

Smart Wearables: Real-Time Contextual Awareness through Prompt Engineering

Raveena¹ Dr. M A kumar² Tanisha³

^{1,2,3}Department of Artificial Intelligence and Data Science Engineering
^{1,2,3}Chandigarh University, India

Abstract — Smart wearable devices have become an integral part of modern digital environments. These devices allow for continuous monitoring of physiological signals, user activities, and environmental parameters. These advancements exist in modern wearable devices; however, most wearable devices still utilise conventional rule-based approaches or machine learning methods. This is because of their inability to effectively interpret complex context information in real-time. With advancements in artificial intelligence, particularly large language models, prompt engineering is recognised as an effective approach to improve context interpretation. This paper proposes an extensive study of context-aware wearable devices. Additionally, it proposes an innovative architecture that utilises prompt engineering to improve context interpretation in wearable devices. The study also discusses various challenges faced by intelligent wearable devices. These challenges include response time, privacy concerns, and computational complexities. Further, it discusses future directions of intelligent wearable devices. The experimental analysis of various scenarios indicates that prompt-engineered inputs improve response accuracy significantly.

Keywords: Smart Wearable Devices; Context-Aware Computing; Prompt Engineering; Artificial Intelligence; Real-Time Data Processing; Privacy and Security

I. INTRODUCTION

In recent times, smart wearable devices have become an integral part of our lives due to their capability to provide continuous monitoring of the user's physical activity, health condition, and surrounding environment. With the increased growth of the Internet of Things (IoT) and artificial intelligence technologies, smart wearable devices like smartwatches, fitness bands, and health tracking devices are being used for applications like healthcare, fitness management, sports performance tracking, and user safety. These devices are provided with sensors like accelerometers, gyroscopes, heart rate monitors, temperature sensors, and GPS that help in collecting useful data.

One of the important advantages associated with wearable devices is that they can be used to facilitate context-aware computing. Context-aware computing can be defined as a system that can understand the user's current situation by analyzing the data collected using sensors and can provide appropriate suggestions. For example, a wearable device can understand if the user is walking, running, resting, or experiencing any abnormalities in their heart rate. However, most wearable devices are based on traditional rules and machine learning approaches. Due to this limitation, these devices are not able to understand complex situations properly and can provide generalized recommendations.

Artificial intelligence has recently improved the efficiency of wearable systems through better recognition and

prediction of activities and health. Machine learning and deep learning techniques have been widely used to analyze sensor data and identify patterns for user activities. However, this improves the accuracy of results but may not be easy to handle in terms of data and computing requirements for wearable systems. Moreover, most traditional artificial intelligence systems have been focused more on prediction than understanding the context of a user's situation.

The development of Large Language Models (LLMs) has provided opportunities to enhance the contextual understanding of intelligent systems. Prompt engineering, which refers to the development of structured inputs for AI models, has proven to be an efficient way of enhancing the contextual understanding of intelligent systems. By transforming the data gathered by sensors into structured inputs, wearable systems can enhance their understanding of the activities and conditions of the users.

The incorporation of prompt engineering with smart wearable devices can help improve the capacity of the device to understand complex situations better than it currently does. The device can, for instance, provide a description of the user's condition in a structured language form, which can then be used to provide the user with relevant recommendations, among other improvements over the personalization and decision-making capabilities of the current wearable device intelligence approaches.

In addition to artificial intelligence technologies, edge computing also plays a significant role in enhancing the efficiency of wearable system performance. This is done by allowing the processing of data close to the wearable device instead of processing all the data using cloud servers. This helps to reduce delay time, enhance efficiency, and maintain user data privacy. Therefore, the integration of wearable sensing technology with context-aware computing, prompt engineering, and edge computing can help to create more intelligent wearable systems.

The research is based on the development of a framework for improving contextual awareness in smart wearables through the use of prompts. The proposed framework works on transforming the data received from sensors into prompts and then processing them through intelligent models to create recommendations. The aim of this research is to improve the responsiveness and accuracy of next-generation wearables. Apart from this section, the structure of this research manuscripts is as follows: Section II, consists of Literature Review. Section III showcases the brief description of the methodology opted for this research. Section IV elaborates the result and Section V contains the discussion, highlighting the key insights. In the last sections, the conclusion and future scope are given.

II. LITERATURE REVIEW

Smart wearable technologies have become an important area of research because they allow continuous monitoring of user health conditions and daily activities through embedded sensors. Early work by Pantelopoulos and Bourbakis [1] provided a detailed overview of wearable sensor-based healthcare systems and highlighted their usefulness in improving patient monitoring and emergency response support. Later studies also showed that wearable devices are increasingly being used in healthcare environments to track physiological signals and support personalized treatment approaches [6].

Context-aware computing plays a major role in making wearable systems more intelligent and adaptive. Gu et al. [2] explained how contextual information such as user activity, location, and surrounding environment can help systems adjust their behavior automatically. Similarly, Dey

[3] introduced the concept of context-aware interaction and demonstrated how understanding user situations improves system usability. Chen and Kotz [4] further discussed the challenges involved in designing mobile systems that can correctly interpret dynamic contextual information in real time.

The integration of wearable devices with Internet of Things (IoT) technologies has further improved connectivity and data exchange between sensors and intelligent applications. Li et al. [5] described how IoT enables efficient communication among smart devices and supports large-scale data-driven applications. Body area networking technologies also contribute to reliable communication between wearable sensors and healthcare monitoring platforms, making realtime observation more practical and effective [9].

Human activity recognition is another important component of smart wearable systems. Lara and Labrador [7] reviewed several activity recognition techniques based on wearable sensors and showed how machine learning methods improve classification accuracy. Zhang et al. [8] demonstrated how sensor data collected from wearable devices can be used to recognize common physical activities such as walking, sitting, and running. More recent deep learningbased approaches further improved recognition performance by combining convolutional and recurrent neural network models for multimodal wearable data analysis [24].

Edge computing has recently emerged as a powerful solution for supporting real-time processing in wearable environments. Instead of transferring all collected data to cloud servers, edge computing allows processing closer to the device, which reduces delay and improves system responsiveness. Shi et al. [11] discussed the vision and challenges of edge computing in IoT-based systems, while Mao et al.

[12] provided a broader overview of mobile edge computing architectures. Sun and Ansari [13] introduced the concept of EdgeIoT, which combines edge computing with IoT devices for efficient data processing. Satyanarayanan [14] further highlighted how edge computing plays a key role in enabling next-generation context-aware applications.

Recent developments in artificial intelligence, especially large language models, have created new opportunities for improving contextual understanding in intelligent wearable systems. Brown et al. [15] showed that large language models can perform multiple tasks effectively using only structured prompts. The GPT-4 technical report [16] further demonstrated improvements in reasoning capability and contextual understanding. Prompt engineering techniques such as chain-of-thought prompting [17] and tree-of-thought reasoning [18] have also been shown to enhance the decision-making ability of language models in complex scenarios.

Researchers have recently started exploring the integration of large language models with wearable sensing environments to improve contextual awareness. Arrotta et al. [19] proposed ContextGPT, which combines language model knowledge with activity recognition systems to improve context interpretation. Lee et al. [20] developed a contextaware multimodal assistant designed for wearable augmented reality applications. Another study by Lee et al. [21] introduced a system architecture for egocentric contextual artificial intelligence in wearable environments. In addition, Pu et al. [22] explored proactive assistance techniques in multimodal wearable devices to improve user interaction and personalization.

Ambient intelligence systems also contribute to contextaware decision-making by enabling smart environments to respond automatically to user needs [23]. Wireless sensor network technologies further support healthcare-related wearable monitoring by providing efficient communication between sensing devices and processing systems [25].

Although these studies have significantly improved the capabilities of wearable intelligence systems, most existing approaches mainly rely on sensor-based classification models and cloud-supported processing methods. Only limited research has explored how prompt engineering techniques can be integrated with wearable sensor environments for improving real-time contextual reasoning. Therefore, this work focuses on combining wearable sensing, edge computing, and prompt-engineering-based artificial intelligence to enhance contextual awareness and personalized assistance in smart wearable systems.

III. RESEARCH AREA

This provides a comprehensive overview of the current state of wearable technology. A critical transition in this domain is the shift from data collection, which has already matured significantly, to meaningful interpretation, which still presents several challenges.

The integration of Large Language Models (LLMs) with prompt engineering transforms wearable devices from passive monitoring tools into intelligent assistants capable of contextual understanding. Instead of simply reporting physiological values such as elevated heart rate, the system can interpret situational context and provide meaningful insights, such as identifying stress before an important event. The interaction between these architectural layers is illustrated in Fig. 1.

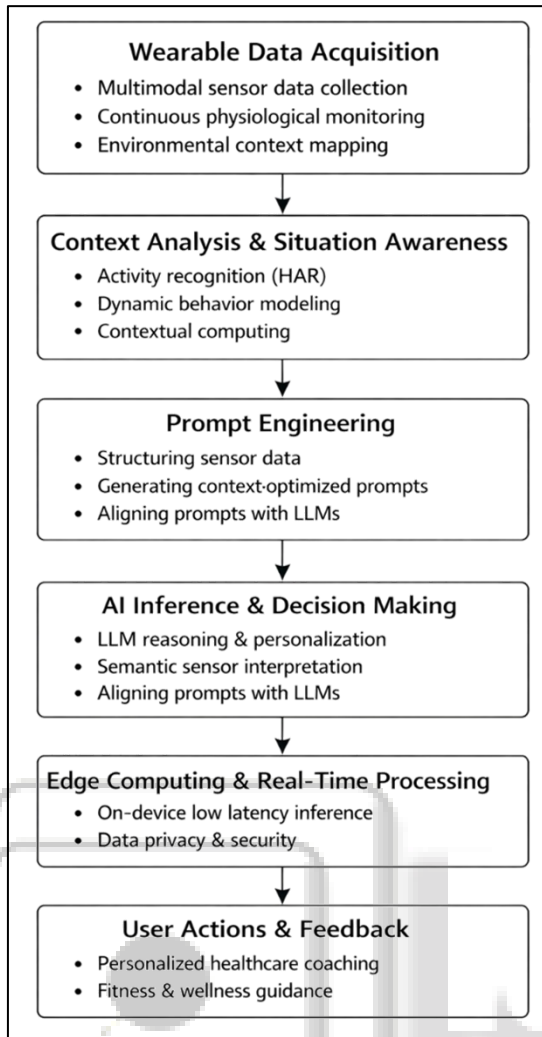


Fig. 1: Proposed Research Flowchart for Context-Aware Wearable System

A. Bridging the Semantic Gap:

One of the major challenges in wearable computing systems is deriving meaningful insights from raw sensor data, commonly referred to as the semantic gap. For example, while a gyroscope sensor can detect downward motion, a

B. Proposed System Architecture

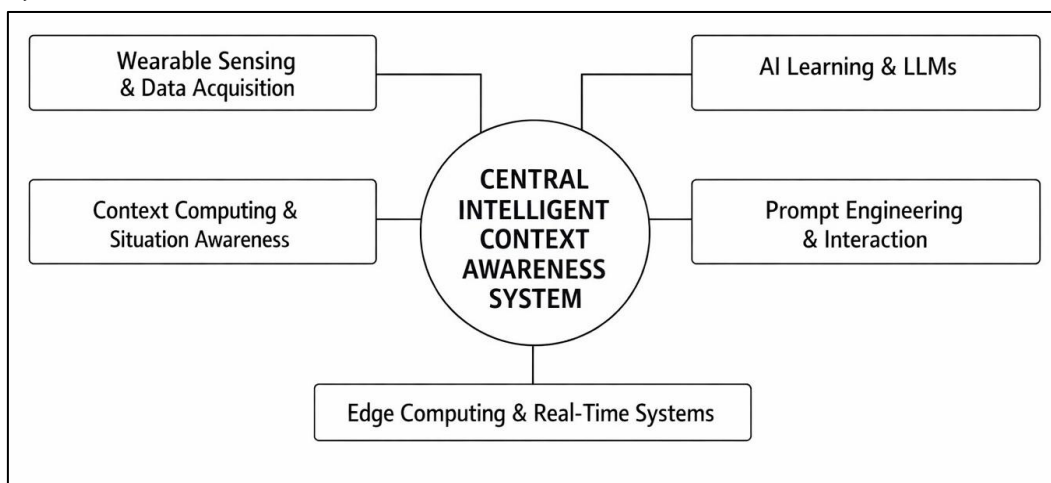


Fig. 2: Smart Wearable Architecture

context-aware intelligent system determines whether the motion corresponds to normal sitting behavior or a potential fall event. Addressing this semantic gap enables smarter decision-making and improves the reliability of real-time wearable assistance systems.

As highlighted earlier, the integration of Edge AI is essential for the following reasons:

- 1) Privacy: Physiological data is highly sensitive. Processing this data locally on the wearable device ensures that personal health information remains secure and does not need to be transmitted to external cloud servers.
- 2) Latency: Real-time applications such as fall detection and emergency alerts require immediate response. Relying on cloud-based processing introduces delays that reduce the effectiveness of time critical healthcare interventions.

IV. PROPOSED WORK

A. Problem Statement:

The problem statement is as follows: Wearable devices such as fitness trackers and smart watches are examples of smart devices that incorporate various sensor devices to collect information in real time regarding their environment. However, it is found that most wearable devices in use today incorporate rule-based processing or machine learning approaches that provide generic responses to situations. These approaches often fail to provide effective responses to changing user behaviour, as well as various factors in the environment and health of an individual. With the incorporation of large language models, prompt engineering has been found to provide effective results in processing sensor information in an intelligent way by providing meaningful input representations. However, there is little attention given to wearable devices in conjunction with prompt engineering approaches for providing real-time contextual awareness. Developing an intelligent wearable device framework is required to provide effective responses to situations by converting sensor information into structured prompts.

C. Figure Description – Central Intelligent Context Awareness System

The diagram shows the structure of the proposed Central Intelligent Context Awareness System for smart wearables. It combines wearable sensing, context computing, AI learning with LLMs, prompt engineering, and edge computing to process sensor data and understand user activities in real time. Together, these components help the system provide faster, intelligent, and personalized contextual responses.

The proposed system will incorporate a prompt-driven contextual awareness framework in smart wearable environments. The architecture of the system will incorporate wearable sensor devices, preprocessing modules, context detection modules, prompt engineering modules, and AI-based response generation modules.

The major components of the system architecture of the proposed system are:

- 1) **Sensor Data Acquisition Module:** This module collects real-time physiological and environmental data using wearable sensors such as:
 - Heart rate sensors
 - Accelerometers
 - Gyroscopes
 - Temperature sensors
 - GPS modules

These sensors continuously monitor user activity and surrounding environmental conditions.

- 2) **Data Preprocessing Module:** The collected data from the sensors is cleaned and normalised. This process removes noise and inconsistencies from the data. This step helps to improve data quality. Typical preprocessing operations include:
 - Noise filtering
 - Missing value handling
 - Signal smoothing
 - Feature extraction

- 3) **Context Detection Module:** This module uses the processed data from the sensors to determine the user's activity and state. For example:
 - Walking
 - Running
 - Resting
 - Stress conditions
 - Abnormal heart rate detection

Machine learning or rule-based classification techniques can be applied in this stage for activity recognition.

- 4) **Prompt Generation Module:** The prompt generation module processes the contextual information and converts it into natural language prompts that can be interpreted by AI models.

Example:

Raw sensor data:

- Heart Rate = 140 bpm Temperature = 32°C Activity = Running
- Generated prompt: "User is running in a high-temperature environment with a heart rate of 140 bpm. Provide safe and personalised recommendations."

- This structured representation significantly improves AI reasoning capability.
- 5) **AI-Based Decision Module:** This structured form greatly improves the reasoning capability of AI. The prompt generated is processed using a large language model to develop intelligent recommendations based on the user context. The AI module processes the contextual information and provides adaptive suggestions like the following:
 - Hydration reminders
 - Activity adjustments
 - Health alerts
 - Stress management recommendations

This improves personalisation compared to traditional wearable systems.

- 6) **Response Delivery Module:** The final recommendations are delivered to the user through wearable interfaces such as:

- Smartwatch notifications
- Mobile application alerts
- Voice assistant responses
- Haptic feedback signals

This ensures real-time interaction between the system and the user.

D. Workflow of the Proposed System

The workflow of the proposed system will be based on the following sequential pipeline:

Sensor Data Collection, Data Preprocessing, Context Detection, Prompt Generation, AI Model Processing, Response Delivery

This pipeline will ensure the smooth conversion of raw sensor data into useful information.

E. Advantages of the Proposed System

The suggested framework has some advantages in comparison to other conventional wearable intelligence system frameworks. These advantages include prompt engineering for quick engineering integration and adaptive health recommendations.

- Enables real-time contextual awareness
- Improves personalization using structured prompts
- Enhances AI reasoning capability
- Reduces ambiguity in sensor interpretation
- Supports adaptive health recommendations
- Improves decision accuracy through prompt engineering integration

F. Implementation Approach (Prototype-Level)

The suggested framework can be validated by developing a prototype model in a Python environment. In developing the prototype model, it is important to note that it will be used to generate contextual recommendations by using sensor prompts that will be processed by the AI model. This implies that prompt engineering can be incorporated into wearable computing.

V. RESULT

The framework based on the proposed prompt engineering method indicates that there is a marked improvement in terms

of the smart wearable devices' understanding of the real-time context of the user. This is because the system is able to understand the activities of the user more accurately using the prompts for the collected data, such as movement patterns and physiological signals, unlike the traditional smart wearable devices.

The utilization of edge-level processing also assists the system in responding quickly since most of the processing is done near the wearable device rather than relying on cloud servers. This enables the system to be efficient enough to support real-time applications such as monitoring activities, fitness tracking, and identifying abnormal health conditions. The second major implication of this suggested model is the personalisation. It is tailored based on the user's behaviour and conditions; therefore, it enhances the interaction between the user and the wearable device.

Based on the overall results, it could be proposed that the integration of wearable sensor information and prompt engineering has the potential to make the smart wearable devices more responsive, intelligent, and helpful.

VI. CONCLUSIONS AND FUTURE WORK

The real-time tracking of activities and health parameters could be ascribed to the significant contributions made by smart wearables. The majority of the current wearable devices rely on pre-defined rules and machine learning algorithms, which are not sufficient in attaining accurate context awareness and intelligent interaction with the wearer. In this research, a framework using prompt engineering has been proposed for improving real-time context awareness in smart wearables by using intelligent analysis of the organized prompts.

The proposed approach has the potential to enhance the process of decision-making, customisation, and response time of the wearable devices by using the integration with the AI models. Although there are some challenges to be addressed in this framework, it has tremendous potential to further enhance the intelligence of the wearable devices in the future. Future work could be done by trying to explore the possibility of using this framework in real-time applications and using various types of sensors to further enhance this framework.

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