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A Survey of LoRaWAN-Integrated Wearable Sensor Networks for Human Activity Recognition: Applications, Challenges and Possible Solutions

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ABSTRACT Long-Range Wide Area Networks (LoRaWAN), a prominent technology within Low-Power Wide Area Networks (LPWANs), have gained traction in remote monitoring due to their long-range communication, scalability, and low energy consumption. Compared to other LPWANs like Sigfox, Ingenu Random Phase Multiple Access (Ingenu-RPMA), Long-Term Evolution for Machines (LTE-M), and Narrowband Internet of Things (NB-IoT), LoRaWAN offers superior adaptability in diverse environments. This adaptability makes it particularly effective for Human Activity Recognition (HAR) systems. These systems utilize wearable sensors to collect data for applications in healthcare, elderly care, sports, and environmental monitoring. Integrating LoRaWAN with edge computing and Internet of Things (IoT) frameworks enhances data processing and transmission efficiency. However, challenges such as sensor wearability, data payload constraints, energy efficiency, and security must be addressed to deploy LoRaWAN-based HAR systems in real-world applications effectively. This survey explores the integration of LoRaWAN technology with wearable sensors for HAR, highlighting its suitability for remote monitoring applications such as Activities of Daily Living (ADL), tracking and localization, healthcare, and safety. We categorize state-of-the-art LoRaWAN-integrated wearable systems into body-worn, hybrid, object-mounted, and ambient sensors. We then discuss their applications and challenges, including energy efficiency, sensor scalability, data constraints, and security. Potential solutions such as advanced edge processing algorithms and secure communication protocols are proposed to enhance system performance and user comfort. The survey also outlines specific future research directions to advance this evolving field.

INDEX TERMS HAR, IoT, LoRaWAN, LPWAN, remote monitoring, wearable sensors, sensor integration, survey.

I. INTRODUCTION

THE EVOLUTION of human activity tracking devices, particularly those requiring remote data transmission, has been significantly influenced by advances in sensing and communication technologies. Wearable sensors, in particular, have benefited from the development of Low-Power Wide Area Networks (LPWANs) [1], notably the Long-Range Wide Area Network (LoRaWAN) developed by the LoRa Alliance [2], [3]. The combination of LPWAN technologies' wide-area mobility and the flexibility of compact wearable sensors is paving the way for innovative Human Activity Recognition (HAR) systems that operate efficiently across diverse environments. This integration not only enhances the scalability of HAR systems but also ensures their adaptability to varying user needs and environmental conditions.

Several LPWAN technologies have been instrumental in this progress, including Sigfox, Long-Term Evolution for Machines (LTE-M), Narrowband Internet of Things (NB-IoT), and Ingenu Random Phase Multiple Access (Ingenu-RPMA) [4], [5], [6], [7], [8], [9], [10]. While these

TABLE 1. Research questions.

#	Research Question
RQ1	What are the practical applications of LoRaWAN in HAR using wearable sensors, and which sensor modalities and types of activities are commonly monitored?
RQ2	How are LoRaWAN parameters optimized for HAR systems, and how do these optimizations affect performance?
RQ3	What challenges and opportunities arise using LoRaWAN-based wearable sensor networks for HAR?

technologies have been instrumental in addressing significant challenges in remote wireless access [11], they are not without limitations. Common issues include limited data transmission distances and energy inefficiencies, which have historically restricted the widespread adoption of wearable HAR systems.

LoRaWAN, however, offers a compelling solution by providing long-range communication coupled with low power consumption. This positions LoRaWAN as a critical enabler for next-generation HAR applications [12]. As LPWAN technologies continue to advance, HAR systems have the potential to revolutionize sectors such as healthcare, sports, and beyond, providing scalable and adaptable solutions.

Current research is increasingly focused on making LoRaWAN-integrated wearable sensor systems more user-friendly, ensuring they are unobtrusive, convenient, and widely accepted. With ongoing advancements, this technology holds significant promise for enhancing applications that improve safety and quality of life across various contexts. Moreover, efforts are being directed toward enhancing these systems' accuracy, reliability, and energy efficiency for effective HAR and processing [13]. This involves effectively managing and interpreting sensor data while accounting for the complexity of human behavior and environmental interactions, whether the data is analyzed directly on the device or after transmission, depending on the specific application [14].

A. MOTIVATION AND RESEARCH QUESTIONS

Integrating LoRaWAN wireless technologies with wearable sensor networks for remote HAR reveals several key research topics. These topics encompass the capabilities, challenges, and potential applications of combining these technologies. While related surveys exist, no recent review focuses explicitly on integrating LoRaWAN technology with wearable sensor networks.

This work fills that gap by examining recent advancements in LoRaWAN-integrated wearable sensor networks for HAR. We explore how this technology transforms the monitoring and analysis of human activities, particularly in remote or challenging environments. This article aims to be a pioneering effort in consolidating, analyzing, and presenting the state-of-the-art in this field.

This study addresses three key research questions, as summarized in Table 1.

B. NOVELTY AND RESEARCH CONTRIBUTION

Remote HAR using LoRaWAN technology presents several challenges. These include the complexity and variability of human activities, the diversity of sensors involved, the inherent noise in sensor data, and the resource constraints of wearable devices. These challenges highlight the need for a detailed review, which this paper addresses through the following key contributions:

- A detailed and current review of recent advancements in wearable sensor networks integrated with LoRaWAN for HAR applications. This work covers the latest developments in wearable sensor technologies, network architectures, and data processing techniques.
- Exploring the primary real-world applications of these systems, such as healthcare monitoring, safety, and tracking. This analysis demonstrates the practical feasibility and benefits of deploying LoRaWAN-integrated HAR systems.
- Assessing the performance of existing HAR systems across various LoRaWAN parameters, including spreading factor, coding rate, and data rate, with a particular focus on energy efficiency. This evaluation reveals how these parameters affect system performance and highlights opportunities for optimization.
- Identifying current limitations, such as sensor wearability, network reliability, and data security. Additionally, the paper explores future research directions, including integrating artificial intelligence to enhance data processing, improving network scalability, and developing more advanced, compact sensors.

C. PAPER FORMULATION

This article is structured as shown in Fig. 1 and is organized as follows:

- Section II provides a review of LPWANs, including Sigfox, LTE-M, NB-IoT, Ingenu-RPMA, and LoRaWAN, with a primary focus on integrating LoRaWAN with HAR.
- Section III describes the research methodology, including the review process, selection criteria, and an overview of related surveys.
- Section IV presents recent developments in LoRaWAN-integrated HAR systems, with a detailed analysis of their architecture, applications, sensor utilization, and other technical specifications.
- Section V discusses critical challenges such as wearability, energy efficiency, security, data accuracy, and scalability and suggests potential future research directions.
- Section VI provides a comprehensive discussion on the scope of this review work.
- Section VII concludes the paper by summarizing the findings and proposing future work, with abbreviations listed in the Appendix.

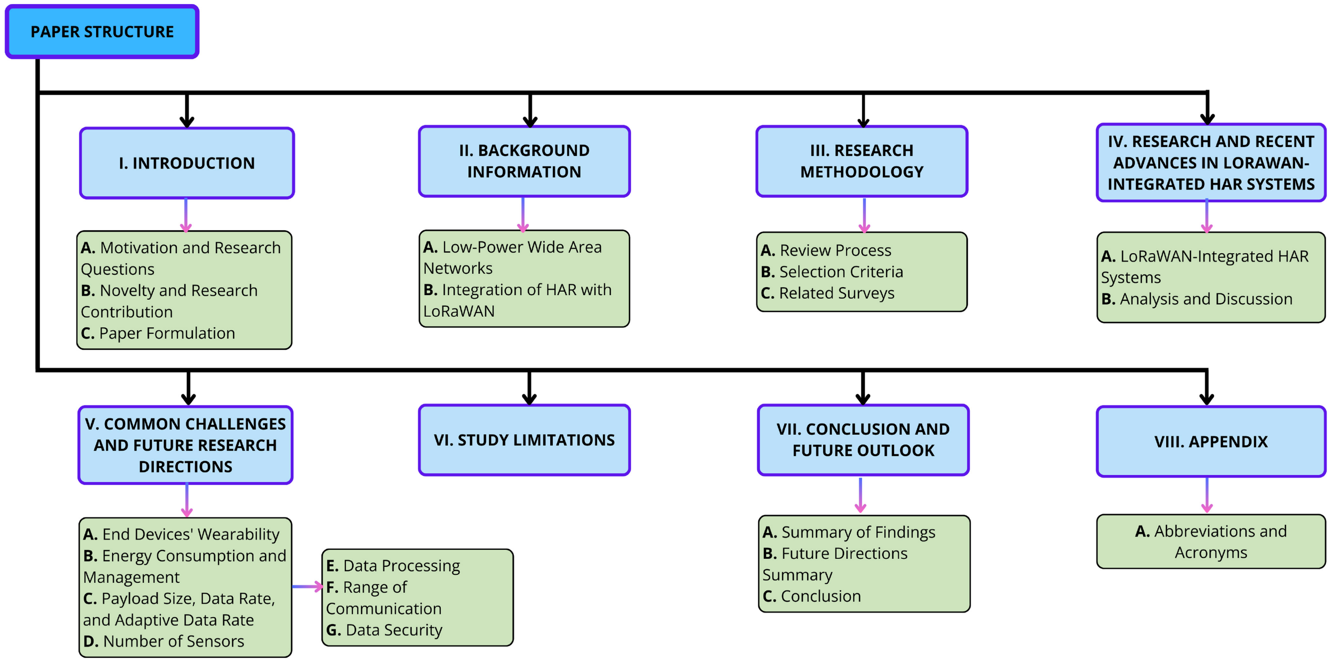

FIGURE 1. Paper outline. This diagram illustrates the structure and flow of this survey paper, connecting key sections from the introduction to the Appendix.

II. BACKGROUND INFORMATION

A. LOW-POWER WIDE AREA NETWORKS

This section discusses the most commonly used LPWAN technologies in the industry today. Table 2 compares these technologies, including LTE-M, NB IoT, Ingenu RPMA, Sigfox, and LoRaWAN, based on features like range, data rate, battery life, security, cost, and latency. These features compare each technology's strengths and limitations, helping identify the best choice for specific IoT applications.

1) SIGFOX

Sigfox is an LPWAN technology that operates across unlicensed sub-1 GHz industrial, scientific, and medical (ISM) band carriers and ultra-narrowband channels [15], [16]. It uses proprietary technology designed for systems with intermittent transmission of low data volumes [17]. Devices connected via the Sigfox protocol can send and receive a maximum of 140 messages, each limited to 12 bytes in length, at a maximum transfer rate of 100 bps. These constraints reduce the effectiveness of the technology for HAR applications [18], [19]. Sigfox achieves outstanding global coverage and low power consumption at a relatively low deployment cost, making it suitable for low-power, intelligent, interconnected devices. However, its weaknesses include a low data rate, high latency, and limited scalability potential compared to newer LPWAN technologies like LoRaWAN, raising concerns about its use in wearable HAR frameworks.

2) LTE-M

LTE-M is a cellular LPWAN wireless communication protocol that utilizes LTE infrastructure to transmit data between connected devices and base stations or servers [20]. LTE-M is well-suited for wearable HAR systems due to its high data rate, low latency, strong connectivity, and scalability potential for over 100,000 devices [5]. However, the deployment cost for LTE-M networks is high because it requires existing LTE infrastructure. Additionally, devices connected via LTE-M generally have higher power consumption rates than other LPWAN protocols. Consequently, these factors can limit the practicality of LTE-M for certain wearable applications where cost and energy efficiency are critical.

3) NB-IOT

NB-IoT is an LPWAN protocol that leverages licensed frequency bands and existing LTE infrastructure for wireless communication [21]. The technology offers enhanced coverage, supporting many devices that require low data volumes over long periods, which is essential for the scalability of wearable HAR systems [17], [19]. The strengths of the NB-IoT protocol include its scalability to support massive connections, low power consumption, low latency, and secure wide-area coverage due to its use of LTE cellular network channels [21], [22]. However, the deployment cost for NB-IoT is higher because it relies on licensed proprietary cellular LTE infrastructure [18]. Consequently, NB-IoT is most suitable for applications requiring low-data-rate transmission, such as smart metering and intelligent environment monitoring. While NB-IoT's features and capabilities are well-aligned with effective remote monitoring needs across multiple devices, the high deployment cost limits its suitability for large-scale wearable HAR systems. This limitation necessitates alternative solutions.

4) INGENU-RPMA

Ingenu-RPMA is a proprietary random-phase multiple-access LPWAN protocol that operates within the 2.4 GHz

TABLE 2. Comparison of key features, strengths, and limitations across various LPWAN technologies.

#	LTE-M	NB-IoT	Ingenu RPMA	Sigfox	LoRaWAN
Range	1-10 km [28]	1-10 km [21]	10-15 km [23]	10-50 km [19]	2-15 km [29]
Data Rate	1 Mbps [18]	200 kbps [5]	624 kbps [26]	100 bps [22]	50 kbps [30]
Battery Life	8 years [17]	10 years [22]	10 years [23]	10 years [15]	10 years [31]
Security Framework / Encryption	Advanced Encryption Standard (AES) 128-bit [5]	Automatic Target Recognition (ATR) 128-bit [17]	High-grade Security [9]	AES 128-bit [32]	AES 128-bit [24]
Deployment Cost	High [20]	Medium [19]	High [25]	Low [15]	Low [33]
Latency	Very Low [35]	Low [18]	Low [23]	High [18]	Medium [26]
Interoperability	Interoperability with LTE network infrastructure [20]	Interoperability with cellular IoT systems [16]	Limited interoperability [25]	Limited Interoperability [24]	Interoperability with IoT ecosystems [35]
Key Strengths	• High data rate • Low latency • Scalability for areas with existing LTE cellular coverage	• Low deployment cost • Low power consumption • Excellent indoor penetration	• High data rate • Low power consumption • Scalability • Robust security encryption	• Low deployment cost • Minimal deployment complexities • Low power consumption	• Low power consumption • Long range • Minimal transmission losses • Scalability • Global availability • Excellent bi-directional communication • Low deployment cost
Key Limitations	• High deployment cost • High power consumption rate • Deployment complexities due to reliance on LTE networks • Inapplicability for areas with limited or lacking LTE cellular infrastructure • Susceptibility to interference	• High deployment cost • Limited data rate • Latency susceptible to heavy traffic • Low interference immunity • Deployment complexities due to integration with cellular networks	• High susceptibility to interference • High deployment cost • Latency susceptibility to spectrum crowding • Reliance on proprietary network infrastructure • Limited global coverage	• Low data rate • High latency • Limited scalability • Limited bidirectional communication • Moderate susceptibility to interference • Limited global coverage • Limited interoperability	• Low data rate • Latency susceptibility to channel congestion • Limited message payload

frequency band [23]. The technology transmits data using the direct sequence spread spectrum technique, limiting the peak data rate to 80 kbps [5]. The strengths of Ingenu-RPMA include low power consumption, high scalability (with each access point capable of covering over 300 square miles by optimizing receiver sensitivity), and robust security encryption frameworks [24], [25], [26]. However, Ingenu-RPMA is vulnerable to interference during data transmission since it operates on the 2.4 GHz frequency band, also used by Bluetooth and Wi-Fi networks [27]. Additionally, the higher deployment costs of Ingenu-RPMA compared to LoRaWAN limit its applicability in large-scale wearable HAR.

5) LORAWAN

LoRaWAN is an open standard protocol that connects multiple sensors across extensive areas, creating wide area networks with high capacity, long range, and low power consumption [31]. This makes it possible to develop more reliable remote activity monitoring systems by leveraging its strengths [5], [24], [36], [37], [38]. This technology is discussed in detail in the coming section of this chapter.

Implementing remote wearable sensor networks for HAR is often constrained by various factors. However, LoRaWAN technology offers several features that make it an ideal choice for these networks [33], [39], [40], [41]. The key advantages of LoRaWAN for wearable sensor networks include:

- *Extended Battery Life:* Wearable sensors are typically compact, with limited battery capacity. LoRaWAN's low-power consumption significantly extends the battery life of these devices, enabling extended periods of monitoring without the need for frequent recharging.

- *Wide Coverage:* LoRaWAN provides extensive coverage, which is particularly advantageous for wearable sensor networks, especially for mobile users in remote areas. This ensures consistent data transmission even when users are far from the data collection point.
- *Reliable Data Transmission:* Integrating LoRaWAN with wearable sensors enhances the accuracy and reliability of data transmission. LoRaWAN's robust modulation techniques help minimize data packet loss, even in noisy environments.
- *Scalability:* LoRaWAN can support many nodes, which is crucial for the scalability of wearable sensor networks. This capability allows for monitoring large populations or expanding the network with additional sensors.
- *Data Security and Privacy:* In HAR, the security and privacy of data, particularly susceptible health information, are paramount. LoRaWAN incorporates robust security measures, including end-to-end encryption, ensuring the secure transmission of data from wearable sensors.

Despite these advantages, some considerations exist when integrating LoRaWAN with specific systems. Its bandwidth may not always be suitable for transmitting large volumes of data or applications requiring real-time transmission, though this is not typically necessary for wearable sensors [10], [42]. In densely populated areas, there is some susceptibility to channel congestion; however, with effective network planning and the integration of complementary technologies, these limitations can be minimized to maintain strong performance.

B. INTEGRATION OF LORAWAN WITH HAR

Integration, in this paper, refers to combining HAR systems with LPWAN technologies. The integration of LPWANs with wearable sensor networks for HAR is a rapidly growing area within wireless communication, and IoT [30], [39], [43]. This section first explores the features and capabilities of LoRaWAN technology, followed by a concise overview of HAR systems. These discussions provide the foundation for understanding how these technologies can be integrated, a topic covered in detail later in this subsection.

1) LORAWAN TECHNOLOGY OVERVIEW

The LoRaWAN protocol operates in the sub-GHz unlicensed ISM radio bands. It uses the physical layer of LoRa radio technology developed by Semtech [44] and employs chirp spread spectrum (CSS) modulation to enhance communication [1], [45]. This modulation encodes a specific number of spreading factor (SF) bits per chirp, effectively creating virtual channels. In Europe, SF values range from 7 to 12, corresponding to data rates between 0.3 and 11 kbps [46]. Without these regional constraints, the data rates can extend up to 51 kbps [47]. Channels using different SF values are nearly orthogonal, allowing for efficient multiplexing. Notably, frames sent at higher SFs, while longer, offer more excellent resistance to interference, facilitating adaptive data rate (ADR) strategies to optimize communication based on network conditions.

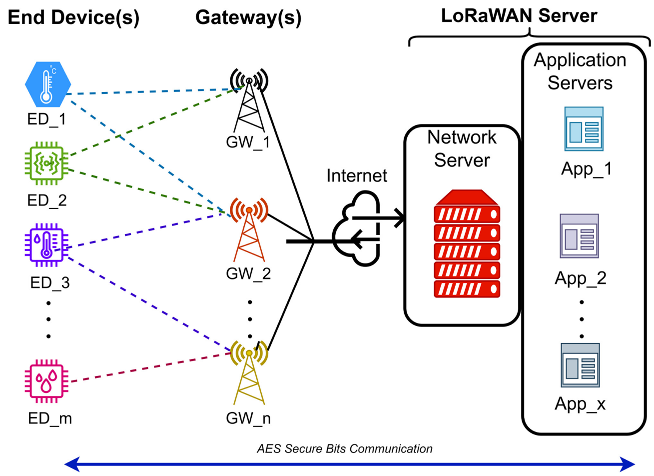

FIGURE 2. Standard LoRaWAN Architecture: An overview showing end devices connecting through gateways to network and application servers via the internet.

LoRaWAN integrates forward error correction (FEC) coding, supporting coding rates (CR) of 4/5, 4/6, 4/7, and 4/8 to enhance data transmission reliability. Key parameters influencing the LoRa link include carrier frequency, transmission power (TP), and bandwidth (BW) [48]. Most chipset implementations operate at frequency bands of 125 kHz, 250 kHz, or 500 kHz, although some versions support frequencies as low as 7.8 kHz [1].

LoRaWAN offers extensive coverage: up to 40 km in rural areas, up to 10 km in urban environments, several kilometers outdoors in general conditions, and hundreds of meters indoors [42], [45], [49], [50], [51], [52]. Coverage can be further extended with the use of range extenders.

To comply with regulations governing unlicensed frequency bands, such as the ISM band at 868 MHz in Europe, LoRaWAN devices must adhere to power limits [1], [45]. The maximum transmission power is restricted to 14 dBm, often regulated through mechanisms like listen-before-talk (LBT) or duty-cycled operations, which help ensure fair usage of the medium. For medium access, LoRaWAN typically uses the Additive Links On-line Hawaii Area (ALOHA) protocol, which imposes a standard duty cycle limit of 1%. This duty cycle limit can vary depending on the specific channel and region [53].

LoRaWAN Network Architecture: The network architecture of LoRaWAN technology and a sample implementation is shown in Fig. 2. It comprises three main components: end devices (mobile or stationary), base station gateways, and a LoRaWAN server. The gateways function similarly to base stations in cellular networks, monitoring all channels and spreading factors (SFs) simultaneously. They forward uplink packet messages to the network server (NS) and manage downlink messages. The maximum size of LoRaWAN messages depends on the data rate and regional

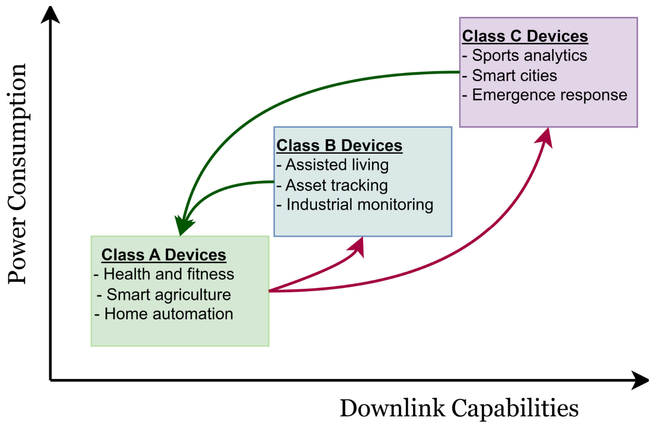

FIGURE 3. LoRaWAN Device Classes: Class A (minimal power), Class B (scheduled downlink), and Class C (continuous downlink) for varied IoT applications.

parameters, typically ranging from 51 to 222 bytes for uplink and slightly less for downlink [8]. Gateways receive LoRa-modulated signals via their antennas and connect to the Internet through options such as Wi-Fi, 4G, 5G, Ethernet, and LTE-M. The network server (NS) within the LoRaWAN server manages network activities and routes data to one or more application servers (AS) for end-user access. The LoRaWAN server can operate as a public, private, or hybrid network.

The LoRaWAN specification does not define the backbone network's implementation or the methods for extracting data from the application server. IP-based wired networks and message-oriented middleware, such as Message Queuing Telemetry Transport (MQTT) and HyperText Transfer Protocol (HTTP), are commonly used to connect end-user applications [54]. This flexible architecture allows for separate ownership of devices, infrastructure, and data, enabling innovative services and business models.

LoRaWAN Security: LoRaWAN supports robust security mechanisms, including AES-128 encryption and message integrity checks, to facilitate secure private networks. For device authentication and registration, LoRaWAN offers two methods: over-the-air activation (OTAA) and activation by personalization (ABP) [1]. The Network Session Key (NwkSKey), managed by the network server (NS), ensures data integrity. On the other hand, the Application Session Key (AppSKey), managed by the application server (AS), encrypts data for each session.

End Device Classes: LoRaWAN end devices can be configured to meet specific power and operational requirements, starting with Class A. In this mode, an end device transmits uplink messages, followed by two short receive windows for downlink messages. This setup minimizes power consumption but leads to higher latency. Fig. 3 illustrates the additional standards, Class B and Class C, which offer enhanced downlink coordination and continuous listening capabilities, respectively. However, they require more power. Class B devices feature scheduled receive windows for downlink messages, whereas Class C devices have continuous receive windows, providing the lowest latency. While Class A devices can switch in either Class B or Class C modes as needed, Class B and Class C devices are not interchangeable due to distinct differences in their operational protocols [24]. This flexibility is crucial for adjusting device behavior to specific network conditions and application needs.

LoRaWAN technology's classification system and efficient network management make it ideal for various IoT applications, including HAR. Each LoRaWAN device class is tailored to specific application needs. For example, Class A devices, which periodically transmit data, are suited for health and fitness tracking by monitoring users' physical activities over time. Class B devices, with scheduled receive windows, are well-suited for continuous monitoring of elderly individuals, enabling the detection of falls or irregular movements to enhance safety in assisted living environments. Class C devices, offering continuous receive windows, are optimal for real-time monitoring of athletes during training or competitions, allowing for precise activity recognition and performance analysis.

2) HUMAN ACTIVITY RECOGNITION

HAR involves the identification and analysis of human movements using various sensing technologies. Typically, HAR systems utilize wearable sensors like accelerometers, gyroscopes, and magnetometers to monitor a range of activities, from basic motions such as walking or sitting to more complex behaviors like exercising or working [55], [56]. The main objective is to translate raw sensor data into meaningful insights for applications in healthcare, sports, surveillance, and ambient assisted living [57], [58], [59], [60].

Recent advancements in machine learning (ML) have significantly enhanced the accuracy and real-time capabilities of HAR systems [61]. In addition to traditional inertial measurement units (IMUs), advanced HAR systems are capable of integrating a more comprehensive array of sensors. Pressure sensors offer insights into weight distribution [62], infrared sensors enable non-contact motion tracking, and environmental sensors provide context by monitoring factors like temperature and lighting [63], [64]. Furthermore, biochemical sensors, which assess physiological parameters such as sweat composition, and Global Positioning System (GPS) technology, essential for outdoor activity recognition, are becoming increasingly important [65].

To ensure effectiveness, HAR systems must accurately detect and evaluate human actions through advanced wearable sensors. The evolution of wearable technology, often termed Wearable 2.0, has introduced smart clothing embedded with a variety of sensors, such as electrocardiogram (ECG) sensors for monitoring heart activity, electromyography (EMG) sensors for muscle activity, and photoplethysmography (PPG) sensors for blood flow detection [66]. These sensors are increasingly integrated with cloud-based intelligence to provide continuous, real-time health monitoring and analysis. This integration allows for more comprehensive data collection and analysis, enabling early detection of health issues and personalized feedback [67]. Additionally, current designs for wearable sensors prioritize stretchability and adaptability to conform to the body's movements, enhancing user comfort and data accuracy. Such advancements are crucial for improving the reliability and applicability of HAR systems in healthcare, fitness, and beyond [68].

HAR systems are primarily categorized into sensor-based and video-based approaches [69]. This paper concentrates on sensor-based HAR, which mainly relies on data from IMUs typically embedded in wearable devices and smartphones [70], [71], [72]. These systems are versatile, widely applicable, and remarkably effective in monitoring health and lifestyle activities. In contrast, video-based HAR, which utilizes cameras to capture and analyze motion, is often constrained to specific environments.

3) LORAWAN-INTEGRATED WEARABLE SENSORS FOR HAR SYSTEMS

Sensor-based modalities for HAR systems are classified into three main categories: ambient, object, and body-worn sensors [73]. Some HAR techniques are specific to a sensor type, while others use hybrid systems that combine different sensors for greater accuracy and reliability [74]. This section outlines these sensor categories and their applications and highlights recent works that integrate LoRaWAN with each sensor type for improved HAR performance.

Ambient Sensors: These sensors detect environmental changes, such as temperature, pressure, sound, and motion, to infer human activity indirectly rather than directly measuring it [58]. Recent advancements, like the work by [75], have successfully integrated these sensors with LoRaWAN technology. This integration not only improves data transmission reliability but also extends the operational range of HAR systems. Many HAR projects have employed ambient sensors in ambient-assisted living applications [76], [77], [78], [79], [80].

Object Sensors: Object sensors are typically mounted on items to track their movement, such as Radio-Frequency Identification (RFID) tags, to facilitate activity recognition [81], [82], [83]. Unlike body-worn sensors, object sensors are designed to monitor the movement of specific objects, offering insights into human activities. For example, an intelligent door can use an accelerometer to detect whether it is open or closed. These sensors have been employed in various applications, including healthcare, physical activity detection [84], and smart home automation. Although they are less commonly used than body-worn sensors due to deployment challenges [58], combining object sensors with other types is increasingly popular for detecting a broader range of activities. In HAR, object sensors integrated with LoRaWAN systems have been applied to scenarios such as emergency and fall detection systems for healthcare monitoring [85], [86].

Body-Worn Sensors: Body-worn sensors, such as accelerometers, magnetometers, and gyroscopes, are typically worn or embedded in portable devices like smartphones, watches, bands, glasses, or helmets. These sensors capture data, specifically acceleration and angular velocity, that vary with respect to human body movements and activity. Analyzing captured data facilitates the detection and classification of various human activities. In previous research, an LPWAN-based wrist-worn end device embedded with an accelerometer and gyroscope sensors was developed to identify and categorize activities of daily living accurately (ADL) [87]. This technology demonstrated high accuracy, proving effective in recognizing everyday tasks. Other studies have also shown that body-worn sensors are increasingly prevalent in LoRaWAN-based HAR systems [35], [88], [89], [90], [91].

Hybrid Sensors: Hybrid sensors combine multiple sensor modalities to improve data accuracy and reliability in HAR systems [74]. By integrating various sensors such as temperature, pressure, motion, and light sensors, hybrid systems provide a more comprehensive understanding of environments and related human activities. This multifaceted data collection is instrumental in complex applications like environmental monitoring, healthcare, and industrial automation, where a single sensor type may only capture some relevant features. For example, in remote healthcare monitoring, a multi-modal sensor system that tracks glucose levels, ECGs, body temperature, and environmental factors like air quality, humidity, and temperature was found to improve illness diagnosis accuracy [92]. Another example is the HuMAn system, which integrates LPWAN with multiple body-worn sensors, such as accelerometers and gyroscopes, placed at different positions on the body to recognize 21 complex daily activities at home [93]. This system improves activity classification by incorporating context awareness from Bluetooth beacons for location and environmental sensors like humidity and temperature for room-specific contexts.

Table 3 illustrates how integrating LoRaWAN technology with various sensor modalities can overcome inherent limitations, thereby enhancing their performance in HAR systems. For instance, ambient sensors often face challenges due to environmental variability, but LoRaWAN's reliable signal penetration improves data consistency. Similarly, body-worn sensors benefit from LoRaWAN's low power consumption, which extends battery life and enhances user comfort by reducing the need for frequent recharging.

In HAR using wearable sensors, the interaction between the number of sensors, n, and the identification of a defined set of activities is vital. A set of activities A is given by:

$$A = \{a_1, a_2, \ldots, a_k\}, \tag{1}$$

where k is the number of activity types. For a sequence s of deployed sensors:

$$s = \{s_1, s_2, \ldots, s_n\}, \tag{2}$$

TABLE 3. Assessing sensor modalities in LoRaWAN-integrated HAR systems: Limitations and LoRaWAN's enhancement potentials.

Sensor Modality	Categorical Drawbacks	LoRaWAN Technology Potentials
Ambient sensors	• Sensitive to environmental variability • Complex deployment requirements	• Improved reliability through signal penetration • Cost-effective deployment • Enhanced accuracy with location-specific data
Object sensors	• Limited flexibility due to fixed locations • Less effective in dynamic environments	• Expanded connectivity over wide areas • Increased flexibility in sensor placement • Scalable networks with low power consumption
Body-worn sensors	• User discomfort during prolonged use • Frequent need for recharging	• Extended battery life with low power consumption • Secure data transmission with AES-128 encryption • Improved usability for continuous monitoring
Hybrid sensors	• Complex deployment and maintenance • Potential high power consumption	• Simplified integration of multiple sensor types • Energy efficiency reduces consumption • Robust connectivity with deep signal penetration

where n denotes the number of wearable sensors, each capturing different aspects of movement or physiological signals. A model function f maps multidimensional sensor data to the identified activity, determining the value of n.

The choice and configuration of sensors depend on the complexity of the HAR task, which determines the required number and types of sensors [94], [95]. Simple activities, like walking, may require fewer sensors, whereas complex activities, such as sports or dance, might need a more extensive sensor array to capture detailed movements. In HAR systems, ML methods, including classifiers and neural networks, are often used to learn the mapping function f from varied sensor inputs, allowing the system to recognize and classify a wide range of activities. However, extensive exploration in this area is beyond the scope of our research.

III. RESEARCH METHODOLOGY

A. REVIEW PROCESS

To understand LoRaWAN integration with HAR wearable sensor systems, we conducted a review using the 27-item PRISMA method. Our search included databases such as Google Scholar, Science Direct, SpringerLink, IEEE Xplore, MDPI, and Web of Science. The search employed keywords like ('LoRa' OR 'LoRaWAN'), ('wearable sensor network' OR 'wearable device' OR 'remote monitoring' OR 'wireless body area network'), and ('human activity recognition' OR 'motion tracking' OR 'physical activity recognition' OR 'activity detection' OR 'gesture recognition' OR 'posture recognition' OR 'context-aware sensing' OR 'wearable computing'). This search strategy initially yielded 147 papers focused on various aspects of HAR and LPWAN technologies, including LoRaWAN. In addition to the broader survey review, we identified 48 recent implementations related to LoRaWAN-integrated HAR systems.

B. SELECTION CRITERIA

From the 147 papers identified, we narrowed down to 8 key surveys that comprehensively covered the topic after excluding irrelevant titles, duplicates, and papers needing more technical depth. Similarly, from the 48 recent implementations of LoRaWAN-integrated HAR systems, we filtered out studies that were irrelevant, duplicates, or lacking in technical detail and focused on 15 systems that were most relevant to the current advancements in the field. We also engaged with authors to clarify points not explicitly detailed in their publications. This was essential, as many studies focused on specific topics, such as ML applications or general IoT solutions, without thoroughly addressing the technical specifications and architecture of LoRaWAN systems, which are central to our study.

C. RELATED SURVEYS

While HAR using wearable sensors has been extensively studied, there needs to be more literature on incorporating LoRaWAN technology in this field, as many evaluations overlook this integration. Some surveys focus on other LPWANs, such as comparing Sigfox and NB-IoT, but do not cover LoRaWAN for HAR specifically [3], [10], [96]. Other works review IoT-based wearables for health and smart cities, mentioning LPWANs generally but not focusing on LoRaWAN's use in HAR [97], [98], [99], [101]. Additionally, some studies discuss sensor modalities for HAR but omit remote monitoring via LPWANs like LoRaWAN [58]. Table 4 presents a focused examination of the most relevant surveys, addressing their notable limitations and providing insights into how these challenges have been managed or mitigated in our review.

This chapter reviews the most relevant surveys on HAR and wireless communication networks that connect end devices to gateways and servers. These surveys contribute to HAR research by addressing challenges such as accuracy, reliability, scalability, and applicability. However, a key *research gap* remains regarding the use of LoRaWAN technology in HAR systems, which is often overlooked. While

TABLE 4. Overview and critical analysis of surveys on wearable HAR systems: Comparative insights on IoT protocols, sensor modalities, and LPWAN/LoRaWAN integration challenges and opportunities.

Survey	Brief Description	Critique
[3]	The survey outlines the evolution, current state-of-the-art architecture, and challenges impeding the adoption/ utilization of wearables technology. It also compares the suitability of Near Field Communication (NFC), Bluetooth, Wi-Fi, ZigBee, Cellular IoT Networks(CIoT), and LPWAN protocols in wearables utilized in wearables applications.	While the survey offers a brief comparison of deployment topologies, operational frequency bands, ranges, data rates, and power profiles, it lacks in-depth analysis, particularly on the specific utilization and benefits of LPWANs such as LoRaWAN in wearable technology.
[10]	The survey investigates the use of LPWAN technologies in Wireless Body Area Networks (WBANs), comparing LoRaWAN, Sigfox, LTE-M, EC-GSM, NB-IoT, and Ingenu-RPMA based on range, data rate, latency, privacy/security, affordability, scalability, and power consumption.	The survey suggests LoRaWAN's superiority in WBANs but lacks depth in evaluating its practical deployment, limitations, and recent advancements. The analysis is already outdated and insufficiently detailed, overlooking newer developments and challenges in LoRaWAN integration for WBANs.
[58]	The survey reviews traditional methods for HAR and examines the impact of deep learning on feature extraction, performance optimization, and the versatility of wearable sensor-based HAR systems. It also identifies future research challenges for advancing HAR.	The research identifies challenges that future scholars should focus research on to usher further advancements in HAR. However, it does not explore the role and potential significance of utilizing LPWAN technologies in HAR systems.
[96]	The study explores the evolution of LPWAN and Tiny Machine Learning (TinyML) concerning applicability to wearable devices. The findings reveal that LPWAN protocols enhance the connectivity of end devices while TinyML enables distributed intelligence data processing mechanisms.	The survey is limited because it fails to adequately explore the applicability, optimizable features, integration/ deployment challenges, and feasible opportunities for addressing potential barriers against LoRaWAN-based wearable HAR systems.
[97]	The paper studies advancements in the integration of wearables and IoT networks. It identifies the key barriers against wearable IoT as end-device wearability, data resolution, power consumption, safety, and security.	The work only compares the suitability of cellular-based IoT networks (LTE-M and NB-IoT). Thus, the survey is limited since it does not explore the role and significance of other LPWAN networks, such as LoRaWAN, in wearable technology.
[98]	The survey examines sensor modalities, data processing techniques, and wireless communication networks in IoT-based wearable technology. It also discusses challenges hindering the widespread adoption of wearables across healthcare, safety, sports, and tracking/localization applications.	While the survey covers various aspects of IoT-based wearables, it lacks a detailed analysis of how LoRaWAN parameters, such as SF and CR, can be fine-tuned to enhance performance, missing a crucial area for optimization in wearable applications.
[99]	The survey reviews advanced IoT sensor technologies and machine-to-machine (M2M) wireless communication networks, such as Wi-Fi, Bluetooth, and RFID, and discusses the challenges of IoT-based activity recognition in smart home environments.	The survey highlights the limitations of Bluetooth and Wi-Fi networks for wearable IoT-based HAR, such as short-range coverage and limited scalability. However, it does not explore how newer LPWAN technologies like LoRaWAN could provide solutions to these challenges.
[100]	The study assesses the potential of combining LoRa wireless RF signal preprocessing with deep learning models to enhance the accuracy of HAR systems. It notes the limitations of LoRa-based HAR, such as Doppler sensitivity, localization precision, and signal penetration, and contrasts these with the range and robustness limitations of RF-based HAR.	The article focuses primarily on deep learning preprocessing for LoRa-based HAR systems, overlooking how other key parameters like SF and CR can be adjusted to improve sensitivity, accuracy, and reliability. A broader exploration of these parameters is needed for a more comprehensive understanding.
This Work	This comprehensive survey focuses on LoRaWAN-based wearable HAR systems. It provides an extensive discussion of the latest state-of-the-art LoRaWAN protocols and examines their applicability across various sensor modalities in wearable HAR technologies. The survey also identifies key challenges in integrating LoRaWAN into wearable HAR systems and analyzes how tuning LoRaWAN parameters can address these challenges, offering insights for optimizing performance and reliability in diverse HAR applications.	The survey effectively fills critical gaps in the existing literature by providing a focused and thorough analysis of LoRaWAN within wearable HAR systems. Unlike prior surveys, it delivers a detailed exploration of the latest protocols and their adaptability to different sensor types, alongside a strategic discussion on overcoming integration challenges. Its emphasis on parameter optimization to enhance performance in specific HAR contexts is particularly valuable, making this work a significant contribution that informs future research and development in LoRaWAN-based HAR systems.

some studies examine LPWANs like Sigfox and NB-IoT, they do not provide a detailed analysis of LoRaWAN's role in wearable HAR. This review aims to fill this gap by offering a comprehensive analysis of LoRaWAN's potential to enhance the efficiency and reliability of HAR technologies.

TABLE 5. A summary of technical design and operations in the recent implementations of LoRaWAN-based HAR systems.

Ref.	Human Activities	Sensor Modality	Hardware Size (mm)	Sensors Deployed	Power Source	Sampling Frequency	Data Processing	
							Edge	Remote
[96]	Not Provided	Body-worn	D = 5	A, G	2000mAh Powerbank	Not Given	✓	
[85]	Fall detection	Object	138.3 × 67.1 × 7.1	IMU	Phone battery 1960 mAh	32		✓
[86]	Gestures, ADL	Body-worn	38 × 30	P	Small Powerbank	50	✓	
[88]	Safety and health	Hybrid	Safe Node: 35 × 35 × 4	EPs	3.6 V battery	Not Given		✓
			Health Node: D = 40	PPG, T	120 mAh battery			
[89]	ADL	Body-worn		A	3.3 V source	Not Given		✓
[90]	ADL (5)	Body-worn	11 × 70 × 36	A, G, M	3.3 V source	25	✓	✓
[91]	Man-down	Hybrid	55 × 20 × 3.5	A, EPs	800 mAh battery	Not Given	✓	
[35]	Fall-detection	Hybrid	Not Provided	A, M, EPs	Not Given	Not Given	✓	
[106]	Fall-detection, health	Hybrid	Not Provided	A, M, G, EEG, ECG, EMG, BP, EPs	3.3 V source	Not Given	✓	✓
[102]	Fall and recovery	Body-worn	51 × 23 × 8	A, F	3.3 V source	Not Given	✓	
[75]	ADL, localization	Hybrid	64 × 44 × 25	A, IR, EPs	2000 mAh battery	10		✓
[46]	Localization	Hybrid	Not Provided	A, UWB, GNSS	Powerbank	Not Given		✓
[12]	Falls, ADL	Body-worn	36 × 26 × 10	A	LiPo battery	20	✓	
[107]	ADL	Body-worn	Not Provided	A, G	Li-ion battery	Not Given		✓
[103]	Localization	Body-worn	Not Provided	A, M, GPS	220 mAh battery	Not Given		✓

A = Accelerometer, M = Magnetometer, G = Gyroscope, P = Pressure sensor, IMU = Inertia Measurement Unit, PPG = Photoplethysmograph, ECG = Electrocardiograph, EEG = Electroencephalograph, EMG = Electromyograph, IR = Infrared Sensor, EP = Environmental Parameter Sensor, T = Temperature, UWB = Ultra-Wideband sensor.

IV. RESEARCH AND RECENT ADVANCES IN LORAWAN-INTEGRATED HAR SYSTEMS

A. LORAWAN-INTEGRATED HAR SYSTEMS

This section explores recent research and advancements in LoRaWAN-integrated HAR systems. Table 5 provides an overview of recent implementations of LoRaWAN-integrated HAR systems, detailing the monitored activities, sensor types, hardware specifications, power sources, and data processing methods. It includes applications such as fall detection, ADL monitoring, and localization, demonstrating the variety of sensor configurations and energy sources utilized.

1) BODY-WORN LORAWAN-INTEGRATED HAR SYSTEMS

In [96], a LoRaWAN-integrated wearable sensor node was evaluated in two key areas: connectivity and the integration of TinyML models into the wearable device. This device, equipped with an Arduino Uno microcontroller, GPS, LoRaWAN module (RN2483) with a 2dBi antenna, and MPU6050 accelerometer and gyroscope sensors, tested communication via virtual serial ports and was powered by a 2000 mAh power bank. The TinyML models, including random forest (RF) and multi-layer perceptron (MLP) models generated with Scikit-learn and converted to C using emlearn, were integrated to assess the complexity of algorithms operable on the wearable unit.

The LPWAN communications, tested on a university campus, showed strong indoor and outdoor connectivity, though some coverage issues occurred due to obstacles like vegetation and buildings. The study highlights LoRaWAN's reliable connectivity for wearable devices in varied environments and demonstrates TinyML's potential to enhance capabilities beyond basic monitoring. However, the limitations in model accuracy and performance for specific tasks were not evaluated.

A wearable emergency system was developed using a regular shoe equipped with ML algorithms for foot gesture recognition [86]. The prototype integrates two force sensors positioned at the toe and heel, connected to an ESP32 microcontroller and an RFM95 LoRa module, which facilitates long-range communication. With a helical antenna, the system can transmit alerts over distances of up to 600 meters, making it adaptable to various environments.

This setup, powered by a small battery, achieves nearly 98% accuracy in detecting specific foot movements, such as double taps at the toe or heel, during activities like walking and running.

The study goes beyond a simple technical overview to demonstrate the effectiveness of integrating ML into wearable devices for emergency scenarios. It illustrates how these systems can function independently and reliably across different environments. The approach of using simple, off-the-shelf components suggests that such wearable systems could be quickly adopted, turning everyday items into critical tools for emergency response combining discretion with functionality.

In Japan, a study explored HAR using LoRaWAN technology with basic sensor components, developing a prototype featuring an Arduino microcontroller and accelerometers to collect movement data [89]. The collected data was wirelessly transmitted to a cloud platform via LoRaWAN, valued for its long-range and low-power capabilities. By analyzing features such as mean, variance, and magnitude, the researchers classified activities into running, standing still, and walking. The scholars compared the accuracy of two ML methods, k-Nearest Neighbour (kNN) and Linear Discriminant Analysis (LDA), in classifying human activities based on transmitted data from the sensor components. The kNN method achieved a higher accuracy of 80%, compared to 73.3% for LDA. This study marks one of the initial uses of LoRaWAN for HAR, demonstrating the feasibility of utilizing accessible technology for practical applications.

This work extends beyond the prototype, showcasing a trend towards affordable IoT solutions for activity monitoring, particularly in healthcare. It highlights the potential of integrating ML into cost-effective, low-maintenance systems, encouraging future research aimed at making activity recognition more accessible and practical. Such approaches align with the increasing demand for intelligent, connected environments that support safety and health monitoring through efficient and user-friendly solutions.

In [90], the researchers developed a wearable system for human posture detection (HPD) using LoRa technology, leveraging its long-range and low-power capabilities for smart city applications. The system comprises four modules: a posture sensor module with accelerometer, gyroscope, and magnetometer sensors integrated into clothing to collect posture data; a wireless transmission module using LoRa nodes and gateways for data transfer; a recognition module that pre-processes data, extracts key features with Random Forest, and reduces noise; and a user interface module that displays the results.

This study demonstrates the potential of integrating LoRa with multisensor data for effective posture detection, highlighting a shift towards accessible and autonomous health monitoring solutions in smart cities. The approach exemplifies how low-cost IoT technologies can enhance wearable systems, making them more practical for continuous monitoring across different environments.

The system presented in [102] integrates fall and recovery detection sensors into smart shoes, embedding three force sensors to assess weight distribution and a 3-axis accelerometer for measuring foot inclination. An Adafruit Feather M0 board, equipped with an RFM95 LoRa radio, facilitates the transmission of alerts to a network server via a custom Raspberry Pi gateway. LoRa technology enables long-range communication, which was enhanced through a preliminary radio coverage study conducted in Ancona, Italy, to map signal strength across different areas. Specific settings were applied for transmitting fall and recovery messages, with payload sizes of 14 and 18 bytes, respectively. The network server handles message storage, notifications, and the forwarding of alerts to caregivers.

The findings from this research highlight the practical application of LoRa for wearable fall detection, demonstrating how low-power, long-range communication can be seamlessly integrated into everyday items like shoes. By facilitating autonomous operation without dependency on smartphones or close-range devices, the study contributes to the development of more practical IoT solutions in health monitoring. This direction supports broader adoption in urban environments where reliability and user convenience are essential.

In [12], a wearable device was developed for monitoring the physical activity of older people, featuring an ATmega328P microcontroller, an LSM9DS1 accelerometer from STMicroelectronics for motion data collection, and an RN2483 LoRaWAN modem from Microchip for data transmission. The device is powered by a small LiPo battery that could last up to two days with continuous sampling and hourly data transmissions. Enclosed in a compact 3D-printed case, the wearable was designed to be unobtrusive and easily integrated into daily routines. The LoRaWAN settings were carefully tuned to optimize both transmission efficiency and energy consumption, ensuring reliable long-range communication.

This work showcases the feasibility of incorporating accessible components like the ATmega328P and LoRaWAN technology into health monitoring wearables. It reflects a shift toward developing scalable and low-maintenance systems that offer continuous support while remaining unobtrusive. By prioritizing minimalistic yet practical designs, the research suggests future health solutions that integrate smoothly into daily life, enhancing the autonomy and well-being of elderly individuals.

The energy-efficient LoRa GPS tracker for dementia patients in Hadwen et al. [103] is a wristband that includes an accelerometer and magnetometer for motion sensing, a microcontroller to manage operations, and a GPS module for location tracking, all powered by a compact battery. A LoRa module enables long-range data communication, allowing location updates to be sent over several kilometers. The device uses power-saving strategies to maximize battery life, including efficient GPS duty cycling and low-power operation modes for the sensors and communication modules.

This work highlights the trend of integrating energy-efficient, long-range communication in wearable devices for health monitoring. By combining compact sensors with LoRa technology, the study demonstrates the potential of developing discreet, reliable trackers that support continuous monitoring and improve patient safety in everyday settings.

2) HYBRID LORAWAN-INTEGRATED HAR SYSTEMS

In [46], a hybrid system was developed for tracking elderly individuals indoors and outdoors using LoRaWAN technology. The scholars proposed and tested a proof-of-concept that focused on indoor localization accuracy and communication latency. The system used motion sensors, Global Navigation Satellite System (GNSS) for outdoor tracking, and Ultra-Wideband (UWB) for precise indoor positioning, all managed by an Atmega328P microcontroller that sent localization data via LoRaWAN every minute. Tests conducted at the University of Brescia showed sub-meter accuracy indoors and low communication delays, demonstrating its suitability for applications like fall detection in elderly care.

This research exemplifies the integration of multiple localization technologies with LoRaWAN to develop a cohesive tracking solution for both indoor and outdoor environments. With the inclusion of an IMU, the system could be further enhanced to monitor movement patterns and detect falls. The findings point towards the development of comprehensive and adaptable monitoring systems that improve safety and autonomy for the elderly, addressing gaps in current assisted living technologies.

In their study [88], researchers developed a wearable sensor network aimed at enhancing safety in outdoor work environments. The system includes two key components: the Health Node [104], which monitors physiological metrics such as heart rate and body temperature using BLE within a body area network, and the Safe Node [105], which measures environmental factors like temperature, humidity, CO_2, and Ultraviolet (UV) levels. Data from both nodes is transmitted over long distances via LoRa technology to a gateway equipped with a Raspberry Pi. This gateway processes and stores the data, detects emergencies and connects to a cloud server using MQTT. The system also incorporates encryption for secure data transfer and provides a Web-based app for data visualization.

This study showcases an integrated IoT platform for simultaneous environmental and health monitoring, reflecting a shift towards all-encompassing safety solutions in workplace environments. By leveraging BLE for short-range communication and LoRa for long-range data transmission, the system optimizes power efficiency while ensuring reliable, real-time monitoring and improved safety management.

The authors of [91] developed a wearable emergency response system utilizing LoRa technology for regions lacking network coverage. The system includes smartwatches equipped with accelerometers, gyroscopes, and PPG sensors to detect health emergencies such as cardiac issues. When an emergency is detected, the smartwatch uses BLE to communicate with an IoT device composed of a Pytrack sensor shield (with GNSS GPS capabilities) and a LoPy 4 board with a LoRa transceiver. This configuration enables the device to broadcast GPS coordinates and alerts to other IoT devices and rescue centers via LoRa. The design emphasizes energy efficiency, allowing both the IoT device and smartwatches to operate for several hours on small batteries.

This research demonstrates the effective integration of wearable and IoT technologies to deliver reliable emergency monitoring in remote areas. It highlights the advancement of autonomous, low-power systems in health and safety contexts. By combining smartwatches, BLE, and LoRa, the system offers a robust solution for emergency response, reinforcing the crucial role of IoT in enhancing personal safety in challenging environments.

In [75], a LoRaWAN-based system was implemented to monitor activities and track the location of individuals with mild cognitive impairments (MCI). The system includes wireless wearable sensors (WWS) based on the RAK5205 board, featuring a three-axis accelerometer for activity tracking, an IR receiver for indoor localization, a GNSS module for outdoor positioning, and an environmental sensor. These components are managed by an ARM Cortex-M3 microcontroller powered by a 1000 mAh battery that lasts 24 hours. Additionally, room-level IR beacons using the ESP32-PICO-D4 SoC emit signals detected by the WWS to determine the user's location indoors. A Lorix-One LoRaWAN gateway relays data to the cloud for processing and visualization, with real-time alerts sent to caregivers via the Telegram app.

This system exemplifies the trend of integrating multiple sensory and localization technologies into a cohesive solution for monitoring vulnerable individuals. By combining long-range LoRaWAN communication with accurate indoor and outdoor tracking, the approach supports independent living. It also enhances caregiver support, reflecting the broader move towards comprehensive and adaptable IoT-based health monitoring solutions.

In [106], a health monitoring and fall detection system was developed using a multi-layer architecture to enhance healthcare, especially in remote areas. The system's sensor layer includes wearable devices with an MPU9250 accelerometer, gyroscope, and magnetometer to collect movement and orientation data. The smart edge gateway, built on a Raspberry Pi 3 with a LoRa shield, processes this data using a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) layers, which are designed to handle time-sequenced data effectively, improving the accuracy of fall detection. Data is transmitted in compact 10-byte packets to fog layer access points, which process and forward the information to cloud servers. The application layer provides real-time alerts to caregivers via a Web interface built with Django and Apache on CentOS.

This study highlights the effectiveness of RNNs with LSTM layers for processing time-dependent data locally,

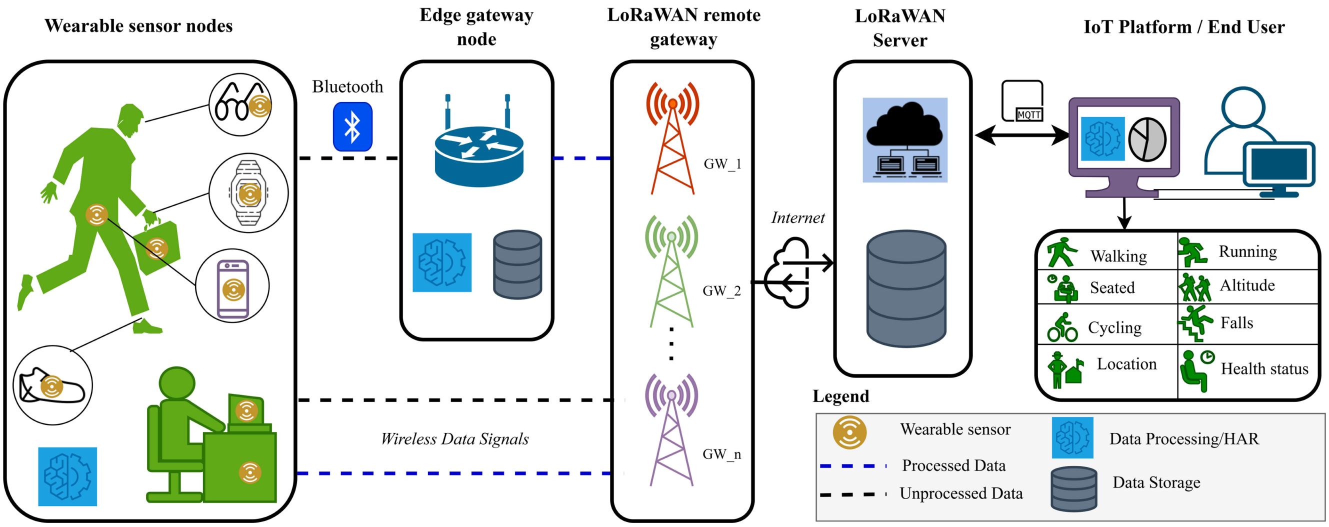

FIGURE 4. Illustration of a LoRaWAN-Integrated Human Activity Recognition (HAR) System: Wearable sensors collect activity data, which is transmitted via gateway(s) through the LoRaWAN technology network to servers and an IoT platform for processing and analysis.

enabling accurate real-time fall detection. By integrating edge and fog computing with LoRa technology, the system reduces dependence on constant cloud connectivity and delivers reliable health monitoring across broad areas. This approach reflects a growing trend towards decentralized, AI-powered healthcare solutions that can operate effectively in remote and underserved regions, enhancing support for both patients and caregivers.

In [107], a HAR system was developed using a wearable wristband powered by a lithium-ion battery. The device combines a sensor module with a gyroscope and accelerometer, integrated into an STM32 microcontroller, along with a LoRa module for wireless communication. A capsule framework was used to track activities like walking, sitting, and jogging, improving the accuracy of recognizing these movements to 95.2%. This method performed better than traditional models such as Convolutional Neural Networks (CNN) and LSTM networks, demonstrating its effectiveness in recognizing daily activities.

This work illustrates the advantage of capsule networks in wearable health monitoring, particularly for real-time activity recognition. By capturing spatial relationships between movements, the system enhances precision and reliability, offering a compelling alternative to conventional methods. This approach reflects a growing trend towards integrating advanced AI techniques with low-power communication technologies in wearables, making them more practical for everyday health and safety applications.

3) OBJECT-MOUNTED LORAWAN-INTEGRATED HAR SYSTEMS

In [85], researchers developed a system to detect falls on construction sites using CNNs with acceleration data collected from a smartphone's built-in sensors. The study aimed to address limitations in traditional methods, such as interference from wearable sensors and difficulties in handling undefined action classes. A 3-axis accelerometer from an iPhone-7 captured movement data from scaffolding, which was processed by a CNN algorithm to identify fall-related actions. The data was transmitted via Bluetooth to a server and then relayed using LoRa technology. Four distinct CNN architectures were proposed, focusing on identifying precursors to falls and effectively managing unseen action classes, achieving high recognition accuracy rates between 93-97%.

This study demonstrates the potential of using object-mounted, structure-based sensors combined with CNNs for real-time activity monitoring on construction sites. By leveraging the spatial patterns captured from scaffolding accelerations, the approach offers a non-invasive, privacy-conscious solution that surpasses traditional models in handling undefined classes. This reflects a broader trend towards using advanced AI techniques to enhance safety monitoring in challenging environments, providing more reliable and adaptable solutions for accident prevention.

B. ANALYSIS AND DISCUSSION

1) TYPICAL STATE-OF-THE-ART ARCHITECTURE OF LORAWAN-INTEGRATED HAR SYSTEMS

A typical state-of-the-art LoRaWAN-integrated HAR system architecture is illustrated in Fig. 4. Each segment of the architecture is discussed in detail below.

Sensor Modalities and Typical Sensors: The sensors are categorized as body-worn, object-based, and hybrid. No system deploying purely ambient sensors was found in the reviewed literature. However, a typical application in a hybrid sensor system was found. A summary of the rest of the sensor modalities is presented in Table 5. Body-worn wearables incorporating IMU sensors such as accelerometers have been used in [12], [89], [90], [102], [103], [107] to acquire movement data for HAR. Others include the gyroscopes and magnetometers. Also, force sensors [86], [102] have

TABLE 6. A summary of LoRaWAN transmission parameters.

Parameter	Value	References
Spreading Factor	7	[12], [46], [89], [102]
	10	[75]
	12	[35], [87], [96], [102]
Bandwidth	125kHz	[35], [75], [89]
	250kHz	[87]
Coding Rate	4/5	[12], [75], [87], [89], [96]

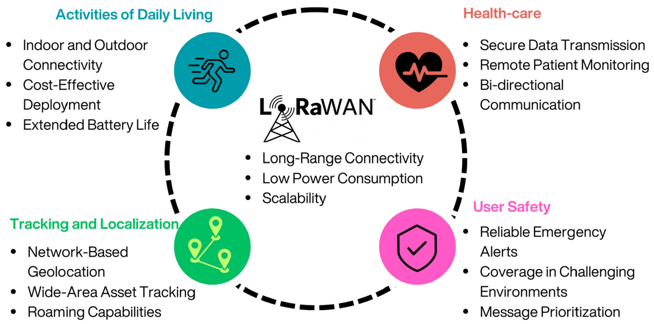

FIGURE 5. Key applications of LoRaWAN-Integrated HAR systems, linked to the main benefits of LoRaWAN as discussed in the literature.

been used for recognition of ADL and gestures, as well as for fall and recovery in LoRaWAN-integrated systems for HAR. Object sensors, making use of an IMU integrated into devices like a smartphone [85], monitoring interactions and usage patterns, have been used for fall detection. Ambient sensors, placed in the environment, assess conditions like IR emissions [75], light, temperature, or movement, contributing to contextual data. Hybrid sensors combine all these aspects, offering a comprehensive overview by correlating data from multiple sources. These include health information from sensors such as PPGs, as in [88] and EEG, ECG, EMG, and BP in the system of [106] to enhance accuracy in activity recognition by primary sensors and health monitoring with applications ranging from fall detection to general health monitoring.

LoRaWAN Transmission Parameters: In most LoRaWAN-integrated HAR systems, the selection parameters like SF, CR, and BW are pivotal. SF can range from 7 to 12, with higher values increasing the range and decreasing the data rate. A summary of the choice of these parameters is presented in Table 6. A CR option of 4/5 in the vast majority of the reviewed systems is deployed to enhance data integrity, which is vital for accurate health data for users. Also, CR is often set to 4/5 for a balance between error correction and payload size. Equally, the BW typically varies from 125 kHz to 500 kHz, affecting data throughput and power usage.

Common combinations for LoRaWAN-integrated HAR systems include SF7/BW125kHz [88], for high data rate and low power consumption in urban settings; SF10/BW125kHz [75], suitable for balanced performance in semi-urban or suburban areas where a compromise between data rate and range is required; and SF12/BW125kHz [91], for long-range rural monitoring with lower data rates. These selections cater to specific deployment scenarios. For instance, a high SF and a low BW for extended coverage in remote activity monitoring versus a lower SF and a higher BW for dense urban environments where higher data throughput and reduced latency are needed.

The payload transmission intervals range from one second [85], [89] for real-time health alerts to one hour [46], [88] for long-term monitoring. For event-triggered options, implementations were done in [86], [91], [102], [106] for specific condition applications. Shorter intervals are critical for immediate response in high-risk scenarios but consume more power and bandwidth, while longer intervals conserve energy and are ideal for non-urgent data. Event-triggered transmissions ensure efficiency by sending data only when necessary. The choice of interval balances the need for timely information with network and energy constraints, tailoring the system to the specific requirements of the application.

Data Handling: In LoRaWAN-integrated wearable HAR systems, processing can be performed at the end device [106] for real-time applications like emergency fall detection, requiring immediate local response. In this case, sampling rates like 20 Hz [12] up to 50 Hz [86] are used for acute data analysis. For less time-sensitive applications, such as daily activity monitoring, data can be processed after transmission, necessitating lower sampling rates such as 10 Hz [75] to conserve energy and bandwidth. This strategy balances the need for detailed data with the limitations of power and network capacity.

LoRaWAN Range of Communication: From the reviewed wearable HAR systems integrated with LoRaWAN technology, a significant variation in communication ranges has been documented. Researchers have observed that these systems can maintain connectivity over distances ranging from several meters [81], [85], [88], [107] to several kilometers in the range of 4 km [102]. This disparity in range is believed to be influenced by several factors, including the experimental test environment, such as urban or rural areas. Generally, the presence of physical barriers such as buildings and trees and specific LoRaWAN configurations like frequency, bandwidth, and power settings also play a key role. Researchers have noted that LoRaWAN-equipped wearable HAR systems have the potential to meet a variety of requirements in wearable HAR system deployments, as compared to other technologies.

2) MAJOR APPLICATIONS

The categorization of applications shown in Fig. 5 reflects the mostly implemented LoRaWAN-integrated HAR systems as observed in recent studies. Some systems focused on ADL alone, while others used ADL data in healthcare or safety applications. Although ADL can cut across categories, the classification is based on the primary focus of each system's

TABLE 7. Principal justifications for choosing LoRaWAN in the specific application areas of HAR systems over other LPWANs (Sigfox, Ingenu-RPMA, LTE-M, and NB-IoT) as identified from the reviewed literature.

Application Area	Principal Justifications for Deploying LoRaWAN over Other LPWANs
Activities of Daily Living	• Exceptional energy efficiency for long-term monitoring; • Scalability for widespread deployment.
Healthcare	• Adequate data rates for real-time vital signs monitoring; • Flexible network architecture for secure, private networks.
Safety	• Robust communication with adaptive data rates for reliable safety alerts; • Interoperability with existing devices due to open standard.
Tracking and Localization	• Superior coverage in both indoor and outdoor environments; • Network-based geolocation without GPS, reducing power consumption and costs.

implementation, demonstrating the versatility of LoRaWAN in various contexts as justified in Table 7.

ADL: LoRaWAN-integrated wearables, equipped with sensors like accelerometers, magnetometers, and gyroscopes, are widely used for monitoring ADL [86], [89], [90]. These wearables capture movement data essential for recognizing activities such as walking, running, climbing stairs, and sitting. LoRaWAN's energy efficiency extends the end device's lifespan, supporting reliable long-term monitoring across various settings. Its wide coverage and cost-effectiveness make it scalable for extended monitoring in elderly care and lifestyle applications. Moreover, LoRaWAN enables efficient, long-range data transmission, making it ideal for remote monitoring applications in personalized healthcare, elderly care, and lifestyle management. By using ML algorithms, the collected data is analyzed to classify activities and provide insights into the wearer's physical well-being, facilitating timely health interventions. Recent advancements have extended the application of these systems across diverse remote settings.

Healthcare: In healthcare, LoRaWAN-integrated HAR systems utilize various sensors to enhance patient monitoring and care. These include bio-potential sensors like EEG, ECG, and EMG for vital signs and environmental sensors to detect conditions that could affect health. IMU sensors also track physical activity, providing comprehensive health monitoring [106]. Additional biomedical sensors, such as photoplethysmographs (PPG) [88] and blood pressure monitors, are often incorporated. LoRaWAN's real-time monitoring capabilities enable swift responses to health emergencies. Its scalability supports a broad range of healthcare devices, and reliable communication enhances safety protocols in remote monitoring scenarios. This timely transmission of data collected via multiple sensor modalities to healthcare providers facilitates early diagnosis and intervention in patient care.

Safety: LoRaWAN-integrated HAR systems significantly contribute to safety, particularly in fall detection and environmental monitoring. These systems utilize inertial and force sensors to detect falls, especially among the elderly, by analyzing factors like body posture, speed, and angular velocity [91]. Advanced algorithms, including threshold-based methods and ML models such as CNN [85], enhance detection accuracy and reduce false positives. LoRaWAN's robust communication ensures accurate fall detection and environmental monitoring. Its open standard promotes interoperability among safety devices, improving accessibility and affordability of comprehensive safety solutions. Additionally, wearables equipped with environmental sensors monitor conditions such as temperature, humidity, and CO_2 levels, providing alerts to hazardous situations through LoRaWAN transmission [35], [88]. These systems play a crucial role in mitigating risks and enhancing personal and public safety across various environments.

Tracking and Localization: For tracking and localization, LoRaWAN-integrated HAR systems employ a range of sensors and technologies to determine the position and movements of users. GPS [103] and GNSS [46] are commonly used for outdoor tracking, while infrared (IR) [75] and ultra-wideband (UWB) [46] technologies are employed indoors. LoRaWAN's robust infrastructure supports accurate tracking and localization without compromising performance. Its extensive coverage and cost-effective implementation foster widespread deployment, enhancing safety and security in various settings. These systems monitor a broad spectrum of activities, from routine movements to specific tasks, providing accurate location data that is crucial for applications such as personal fitness, sports analytics, and the monitoring of vulnerable individuals like the elderly or those with cognitive impairments.

V. COMMON CHALLENGES AND FUTURE RESEARCH DIRECTIONS

This section examines the key challenges of integrating LoRaWAN in wearable sensor networks for HAR, as highlighted in recent studies. These include device wearability, energy management, data security, and network coverage, as well as providing a detailed analysis, proposed solutions, and future research directions. The insights aim to advance the design and optimization of next-generation wearable systems for enhanced functionality and user experience.

A. END DEVICES' WEARABILITY

Improving wearability is a priority for LoRaWAN-integrated wearable sensor networks in remote HAR. The goal is to design lightweight, comfortable, and unobtrusive devices, allowing for long-term use without discomfort. Advances in material science have enabled the creation of flexible, breathable fabrics with embedded sensors, enhancing user comfort [108]. Most reviewed systems (93%) are body-worn, reflecting a preference for this approach despite available alternatives.

However, challenges persist as many devices remain bulky and intrusive, with sizes ranging from 36 mm × 26 mm × 10 mm [12] to 138.3 mm × 67.1 mm × 7.1 mm [85]. Achieving a balance among comfort, aesthetics, and sensor performance without compromising usability is still a significant design challenge [109].

Future research should focus on further miniaturization, innovative materials, and integrating sensors into everyday items like clothing or accessories [110]. A helpful approach could be to develop a wearability score W, defined by:

$$W = \frac{1}{1 + e^{-a(s-t)}}, \tag{3}$$

where s is the device size, a is the adaptability factor (how well the device can be modified for comfort), and t is the target comfort threshold size. This formula provides a wearability score between 0 and 1, helping designers balance miniaturization with comfort to guide the creation of next-generation wearables.

Furthermore, exploring non-body-worn (object-mounted) sensors could broaden the application and enhance the accuracy of HAR systems, offering a more comprehensive understanding of user activities. Future advancements should optimize these integrations to meet user expectations for functionality and comfort.

B. ENERGY CONSUMPTION AND MANAGEMENT

Recent advancements in LoRaWAN sensor networks for HAR have targeted energy efficiency, primarily through low-power algorithms that reduce consumption during data processing and transmission [111]. These improvements aim to extend battery life, allowing devices to operate longer without frequent recharging.

Energy consumption, however, remains a key challenge due to the continuous operation of sensors and frequent data transmissions needed for accurate HAR. Integrating technologies like Bluetooth [35], [85], [106] further increases power demands because of added hardware and communication exchanges. Current battery and energy harvesting technologies still need to be improved for sustained operation, with only 7% of systems reviewed employing harvesting methods.

Future efforts should focus on advanced energy harvesting techniques, such as utilizing solar, thermal, or kinetic energy [112], [113] alongside efficient power management algorithms that adjust sensor activities based on context [114], such as adaptive sampling rates, to significantly improve battery longevity. As food for thought, for instance, power consumed during data transmission, P_{tx}, and processing, P_{proc}, can be modeled as:

$$P_{tx} = P_{idle} + \Delta P \cdot t_{tx} \tag{4}$$

and

$$P_{proc} = P_{idle} + \Delta P_{proc} \cdot t_{proc}. \tag{5}$$

P_{idle} is the power consumption in idle mode, ΔP and ΔP_{proc} represent the incremental power used during transmission and processing, while t_{tx} and t_{proc} are the durations of transmission and processing, respectively. To minimize energy consumption, an objective function can be constructed to find the optimal balance between transmission frequency and power used during idle and active states [115], [116]. The optimization problem can be stated as:

$$\min_{t_{tx}, t_{proc}} E\left(t_{tx}, t_{proc}\right) = \min_{t_{tx}, t_{proc}} \left(P_{tx} \cdot t_{tx} + P_{proc} \cdot t_{proc}\right), \tag{6}$$

subject to constraints on data integrity and system performance. The solution to this problem will dictate the optimal intervals for data transmission and the best strategies for processing, balancing energy efficiency with operational requirements.

C. PAYLOAD SIZE, DATA RATE, AND ADAPTIVE DATA RATE (ADR)

LoRaWAN offers valuable capabilities for IoT, but its limited bandwidth creates challenges, especially with payload size, data rate, and transmission delays, impacting wearable systems for remote HAR [117]. Optimizing the interaction between payload size, data rate, and ADR is essential to improve data transmission in constrained settings [116].

LoRaWAN payloads range from 51 to 242 bytes [47], requiring efficient encoding to maximize the information content. We introduce the concept of information density, $\delta(p)$:

$$\delta(p) = \frac{H(p)}{p}, \tag{7}$$

where $H(p)$ is the Shannon entropy of payload p, representing the average information per byte. Future work should focus on maximizing $\delta(p)$ with advanced encoding methods that increase informational value. Additionally, using algorithms that handle compressed or reduced datasets can make better use of limited payloads [118], ensuring key data is transmitted effectively.

LoRaWAN's data rates from 0.3 to 27 kbps limit data transfer capacity [119], posing challenges for HAR applications that need frequent sensor data sampling. To address this, on-device preprocessing and feature extraction can reduce the need for extensive data transmissions [120], such as by sending summary statistics instead of raw data. This can be measured by sampling efficiency, η:

$$\eta = \frac{I_e}{D_t}, \tag{8}$$

where I_e is the essential information extracted, and D_t is the data transmitted. Future research should maximize η by refining on-device processing to reduce transmission volumes while retaining crucial information.

The ADR mechanism in LoRaWAN adjusts data rate, airtime, and energy use based on network conditions, balancing performance and efficiency. However, ADR can introduce variability in transmission [116], affecting HAR accuracy. HAR algorithms must be resilient to these fluctuations to maintain accuracy. A utility function, $U(d, a)$, can help evaluate ADR adjustments:

$$U(d, a) = \alpha \cdot \log(1 + d) - \beta \cdot \varphi(a), \tag{9}$$

where d is the data rate, a represents adaptability (variability in data rate), α and β are weighting factors, and $\varphi(a)$ penalizes the impact of adaptability on data consistency. Future efforts should refine this function to balance better data rate improvements with the need for stable transmission, supporting robust HAR performance across varying conditions.

D. NUMBER OF SENSORS

The integration of multiple sensors, such as accelerometers, gyroscopes, and heart rate monitors, has advanced significantly, allowing systems to provide detailed insights into user behavior and health status [121], [122]. Recent developments have focused on optimizing sensor placement and fusion algorithms to improve data accuracy and reliability.

A primary challenge is determining the optimal number of sensors to capture accurate data without overwhelming the system or user. For example, [35] used an accelerometer, a magnetometer, and environmental sensors for fall detection, while [88] added PPG and body temperature sensors for safety monitoring, highlighting potential redundancies. This highlights the importance of careful sensor selection to enhance efficiency without over-complicating the system. Excessive sensors can increase power consumption, data redundancy, and user discomfort. In contrast, inadequate sensors can pose a substantial risk to activity recognition accuracy.

A mathematical model can be formulated to optimize the number of sensors. Let S be the set of all possible sensors, and $f(S)$ represent the functionality or coverage provided. The objective is to minimize sensor count while maximizing functionality:

$$\min |S| \quad \text{such that} \quad f(S) \geq \tau, \tag{10}$$

where τ is the desired threshold of activity recognition accuracy. This optimization can be approached using combinatorial optimization and integer programming techniques.

Future research should develop intelligent algorithms that maximize information extraction from minimal sensor inputs and dynamically adjust the number and type of sensors based on the monitored activity [123], [124]. This adaptive sensor management approach balances accuracy, power consumption, and user comfort. Leveraging ML and context-aware computing, future systems could self-configure to operate efficiently in various scenarios, using the fewest sensors necessary while maintaining high accuracy.

E. DATA PROCESSING

Edge processing in LoRaWAN-integrated wearable sensor networks has been underutilized due to the resource constraints of IoT devices. This leads to over-reliance on cloud-based processing for data analysis [125]. This approach introduces latency from data transmission and requires continuous network connectivity, which can reduce system responsiveness and efficiency.

Over 60% of surveyed systems favor remote processing, yet this trend toward cloud dependency misses the benefits of edge processing, such as reduced data transmission, energy savings, and faster decision-making. Processing data locally or at the network edge can significantly enhance the performance of wearable sensor networks [123].

To quantify the advantages of edge computing, we can model the performance improvement (ΔP) as:

$$\Delta P = (\Delta L \times C_L) + (\Delta E \times C_E). \tag{11}$$

where $\Delta L = L_{\text{cloud}} - L_{\text{edge}}$ measures latency reduction, with L_{cloud} and L_{edge} being latencies for cloud and edge processing, respectively. Similarly, $\Delta E = E_{\text{trans}} - E_{\text{edge}}$ measures energy savings, where E_{trans} is the energy for cloud transmission and E_{edge} is for edge processing. The coefficients C_L and C_E reflect the relative importance of latency reduction and energy savings in the specific application context. A positive ΔP indicates that edge computing provides net gains in efficiency by reducing both latency and energy consumption.

Future research should prioritize developing energy-efficient edge computing solutions such as those proposed in [126], [127] for wearable devices to decrease cloud dependence and improve autonomy [123]. This will involve innovations in algorithms and hardware design to maximize the benefits of near-device processing, ultimately boosting the efficiency and responsiveness of wearable sensor networks.

F. RANGE OF COMMUNICATION

Achieving reliable long-range coverage is crucial for LoRaWAN-integrated wearable networks, especially in remote areas where the technology is most beneficial. However, physical and environmental obstacles can degrade signal strength and reliability.

Although LoRaWAN can have long-range coverage, practical deployments often need to be revised. Studies in [85], [88], [107] have shown that environmental factors, network congestion, or sub-optimal device configurations can limit LoRaWAN range to less than 1 kilometer. This susceptibility poses significant concerns for sub-optimal HAR system performance.

To improve coverage, future efforts should optimize network infrastructure, such as strategic gateway placement, enhancing device hardware, and developing adaptive networking protocols [111], that adjust to environmental conditions and network loads. To model and optimize network performance, we propose three fundamental approaches:

- *Signal Attenuation Model:* Signal attenuation due to environmental factors is critical for long-range communication, outdoors as in the case of [54] and indoors. For an outdoor environment, the received power at a distance d can be modeled as:

$$P_r(d) = P_t - 10 \cdot n \cdot \log_{10}(d) - L_{\text{env}}, \tag{12}$$

  where $P_r(d)$ is the received power, P_t is the transmitted power, n is the path loss exponent (varies by environment), and L_{env} accounts for additional losses due to environmental factors such as temperature, humidity, barometric pressure, and other conditions. For indoor environments, modified and refined equations should account for the attenuation caused by specific factors such as wall composition, the presence of electronic devices, and various household materials. These adjustments ensure a more accurate representation of signal degradation in realistic indoor settings.
- *Optimization of Gateway Placement:* Optimizing gateway locations maximizes coverage and minimizes costs [128], [129]. This can be formulated as:

$$\max_{\{x_i, y_i\}} \left(\bigcup_{i=1}^{k} A_i \right) \quad \text{subject to} \quad k \leq K, \tag{13}$$

  where $\{x_i, y_i\}$ are the coordinates of each gateway, A_i is the area covered by gateway i, k is the current number of gateways, and K is the maximum allowed due to constraints.
- *Enhanced ADR and Power Adjustment Model:* An enhanced ADR model adjusts both data rate and transmission power dynamically [130], based on distance and real-time conditions:

$$P_t(d) = \min\left(P_{\max}, P_{\text{base}} + 10 \cdot n \cdot \log_{10}(d) + L_{\text{adapt}}\right), \tag{14}$$

  where $P_t(d)$ is the transmission power, $P_{\max}$ is the maximum permitted power, P_{base} is the base power at minimum distance, and L_{adapt} adjusts based on real-time environmental and network data.

These models provide a framework for enhancing the range and reliability of LoRaWAN-integrated wearable networks, especially in complex environments. Future research should continue to refine approaches such as those in [111] to maximize network performance in wearables.

G. DATA SECURITY

Recent advancements in LoRa and LoRaWAN-integrated wearable sensor networks have focused on enhancing data security through robust encryption protocols and secure authentication mechanisms. LoRaWAN provides strong security features like unique network keys for secure communication and application keys for end-to-end encryption.

However, security challenges persist, especially due to the distinction between LoRa (physical layer) and LoRaWAN (network protocol). While LoRaWAN includes built-in security protocols, LoRa lacks these and relies on the application layer, creating vulnerabilities when used alone for simpler or low-power applications, as seen in some systems [90], [91], [103], [106]. Wearable devices collecting sensitive data are particularly at risk.

Future research should enhance both hardware and software security, particularly for LoRa-only systems. Key areas include developing lightweight encryption algorithms suitable for low-power devices, and secure, efficient key management and authentication methods tailored for scalable, mobile wearable networks [131]. Additionally, exploring blockchain technology [132], could provide decentralized solutions to boost data integrity and privacy, regardless of whether LoRa or LoRaWAN is used.

To address these security concerns, we propose a Streamlined Unified Security Model (SUM) to assess overall security effectiveness (OSE) against computational and energy overhead:

$$OSE = \alpha \cdot E + \beta \cdot T + \gamma \cdot A + \delta \cdot B, \tag{15}$$

where E is encryption efficiency (energy consumption and computational overhead), T is key management efficiency (resource usage for key operations), A is authentication effectiveness (robustness and speed), and B is blockchain efficiency (transaction processing and data integrity). The coefficients $\alpha, \beta, \gamma, \delta$ adjust the impact of each component based on specific needs.

This model helps evaluate the impact of technology changes on security, guide investments to improve security (e.g., better encryption or new authentication), and compare security configurations to find the best balance between security and performance.

VI. STUDY LIMITATIONS

This paper investigates the integration of LoRaWAN technology with HAR systems, focusing on wearable sensors. While a brief comparison of other LPWAN technologies is provided, the emphasis is on LoRaWAN due to its relative suitability in HAR applications. The adequacy of LoRaWAN in wearable HAR is driven by the protocols distinct advantages in long-range communication, low power consumption, and scalability, which are essential for practical deployment.

The paper offers a focused review of HAR techniques and wearable sensors, particularly those integrated with LoRaWAN, to gain a deep understanding of current applications. Thus, we analyze the design and performance of existing LoRaWAN-integrated HAR systems, identifying critical technical challenges and proposing potential solutions. Our analysis is limited to academic systems rather than commercial ones due to the accessibility of detailed technical data and the ability to assess and compare the underlying technologies objectively.

Although this review does not include experimental work, some related experiments are planned for future studies. The presented insights and recommendations aim to orient future research and developments towards addressing identified challenges and optimizing the effectiveness of LoRaWAN-based HAR systems.

VII. CONCLUSION AND FUTURE OUTLOOK

A. SUMMARY OF FINDINGS

1) RQ1: PRACTICAL APPLICATIONS OF LORAWAN-INTEGRATED WEARABLE SENSORS IN HAR

LoRaWAN technology is well-suited for HAR using wearable sensors due to its low power consumption, long-range communication, scalability, and secure data transmission. It integrates seamlessly with sensors like accelerometers, gyroscopes, magnetometers, and environmental sensors for diverse applications in healthcare, elderly care, sports, and safety monitoring. LoRaWAN-based systems excel in monitoring ADL, fall detection, and real-time emergency response, particularly in remote settings where battery efficiency and connectivity are vital. Devices can be configured as Class A, B, or C to optimize power use, data latency, or responsiveness. LoRaWAN's capacity to support various sensor setups, including body-worn, object-mounted, and ambient sensors, makes it highly versatile for HAR. At the same time, its robust encryption ensures data security in sensitive applications.

2) RQ2: OPTIMIZATION OF LORAWAN PARAMETERS FOR HAR SYSTEMS

Optimizing LoRaWAN parameters like SF, BW, and CR enhances HAR system performance. Higher SF values extend range but lower data rates, suitable for remote areas, while lower SF values are ideal for urban settings requiring high data throughput. Adjusting BW between 125 kHz and 500 kHz balances power use and data rate, and a CR of 4/5 ensures data reliability without compromising payload efficiency. Combining multiple sensor types and processing data at the edge reduces energy use and minimizes network congestion. Effective parameter tuning enables adaptable, efficient HAR systems across diverse environments, from real-time alerts to routine health monitoring.

3) RQ3: CHALLENGES AND OPPORTUNITIES IN LORAWAN-BASED HAR SYSTEMS

Implementing LoRaWAN for wearable HAR systems involves challenges like enhancing wearability, managing energy use, optimizing data rates, and ensuring secure data transmission. Sensors must be lightweight and comfortable, requiring advances in materials and miniaturization. Energy efficiency is vital due to the need for continuous operation, pushing for low-power designs and energy harvesting methods. Data security is crucial, especially in healthcare, necessitating robust encryption. Despite these challenges, LoRaWAN offers significant opportunities with its flexibility, low cost, wide coverage, and scalability, making it ideal for large-scale deployments in health monitoring, safety, and smart environments. Future research should focus on improving sensor integration, refining network configurations, and using AI for more innovative data processing, paving the way for reliable, secure, and efficient HAR solutions.

B. FUTURE DIRECTIONS SUMMARY

Future research in LoRaWAN-based HAR systems should aim to integrate advanced wearable sensors that improve comfort, energy efficiency, and data security for diverse applications as follows:

- End devices should be designed to be lightweight, flexible, and miniaturized to ensure comfort during prolonged use.
- Energy management has to be optimized through low-power algorithms, adaptive transmission settings, and energy harvesting techniques to extend battery life without compromising performance.
- LoRaWAN settings, such as the SF and BW, should be dynamically adjusted to reduce network congestion and enhance data reliability.
- The number of sensors should be carefully balanced to ensure high data accuracy while minimizing system complexity and power consumption.
- ML at the edge should be leveraged to improve data processing efficiency, reduce latency, and enable real-time applications such as health monitoring.
- Improving long-range communication capabilities is crucial for effectively operating wearable networks in remote and varied environments.
- Strong encryption and security protocols are essential to protect sensitive health and activity data from cyber threats.

Overall, the ultimate goal is to develop adaptable and intelligent LoRaWAN-integrated HAR systems that function efficiently across diverse settings, from healthcare environments to smart cities.

C. CONCLUSION

This review highlights the transformative impact of LoRaWAN-integrated wearable sensor networks on remote Human Activity Recognition (HAR). By enabling long-range data transmission, improving power efficiency, and supporting diverse deployments, LoRaWAN is advancing applications in healthcare, elderly care, fitness, and safety, providing detailed insights into human activities and health. However, challenges such as wearability, energy efficiency, data rate limitations, and security must be addressed for broader adoption. Future research should focus on developing user-friendly, energy-efficient devices with advanced data processing and secure protocols to meet user needs and expectations. Continued innovation in sensor technology, ML, and IoT integration, supported by collaboration between academia and industry, will further enhance HAR systems, leading to better health outcomes, safer environments, and an improved quality of life.

APPENDIX

ABBREVIATIONS AND ACRONYMS

Abbreviations	Description
ADR	Adaptive Data Rate
ADL	Activities of Daily Living
AES	Advanced Encryption Standard
AS	Application Server
BLE	Bluetooth Low Energy
BW	Bandwidth
CNN	Convolutional Neural Network
CR	Coding Rate
ECG	Electrocardiograph
EEG	Electroencephalograph
EN	End Device
EMG	Electromyograph
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HAR	Human Activity Recognition
IMU	Inertia Measurement Unit
IoT	Internet of Things
IR	Infrared Sensor
ISM	Industrial, Scientific and Medical
kNN	k-Nearest Neighbour
LDA	Linear Discriminant Analysis
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
LPWAN	Low-Power Wide Area Network
LSTM	Long Short-term Memory
LTE-M	Long-Term Evolution Machine Type Communication
MCU	Microcontroller Unit
MQTT	Message Queuing Telemetry Transport
NB-IoT	Narrowband-Internet of Things
NS	Network Server
PPG	Photoplethysmograph
RF	Radio Frequency
RFID	Radio-Frequency Identification
SF	Spreading Factor
TinyML	Tiny Machine Learning
UWB	Ultra Wideband
WBAN	Wireless Body Area Networks
WWS	Wireless Wearable Sensors

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