventory information and predefined test-case content. Its output is matched against the medicine names stored in the inventory configuration, after which the corresponding retrieval waypoint is passed to the robotic control stage. Requests that do not produce a matching inventory item return the message “No suitable item found.”

Code 4 Choose Medicine with GPT-4

```
Input: command
Set api_key ← OPENAI_API_KEY
medicines ← LOAD_MEDICINES_WITH_POSITIONS
medicine_names ← names from medicines
aipharmacy_txt_content ← LOAD_FILE_CONTENT(aipharmacy.txt)
testcases_json_content ← LOAD_FILE_CONTENT(testcases.json)
Build prompt with aipharmacy_txt_content, testcases_json_content, and command
if OpenAI API call is successful then
    chosen_medicine ← parsed response from ChatCompletion
    if chosen_medicine is in medicine_names then
        return chosen_medicine
    else
        return “No suitable medicine found.”
    end if
else
    Print error message
    return “Error processing your request.”
end if
```

Code 5 Gripper Control Subroutines

```
procedure OPEN_GRIPPER
    open_command ← Float64()
    open_command.data ← 0.1
    gripper_publisher.publish(open_command)
    rospy.loginfo("Gripper opened.")
end procedure
procedure CLOSE_GRIPPER
    close_command ← Float64()
    close_command.data ← 0.0
    gripper_publisher.publish(close_command)
    rospy.loginfo("Gripper closed.")
end procedure
```

Code 6 Start Process Routine

```
procedure START_PROCESS
    self.text_area.delete('1.0', END)
    rospy.init_node('panda_waypoint_control', anonymous=True)
    move_group ← MoveGroupCommander(GROUP_NAME_ARM)
    record_audio()
    command ← transcribe_audio()
    chosen_medicine ← choose_medicine_with_gpt4(command)
    waypoint ← get_medicine_waypoint(chosen_medicine)
    operate_gripper(gripper_publisher, 0.1)   ▷ Open gripper
    move_to_position(move_group, waypoint)
    operate_gripper(gripper_publisher, 0.0)   ▷ Close gripper
    move_to_position(move_group, Pose(Point(0, 0, 0.5), Quaternion(0, 0, 0, 1)))   ▷ Home position
    self.update_text("Process completed.")
end procedure
procedure UPDATE_TEXT(message)
    self.text_area.insert(END, message + "\n")
end procedure
```

Code 7 GUI Initialization for Robot Control Interface

```
procedure APPLICATION.__INIT__(master)
    self.master ← master
    master.title("Robot Control Interface")
    dark_background ← "#333333"
    light_text ← "#FFFFFF"
    button_background ← "#555555"
    self.style ← ttk.Style()
    self.style.theme_use('clam')
    self.style.configure('TButton', background=button_background,
        foreground=light_text)
    self.customFont ← font.Font(family="Helvetica", size=12)
    self.start_button ← ttk.Button(master, text="Start Process",
        command=self.start_process)
    self.start_button.pack(pady=10)
    self.text_area ← Text(master, height=20, width=50, font=self.customFont,
        bg=dark_background, fg=light_text)
    self.text_area.pack(side="left", fill="y", padx=10, pady=10)
    self.scrollbar ← Scrollbar(master, command=self.text_area.yview, orient=VERTICAL)
    self.scrollbar.pack(side="left", fill="y")
    self.text_area.configure
(yscrollcommand=self.scrollbar.set)
    master.configure(bg=dark_background)
end procedure
```

The implemented system combines separate modules for speech transcription, language-based item selection, inventory-to-waypoint mapping, and robotic control through ROS. The pseudocode presented in this section outlines the sequence of information flow from the user request to the corresponding robotic retrieval action.

Experimental Results and Evaluation

The experiments used a Franka Emika Panda robotic system comprising a 7-DoF manipulator, end effector, control hardware, the Franka Control Interface, and the associated research software [21]. The software was executed on a laptop equipped with an Intel Core i7-7660U processor operating at 2.50 GHz and 16 GB of RAM.

For the experimental evaluation, a "correct medicine" was defined operationally with respect to the predefined test-case mapping and the available inventory. Before testing, each representative user request was associated with an expected inventory item based on the configured medicine dataset used by the system. A response was counted as correct when the AI returned this expected item. When a request corresponded to an item that was intentionally unavailable in the predefined inventory, a "not found" response was treated as a valid outcome rather than an incorrect selection. This definition evaluates the consistency of the language-to-inventory mapping and does not represent an independent clinical diagnosis or medical recommendation assessment.

The AI movement-response simulation test evaluated the ability of the language-processing workflow to interpret diverse medication-related requests associated with the predefined OTC inventory. Representative requests were collected from 100 students and subsequently rephrased to generate approximately 500 linguistic query variations. These input cases were used to examine the consistency of the AI-based request-interpretation process.

The experimental configuration used a predefined OTC inventory arranged in the laboratory workspace. Each available item was associated with a medicine name and a corresponding retrieval position stored in the system configuration, enabling the selected inventory item to be translated into a robotic waypoint for the retrieval task.

Table 3 presents 40 representative query-level examples selected from the broader evaluation. The requests are reported in their original phrasing to illustrate the linguistic variability considered in the language-processing evaluation, including both concise and more descriptive user expressions.

The real-time experiments evaluated the voice-to-retrieval workflow during live operation, considering response time, inventory-item mapping, process completion, and robotic execution. Each trial involved speech recording, transcription, item selection, waypoint retrieval, grasping, delivery, and return to the home position. Figures 3 and 4 illustrate the real-time workflow from voice input to robotic retrieval. In Figure 3, the pro-

Table (3): Representative AI-based inventory-item mapping results for medication-related user requests.

No	User Request	AI Response	Correct Item Mapping
1	I have been experiencing severe headaches lately.	Blue Panadol	Yes
2	The intensity of my nocturnal lumbar discomfort is particularly distressing.	Red (Panadol Extra)	Yes
3	I twisted my ankle while playing basketball.	Diclofenac Gel	Yes
4	I cannot seem to get rid of this toothache.	Red Panadol (Extra)	Yes
5	I have been having muscle spasms after my workout.	Baclofen	Yes
6	My arthritis has been acting up with the cold weather.	Panadol Joint	Yes
7	I am having menstrual cramps.	Pink Panadol	Yes
8	I have caught a cold and cannot stop sneezing.	Panadol Sinus	Yes
9	The pain from my migraine is unbearable.	Panadol Cold & Flu	Yes
10	I have had a migraine for the past two days, and light bothers me.	Panadol Migraine	Yes
11	What is good for a headache that will not go away?	Excedrin Migraine	Not Found
12	The severity of my dental agony necessitates a potent analgesic.	Blue Panadol	Yes
13	I can barely breathe because of my sinus congestion.	Panadol Cold & Flu	Yes
14	Is there something I can take for severe menstrual pain?	Pink Panadol	Yes
15	I am looking for medication to help with joint pain.	Panadol Joint	Yes
16	I have been sneezing a lot with a runny nose. I think I have allergies.	Diphenhydramine	Yes
17	I need something for the flu, I am feeling really under the weather.	Panadol Cold & Flu	Yes
18	I cannot seem to shake off this nagging cough and sore throat from the flu.	Robitussin	Not Found
19	I have a really bad migraine, what should I take?	Panadol Migraine	Yes
20	I have been having trouble sleeping because of my back pain.	Panadol Night	Yes
21	My muscles have been aching after starting a new workout routine.	Baclofen	Yes
22	I got sunburned and now my skin is really painful.	Diclofenac Gel	Yes
23	I have been feeling tension headaches after long hours at the computer.	Blue Panadol	Yes
24	My sinuses are blocked, and my head feels heavy.	Panadol Sinus	Yes
25	I cannot seem to shake off this nagging cough and sore throat from the flu.	Panadol Cold & Flu	Yes
26	I have had a migraine for the past two days, and light bothers me.	Panadol Migraine	Yes
27	I need something for chronic back pain that flares up at night.	Panadol Night	Yes
28	I have been experiencing discomfort from stomach acid.	Nexium	Yes
29	My knee joints have been hurting due to arthritis.	Tylenol PM	Yes
30	I urgently require alleviation from excruciating dysmenorrhea.	Ibuprofen	Yes
31	I need something for chronic back pain that flares up at night.	Tylenol PM	Not Found
32	What can relieve severe itching from mosquito bites?	Hydrocortisone cream	Yes
33	I have persistent ear pain after swimming.	Antibiotic ear drops	Yes
34	What should I take for seasonal allergies?	Cetirizine	Yes
35	I am experiencing burning when urinating.	Phenazopyridine	Yes
36	What helps with the pain after dental surgery?	Ibuprofen	Yes
37	I have a persistent dry cough that worsens at night.	Dextromethorphan	Yes
38	I have been experiencing discomfort from stomach acid.	Prilosec	Not Found
39	My child has chickenpox and is very itchy.	Calamine lotion	Yes
40	What is effective for relieving the symptoms of a sore throat?	Benzocaine lozenges	Yes

cess begins when the user starts on the interface, which initiates audio recording. The recorded voice is then sent to a speech-to-text API, which converts the spoken input into written text. This text is subsequently processed by the integrated AI system to identify a corresponding inventory item or to return an unavailable-item response when no suitable match is obtained.

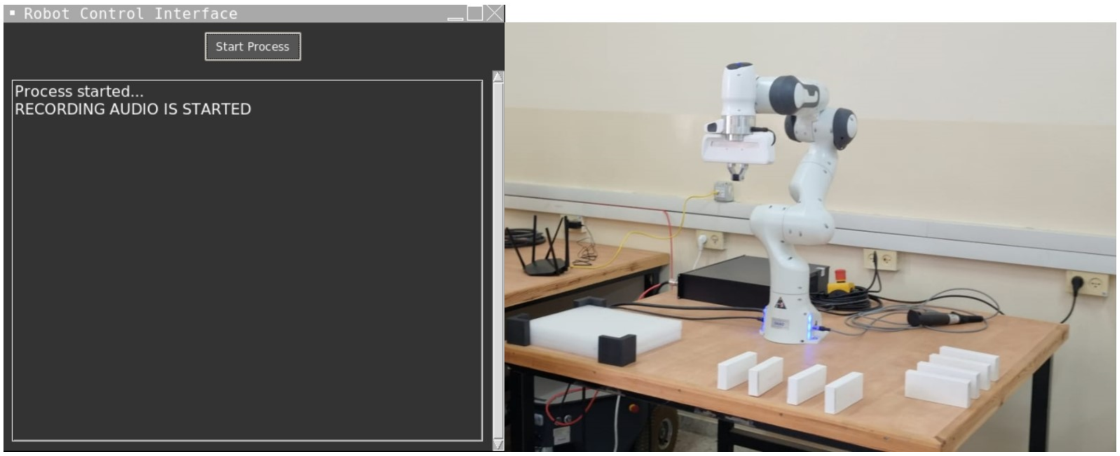

Figure (3): System initialization: The process is initiated when the user presses the start button and provides a voice request. The language-processing pipeline interprets the request and identifies the corresponding item within the predefined inventory.

Figure 4 shows the robotic sequence, beginning with gripper opening and motion toward the selected inventory item. Once positioned, the gripper closes to grasp the medication packet. The robot then transports the packet to the designated delivery plate, releases it by opening the gripper, and finally returns to its home position, ready for the next task.

After the retrieval sequence is completed, the interface displays the selected inventory item and confirms task completion. Upon completion, it is confirmed that the correct medicine has been successfully delivered to the designated plate as shown, e.g., in Figure 5

The previously described step-by-step sequence was repeated 500 times to assess the effectiveness and reliability of the AI-driven OTC pharmacy system during real-time operation. The evaluation considered AI response accuracy, process completion, response time, and overall execution performance under live operating conditions. Table 4 presents 40 representative real-time cases, including correct item retrievals, unavailable-item responses, and one incorrect selection. The incorrect case represented approximately 0.2% of the 500 real-time trials. The observed response time for the representative cases ranged from 1.5 s to 6.0 s.
The single incorrect real-time result was associated with a noisy speech recording, which altered the interpretation of the spoken request. Speech-input quality is therefore an important factor in the overall voice-to-retrieval workflow, particularly when operating under more varied acoustic conditions.
For the real-time evaluation, a successful case required both a correct inventory-item selection according to the predefined test-case mapping and successful completion of the corresponding robotic retrieval sequence.

Table 5 reports the aggregate outcomes of the 500 query-interpretation variations and 500 real-time end-to-end trials. Tables 3 and 4 show representative query-level examples. A “not found” response indicates that no corresponding item was available in the predefined inventory and is distinguished from an incorrect item selection.

Table (5): Aggregate summary of the experimental outcomes.

Evaluation	Total trials	Correct selections	Valid “not found”	Incorrect cases
Query-interpretation evaluation	500	496	4	0
Real-time end-to-end retrieval evaluation	500	495	4	1

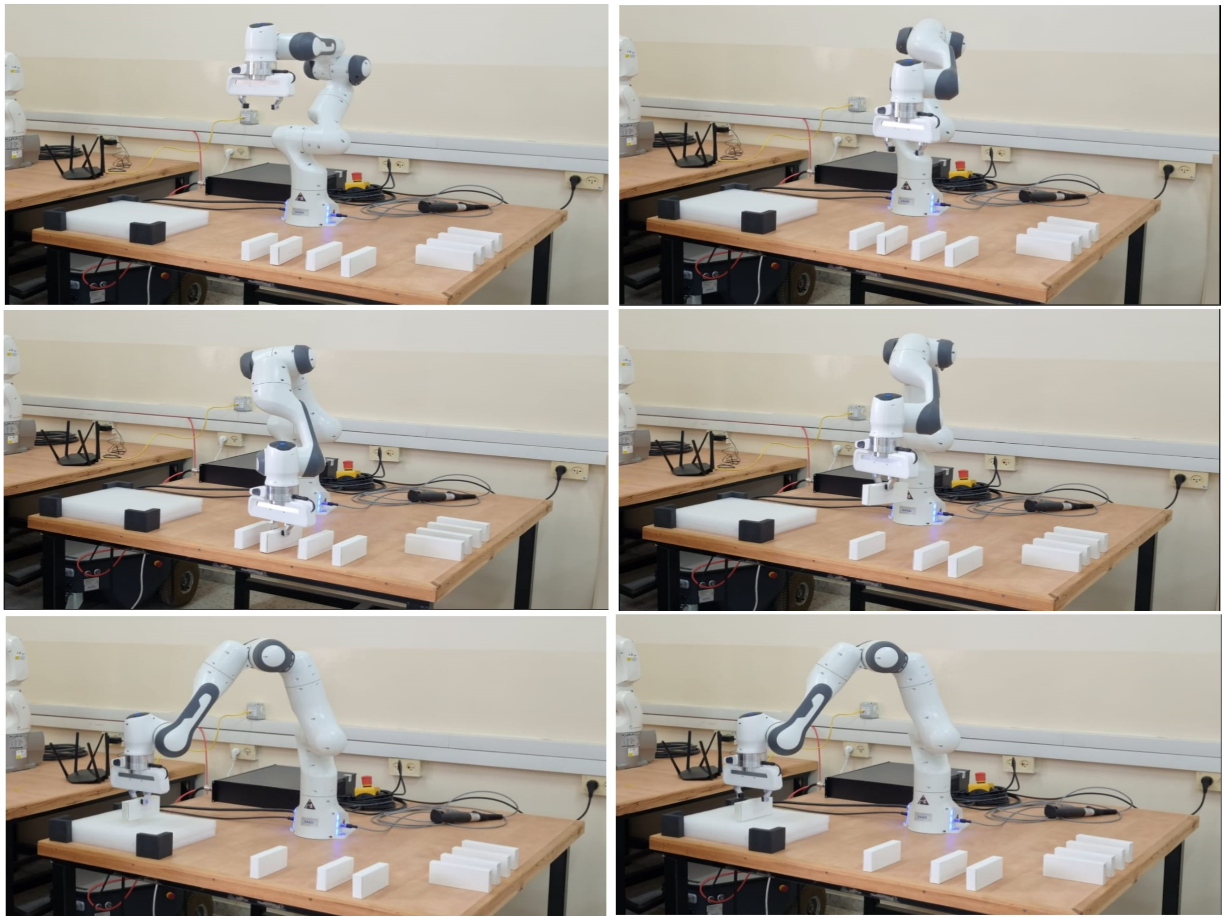

Figure (4): Robotic retrieval sequence after a matching inventory item is identified: (a) gripper opening, (b) motion toward the selected item, (c) grasping, (d) transfer to the delivery location, (e) release, and (f) return toward the home position.

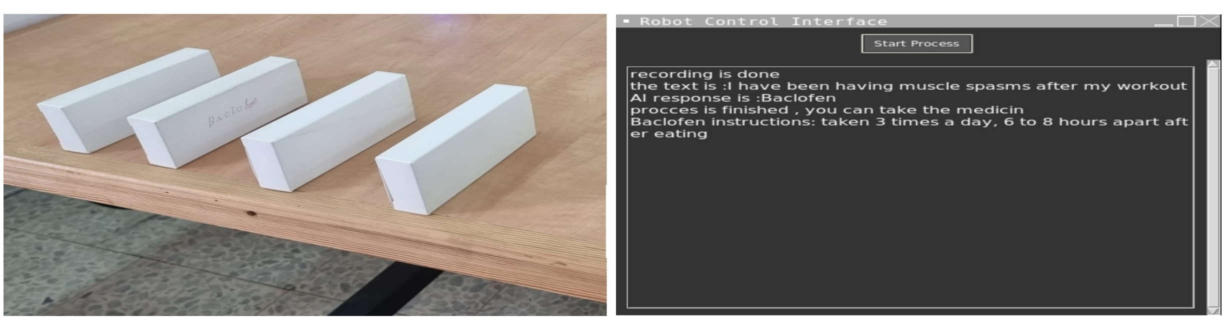

Figure (5): Example of the retrieval interface: (a) the selected inventory item and associated retrieval location; and (b) the corresponding item-selection result displayed in the user interface.

Table (4): Representative real-time voice-to-retrieval test cases and observed system outcomes.

No	User Request	AI Response	Time (s)	Correct Item Mapping	Process Completed
1	I have been experiencing severe headaches lately.	Blue Panadol	5.0	Yes	Yes
2	The intensity of my nocturnal lumbar discomfort is particularly distressing.	Red (Panadol Extra)	6	Yes	Yes
3	I twisted my ankle while playing basketball.	Diclofenac Gel	4.5	Yes	Yes
4	I cannot seem to get rid of this toothache.	Red Panadol (Extra)	3.2	Yes	Yes
5	I have been having muscle spasms after my workout.	Baclofen	2.1	Yes	Yes
6	My arthritis has been acting up with the cold weather.	Panadol Joint	4.3	Yes	Yes
7	I am having menstrual cramps.	Pink Panadol	2.7	Yes	Yes
8	I can barely breathe because of my sinus congestion.	Panadol Sinus	5.6	Yes	Yes
9	I have caught a cold and cannot stop sneezing.	Panadol Cold & Flu	3.8	Yes	Yes
10	The pain from my migraine is unbearable.	Panadol Migraine	2.9	Yes	Yes
11	I have had a migraine for the past two days, and light bothers me.	Excedrin Migraine	3.5	Not Found	Yes
12	What is good for a headache that will not go away?	Blue Panadol	4.2	Yes	Yes
13	The severity of my dental agony necessitates a potent analgesic.	Panadol Cold & Flu	3.0	Incorrect	No
14	Is there something I can take for severe menstrual pain?	Pink Panadol	4.4	Yes	Yes
15	I am looking for medication to help with joint pain.	Panadol Joint	5.1	Yes	Yes
16	I have been sneezing a lot with a runny nose. I think I have allergies.	Diphenhydramine	2.6	Yes	Yes
17	I need something for the flu, I am feeling really under the weather.	Panadol Cold & Flu	5.3	Yes	Yes
18	I cannot seem to shake off this nagging cough and sore throat from the flu.	Robitussin	4.1	Not found	Yes
19	I have a really bad migraine, what should I take?	Panadol Migraine	2.3	Yes	Yes
20	I have been having trouble sleeping because of my back pain.	Panadol Night	3.9	Yes	Yes
21	My muscles have been aching after starting a new workout routine.	Baclofen	2.1	Yes	Yes
22	I got sunburned and now my skin is really painful.	Diclofenac Gel	4.6	Yes	Yes
23	I have been feeling tension headaches after long hours at the computer.	Blue Panadol	1.5	Yes	Yes
24	My sinuses are blocked, and my head feels heavy.	Panadol Sinus	5.0	Yes	Yes
25	I cannot seem to shake off this nagging cough and sore throat from the flu.	Panadol Cold & Flu	4.7	Yes	Yes
26	I have had a migraine for the past two days, and light bothers me.	Panadol Migraine	3.6	Yes	Yes
27	I need something for chronic back pain that flares up at night.	Panadol Night	3.4	Yes	Yes
28	I have been experiencing discomfort from stomach acid.	Nexium	2.8	Yes	Yes
29	My knee joints have been hurting due to arthritis.	Tylenol PM	4.8	Not found	Yes
30	I urgently require alleviation from excruciating dysmenorrhea.	Ibuprofen	3.7	Yes	Yes
31	I need something for chronic back pain that flares up at night.	Tylenol PM	3.2	Not found	Yes
32	What can relieve severe itching from mosquito bites?	Hydrocortisone cream	2.4	Yes	Yes
33	I have persistent ear pain after swimming.	Antibiotic ear drops	3.1	Yes	Yes
34	What should I take for seasonal allergies?	Cetirizine	4.9	Yes	Yes
35	I am experiencing burning when urinating.	Phenazopyridine	3.3	Yes	Yes
36	What helps with the pain after dental surgery?	Ibuprofen	2.0	Yes	Yes
37	I have a persistent dry cough that worsens at night.	Dextromethorphan	4.5	Yes	Yes
38	I have been experiencing discomfort from stomach acid.	Prilosec	3.9	Not found	Yes
39	My child has chickenpox and is very itchy.	Calamine lotion	2.1	Yes	Yes
40	What is effective for relieving the symptoms of a sore throat?	Benzocaine lozenges	4.3	Yes	Yes

In the query-interpretation evaluation, 496 trials resulted in correct inventory-item selections and four trials produced valid “not found” responses; thus, all 500 responses were appropriate for the predefined inventory. In the real-time evaluation, 499 of the 500 trials completed successfully, comprising 495 correct inventory-item selections and four valid “not found” responses. This corresponds to a completion rate of 99.8%, with 95% confidence bounds of 98.9%–100.0%. For the representative real-time cases, the observed response time ranged from 1.5 s to 6.0 s.

Operational, Safety, and Deployment Considerations

The proposed architecture combines conversational interaction with robotic retrieval from a predefined OTC inventory, providing a practical basis for intelligent dispensing environments. In the current implementation, the language-processing module supports the interpretation of user requests and the selection of an associated inventory item, whereas the robotic subsystem executes the corresponding retrieval operation. This separation between conversational interaction, inventory selection, and physical execution provides a modular structure that can be extended with additional pharmacy workflow and safety functions according to the requirements of a particular deployment setting.

For broader operational use, the interaction layer may be complemented by structured decision rules and inventory-management policies that account for request ambiguity, unavailable items, and other dispensing constraints. For example, when a request cannot be matched reliably to the available inventory, the system can return a “no suitable item found” message and refer the request for further assistance. Such a design supports conservative operation while preserving the flexibility of natural-language interaction. Similarly, medicine-related information such as dosage guidance, contraindications, allergy information, age restrictions, pregnancy-related considerations, and drug interactions may be incorporated through appropriate domain-specific databases and workflow policies where required.

The voice-to-retrieval workflow depends on the quality of speech transcription, the availability of cloud-based services, the consistency of the inventory configuration, and the accuracy of robotic motion and grasping. Requests that cannot be associated with an available inventory item are returned as ”not found,” while the retrieval sequence is executed only after a matching item and waypoint have been identified.

The physical dispensing stage can also be strengthened through additional verification and monitoring layers. Barcode, RFID, or vision-based package identification may be integrated to confirm the selected item before delivery, while workspace monitoring, collision-aware motion planning, and user-confirmation procedures can further support dependable operation in shared environments. These extensions are particularly relevant when the inventory size, packaging diversity, or level of user interaction increases beyond the controlled configuration evaluated in this study.

The reported results should be interpreted within the controlled configuration evaluated in this study. The current workflow processes one request at a time and relies on predefined waypoints, a fixed inventory arrangement, and cloud-based speech-to-text and language-model services. Consequently, larger-scale deployment may be affected by communication latency, increased request volume, heterogeneous package geometries, inventory rearrangement, and the need to maintain accurate correspondence between physical items and the waypoint database. Future extensions may therefore incorporate adaptive grasping, automated inventory updates, task scheduling, and broader evaluation under diverse speech, environmental, and repeated-use conditions.

Because the present implementation uses cloud-based speech-to-text and language-model services, deployment in user-facing environments should also consider data-governance and communication-security requirements. Practical implementations may incorporate data minimization, secure transmission, user-consent procedures, and access-control mechanisms in accordance with the applicable pharmacy and data-protection context. Together, these operational considerations provide a pathway for extending the proposed architecture from a controlled research platform toward more comprehensive intelligent dispensing applications [1, 2, 23].

The present evaluation was conducted in a single controlled laboratory configuration; therefore, performance across different physical environments was not established and should be assessed in future multi-environment studies. Within the evaluated setup, the Franka Emika Panda arm incorporates joint-torque sensing that supports the detection of external contact and a prompt collision response during operation [21].

Conclusion

This work demonstrates the integration of conversational AI, speech-to-text processing, ROS-based control, and a Franka Emika Panda manipulator for voice-driven retrieval from a predefined OTC inventory. The experimental results show that the proposed workflow can map tested user requests to configured inventory items and execute the associated robotic retrieval sequence under controlled laboratory conditions.

The system is intended as a controlled engineering proof-of-concept rather than a clinically ready autonomous pharmacy system. Its present scope is limited by the predefined inventory, fixed laboratory arrangement, cloud-service dependence, and the controlled acoustic and operational conditions used during evaluation.

Future development should consider broader inventory configurations, more diverse speech and environmental conditions, inventory-verification mechanisms, safety-oriented monitoring, privacy and security assessment, and professional validation of medicine-related mappings before deployment in operational pharmacy settings.

Accordingly, the proposed system is intended to complement established pharmacy workflows within controlled dispensing environments.

Ethical Approval and Consent to Participate

Not applicable

Consent for publication

Not applicable.

Availability of Data and Materials

The data supporting the findings of this study are available in the body, tables, and figures of this manuscript.

Authors' Contribution

- JT: Conceptualization, methodology, analysis, software development, supervision, experimental supervision and follow-up, manuscript writing, and preparation of the responses to reviewers.
- MD: Experimental implementation, software development, and drafting of the results.
- MH: Experimental implementation, software development, and drafting of the results.

Source of Research

This research is not derived from a Master's or PhD thesis.

Conflict of Interest

The authors declare no conflict of interest.

Funding

The authors received no external funding for the design, implementation, experiments, or analysis reported in this study.

Acknowledgements

The authors acknowledge the Palestinian Quebecer Science Bridge (PQSB), through the Palestine Academy for Science and Technology and the Fonds de recherche du Québec (FRQ), for supporting the research visit during which this manuscript was prepared. The authors also thank Professor Wen-Fang Xie of the Department of Mechanical, Industrial and Aerospace Engineering at Concordia University for hosting the research visit and providing a stimulating research environment.

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