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Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

*Digital Object Identifier 10.1109/ACCESS.2024.0429000*

# Vega: Intelligent Chatbot Platform for Internet of Things and Embedded Systems Development

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This paragraph of the first footnote will contain support information, including sponsor and financial support acknowledgment. For example, "This work was supported in part by the U.S. Department of Commerce under Grant BS123456."

**ABSTRACT** Large language models (LLMs) have revolutionized natural language processing, yet their potential in Internet of Things (IoT) and embedded systems (ESys) applications remains largely untapped. Traditional IoT interfaces often require specialized knowledge, creating barriers for non-technical users. We present a modular system that leverages LLMs to enable intuitive, natural language control of IoT devices, specifically a Raspberry Pi (RPi) connected to various sensors and devices. Our solution comprises three key components: a physical circuit with input and output devices, an RPi integrating a control server, and a web application integrating LLM logic. Users interact with the system through natural language commands, which the LLM interprets to call appropriate commands for the RPi. The RPi executes these instructions on the connected circuit, with outcomes communicated back to the user via LLM-generated responses. We empirically evaluate our system's performance across a range of task complexities and user scenarios, demonstrating its ability to handle complex, conditional logic without additional RPi-level coding. Our findings reveal that LLM-driven IoT control can effectively bridge the gap between complex device functionality and user-friendly interaction. We discuss the system's scalability, exploring its potential applications in diverse settings such as smart homes, industrial monitoring, and educational environments. By enabling natural language interaction with IoT devices, our approach not only enhances accessibility for non-technical users but also opens new avenues for creative and intelligent IoT applications. This research contributes to the growing body of work on interactive intelligent systems for IoT, offering insights into the design and implementation of LLM-integrated IoT interfaces.

**INDEX TERMS** Enter key words or phrases in alphabetical order, separated by commas. Autocorrelation, beamforming, communications technology, dictionary learning, feedback, fMRI, mmWave, multipath, system design, multipath, slight fault, underlubrication fault.

## I. INTRODUCTION

Large language models (LLMs) have revolutionized natural language processing, demonstrating unprecedented capabilities in understanding and generating human-like text [1]. However, their potential in Internet of Things (IoT) and embedded systems (ESys) applications remains largely untapped. IoT systems have become increasingly prevalent across various domains, from smart homes to industrial automation [2]. Despite their widespread adoption, developing and interacting with IoT systems often requires specialized knowledge and programming skills, creating significant barriers for non-technical users [3].

Traditional IoT interfaces typically rely on graphical user interfaces (GUIs) or specific programming languages, which can be challenging for users without technical expertise [3]. This limitation hinders the widespread adoption and utilization of IoT technologies, particularly in scenarios where rapid deployment and intuitive interaction are crucial. While research has been conducted on natural language interfaces for IoT, the application of advanced language models to IoT control and interaction remains an underexplored area [4].

To address these challenges, we propose Vega, an intelligent chatbot platform that leverages LLMs to enable intuitive, natural language control of IoT devices. Our system focuses on a Raspberry Pi (RPi) connected to various sensors and devices as a representative IoT setup. By integrating LLMs with IoT infrastructure, we aim to bridge the gap between complex device functionality and user-friendly interaction, allowing users to control and query IoT systems using everyday language.

Our research builds upon recent advancements in LLMs, specifically OpenAI's GPT-based models [5], which utilize transformer neural network architectures to capture context and relationships within text data. By applying these powerful language understanding capabilities to IoT interaction, we aim to create a more accessible and flexible approach to device control and monitoring. Our approach not only enhances accessibility for non-technical users but also opens new avenues for creative and intelligent IoT applications, addressing the standardization challenges highlighted in the literature [6].

Vega's architecture comprises three key components: a physical circuit with input and output devices, an RPi integrating a control server, and a web application incorporating LLM logic. This modular design allows for flexibility and scalability, enabling the system to adapt to various IoT scenarios and user requirements [7]. By utilizing the RPi as a central hub, we can leverage its versatility and widespread adoption in the IoT community [8].

The main contributions of this paper are as follows:

1) We present a modular architecture that integrates LLMs with IoT systems, specifically designed for natural language interaction with RPi-based setups.
2) We develop a novel approach for translating natural language commands into executable instructions for IoT devices, capable of handling complex, conditional logic without additional RPi-level coding.
3) We implement and evaluate a prototype system demonstrating the feasibility and effectiveness of LLM-driven IoT control across a range of task complexities and user scenarios.
4) We provide insights into the scalability and potential applications of our approach in diverse settings such as smart homes, industrial monitoring, and educational environments.

The rest of this paper is organized as follows: Section II provides background information and discusses related work in IoT interfaces and natural language processing. Section III details our methodology, including the overall system architecture, physical circuit design, RPi configuration, and web application implementation. Section IV presents our experimental setup, results, and analysis, showcasing the system's performance in handling complex commands and its potential real-world applications. Finally, Section V concludes the paper and outlines directions for future research.

## II. BACKGROUND AND RELATED WORK

### A. NLP IN IOT AND ESYS

### B. LLM'S IN INDUSTRIAL APPLICATIONS

### C. ACCESSIBLE CHATBOT

## III. METHODOLOGY

Hi [7] how are you

### A. OVERALL ARCHITECTURE

### B. PHYSICAL CIRCUIT DESIGN

**TABLE 1. Physical devices defined on the Control Server, which are then supplied to the LLM**

| Symbol | Type | Description |
|---|---|---|
| ULTS | Input | Ultrasonic Distance Sensor in 'cm' |
| CAM | Input | Camera device for picture input |
| GPS | Input | GPS device for longitude and latitude coordinates |
| TMP | Input | Temperature sensor giving response in degree celcuis |
| FAN | Output | 12V fan controled by a digital GPIO pin through a relay |
| LCD | Output | I2C LCD for displaying strings |
| SRV | Output | Servo motor rotates using PWM to a given angles |
| LED1 | Output | Yellow LED light |
| LED2 | Output | Red LED light |
| LED3 | Output | Blue LED light |

**TABLE 2. Defined functions on the Control Server, called by the LLM based on user input, executes on the RPi and processed on the webapp**

| Function | Description | Use Case |
|---|---|---|
| set_led | Toggles specefic LED | "Turn on yellow LED" |
| set_fan | Toggles fan on or off | "Turn on the fan" |
| get_recorded_sensor_data | Gets interval sensor data from database | "Plot me the distance data in last 30 seconds" |
| get_raspberry_stats | Gets CPU, RAM, Disk of RPi | "What is the currrent disk usage" |
| capture_image | Capture and upload image to Imgur | "Capture an image, does it contain a pen?" |
| get_connected_devices | Fetches the data of connected devices | "What is the current humidity and temperature" |
| get_location_ | Gets the current location from GPS | "From the location are we currently in Leeds?" |
| set_servo_angles | Turn servo to certain angle | "Turn the servo to 10 then 180 degrees" |

### C. RASPBERRY PI DESIGN

### D. WEB APP USER INTERFACE

### E. WEB APP LLM LOGIC

## IV. EXPERIMENT AND RESULTS

### A. COMPLEX COMMANDS IN ACTION

### B. AUTOMATED EVALUATION

### C. RESULT ANALYSIS

### D. REAL LIFE APPLICABILITY

## V. CONCLUSION AND FUTURE WORK

## ACKNOWLEDGMENT

## REFERENCES

[1] Yupeng Chang, Xu Wang, Jindong Wang, Yuan Wu, Linyi Yang, Kaijie Zhu, Hao Chen, Xiaoyuan Yi, Cunxiang Wang, Yidong Wang, Wei Ye, Yue Zhang, Yi Chang, Philip S. Yu, Qiang Yang, and Xing Xie. A survey on evaluation of large language models. *ACM Trans. Intell. Syst. Technol.*, 15(3), mar 2024.

[2] Yongxin Liao, Eduardo de Freitas Rocha Loures, and Fernando Deschamps. Industrial internet of things: A systematic literature review and insights. *IEEE Internet of Things Journal*, 5(6):4515–4525, Dec 2018.

[3] Lukas A. Flohr, Sofie Kalinke, Antonio Krüger, and Dieter P. Wallach. Chat or tap? – comparing chatbots with 'classic' graphical user interfaces for mobile interaction with autonomous mobility-on-demand systems. In *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction*, MobileHCI '21, New York, NY, USA, 2021. Association for Computing Machinery.

[4] Wafa'a Kassab and Khalid A. Darabkh. A–z survey of internet of things: Architectures, protocols, applications, recent advances, future directions and recommendations. *Journal of Network and Computer Applications*, 163:102663, 2020.

[5] OpenAI. *Generative Pre-trained Transformer (GPT) Models*, 2023. Accessed: 2024-07-24.

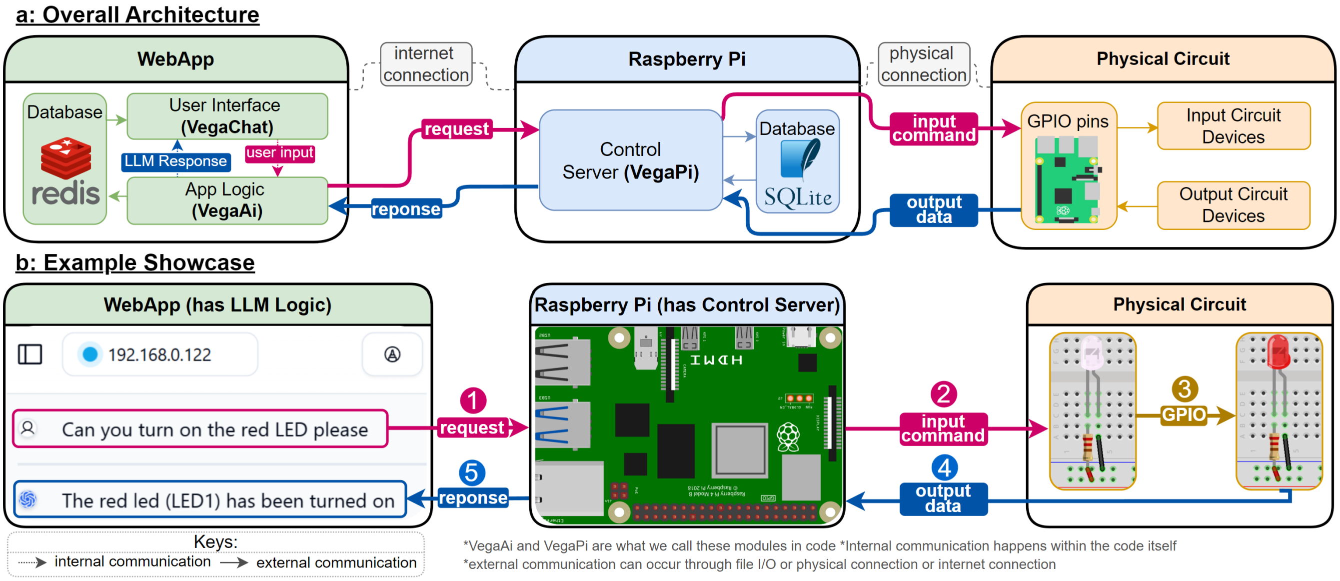


**FIGURE 1. Magnetization as a function of applied field. It is good practice to explain the significance of the figure in the caption.**

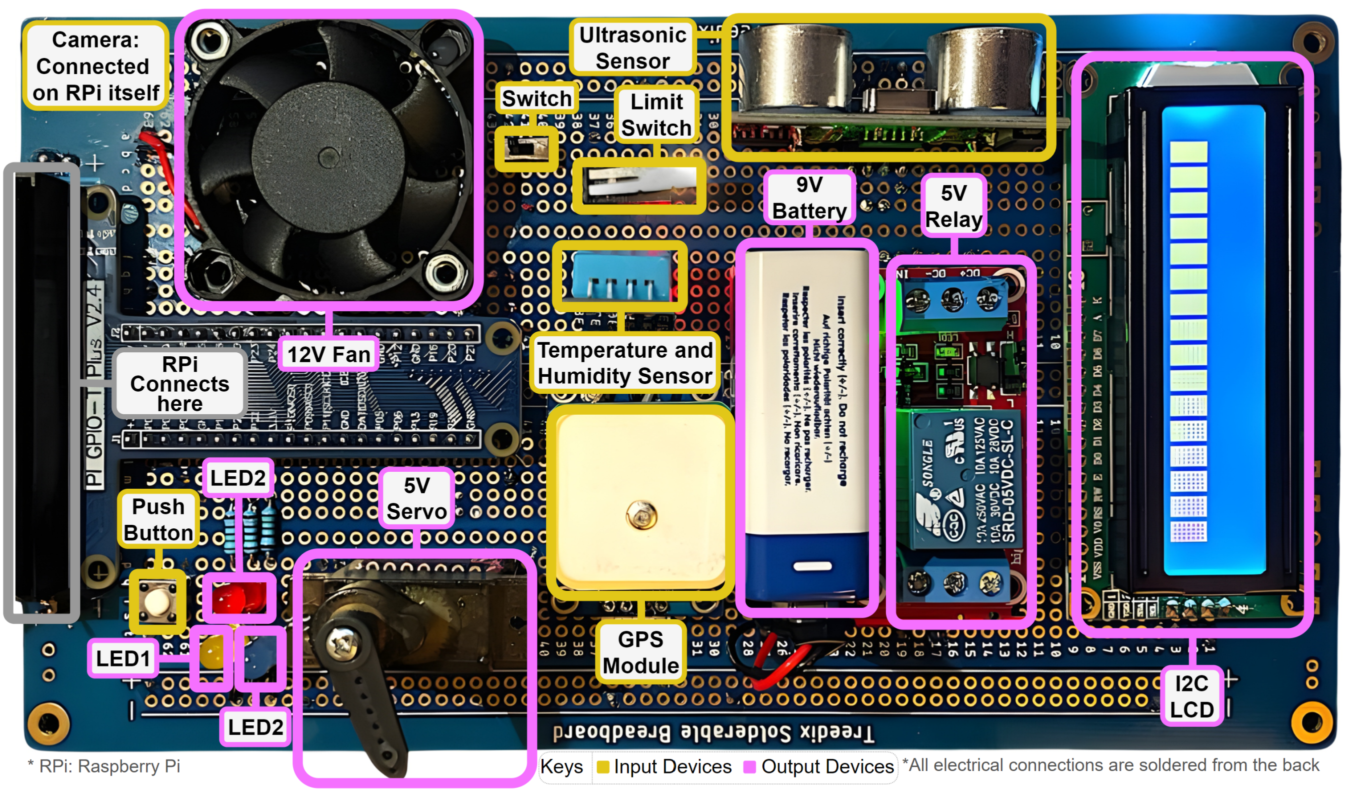


**FIGURE 2. Soldered physical circuit connected to the RPi**

[6] Sarah A. Al-Qaseemi, Hajer A. Almulhim, Maria F. Almulhim, and Saqib Rasool Chaudhry. Iot architecture challenges and issues: Lack of standardization. In *2016 Future Technologies Conference (FTC)*, pages 731–738, 2016.
[7] Richard N. Taylor, Nenad Medvidovic, and Eric M. Dashofy. *Software Architecture: Foundations, Theory, and Practice*. John Wiley & Sons, 2010.
[8] Elizabeth Kadiyala, Shravya Meda, Revathi Basani, and S. Muthulakshmi. Global industrial process monitoring through iot using raspberry pi. In *2017 International Conference on Nextgen Electronic Technologies: Silicon to Software (ICNETS2)*, pages 260–262, 2017.

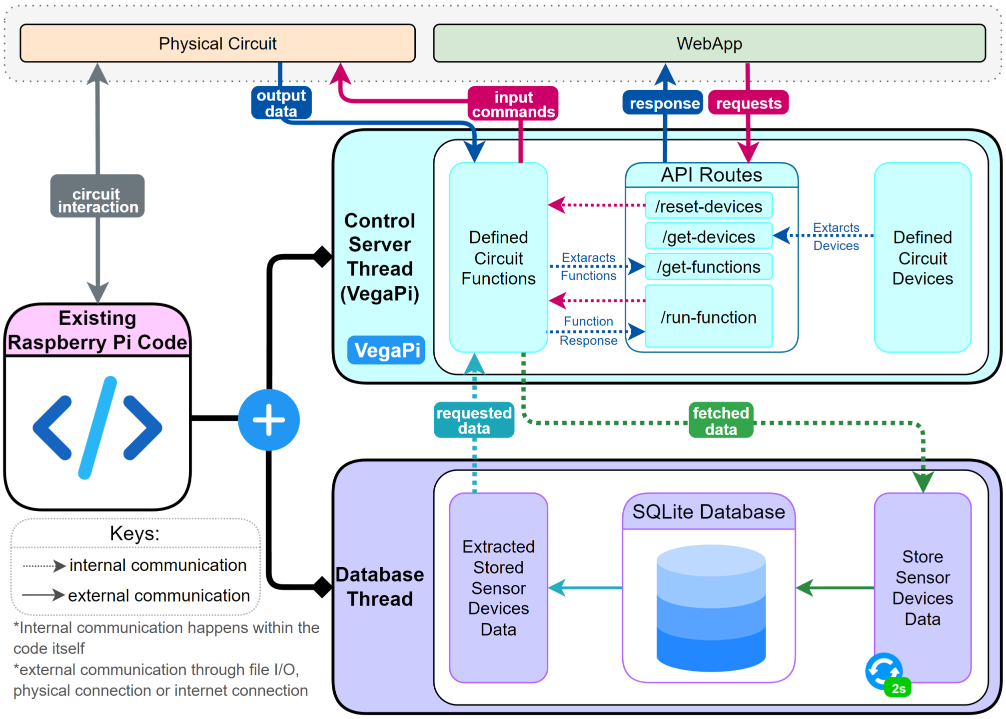


**FIGURE 3.** Architecture design of the RPi control server

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**SECOND B. AUTHOR** (M'76–SM'81–F'87) and all authors may include biographies. Biographies are often not included in conference-related papers. This author became a Member (M) of IEEE in 1976, a Senior Member (SM) in 1981, and a Fellow (F) in 1987. The first paragraph may contain a place and/or date of birth (list place, then date). Next, the author's educational background is listed. The degrees should be listed with type of degree in what field, which institution, city, state, and country, and year the degree was earned. The author's major field of study should be lower-cased.

The second paragraph uses the pronoun of the person (he or she) and not the author's last name. It lists military and work experience, including summer and fellowship jobs. Job titles are capitalized. The current job must have a location; previous positions may be listed without one. Information concerning previous publications may be included. Try not to list more than three books or published articles. The format for listing publishers of a book within the biography is: title of book (publisher name, year) similar to a reference. Current and previous research interests end the paragraph.

The third paragraph begins with the author's title and last name (e.g., Dr. Smith, Prof. Jones, Mr. Kajor, Ms. Hunter). List any memberships in professional societies other than the IEEE. Finally, list any awards and work for IEEE committees and publications. If a photograph is provided, it should be of good quality, and professional-looking. Following are two examples of an author's biography.

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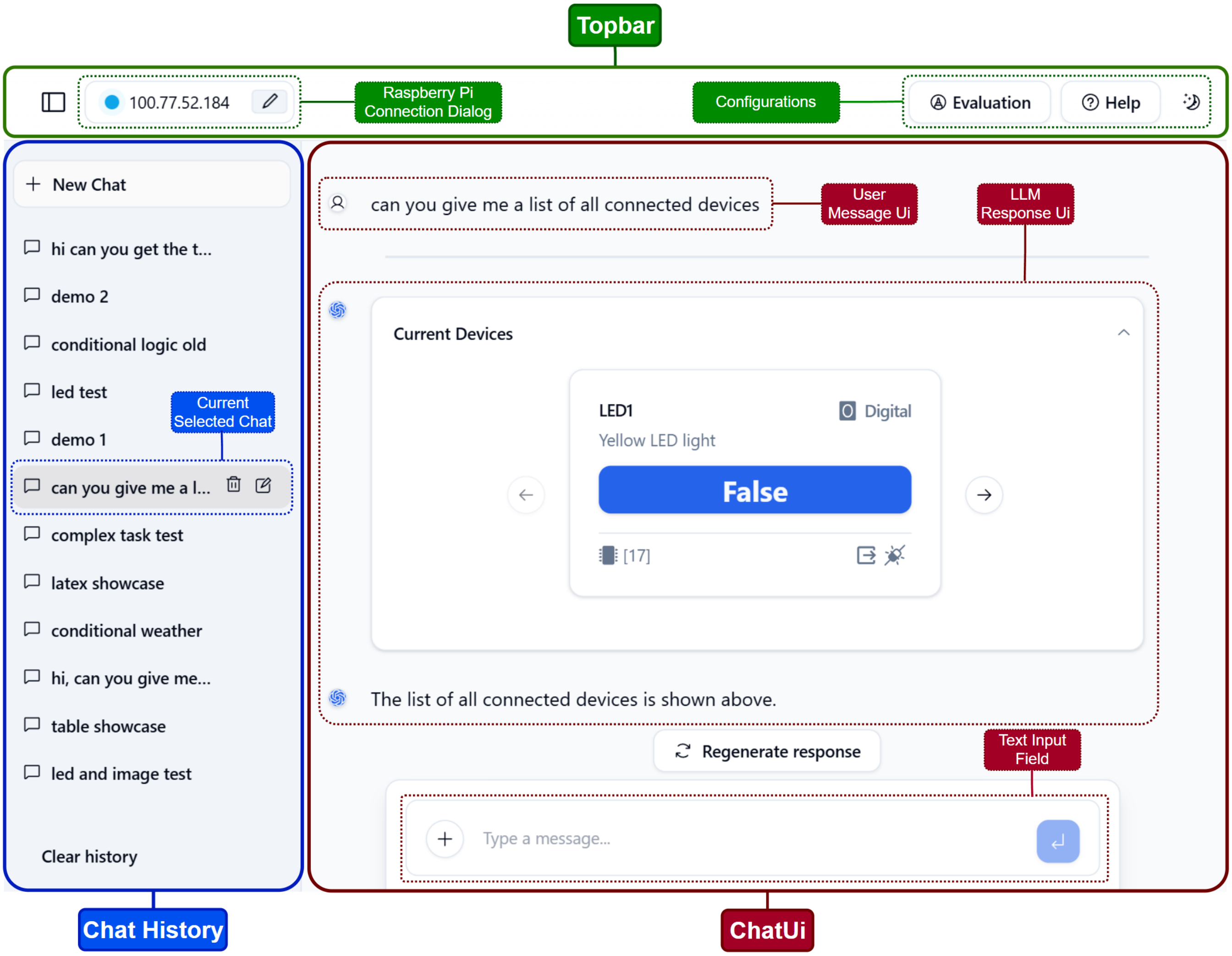


**FIGURE 4.** Webapp user interface implementation

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Mr. Author's awards and honors include the Frew Fellowship (Australian Academy of Science), the I. I. Rabi Prize (APS), the European Frequency and Time Forum Award, the Carl Zeiss Research Award, the William F. Meggers Award and the Adolph Lomb Medal (OSA).

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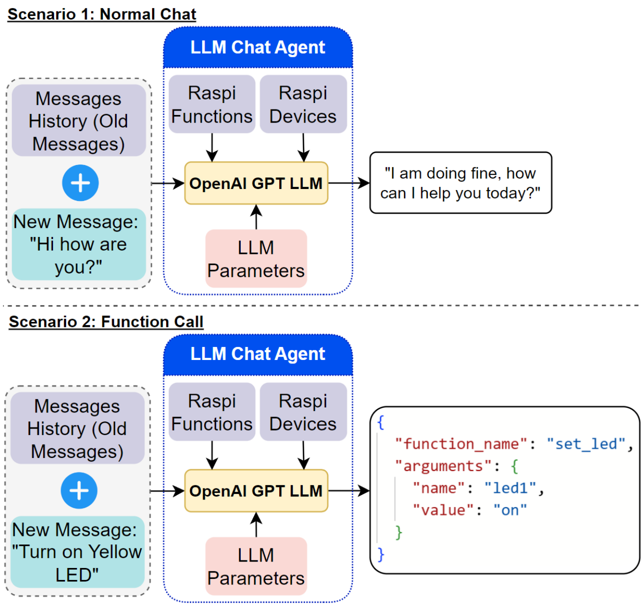


**FIGURE 5.** **Evaluation metrics for the functions defined earlier in .**

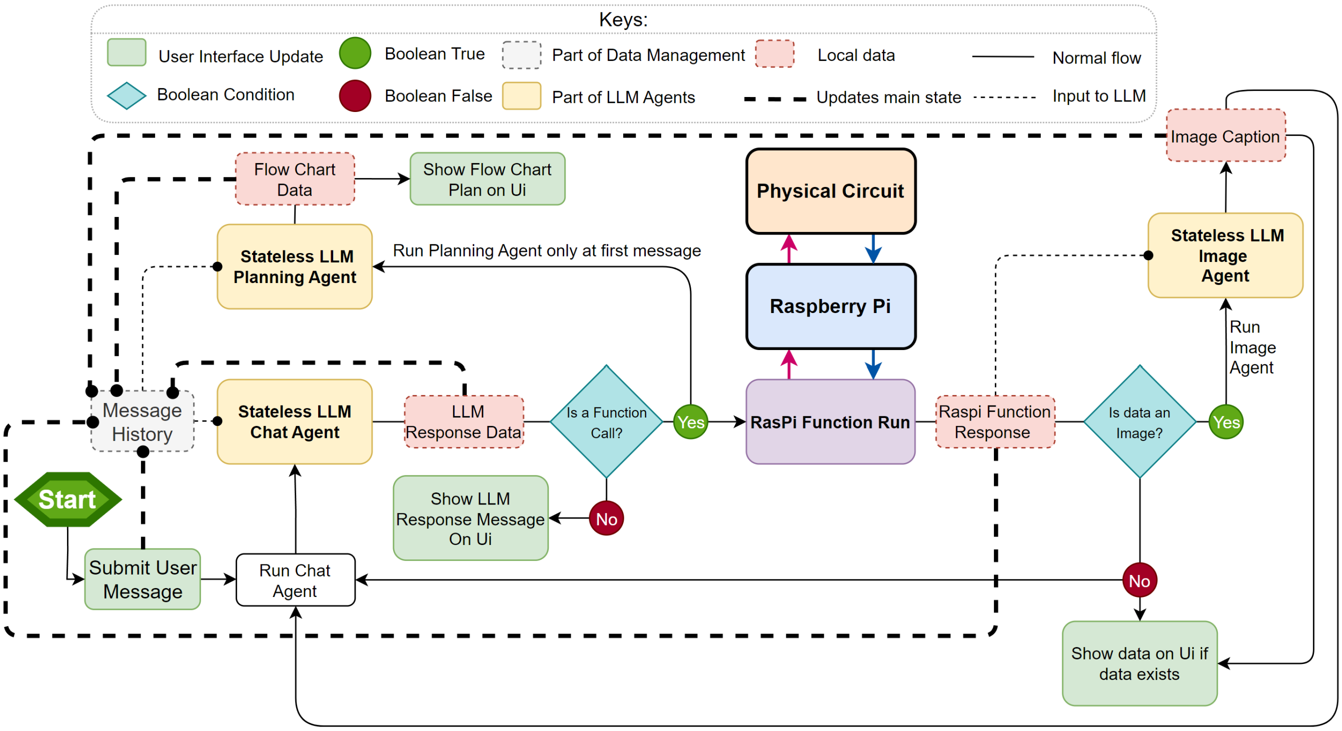


FIGURE 6. Webapp logic design

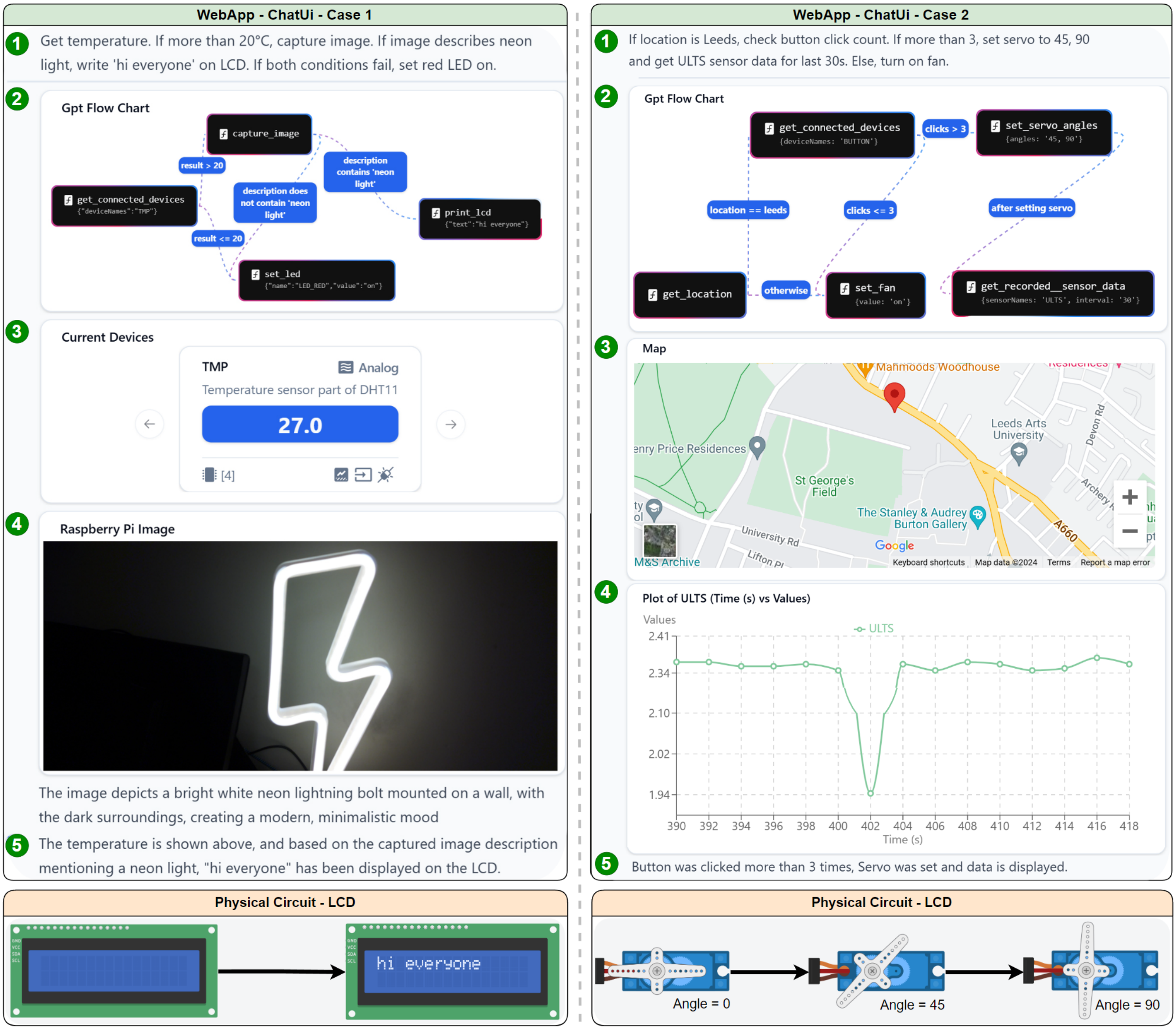


**FIGURE 7.** System case studies

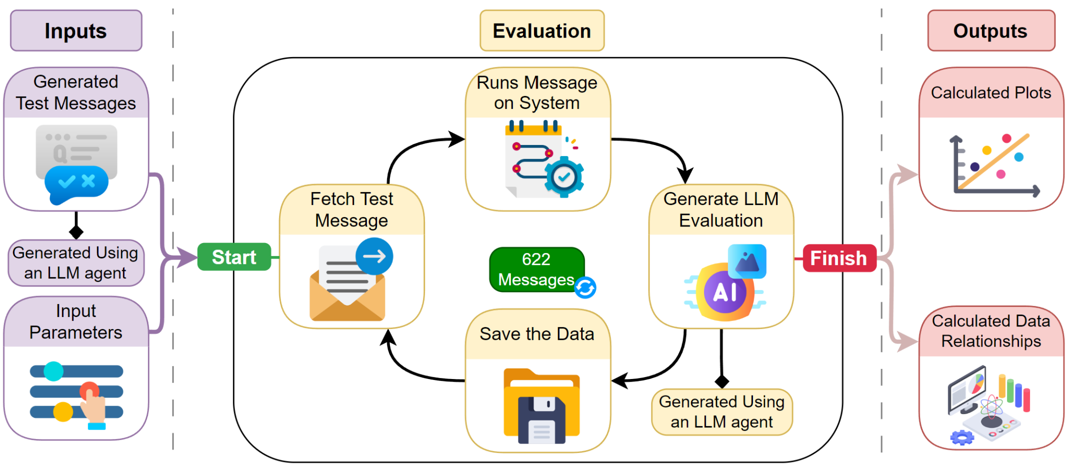


**FIGURE 8. Magnetization as a function of applied field. It is good practice to explain the significance of the figure in the caption.**

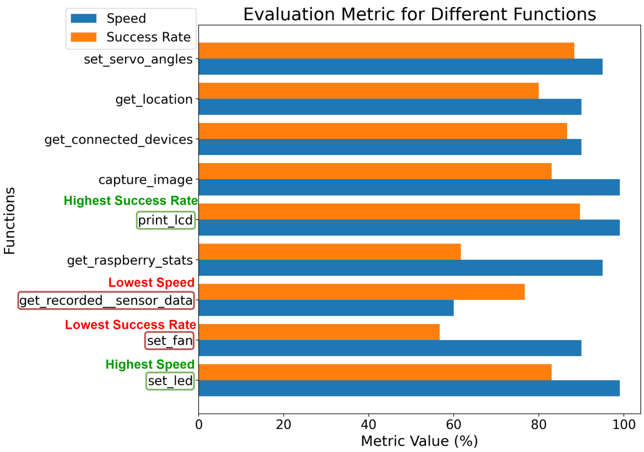


**FIGURE 9. Evaluation metrics for the functions defined earlier in .**

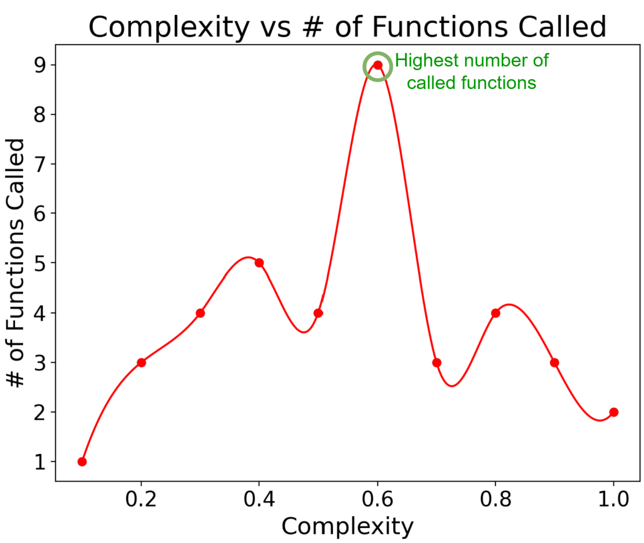


**FIGURE 10. Message complexity against the number of functions called per message.**

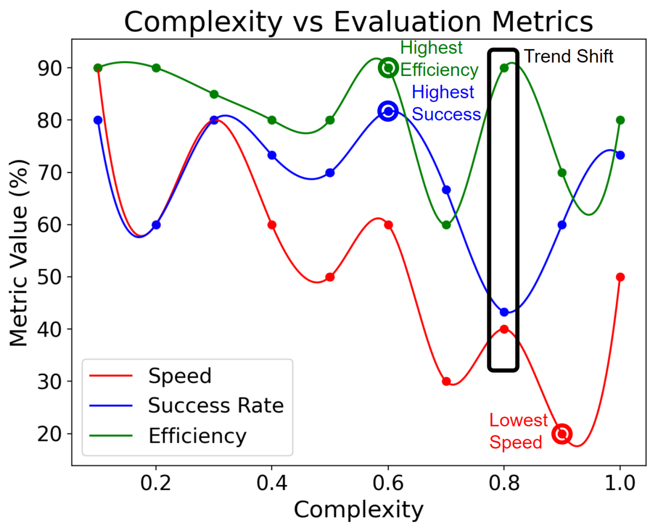


**FIGURE 11. Message complexity against all evaluation metrics and most importantly the success rate.**

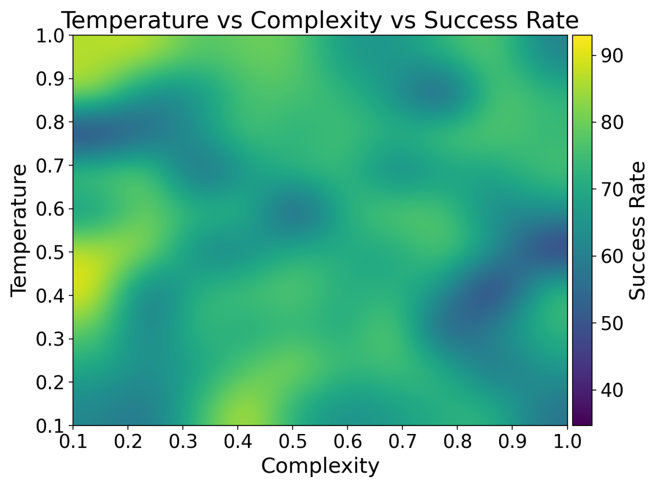


**FIGURE 12. Success rate against message complexity and temperature of the LLM.**

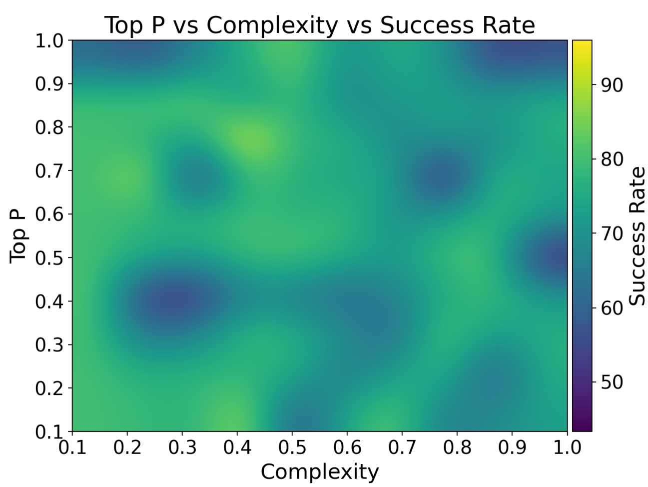


**FIGURE 13. Success rate against message complexity and Top P of the LLM.**

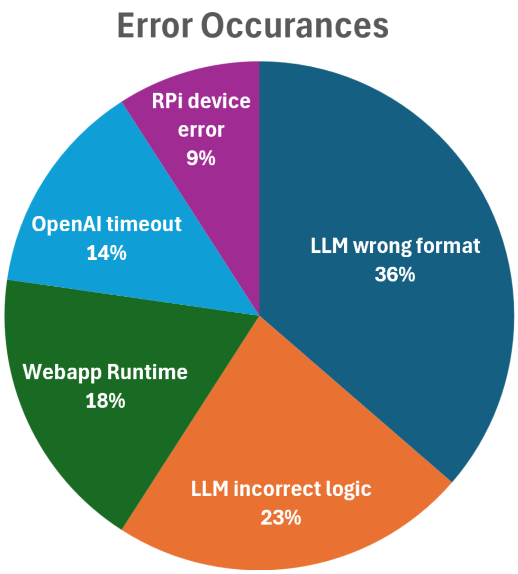


**FIGURE 14.** **What types of errors occured throughout testing.**

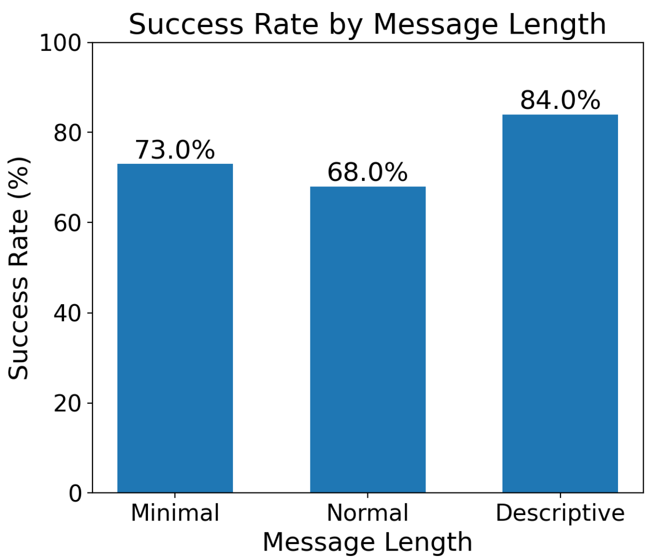


**FIGURE 15.** **Success rate of different tones of the same message.**