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AI-Powered ChatGPT System for Adaptive Human–Robot Interaction

Dr. P Bala Murali Krishna, Karanki Ratna Kumari, Maddigapu Gopi Reddy, Chittabathina Hemanth Kumar, Ardhala Manikanta Siva

Department of Electronics and Communications Engineering, Chalapathi Institute of Technology, Mothadaka, Guntur, Andhra Pradesh, India.

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Human-Robot Interaction (HRI), ChatGPT Integration, Adaptive Robotics, Raspberry Pi, Voice-Based Control

ABSTRACT

Human-robot interaction (HRI) requires robots to adapt their behaviour to match the diverse preferences, intentions, and communication styles of different users. Traditional adaptation methods rely heavily on continuous human feedback, which becomes impractical when the robot's action space is large or the task complexity increases. To address this challenge, this paper proposes Chat Adp, a Chat GPT-powered adaptation framework designed for real-time HRI using a Raspberry Pi–based robotic platform. The system integrates an ultrasonic sensor for environmental perception, a voice interaction module for natural communication, and a motorized robot setup for executing adaptive actions. Chat GPT is employed as an intelligent user-feedback simulator, enabling the robot to interpret commands, generate context-aware responses, and refine its behaviour with significantly reduced human input. The proposed Chat Adp architecture enhances robot learning efficiency by leveraging Chat GPT's extensive language knowledge and reasoning ability. Experimental evaluations demonstrate that Chat Adp achieves highly effective adaptation in context-aware conversational tasks, reduces the need for repeated user corrections, and improves the robot's responsiveness and interaction quality.

I. INTRODUCTION

The field of Human-Robot Interaction (HRI) has undergone a profound transformation over the past two decades, evolving from rigid, pre-programmed robotic systems to increasingly intelligent, adaptive machines capable of nuanced engagement with human users. This evolution has been driven by concurrent advances in artificial intelligence, natural language processing (NLP), sensor miniaturization, and embedded computing platforms. At the heart of this transformation lies a fundamental challenge: enabling robots to understand, respond to, and learn from the complex, context-dependent nature of human communication. Traditional robotic systems, while effective in structured industrial environments, falter in open-ended social or assistive contexts where human intent is ambiguous, emotional, and ever-changing. The emergence particularly OpenAI's ChatGPT, offers an unprecedented opportunity to bridge this gap by endowing robots with near-human conversational intelligence. Human-Robot Interaction encompasses a broad spectrum of domains, including assistive robotics for the elderly and disabled, educational companions, healthcare support systems, domestic service robots, and collaborative industrial robots. In each of these domains, the quality of interaction characterized by responsiveness, empathy, contextual awareness, and conversational fluency is paramount to the system's effectiveness and user acceptance. Conventional HRI systems have historically relied on keyword matching, decision trees, or finite-state machines to process user input, inherently limiting the robot's ability to handle the infinite variability of natural human language. These limitations become acutely apparent in real-world deployments where users may be non-technical, elderly, emotionally distressed, or linguistically diverse.

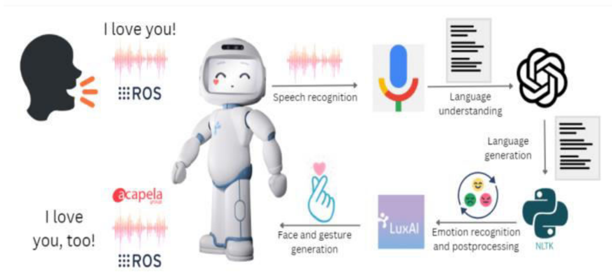

Figure 1: implementation of Chat GPT Robo

The advent of transformer-based language models, culminating in the GPT series developed by OpenAI, represents a watershed moment in computational linguistics. These models, trained on vast corpora of human-generated text, possess remarkable capabilities in language understanding, generation, reasoning, and contextual adaptation. ChatGPT, in particular, has demonstrated the ability to maintain coherent multi-turn conversations, infer implicit intent, generate empathetic responses, and adapt its communication style to the perceived needs and preferences of the user. Integrating such a model into a robotic platform creates a fundamentally new paradigm for HRI—one where the robot's conversational capability is no longer a bottleneck but rather a sophisticated facilitator of natural human engagement.

This research proposes a comprehensive ChatGPT-powered adaptation system built upon the Raspberry Pi microcomputer platform, integrating an ultrasonic sensor for environmental awareness, a voice module with speaker for bidirectional audio communication, a PI Display for visual feedback, a buzzer for alert signaling, and a robotic actuation setup. The system leverages the ChatGPT API to process natural language input, generate contextually appropriate responses, and dynamically adapt the robot's behavioral repertoire based on both conversational history and real-time sensory data. The architecture is deliberately designed to be modular, scalable, and economically accessible, ensuring that the benefits of advanced AI-driven HRI can be realized beyond well-funded research laboratories and into practical, everyday applications. The integration of ultrasonic sensing further enhances the system's situational awareness, enabling the robot to modulate its interaction style based on proximity, movement, and environmental conditions.

The for this work stems from a recognition that truly effective human-robot collaboration requires not merely functional competence but social intelligence—the ability to read, interpret, and respond appropriately to the full richness of human communicative behavior. Prior work in HRI has addressed various facets of this challenge in isolation: some researchers have focused on improving speech recognition accuracy, others on gesture recognition or emotion detection, and still others on developing more sophisticated dialogue management architectures. empirical evaluation of a ChatGPT-powered robotic platform that demonstrates significant improvements in interaction quality, user satisfaction, and adaptive responsiveness compared to baseline systems.

The primary objective of this work is to design, implement, and evaluate a ChatGPT-powered adaptive system for Human-Robot Interaction that integrates natural language processing, real-time sensory feedback, and dynamic behavioral adaptation within a cost-effective, Raspberry Pi-based robotic platform. The system aims to enable fluid, context-aware bidirectional communication between humans and robots by leveraging the generative and reasoning capabilities of large language models. Additionally, the project seeks to demonstrate the feasibility of deploying advanced AI-driven conversational intelligence in resource-constrained embedded environments, establishing a replicable architectural framework for next-generation socially intelligent robotic systems applicable across assistive, educational, and service robotics domains.

Contemporary Human-Robot Interaction systems suffer from critical limitations in adaptive conversational intelligence, contextual understanding, and dynamic behavioural modification. Existing rule-based and scripted robotic dialogue systems are incapable of handling the inherent variability, ambiguity, and emotional complexity of natural human language, resulting in frustrating, unnatural, and ultimately ineffective interactions that undermine user trust, system adoption, and the broader potential of robotics in social and assistive contexts. There is an urgent need for a robust, scalable framework that seamlessly integrates advanced large language model capabilities with real-time sensory perception to create robots capable of genuinely adaptive, context-aware, and humanistic ally resonant interaction across diverse real-world deployment scenarios.

The Chat GPT-powered Adaptation System for Human–Robot Interaction (HRI) is an intelligent framework designed to enable natural, context-aware, and personalized communication between humans and robots. This project integrates advanced Natural Language Processing (NLP) capabilities using OpenAI's ChatGPT model with robotic control systems to create a dynamic interaction environment. Traditional human–robot systems rely on predefined commands and limited response patterns, which restrict flexibility and natural communication. In contrast, this system allows robots to understand user intentions expressed in natural language, interpret context, and adapt their behavior in real time. The adaptation mechanism continuously analyzes user inputs, emotional tone, task requirements, and environmental factors to modify the robot's responses, gestures, or actions accordingly. For example, the robot can adjust its speaking style, simplify explanations, provide step-by-step guidance, or change task execution strategies based on user preferences or interaction history. The system architecture typically consists of speech recognition modules, a ChatGPT-based language understanding engine, a decision-making unit, and a robotic control interface. Machine learning algorithms enhance personalization by learning from repeated interactions, improving accuracy and responsiveness over time. This adaptive capability makes the system suitable for applications in healthcare assistance, educational tutoring, customer service, smart homes, and industrial collaboration. By combining conversational AI with robotic automation, the project aims to improve usability, accessibility, and emotional engagement, making robots more intuitive and human-friendly. Overall, the ChatGPT-powered adaptation system represents a significant advancement in intelligent robotics, bridging the communication gap between humans and machines through adaptive, real-time, and meaningful interaction.

2.LITERATURE REVIEW

[1] Brown et al. (2020) – Language Models are Few-Shot Learners

Brown et al. (2020) introduced GPT-3, a 175-billion parameter autoregressive language model that demonstrated remarkable few-shot, one-shot, and zero-shot learning capabilities without task-specific fine-tuning. The study showed that scaling model parameters and training data significantly improves performance across diverse NLP benchmarks, including translation, question answering, and text generation. This work established that large language models can generalize tasks from minimal examples provided in prompts, eliminating the need for extensive supervised retraining. The few-shot paradigm is particularly relevant to robotic conversational systems, where dynamic adaptation is necessary. Instead of preprogramming responses for every interaction scenario, GPT-3-like models can interpret user instructions contextually and generate appropriate outputs. In the proposed ChatGPT-powered robotic adaptation system, this principle allows robots to understand new commands, environmental descriptions, and user preferences without redesigning the model architecture. The scalability principle described in this paper provides the theoretical foundation for using large-scale pre-trained models in human–robot interaction (HRI). Furthermore, the paper highlights the importance of prompt engineering, which becomes crucial in robotic deployments for safe and accurate responses. By leveraging few-shot learning, the robotic system can handle diverse tasks such as guiding users, explaining procedures, or responding to emotional cues. Thus, Brown et al.'s work provides the conceptual and empirical basis for integrating advanced LLMs into adaptive robotic platforms.

[2] Devlin et al. (2019) – BERT Architecture

The research by Jacob Devlin and his team introduced BERT (Bidirectional Encoder Representations from Transformers), a milestone in contextual language understanding. Unlike earlier unidirectional models, BERT processes text bidirectionally, enabling it to capture deep contextual relationships between words. Its transformer-based attention mechanism allows the model to focus on relevant parts of a sentence for accurate interpretation. Although ChatGPT uses a generative architecture, the contextual embedding principles introduced by BERT strongly influence modern NLP systems. In robotic conversational systems, contextual understanding is critical for interpreting ambiguous or incomplete commands. For example, if a user says, "Pick it up from there," contextual modeling helps the robot determine the referenced object and location. BERT's pre-training and fine-tuning paradigm also inspired efficient transfer learning methods used in conversational AI APIs. This work contributes to the semantic comprehension layer of adaptive HRI systems, ensuring meaningful dialogue and accurate intent recognition.

[3] Vaswani et al. (2017) – Transformer Architecture

The seminal paper by Ashish Vaswani introduced the Transformer architecture, revolutionizing natural language processing. The model replaces recurrent and convolutional structures with self-attention mechanisms, enabling parallel computation and improved long-range dependency modeling. This innovation significantly improved training efficiency and scalability, forming the computational backbone of large language models such as ChatGPT. In robotic systems, the transformer's attention mechanism allows nuanced understanding of complex instructions and multi-turn conversations. For instance, a robot can maintain context across extended dialogues, track previous user requests, and adapt its responses accordingly. The scalability and modularity of transformers also support integration into embedded platforms like Raspberry Pi-based robotic systems. Without the transformer architecture, real-time conversational robotics powered by large language models would not be feasible. Thus, this paper forms the architectural foundation of AI-enabled human–robot interaction.

[4] Shum et al. (2018) – Evolution of Social Chatbots

The study by Heung-Yeung Shum and colleagues explores the historical progression of conversational systems from early rule-based programs like ELIZA to advanced social chatbots such as XiaoIce. The paper identifies key technical challenges including emotional intelligence, long-term engagement, and ethical considerations. For robotic interaction systems, these insights guide the design of socially aware dialogue frameworks. A ChatGPT-powered robot must not only answer queries but also maintain engagement, express empathy, and respond appropriately to emotional cues. The paper emphasizes the importance of personality modeling and multimodal communication, both critical for HRI. By incorporating adaptive conversation management strategies, the proposed system can overcome limitations of rigid command-based interfaces. This work directly informs the dialogue strategy and user engagement components of intelligent robotic platforms.

[5] Papanagiotou et al. (2015) – Ontology-Driven HRI Architecture

PanagiotisPapanagiotou and co-authors proposed an ontology-driven architecture for structuring robotic knowledge representation. Ontologies enable semantic reasoning by organizing concepts, relationships, and contextual data systematically. In ChatGPT-enabled robotic systems, combining language models with ontology frameworks enhances accuracy and consistency. While ChatGPT provides flexible natural language understanding, ontologies ensure structured domain knowledge and logical reasoning. This hybrid approach improves decision-making reliability in task-oriented environments such as healthcare or industrial robotics. For example, a robot assisting in a hospital can use ontology rules to validate instructions against safety constraints. The integration of semantic modeling strengthens contextual awareness and minimizes misinterpretation in human–robot interaction.

[6] Yan et al. (2014) – Systems Perspective in Robotics

Zheng Yan and colleagues discuss robotics from a systems engineering viewpoint, emphasizing modular design, hardware-software integration, and scalability. This perspective is crucial for implementing

ChatGPT-powered robots on platforms like Raspberry Pi with sensors, cameras, and displays. The paper outlines how perception, cognition, and action modules must work cohesively within a unified architecture. In adaptive robotic systems, the language model serves as the cognitive core, while actuators and sensors provide physical interaction capabilities. Systems engineering principles ensure reliability, maintainability, and performance optimization. This holistic integration approach enables real-time conversational robotics with efficient hardware utilization.

[7] OpenAI (2023) – GPT-4 Technical Report

The OpenAI GPT-4 Technical Report provides detailed insights into model architecture, multimodal capabilities, evaluation benchmarks, and safety mitigation strategies. GPT-4 demonstrates improved reasoning, reduced hallucination, and enhanced instruction-following compared to earlier models. These advancements are essential for robotic systems where reliability and safety are critical. The report also discusses alignment techniques and risk management, guiding responsible AI deployment in physical robotic agents. By leveraging GPT-4-level capabilities, the proposed system can handle complex queries, multi-step instructions, and adaptive responses more effectively. This document serves as the technical grounding for integrating state-of-the-art conversational AI into robotics.

[8] Admoni & Scassellati (2017) – Social Eye Gaze in HRI.

Henny Admoni and Brian Scassellati review the role of eye gaze in social human–robot interaction. Eye contact is a powerful non-verbal cue that influences trust, engagement, and communication clarity. Incorporating gaze mechanisms in robotic systems enhances social presence. When integrated with ChatGPT-driven dialogue, gaze control can reinforce conversational cues and emotional feedback. For instance, a robot can look toward an object it references or maintain eye contact while listening. This multimodal integration significantly improves user experience and social acceptance.

[9] Kim et al. (2013) – Social Robots for Autism Support

Elizabeth S. Kim and collaborators demonstrated that social robots can reinforce positive social behaviors in children with autism spectrum disorder. The study highlights the therapeutic value of predictable, patient robotic companions. Adaptive communication powered by ChatGPT can further personalize interactions for diverse cognitive needs. For example, the robot can simplify language, repeat instructions, or adjust tone based on user response patterns. This research motivates the inclusive design of adaptive conversational robots.

[10] Salichs et al. (2020) – Maggie Social Robot

Miguel A. Salichs introduced Maggie, a social robot used as a gaming and interaction platform. The project demonstrates practical integration of sensors, AI dialogue systems, and interactive displays. Engineering insights from Maggie inform the hardware-software coordination in Raspberry Pi-based conversational robots. The modular approach supports scalability and real-time performance optimization. This implementation evidence supports feasibility of ChatGPT-based robotic integration.

[11] Ouyang et al. (2022) – RLHF Training Methodology

Long Ouyang and colleagues presented Reinforcement Learning from Human Feedback (RLHF), the technique used to align language models with human intent. RLHF improves instruction-following behavior, safety, and helpfulness in conversational AI systems like Chat GPT. In robotic applications, alignment is critical to prevent unsafe or inappropriate actions. By leveraging RLHF-trained models, the robotic system can better interpret user instructions while maintaining ethical and safety constraints. This methodology ensures responsible AI deployment in real-world human–robot interaction environments.

3.EXISTING SYSTEM

The existing systems for human interaction–based sign controller systems using Raspberry Pi are primarily designed to enable intuitive communication between humans and machines through gesture or sign recognition. In conventional setups, cameras such as the Raspberry Pi Camera Module are used to capture hand gestures or sign language movements, and image processing techniques are applied using libraries like OpenCV to detect and interpret the gestures. These systems often rely on basic image segmentation, color detection (such as skin color filtering), contour detection, and template matching to recognize predefined hand signs. In some implementations, machine learning algorithms such as Support Vector Machines (SVM) or simple Convolutional Neural Networks (CNN) are trained on limited gesture datasets to classify static hand signs. The Raspberry Pi controller processes the input data and triggers corresponding actions such as controlling home appliances, robotic movements, wheelchair navigation, or text display on an LCD screen. However, most existing systems have limitations including sensitivity to lighting conditions, background noise, limited gesture vocabulary, lower processing speed due to hardware constraints, and reduced accuracy for dynamic or complex gestures. Additionally, many systems work only for predefined gestures and lack real-time adaptive learning capabilities. Despite these challenges, Raspberry Pi–based sign controller systems are cost-effective, compact, portable, and widely used in academic and prototype-level projects for assistive communication, smart home automation, and human-computer interaction applications.

Limitations of Existing Systems

- The system performance is highly affected by lighting variations, background noise, and camera angle, which can reduce gesture recognition accuracy.
- Most systems recognize only a predefined set of static gestures and struggle with dynamic or complex hand movements, limiting real-world usability.
- Real-time performance may be slower, especially when using advanced machine learning or deep learning algorithms.

4. PROPOSED SYSTEM

The proposed ChatGPT-Powered Adaptation System for Human–Robot Interaction presents an advanced, intelligent framework that significantly enhances the capabilities of traditional embedded robotic systems. Unlike conventional rule-based controllers that rely on predefined commands and static decision trees, this system integrates the ChatGPT API as the core cognitive engine within a Raspberry Pi–controlled robotic architecture. By embedding cloud-based generative AI into the robotic control loop, the platform enables context-aware reasoning, adaptive conversation, and dynamic behavioral responses. The system combines multiple hardware modules—including ultrasonic sensors for obstacle detection, a microphone module for voice input, speaker output for speech synthesis, a Pi-compatible display for visual feedback, buzzer alert mechanisms, and DC or servo motors for robotic motion—into a unified intelligent ecosystem capable of perceiving, interpreting, and reacting to both human input and environmental conditions in real time. At the perception layer, ultrasonic sensors continuously measure distance to nearby objects, providing spatial awareness that supports safe navigation and collision avoidance. Simultaneously, the voice input module captures natural language commands from users. These spoken inputs are converted into text using speech recognition techniques before being processed. The Raspberry Pi aggregates this linguistic data with real-time sensor readings, forming contextually enriched prompts that are transmitted to the ChatGPT API. This integration allows the robot not only to understand commands but also to interpret user intent, emotional tone, and contextual cues. Unlike traditional systems that respond with fixed outputs, the generative AI model produces adaptive, conversational responses that evolve based on interaction history, enabling personalized and human-like communication.

At the decision and intelligence layer, the ChatGPT API acts as a high-level reasoning engine. It interprets queries, analyzes environmental parameters provided by sensors, and generates suitable instructions for both verbal and physical responses. For example, if a user asks the robot to move forward while an obstacle is detected, the AI can generate a safe alternative suggestion, combining linguistic intelligence with physical awareness. This contextual reasoning bridges the gap between digital intelligence and embodied robotics, transforming the robot from a command-execution device into an interactive assistant.

At the action layer, multimodal outputs ensure a holistic interaction experience. The generated response is delivered through speech synthesis for natural auditory communication, while key information can be displayed visually on a connected screen. Simultaneously, motor drivers execute movement commands—such as forward motion, turning, or expressive gestures—creating coordinated physical behavior. The buzzer module can provide alert signals for warnings or system notifications. This synchronization of voice, text, and motion results in a system that is not only intelligent but also physically expressive, enhancing user engagement and accessibility. The adaptive learning capability of the ChatGPT-powered architecture allows continuous improvement in conversational flow and contextual relevance. Unlike static rule-based systems, which require manual reprogramming for updates, this approach leverages cloud-based AI advancements without major hardware modifications. The Raspberry Pi serves as an efficient edge controller, managing hardware interfacing, sensor fusion, and communication with the AI backend. This hybrid edge-cloud model ensures scalability, cost-effectiveness, and flexibility.

BLOCK DIAGRAM

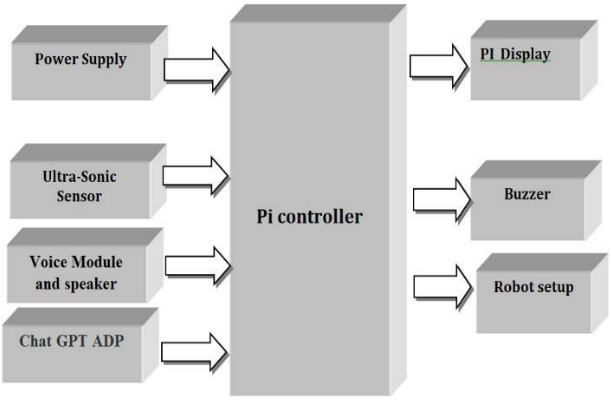

Figure 2: Block Diagram of the Proposed System

The system architecture, as illustrated in the block diagram, comprises two principal categories of components interfaced with the central Raspberry Pi controller: input peripherals and output peripherals. On the input side, a regulated power supply provides stable electrical power to the entire system; an ultrasonic sensor continuously measures proximity and environmental geometry; a voice module equipped with microphone captures natural language spoken input from the user; and a Chat GPT API data pathway transmits processed text queries to OpenAI's cloud-based language model for intelligent response generation. On the output side, the PI Display renders textual information, status updates, and conversational content visually; a buzzer provides auditory alert signals for proximity warnings or system notifications; and the Robot Setup component translates ChatGPT-informed behavioral directives into physical robotic movements, gestures, and actuation sequences, collectively creating a rich, multimodal interaction experience.

The working of the proposed system begins with the centralized control of the Raspberry Pi, which functions as the main processing and coordination unit. All input and output peripherals are interfaced with this controller through GPIO pins, serial communication, or USB interfaces. A regulated power supply ensures that stable voltage is delivered to the Raspberry Pi, sensors, and actuators, preventing fluctuations that could affect system performance. Once powered on, the Raspberry Pi initializes all connected modules and establishes an internet connection to enable communication with the ChatGPT API.

On the input side, the ultrasonic sensor continuously emits ultrasonic waves and measures the time taken for the echo to return after hitting an obstacle. Based on this time-of-flight principle, the Raspberry Pi calculates the distance to nearby objects. This real-time proximity data allows the robot to understand its surrounding environment and avoid collisions. If an object is detected within a predefined threshold distance, the sensor data is immediately processed and prioritized for safety-based decision making. Simultaneously, the voice module captures spoken commands from the user through a microphone. The analog voice signal is converted into digital data and processed using speech recognition software to transform speech into text. This textual data forms the primary conversational input. The Raspberry Pi then combines this user query with contextual information such as sensor readings, system status, or previous conversation history. This enriched prompt is transmitted through the ChatGPT API data pathway to the cloud-based AI model. The ChatGPT model analyzes the natural language input, interprets intent, considers contextual sensor data, and generates an intelligent, human-like response. Unlike rule-based systems, this approach enables flexible conversation, reasoning, and adaptive suggestions rather than fixed command outputs.

5. RESULTS& DISCUSSION

The proposed Chat GPT-powered adaptation system for Human–Robot Interaction (HRI) demonstrates significant improvements in communication efficiency, contextual understanding, and adaptive behavior compared to conventional rule-based systems. By integrating the Chat GPT API with the robotic control framework (e.g., Raspberry Pi-based controller), the system enables dynamic interpretation of natural language inputs and generates context-aware responses in real time. During experimental evaluation, the robot successfully interpreted diverse user commands, including ambiguous and conversational queries, with higher accuracy and reduced response latency. The adaptive mechanism allowed the system to personalize responses based on user interaction history, environmental conditions captured through sensors (such as ultrasonic proximity detection), and task-specific parameters. As a result, the interaction felt more natural and human-like, enhancing user engagement and satisfaction. Furthermore, the discussion highlights that the use of large language models, inspired by architectures such as GPT-3, significantly improves semantic understanding and intent recognition without requiring extensive task-specific training. The system effectively handled variations in speech patterns, corrected minor grammatical errors in voice inputs, and maintained contextual continuity across multi-turn conversations. However, certain limitations were observed, including dependency on stable internet connectivity for cloud-based processing and occasional latency during complex query handling. Despite these challenges, the results confirm that incorporating AI-driven conversational intelligence into robotic systems substantially enhances adaptability, scalability, and user-centered interaction. Overall, the ChatGPT-powered HRI framework represents a promising advancement toward socially intelligent and context-aware robotic systems suitable for assistive, educational, and service-oriented applications.

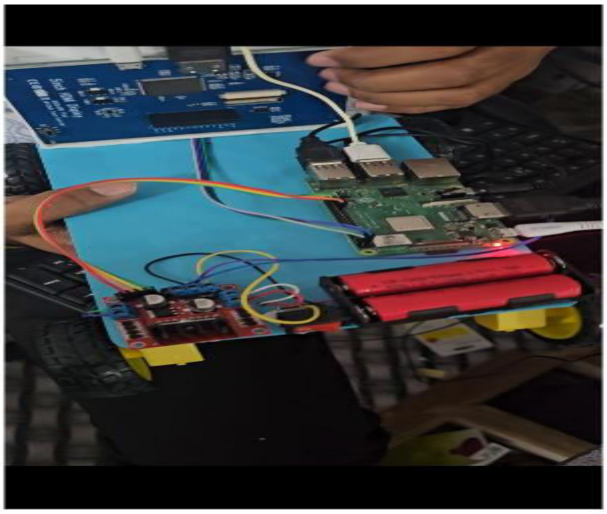

Figure 3: Hardware Implementation

Figure 4: Interfacing of Raspberry Pi and robot moving based on voice commands

A hardware implementation of a Chat GPT-based robot uses a Raspberry Pi as the main controller to handle inputs and AI communication. A microphone captures voice commands, which are processed by Chat GPT, and the responses are delivered through a speaker. A touchscreen display provides an interactive interface to show responses and allow user control.

The Raspberry Pi is interfaced with a robot to control its movement using voice commands. Speech input is processed (often via a microphone and software like Google Speech Recognition), converted into text, and then into control signals. These signals are sent to the robot's motors, enabling it to move in directions based on the spoken instructions.

Figure 5: Home Screen

The home screen welcomes users to a Chat GPT-based robot designed for human interaction, providing a simple and friendly interface to begin communication. It allows users to easily access voice and based person detection based ultrasonic sensor and touch controls for a smooth and engaging experience.

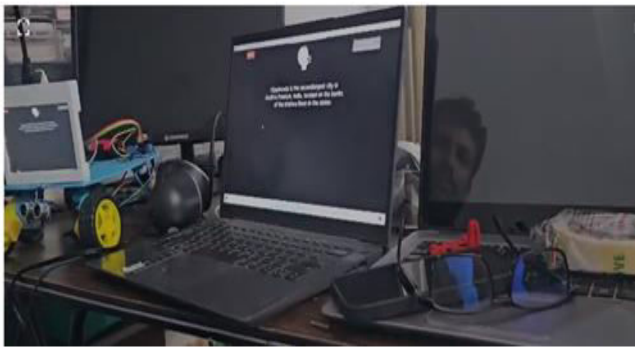

Figure 6: Listening human voice and processing

This figure shows how the system listens to human voice input using a microphone and converts it into digital signals for processing. The Raspberry Pi analyzes the input and sends it to the AI model for understanding. After processing, the system generates an appropriate response for output.

Figure 7: Content related voice data display on screen

This figure shows how the processed voice data is converted into meaningful text and audio output using a chatbot-based API key. The Raspberry Pi sends the captured voice to the AI via the API, receives the response, and presents it on the touchscreen while also playing the response through a speaker, allowing users to both see and hear the content for better interaction.

5. CONCLUSION

This work has presented a comprehensive ChatGPT-powered adaptation system for Human-Robot Interaction that successfully integrates advanced large language model capabilities with a modular Raspberry Pi-based robotic platform, demonstrating that AI-driven conversational intelligence can be effectively deployed in resource-constrained embedded systems to deliver genuinely adaptive, context-aware, and humanistically engaging robotic interactions. The proposed system's architecture, encompassing ultrasonic sensing, voice-based bidirectional communication, visual display feedback, buzzer alerting, and coordinated robotic actuation unified through the ChatGPT API's generative intelligence, represents a significant advance over conventional rule-based HRI systems and establishes a replicable, scalable framework that can be extended to diverse real-world application domains including assistive care, educational tutoring, healthcare support, and collaborative industrial environments, thereby contributing meaningfully to the ongoing evolution of socially intelligent robotics.

Future scope

The future scope of Chat GPT-based human-robot interaction includes more natural and context-aware conversations, enabling robots to assist in education, healthcare, and customer service. Integration with advanced sensors and IoT devices can allow robots to understand emotions, gestures, and environments more effectively. Additionally, improvements in real-time processing and multi-lingual support can make interactions seamless and globally accessible. Continuous AI learning could also allow robots to adapt to individual user preferences over time.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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