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Enhancing Elderly Care through Low-Cost Wireless Sensor Networks and Artificial Intelligence: A Study on Vital Sign Monitoring and Sleep Improvement

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Abstract: This research explores the application of wireless sensor networks for the non-invasive monitoring of sleep quality and vital signs in elderly individuals, addressing significant challenges faced by the aging population. The study implemented and evaluated WSNs in home environments, focusing on variables such as breathing frequency, deep sleep, snoring, heart rate, heart rate variability (HRV), oxygen saturation, Rapid Eye Movement (REM sleep), and temperature. The results demonstrated substantial improvements in key metrics: 68% in breathing frequency, 68% in deep sleep, 70% in snoring reduction, 91% in HRV, and 85% in REM sleep. Additionally, temperature control was identified as a critical factor, with higher temperatures negatively impacting sleep quality. By integrating AI with WSN data, this study provided personalized health recommendations, enhancing sleep quality and overall health. This approach also offered significant support to caregivers, reducing their burden. This research highlights the cost-effectiveness and scalability of WSN technology, suggesting its feasibility for widespread adoption. The findings represent a significant advancement in geriatric health monitoring, paving the way for more comprehensive and integrated care solutions.

Keywords: wireless sensor networks; elderly health monitoring; sleep quality; artificial intelligence integration

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Citation: Del-Valle-Soto, C.; Briseño, R.A.; Velázquez, R.; Guerra-Rosales, G.; Perez-Ochoa, S.; Preciado-Bazavilvazo, I.H.; Visconti, P.; Varela-Aldás, J. Enhancing Elderly Care through Low-Cost Wireless Sensor Networks and Artificial Intelligence: A Study on Vital Sign Monitoring and Sleep Improvement. *Future Internet* **2024**, *16*, 323. https://doi.org/10.3390/fi16090323

Academic Editor: Djamel Djenouri

Received: 8 August 2024
Revised: 1 September 2024
Accepted: 4 September 2024
Published: 6 September 2024

1. Introduction

The aging population faces significant challenges in terms of health and safety, particularly within home environments. Older adults often experience deteriorating sleep quality, which can lead to numerous physical and mental health issues [1]. According to a 2021 survey by the National Institute of Statistics and Geography (INEGI) in Mexico, 62.3% of individuals aged 53 and older reported their health status as fair to poor [2]. Sleep disorders are prevalent among this demographic, with nearly half experiencing poor sleep quality and a substantial portion suffering from insomnia and daytime sleepiness. These issues underscore the urgent need for innovative solutions to monitor and improve the health and well-being of elderly individuals.

This research addresses these challenges through the application of wireless sensor networks (WSNs), an advanced technology that enables the continuous, non-invasive monitoring of sleep quality and vital signs in older adults. WSNs offer a promising solution by providing real-time data on various environmental and physiological parameters, such as noise, temperature, and illumination [3]. These data are critical for understanding the factors that adversely affect sleep and health in elderly populations.

The primary contribution of this study lies in the implementation and evaluation of WSNs to monitor sleep quality and vital signs in elderly individuals within their homes. This approach leverages the advantages of WSNs, including low cost, ease of installation, and the ability to provide continuous and accurate monitoring. By integrating these networks with artificial intelligence (AI) for data analysis, this study aims to offer personalized recommendations and interventions to improve sleep quality and overall health.

Moreover, this study not only focuses on the technical aspects of WSN implementation but also considers the broader social and familial impacts. Providing a reliable monitoring system alleviates the burden on family members who care for elderly relatives, offering them peace of mind and reducing their caregiving load. This holistic approach ensures that the benefits of the technology extend beyond the individual to their support network.

This research represents a significant advancement in the use of technology to address the health needs of the aging population. By employing WSNs for non-invasive monitoring, it offers a novel and effective means of enhancing the quality of life for older adults. The findings from this study are expected to inform future research and development in the field of geriatric health monitoring, paving the way for more comprehensive and integrated care solutions.

Contribution

The primary objectives of this research are to implement and evaluate the effectiveness of low-cost wireless sensor networks in monitoring the sleep quality and vital signs of elderly individuals within their home environments. By utilizing a WSN, the study aims to enable the continuous, non-invasive monitoring of key physiological parameters, such as heart rate, respiratory rate, and sleep stages, along with environmental factors like temperature and noise levels. Additionally, the research seeks to integrate these networks with artificial intelligence algorithms to generate personalized health recommendations aimed at improving sleep quality and overall well-being. Furthermore, the study endeavors to assess the broader impact of WSN technology on reducing the burden of caregiving for families, thereby enhancing the quality of care for elderly individuals. Through these objectives, this research contributes to the development of scalable, cost-effective solutions that address the unique health challenges faced by aging populations, paving the way for more comprehensive and integrated care strategies in geriatric health monitoring.

Our research makes a novel contribution to the field of geriatric health care through the following:

- Innovative Use of Technology: The deployment of WSNs provides a modern, advanced method for the continuous and non-intrusive monitoring of sleep and vital signs in elderly individuals.
- Personalized Health Interventions: By integrating AI with WSN data, this study offers tailored recommendations to improve sleep quality, addressing the specific needs of each individual.
- Enhanced Caregiving Support: The system reduces the burden on family caregivers by providing reliable, real-time health monitoring, thereby improving the overall caregiving environment.
- Cost-Effective Solution: Utilizing low-cost sensors ensures that the solution is accessible and scalable, making it feasible for widespread adoption in various socioeconomic contexts.
- Comprehensive Health Monitoring: This research not only focuses on sleep but also monitors other vital signs, providing a holistic view of the elderly individual's health status.

There is a relationship between people's habits and improvements in their rest, which is reflected in the behavior of their vital signs on a daily basis. This work demonstrates the relationships (some strong and others weaker) between the recommendations obtained from a simple sensor network installed at home. These recommendations are based on a threshold analysis algorithm applied by the sensors to assess possible behaviors or improve certain ones for optimal rest. The sensors provide three groups of recommendations that, day by day, show that they can have an impact on the rest and vital signs of an elderly adult. The technical contribution of this document is based on the implementation of a non-invasive sensor network in the home to measure simple parameters such as noise, air quality, movements, and the use of different areas of the house. With these parameters and based on an algorithm, the sensors can provide a series of recommendations that may influence the person's habits and potentially improve their quality of life.

Figure 1 provides a comprehensive summary of the research on WSNs for monitoring sleep quality and vital signs in the elderly. The mindmap diagram outlines the background of the study, emphasizing the challenges faced by the aging population regarding health and sleep quality. It details the problem definition, highlighting the health and safety concerns for the elderly at home and the need to identify variables affecting sleep. The justification section underscores the importance of addressing elderly health needs through non-invasive monitoring technologies to improve their quality of life. Objectives include the implementation and data analysis of WSNs to monitor sleep and provide personalized recommendations. The diagram also covers hypotheses related to the impact of environmental factors on sleep, the theoretical framework of medical diagnostics' evolution, the methodology of WSN usage and data collection, the results showing improvements in sleep quality, and the conclusions about the effectiveness of WSNs in health monitoring with suggestions for future research.

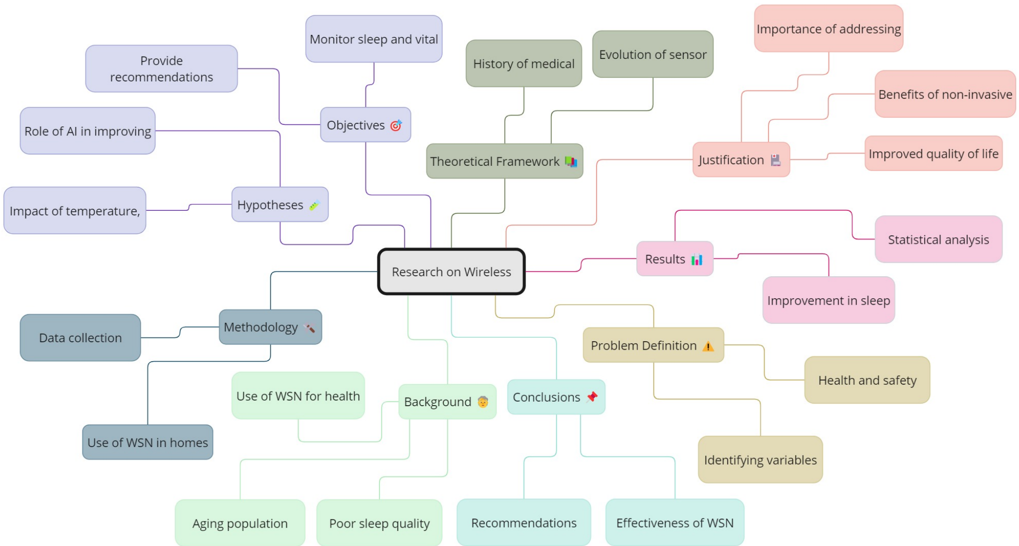

Figure 1. Summary of research on wireless sensor networks for monitoring sleep quality and vital signs in the elderly [4].

2. Related Work

Advancements in WSNs have significantly contributed to various applications, including health monitoring for elderly populations. These systems have evolved through several historical phases, from relying on human senses to incorporating sophisticated remote sensors and wearable technologies [5]. Early diagnostic methods were heavily dependent on human observation, which limited the precision and scope of medical assessments. The invention of tools like the stethoscope and the microscope marked the beginning of the "enhanced human senses" era, allowing healthcare providers to gain deeper insights into patients' conditions [6].

In recent years, the development and implementation of WSNs have become integral to modern medical diagnostics, particularly for continuous health monitoring. These networks comprise spatially distributed sensors that collect and transmit data regarding various environmental and physiological parameters, such as temperature, noise levels, and vital signs [7]. This innovation is especially pertinent for the elderly, who often face challenges related to mobility and access to healthcare services. Studies have demonstrated that integrating WSNs into home settings can lead to significant improvements in monitoring sleep quality and vital signs, thus enhancing the overall health and safety of older adults. Recent research has expanded on these findings by exploring the application of WSNs in detecting and managing chronic conditions like diabetes and cardiovascular diseases. For example, wearable WSN devices capable of continuous glucose monitoring have shown promise in providing non-invasive, real-time data, which is crucial for timely medical interventions and effective disease management [8]. Furthermore, advancements in WSN technology have facilitated the development of sophisticated fall detection systems, which utilize a combination of accelerometers and gyroscopes to monitor and alert caregivers about falls in real time, significantly reducing the risk of severe injuries among the elderly [9].

A critical review of the current literature reveals a growing interest in non-invasive monitoring technologies that leverage WSNs. These technologies offer a promising solution for managing chronic health conditions and improving the quality of life for elderly individuals. Research has highlighted the effectiveness of WSNs in detecting and analyzing sleep patterns, which are crucial for diagnosing sleep disorders and related health issues. For instance, studies have shown that nearly 50% of older adults suffer from poor sleep quality, and a significant portion experience daytime sleepiness and insomnia. By utilizing WSNs, researchers aim to gather comprehensive data on sleep environments and physiological responses, providing valuable insights for developing personalized healthcare interventions. Recent advancements have also extended the application of WSNs to cardiovascular monitoring. For example, wearable sensors integrated into WSNs can continuously track heart rate variability (HRV) and other cardiovascular indicators, offering critical data for the early detection of heart-related anomalies and enhancing proactive healthcare measures [10]. The application of wireless sensor networks in healthcare has demonstrated remarkable versatility, seamlessly integrating various aspects of patient monitoring and care. For instance, WSNs have been effectively utilized in fall detection systems, where data from accelerometers and gyroscopes are leveraged to provide real-time alerts, thereby reducing the risk of injury among elderly populations. This capability not only enhances immediate response times but also contributes to long-term health assessments and preventive strategies [11]. Additionally, significant progress has been made in employing WSNs for remote rehabilitation and physical therapy, enabling the continuous monitoring of patients' physical activities, ensuring adherence to prescribed exercises, and offering valuable feedback to therapists for better management of rehabilitation programs. These innovations underscore the flexibility of WSNs in addressing a wide spectrum of healthcare needs, reinforcing their critical role in modern medical practice [12].

The impact of WSNs extends beyond the scope of monitoring sleep quality, playing a pivotal role in the early detection and management of various health conditions, such as cardiovascular diseases and diabetes. Recent studies have introduced non-invasive glucose monitoring systems that employ infrared spectroscopy and photoacoustic techniques, offering a less intrusive alternative to traditional methods. These advancements emphasize the transformative potential of WSNs in healthcare, enabling continuous, real-time data collection that supports proactive health management and timely medical interventions. Furthermore, WSNs have shown significant promise in managing respiratory conditions. For example, the work cited in [13] details the design of a wireless body area network (WBAN) for the remote monitoring of physiological signals, integrating sensors for temperature, heart rate, and fall detection. This system wirelessly transmits data to a central control unit, validated with medically certified sensors, and can be accessed remotely via a Zigbee mesh topology and GSM-enabled gateway. Another noteworthy example is the development of advanced WSN systems that monitor respiratory rates and detect anomalies such as sleep apnea. By utilizing a combination of accelerometers and acoustic sensors, these systems provide accurate, real-time monitoring, enabling early intervention and reducing the risk of severe complications [14]. Likewise, the integration of WSNs in telemedicine platforms has significantly enhanced remote patient monitoring capabilities. This integration allows healthcare providers to track vital signs and other health metrics from a distance, facilitating continuous patient care, particularly for those with chronic conditions who require regular monitoring. As a result, overall patient outcomes are improved, and the burden on healthcare facilities is reduced [15]. WSNs also play a crucial role in enhancing patient mobility and independence through the development of wearable devices that monitor physical activity levels and detect falls. Equipped with sensors that track movement patterns and send alerts in the event of abnormal activity or potential falls, these devices ensure timely assistance, reducing the risk of injury. These applications highlight the expansive role of WSNs in advancing healthcare technologies, providing comprehensive, patient-centered care [16].

Table 1 presents a summary of current references on the use of WSNs for elderly health monitoring and behavioral change techniques. The knowledge areas covered range from wireless sensor networks and healthcare IoT to smart healthcare, geriatric care, telemedicine, and wearable technology. The key topics addressed in these references include the monitoring of health parameters, the real-time tracking of vital signs, the continuous monitoring of chronic conditions, and the encouragement of behavioral changes among the elderly. The solutions proposed involve integrating WSNs with IoT, behavior analysis tools, smart sensor networks, and telemedicine systems, aiming to improve health tracking, promote healthier lifestyles, and enhance remote health monitoring and emergency response capabilities.

Table 1. Current references on wireless sensor networks and their applications for elderly health monitoring and behavioral change techniques.

Reference	Year	Knowledge Area	Document Type	Keywords	Problem	Solution Method	Contribution
[17]	2019	Wireless Sensor Networks	Journal Article	Elderly, WSN, Health Monitoring	Monitoring health parameters of elderly	Integrated WSN with IoT	Improved health tracking and emergency response
[18]	2022	Healthcare IoT	Journal Article	IoT, Vital Signs, Elderly Care	Real-time monitoring of vital signs	IoT-based health monitoring system	Enhanced real-time monitoring capabilities
[19]	2016	Sensor Networks	Journal Article	WSN, Behavioral Change, Elderly	Encouraging behavioral changes in elderly	WSN integrated with behavior analysis tools	Promoted healthier lifestyles
[20]	2011	Medical Informatics	Journal Article	Health Monitoring, WSN, Elderly	Continuous monitoring of chronic conditions	Wearable sensors with WSN	Improved chronic condition management
[21]	2018	Smart Healthcare	Journal Article	Smart Sensors, Elderly, Vital Signs	Managing multiple health parameters	Smart sensor networks	Comprehensive health management
[22]	2019	Geriatric Care	Conference	Elderly Care, WSN, Health Data	Enhancing care for elderly patients	Data-driven WSN solutions	Better elderly care management
[23]	2021	Telemedicine	Review	Telehealth, WSN, Vital Signs	Remote health monitoring for elderly	Telemedicine with WSN integration	Enhanced remote monitoring
[24]	2011	Behavioral Health	PhD Thesis	Behavior Change, WSN, Elderly	Modifying unhealthy behaviors	WSN-based behavioral interventions	Effective behavior modification
[25]	2018	Health Informatics	Review	WSN, Health Monitoring, Elderly	Real-time health data collection	Advanced WSN technologies	Real-time health insights
[26]	2019	IoT Healthcare	Journal Article	IoT, Elderly, Health Monitoring	Continuous health monitoring	IoT-enabled sensor networks	Improved health outcomes
[27]	2019	Wearable Technology	Journal Article	Wearables, WSN, Elderly	Wearable health monitoring	Integrated wearables with WSN	Enhanced mobility and monitoring
[28]	2020	Health Technology	Review	Health Sensors, Elderly, WSN	Monitoring vital signs remotely	Health sensors integrated with WSN	Improved remote health monitoring
[29]	2022	Mobile Health	Journal Article	mHealth, WSN, Elderly Care	Mobile health solutions for elderly	Mobile apps with WSN	Better health management
[30]	2020	Smart Health Devices	Review	Smart Devices, Elderly, WSN	Smart health monitoring	Smart health devices integrated with WSN	Advanced monitoring capabilities
[31]	2024	Geriatric Technology	Journal Article	Technology, Elderly Care, WSN	Technology for elderly health	Advanced WSN for health tracking	Enhanced elderly care

Table 1. *Cont.*

Reference	Year	Knowledge Area	Document Type	Keywords	Problem	Solution Method	Contribution
[32]	2021	Healthcare Monitoring	Conference Paper	Health Monitoring, WSN, Elderly	Monitoring elderly health parameters	Comprehensive WSN solutions	Improved health data collection
[33]	2020	Health Systems	Conference	Health Systems, WSN, Elderly	Integrating health systems with WSN	Health systems integration	Streamlined health monitoring
[34]	2022	Remote Monitoring	Review	Remote Health, WSN, Elderly	Remote monitoring for elderly	Remote monitoring systems with WSN	Enhanced remote care capabilities
[35]	2020	Health Innovation	Review	Health Innovation, WSN, Elderly	Innovative health monitoring	Innovative WSN technologies	Advanced health solutions
[36]	2024	Elderly Care Technology	Conference Paper	Technology, Elderly, WSN	Leveraging technology for elderly care	Technological interventions with WSN	Improved elderly care solutions
[37]	2020	Smart Health	Journal Article	Smart Health, WSN, Elderly	Integrating smart health solutions	WSN with smart health devices	Enhanced health monitoring
[4]	2023	Healthcare IoT	Conference Paper	IoT, Elderly, Vital Signs	Real-time vital sign monitoring	IoT and WSN integration	Improved monitoring accuracy
[38]	2022	Telemedicine	Conference	Telehealth, WSN, Elderly	Remote health management	Telemedicine with WSN	Better remote health care
[39]	2020	Geriatric Care, elderly	Review	Elderly Care, WSN	Enhancing elderly care	Advanced WSN solutions	Improved care for elderly
[40]	2020	Behavioral Health	Conference	Behavior Change Techniques, WSN, Elderly	Modifying unhealthy behaviors	WSN-based behavioral interventions	Effective behavior modification

3. Materials and Methods

In this research study, we conducted a four-week trial. For the first two weeks, there was no network installed in the participants' homes. For the next two weeks, we implemented a simple sensor network in the homes of 100 individuals, utilizing an adaptive sensor algorithm to generate a series of daily recommendations for these participants. The participants in both experiments were between 55 and 70 years old. In both scenarios, we measured vital signs (as presented in Table 2) three times a day for all participants. The sensor network consisted of motion, pressure, temperature, humidity, noise, light, gyroscope, and air quality sensors (14 nodes in total). These nodes were equipped with an algorithm that we developed to establish thresholds for changes in behavior or movement within the participants' homes, enabling us to generate recommendations aimed at improving their quality of life and sleep at night.

Table 2. Analyzed variables in the research study.

Variable	Description	Impact on Sleep Quality
Breathing frequency (BF)	The rate at which a person breathes per minute	Positive impact, with a 68% improvement in participants
Deep sleep (DS)	The percentage of deep sleep during total sleep time	Positive impact, with a 68% improvement in participants
Snoring (S)	The frequency and intensity of snoring during sleep	Positive impact, with a 70% improvement in participants
Heart rate (HR)	The number of heartbeats per minute	60% improvement, not statistically significant for sleep quality
Heart rate variability (HRV)	The variation in time between each heartbeat	Highly positive impact, with a 91% improvement in participants
Oxygen saturation (OS)	The level of oxygen saturation in the blood	59% improvement, not statistically significant for sleep quality
REM sleep (REMS)	The percentage of REM sleep during total sleep time	Highly positive impact with an 85% improvement in participants
Temperature (T)	The temperature of the sleeping environment	Negative impact, with higher temperatures affecting sleep negatively
Total sleep time (TST)	The total amount of time a person spends asleep during a monitoring period, usually overnight	Calculated by subtracting the wake time from the total time in bed; a key metric for assessing sleep quality and duration

Thus, for a period of two weeks, the vital signs of individuals were measured without the presence of the sensor network, meaning in their normal home conditions and daily routines. Subsequently, during the following two weeks, we implemented a basic sensor network in their homes, utilizing specific and low-cost sensors along with an algorithm that generates daily recommendations to modify certain habits as the days progress. During these two weeks, with the sensor network in place, the individuals' vital signs were also measured. Therefore, throughout this document, when we refer to "without WSN", it means that the sensor network was not implemented in the individuals' homes, and "with WSN" refers to when the sensor system was installed in the homes. These are two different scenarios, and in both, the same vital signs were measured three times a day in adults.

We have clarified that the groups of recommendations are taken into account by the algorithm based on variations in the thresholds of certain sensors. This is why there are three groups of recommendations. Not all sensors monitor the same parts of the house or the same behaviors of the individuals. So, when a participant follows one of the three groups of recommendations, they begin to adjust physical aspects of their home, for example, closing windows at certain times, moving lights or lamps, changing sleeping positions, or going to bed at specific times, among others. These recommendations are simple but adapted to variations in the thresholds of a certain group of sensors.

Table 3 provides a comprehensive overview of the key methodological considerations for this research on the evaluation of WSNs in monitoring the sleep quality and vital signs of the elderly. It details the research objectives, including the implementation of a WSN to measure various environmental variables, the collection and analysis of real-time data, and the provision of personalized recommendations based on the findings. The hypotheses highlight the expected impacts of temperature, noise, and light intensity on sleep quality. The table also enumerates the specific variables analyzed, data collection methods, and statistical techniques used for data analysis. Ethical considerations, such as informed consent and data protection, are emphasized to ensure the privacy and confidentiality of participants. Overall, the table aims to outline the methodological framework that guided the study, ensuring a systematic approach to improving the healthcare and quality of life of the elderly through innovative non-invasive monitoring technologies.

Table 2 provides a detailed overview of the variables analyzed in this research study, focusing on their descriptions and their respective impacts on sleep quality among elderly participants. Breathing frequency, deep sleep, snoring, heart rate, heart rate variability, oxygen saturation, REM sleep, temperature, and total sleep time were the primary variables monitored using wireless sensor networks. The difference between REM sleep and total sleep time is that REM sleep is one specific stage within the overall sleep cycle, whereas total sleep refers to the entire amount of sleep time across all stages. The study found significant positive impacts on sleep quality for variables such as breathing frequency, deep sleep, snoring, heart rate variability, and REM sleep, indicating improvements in participants' sleep patterns. Temperature, on the other hand, negatively affected sleep quality, with higher temperatures correlating with poorer sleep. These findings highlight the importance of continuous and non-invasive monitoring of these variables to enhance the sleep quality and overall well-being of the elderly.

Table 3. Important methodological considerations.

Consideration	Description
Research Objectives	This study aims to find detrimental patterns affecting sleep in elderly people through constant sleep monitoring with WSNs and remote vital sign measurement. It also aims to present daily recommendations and best practices to address the problem, improving the sleep quality and overall healthcare of the elderly at home.
Specific Objectives	1. Implement WSNs to measure various variables (e.g., temperature, pressure, noise, light) in the homes and bedrooms of the elderly. 2. Collect real-time data from WSNs before and after installation. 3. Measure the impact of the device post-implementation. 4. Develop data analysis schemes to assess sensor performance. 5. Provide personalized measures and recommendations based on analyzed data. 6. Present monitoring results and potential improvement areas.
Hypotheses	The non-invasive monitoring of vital signs through a low-cost WSN results in a significant decrease in sleep quality in elderly people when temperatures exceed 23 °C and noise levels exceed 60 decibels. Additionally, light intensity above 480 nanometers is a significant factor affecting sleep quality. The implementation of this technology is expected to raise awareness of sleep patterns, enabling early interventions in case of anomalies and improving security by providing discreet yet effective home monitoring.

Table 3. *Cont.*

Consideration	Description
Variables Analyzed	• **Patient's disease:** Qualitative ordinal independent • **Sensor precision:** Quantitative interval dependent • **Temperature:** Quantitative interval dependent • **Sleep schedule:** Quantitative interval independent • **Light intensity:** Quantitative interval dependent • **Noise:** Quantitative interval dependent • **Stress:** Quantitative interval dependent • **External medications:** Qualitative nominal independent
Data Collection Methods	Data were collected using WSNs installed in the bedrooms of 100 elderly participants. Variables such as breathing frequency, deep sleep, snoring, heart rate, heart rate variability, oxygen saturation, REM sleep, and room temperature were monitored and recorded.
Data Analysis	The data analysis involved Student's t-tests and Wilcoxon tests to determine whether each of the measured metrics showed significant improvement with the implementation of the sensor network. Furthermore, chi-square tests were conducted to identify the metrics where the greatest number of people experienced improvements. Additionally, the variables with the most statistically significant improvement in the chi-square test were converted from quantitative to qualitative with four classes, representing low, medium-low, medium-high, and high performance. Using association rules, the most significant patterns before and after the experiment were identified and discussed. Finally, the relationships between the metrics are analyzed using contingency tables represented by sieve diagrams.
Ethical Considerations	This study emphasizes ethical concerns such as informed consent and data protection. It ensures the privacy and confidentiality of participants' data and considers the potential ethical implications of using non-invasive monitoring technology.

The provided informed consent form in Figure 2 was designed to ensure that participants in our research study were fully aware of the purpose, procedures, risks, and benefits of their involvement. The study involved the installation of sensor networks in the homes of elderly individuals to monitor health-related data such as sleep patterns and vital signs. The form outlines the voluntary nature of participation, guaranteeing that participants can withdraw at any time without penalty. It also emphasizes the confidentiality of all collected data and assures participants that their personal information will be securely stored and anonymized. By signing the consent form, participants acknowledged their understanding of the study and agreed to take part in it under the terms specified.

You are being invited to participate in a research study that involves the installation of a sensor network in your home. This study is being conducted by a reserarcher team at Universidad Panamericana. The purpose of this form is to provide you with information about the study, so you can decide whether you would like to participate. Please read this form carefully and ask any questions you may have before agreeing to take part in the study.

Purpose of the Study:
The purpose of this research is to investigate how a network of sensors installed in the home environment can monitor and improve well-being, particularly focusing on sleep quality, vital signs, and daily habits. The study aims to provide insights that could lead to better healthcare strategies for older adults.

Procedures:
If you agree to participate, the following procedures will take place:
1.Installation of Sensors: A team of researchers will install a network of sensors in your home. These sensors will monitor various factors such as movement, temperature, noise levels.
2.Monitoring Period: The study will involve monitoring over a four-week period. For the first two weeks, no sensor network will be active in your home, allowing us to gather baseline data. During the following two weeks, the sensors will be activated, and data will be collected.
3.Data Collection: The sensors will collect data continuously throughout the monitoring period. This data will include information about your environment and certain aspects of your health, such as sleep patterns and vital signs.
4.Health Recommendations: Based on the data collected, the research team may provide daily recommendations to improve your well-being.

Voluntary Participation:
Your participation in this study is entirely voluntary. You may choose not to participate or withdraw from the study at any time without any penalty or loss of benefits to which you are otherwise entitled. If you decide to withdraw, please contact the research team using the contact information provided above.

Risks and Benefits:
•**Risks:** The risks associated with this study are minimal. The sensors are non-invasive and will not interfere with your daily activities. However, there may be a slight discomfort or inconvenience due to the presence of sensors in your home.
•**Benefits:** While there may be no direct benefit to you, your participation may help improve health monitoring technologies and healthcare strategies for older adults in the future.

Confidentiality:
All information collected in this study will be kept confidential. Your personal information will be coded to ensure that your identity is not disclosed. Data will be stored securely and only accessible to the research team. Results from the study may be published or presented, but your identity will not be revealed.

Compensation:
You will not receive monetary compensation for participating in this study. However, the installation and monitoring equipment will be provided at no cost to you.

Contact Information:
If you have any questions about the study, your rights as a participant, or if you experience any issues related to the study, please contact the Principal Investigator at cvalle@up.edu.mx.
Statement of Consent:
By signing below, you indicate that you have read and understood the information provided in this form, that you voluntarily agree to participate in the study, and that you understand you can withdraw from the study at any time.

Participant's Name: ___________________________
Participant's Signature: ___________________________ **Date:** ___________________

Figure 2. Informed consent form for elderly participants in home sensor network research.

Wireless Sensor Network Installed

The proposed system features sensors across 14 nodes, designed to monitor key areas in a house and provide user alerts via email or SMS. The sensors include the following:

- Motion sensor: Operates at 4.5–20 V with an adjustable delay (5–200 s), a temperature range of −15 to +70 °C, and a detection range of 3 to 7 m.
- Pressure, temperature, and humidity sensor: Measures temperature (−40 to +85 °C, ±1 °C accuracy), pressure (300–1100 hPa, ±1 Pa accuracy), and relative humidity (±3% tolerance), with a supply voltage of 1.71 to 3.6 V.
- Noise sensor: Uses an ultrasonic sensor with a frequency range of 20–20 kHz, an operating voltage of 2.4–5 VDC, and a maximum detection distance of 765 cm.
- Light sensor: An LDR photoresistor with a supply voltage range of 3.3–5 V and a maximum rating of 38 V.
- Gyroscope: A single-axis sensor with a typical angular velocity of ±300°/s, an operating voltage of 3.3–5 V, and a temperature range of −40 to 105 °C.
- Air quality sensor: Monitors PM2.5, CO_2, CH_2O, TVOC, temperature, and humidity, applicable to various air quality monitoring and HVAC systems.

Figure 3 presents a Development Kit for the Wireless Self-organizing Network, featuring RF nodes that provide real-time data using a proprietary IEEE 802.15.4 protocol. The network structure includes a coordinator, routers, and sensors. Testing is done through Python scripts for route queries and sensor readings. The hardware supports 2.4 GHz, RS-485, USB connections, and can manage up to 100 nodes with an SMA connector and a 2.37 dBi antenna. Power supply options include a 12 V DC battery, solar power (10 W, 12 V DC), and an AC adapter (110–220 V AC to 12 V DC), offering flexibility for different setups.

Figure 4 presents actual photographs of the devices installed as part of the monitoring system. The distributed sensor network includes a hub node, which connects to the computer via USB and is responsible for receiving and managing all transmitted data. This network features three router nodes, each with sensors attached to its communication ports, monitoring parameters such as temperature, pressure, humidity, light, sound, and other variables based on additional activated sensors. The gathered data are sent via radio frequency to the network, ultimately reaching the concentrator node, which can also function as a repeater. The power supply operates in two modes: (1) Input Voltage 1 (BAT): Lead–Acid Battery (12 V DC at 3.3 Ah); (2) Input Voltage 2 (CS): Solar Cell (12 V DC, 10 W, 0.5 A). The network's graphic software displays the logical neighbors of each node, showing their relationships based on the RSSI (Received Signal Strength Indicator) and LQI (Link Quality Indicator) signals.

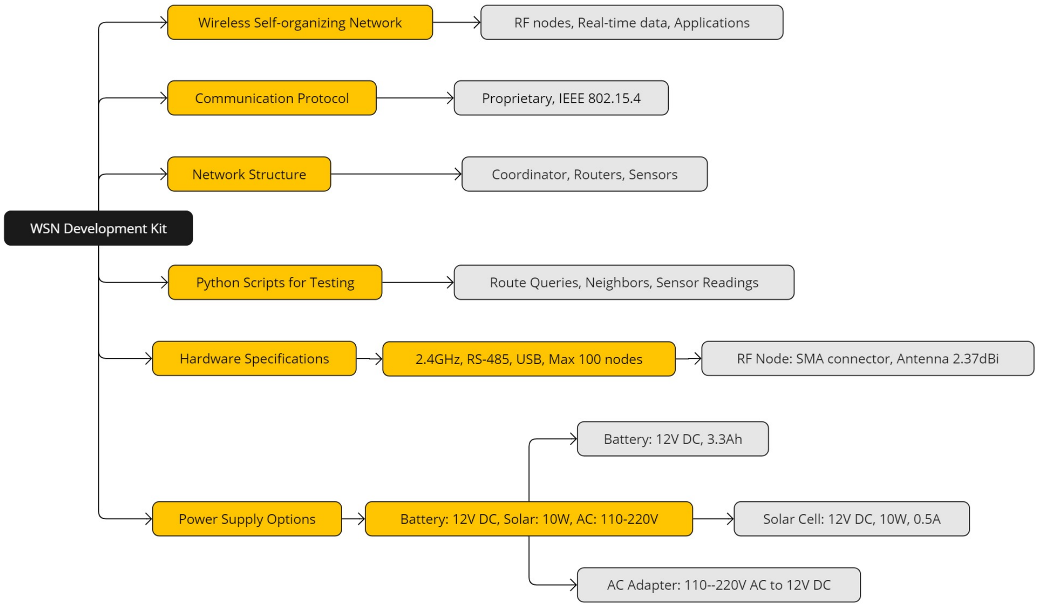

Figure 3. A block diagram summarizing the WSN Development Kit, including network structure, communication protocols, hardware specifications, and power supply options.

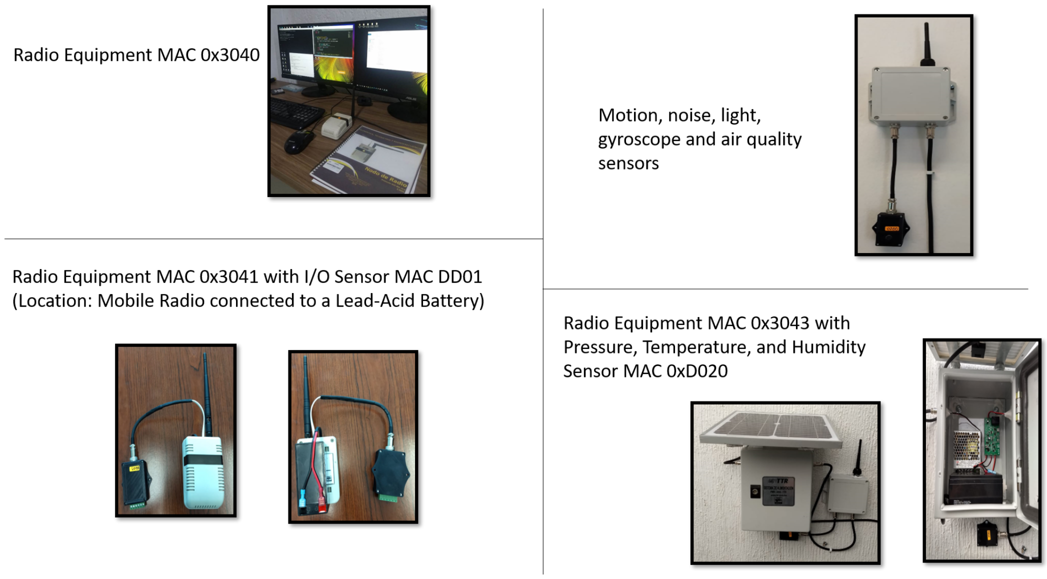

Figure 4. The implementation of the wireless sensor network.

The sensor network is designed to learn a person's habits and keeps certain sensors active in the locations where they spend the most time. It also recognizes routine behaviors, such as opening and closing windows or doors, to prevent unnecessary alerts. The system tracks various environmental factors like noise, movement, air quality, light levels, door usage, and lighting conditions. It sends notifications with suggestions for improving sleep quality, which is also monitored through a conventional smartwatch. The alert algorithm is tailored to enhance the user's sleep. For example, it might recommend adjusting fluid intake if the person frequently wakes up to use the bathroom, reducing light in the sleeping area, or modifying the positions of doors and windows to manage noise levels. Daily recommendations are delivered via email or SMS, helping the person gradually improve their sleep habits. The system is non-intrusive and does not require constant user adjustments. It also includes an energy-efficient algorithm that adapts based on how the sensors are used in different parts of the home.

The algorithm that governs this system operates in tandem with a central coordinator node. When the network is activated, the coordinator sends out packets to map the network's topology. Each node is assigned a hierarchy level based on its sensor readings and RSSI and LQI values, which are indicators of link quality. These nodes take measurements according to a predefined schedule. If the difference between a node's current reading and its default value exceeds 50%, the node's hierarchy level increases, signaling that the parameter being monitored is highly variable and requires close attention. If the node's hierarchy surpasses a certain threshold, and its RSSI and LQI values are significantly higher than normal, the node switches to a proactive mode, ensuring that it monitors its environment continuously. If the conditions are stable, the node operates in a reactive mode, which conserves energy by only taking measurements as needed. This allows the network to adapt dynamically to each home environment.

```
Algorithm pseudocode of the network system.
Start:
    // Turn ON all nodes
    Turn_ON_All_Nodes()

    // Set request_time
    request_time = Set_Request_Time()

    // Coordinator node starts
    Coordinator_Node_Starts()

    // For each node in the network
    FOR each node_i IN nodes:
        // Initialize variables
        hierarchy_i = 0
        default_measurement_i = Set_Default_Measurement()
        LQI_initial = Set_LQI_Initial()
        RSSI_initial = Set_RSSI_Initial()

        // For each request_time
        FOR each request_time IN request_times:
            // Set measurement
            measurement_i = Set_Measurement()

        // Calculate difference in measurement
        d_measurement_i = ABS(default_measurement_i - measurement_i)

        // Check if the difference in measurement is significant
        IF d_measurement_i > 0.05 * default_measurement_i THEN:
            hierarchy_i = hierarchy_i + 1

        // Check conditions for proactive mode
        IF hierarchy_i > 3 AND ABS(LQI_initial - LQI_i) > 0.05 * LQI_i AND
        ABS(RSSI_initial - RSSI_i) > 0.05 * RSSI_i THEN:
            Set_Node_Proactive_Mode(node_i)
        ELSE:
            Set_Node_Reactive_Mode(node_i)

        // Hierarchy-based recommendations
        IF hierarchy_i == 3 THEN:
            Send_Recommendations(Group_1)
        ELSE IF hierarchy_i >= 2 THEN:
            Send_Recommendations(Group_2)
        ELSE IF hierarchy_i >= 1 THEN:
            Send_Recommendations(Group_3)
        ELSE:
            No_Recommendations()

End
```

Nodes, which may contain multiple sensors, generally maintain stable RSSI and LQI values unless influenced by other devices or changes in the environment. These fluctuations can indicate unusual conditions that the system uses to generate recommendations.

The sensor system is standardized for general use but adapts its operations, energy consumption, and recommendations to suit individual households. The recommendations for improving sleep are categorized into three groups:

1. Environment Optimization: Suggestions include closing windows to reduce noise, using comfortable bedding, employing noise machines or earplugs, maintaining a cool room temperature, using a humidifier for better air quality, keeping the room dark with blackout curtains, and minimizing electronic devices in the bedroom.
2. Pre-Sleep Relaxation: Recommendations focus on relaxation techniques before bed, maintaining a consistent sleep schedule, using a weighted blanket, experimenting with aromatherapy, avoiding caffeine and heavy meals before sleep, utilizing a white noise machine, and trying a sleep mask.
3. Sleep Habit Development: Tips include establishing a regular bedtime routine, engaging in regular exercise but not close to bedtime, avoiding exposure to blue light before sleep, considering sleep aids if necessary, avoiding daytime naps, experimenting with natural sleep remedies like melatonin, and ensuring that the bed is comfortable and supportive.

In this study, the wireless sensor network was configured to monitor vital signs and environmental factors within the homes of elderly participants, with sensors deployed in key areas, such as bedrooms and living spaces. The data collected from these sensors were analyzed to provide daily recommendations aimed at improving sleep quality and overall living conditions, such as adjusting the room temperature, changing light levels, or reducing noise.

4. Results

By conducting paired hypothesis tests to compare the performance of the vital sign metrics for older adults with the implementation of the sensor network, it was found that, as in previous studies [4], all nine metrics (breathing frequency (BF), deep sleep (DS), snoring (S), heart rate (HR), heart rate variability (HRV), oxygen saturation (OS), REM sleep (REMS), temperature (T), total sleep time (TST)) generally improved significantly. Table 4 shows the p-value results of the paired hypothesis tests conducted.

Table 4. The results of the paired hypothesis tests [4].

Metric	p-Value	Test
Deep sleep	0.000	Wilcoxon
Heart rate	0.006	t-test
Breathing frequency	0.000	t-test
Temperature	0.000	Wilcoxon
REM sleep	0.000	Wilcoxon
Oxygen saturation	0.004	Wilcoxon
Heart rate variability	0.000	t-test
Snoring	0.000	Wilcoxon
Total sleep time	0.000	Wilcoxon

The frequencies of improvements in the experiment participants are analyzed in Table 5, which shows the observed counts of older adults who improved in each performance metric with the use of the sensor network.

Table 5. Observed improvement data by metric with the use of the sensor network.

Metric	Improved	Not Improved	TOTAL
Breathing frequency (BF)	68	32	100
Deep sleep (DS)	68	32	100
Snoring (S)	70	30	100
Heart rate (HR)	60	40	100
Heart rate variability (HRV)	91	9	100
Oxygen saturation (OS)	59	41	100
REM sleep (REMS)	85	15	100
Temperature (T)	89	11	100
Total sleep time (TST)	80	20	100
TOTAL	**670**	**230**	**900**

Considering that, for all variables, 50% of the people would randomly improve and 50% would not, the chi-square was calculated (see Equation (1)) for each metric and for the entire table overall. Table 6 shows the chi-square calculation for each metric.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (1)$$

where
χ^2 is the chi-square value.
O_i is the observed frequency of metric i.
E_i is the expected frequency of metric i.

Table 6. Chi-square calculations for each metric.

Variable	χ^2 Improved	χ^2 Not Improved	Total χ^2
Breathing frequency (BF)	6.48	6.48	12.96
Deep sleep (DS)	6.48	6.48	12.96
Snoring (S)	8	8	16
Heart rate (HR)	2	2	4
Heart rate variability (HRV)	33.62	33.62	67.24
Oxygen saturation (OS)	1.62	1.62	3.24
REM sleep (REMS)	24.5	24.5	49
Temperature (T)	30.42	30.42	60.84
Total sleep time (TST)	18	18	36

The critical chi-square value for the table of variables with a significance level of 0.05% and 8 degrees of freedom is 15.50731306, which is exceeded by the sum of the chi-square values for each variable, which is 262.24. The null hypothesis of independence is rejected, indicating that there are associations between the variables. The critical chi-square value with a significance level of 0.05% for each of the variables is 3.841458821, indicating that all variables except oxygen saturation had significant differences between the expected and observed values. With these chi-square test results, it is confirmed that by following the advice of the sensor network, the adult participants in the experiment improved in breathing frequency, deep sleep, snoring, heart rate, heart rate variability, REM sleep, temperature, and total sleep time.

The five metrics with the highest chi-square values (HRV, T, S, TST, and REMS) were normalized to a range of 0 to 1 using the MinMax algorithm (see Equation (2)) and subsequently converted to four-level categorical variables. The purpose of this step is to find association patterns using the FP-growth frequent pattern mining algorithm [41] among the five variables that had the best performance in the chi-square test. The process of transforming quantitative variables into qualitative variables is called discretization, and it is necessary to apply algorithms that detect categorical associations. For this paper, the FP-growth frequent pattern algorithm identifies when categories of different metrics occur together in a group of participants in the experiment.

The minimum and maximum values for each metric are chosen from the values collected with and without the sensor network to ensure they are comparable. Finally, to assign a categorical level to each value of each variable, the following process is followed: if the value is equal to or less than 0.25, it is assigned the low level; if the value is greater than 0.25 and less than or equal to 0.50, it is assigned the medium-low level; if the value is greater than 0.50 and less than or equal to 0.75, it is assigned the medium-high level; and if the value is greater than 0.75, it is assigned the high level.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{2}$$

To search for patterns in the form of rules with an antecedent and consequent, the FP-growth frequent pattern algorithm was used. FP-growth frequent pattern identifies the most frequent occurrences among the categorical levels of performance of the sleep metrics measured in the experiment. Significant association rules were identified using a minimum support of 15% and a confidence of 60% across the HRV, T, S, TST, and REMS metrics. A support of 15% means that at least 15% of the people involved in the experiment have the found pattern. A confidence of 60% means that at least 60% of the people who have the antecedent of the rule also have the consequent. The following patterns were found with and without the use of the sensor network:

- Without the use of the sensor network, 63.3% of the people who presented high-level temperature had medium-low snoring, equivalent to 31 people. On the other hand, with the use of the sensor network, 61.1% of the people who presented medium-high temperature had medium-low snoring, equivalent to 22 people. This pair of patterns may indicate that people with medium-low snoring lowered the temperature of their environment following the algorithm's recommendations.
- Without the use of the sensor network, 61.7% of the people who presented low HRV had medium-low REM sleep, equivalent to 29 people. On the other hand, with the use of the sensor network, 62.9% of the people who presented high HRV had high REM sleep, equivalent to 22 people. It was also observed that with the sensor network, 68.2% of the people with medium-low HRV had medium-high REM sleep, equivalent to 15 people. These three patterns may indicate that people with low levels of HRV and REM sleep improved their HRV and REM metrics by following the algorithm's recommendations.
- Without the use of the sensor network, 61.7% of the people who presented low HRV had medium-low total sleep, equivalent to 29 people. This pattern may indicate that low HRV negatively impacts people's total hours of sleep.
- Without the use of the sensor network, 62.5% of the people who presented medium-high temperature had medium-low total sleep, equivalent to 25 people. On the other hand, with the use of the sensor network, a pattern with the same metrics in a different order appeared: 61.3% of the people who had high total sleep presented medium-low temperature, equivalent to 19 people. This pair of patterns may indicate that by

lowering the room temperature, following the algorithm's recommendations, people increased their total hours of sleep.

- Without the use of the sensor network, 61.1% of the people who presented low total sleep hours had medium-low snoring, equivalent to 22 people. On the other hand, with the use of the sensor network, 61.3% of the people who presented high total sleep hours had low snoring, equivalent to 19 people. This pair of patterns may indicate that, following the algorithm's recommendations, people increased their total hours of sleep and reduced their level of snoring.
- Without the use of the sensor network, 65.5% of the people who presented medium-high REM sleep had medium-low snoring, equivalent to 19 people with this association.
- With the use of the sensor network, 66.7% of the people who presented medium-high temperature had medium-high REM sleep, equivalent to 24 people.
- Without the use of the sensor network, 69.2% of the people who presented high temperature and medium-low REM sleep had medium-low snoring, equivalent to 18 people. On the other hand, with the sensor network, a pattern with the same three metrics in a different order was found: 63% of the people with medium-low temperature and medium-low snoring had medium-high REM sleep, equivalent to 17 people. This pair of patterns may suggest an association between REM sleep and ambient temperature. Following the algorithm's recommendations, lowering ambient temperature increases REM sleep levels.
- Without the use of the sensor network, 68% of the people with low HRV and low snoring had medium-low total sleep hours, equivalent to 17 people.
- Without the use of the sensor network, 61.5% of the people who presented medium-low REM sleep and medium-low total sleep hours had low HRV, equivalent to 16 people.
- Without the use of the sensor network, 64% of the people who presented low HRV and medium-low snoring had medium-low REM sleep, equivalent to 16 people.
- Without the use of the sensor network, 65.2% of the people who presented high temperature and low HRV had medium-low REM sleep, equivalent to 15 people.
- Without the use of the sensor network, 65.5% of the people who presented high temperature and low HRV had medium-low total sleep hours, equivalent to 15 people.
- Without the use of the sensor network, 68.2% of the people who presented high temperature and medium-low total sleep hours had low HRV, equivalent to 15 people.
- With the use of the sensor network, 60% of the people who presented medium-high total sleep hours and medium-low snoring had medium-high REM sleep, equivalent to 18 people.
- Without the use of the sensor network, 65.5% of the people who presented medium-high REM sleep and medium-high total sleep hours had medium-low snoring, equivalent to 18 people.

Finally, once the metrics that improved or did not improve with the sensor network were identified, contingency tables were created, where four significant relationships were observed: DS with S; BF with S; HRV with T; and HR with T. In Figures 5–8, the relationships are observed. The intensity of red shows a relationship where fewer incidents were observed than expected, whereas the intensity of blue indicates a relationship where more incidents were observed than expected.

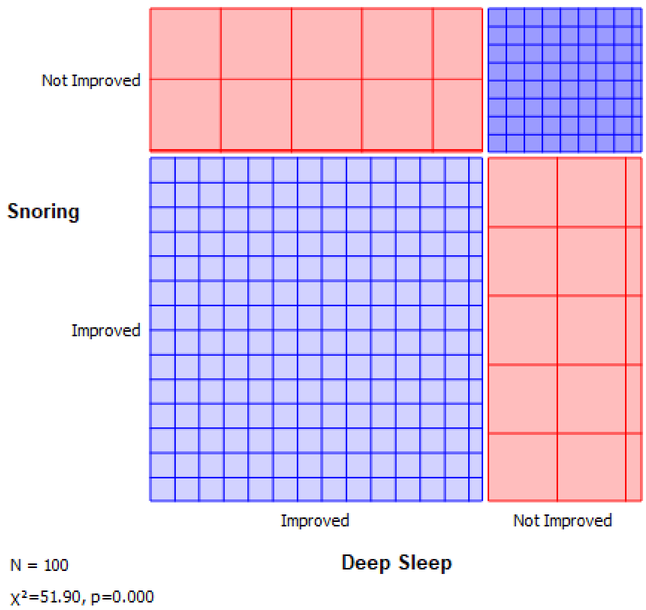

Figure 5. Sieve diagram for the variables deep sleep (DS) and snoring (S).

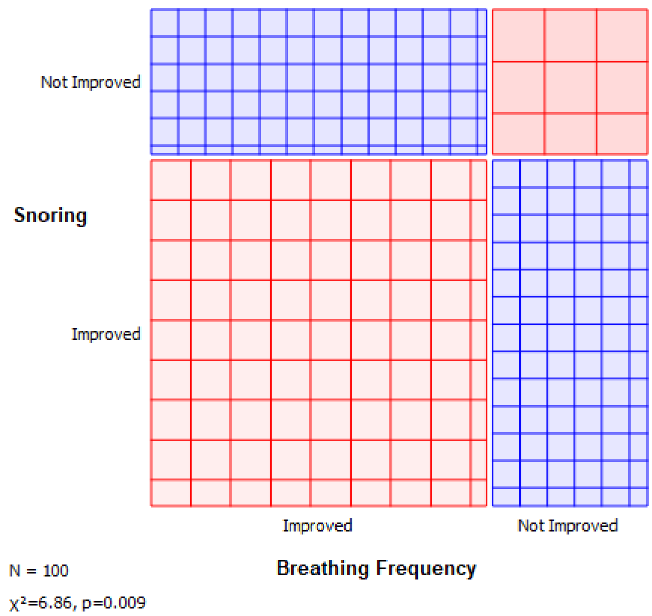

Figure 6. Sieve diagram for the variables breathing frequency (BF) and snoring (S).

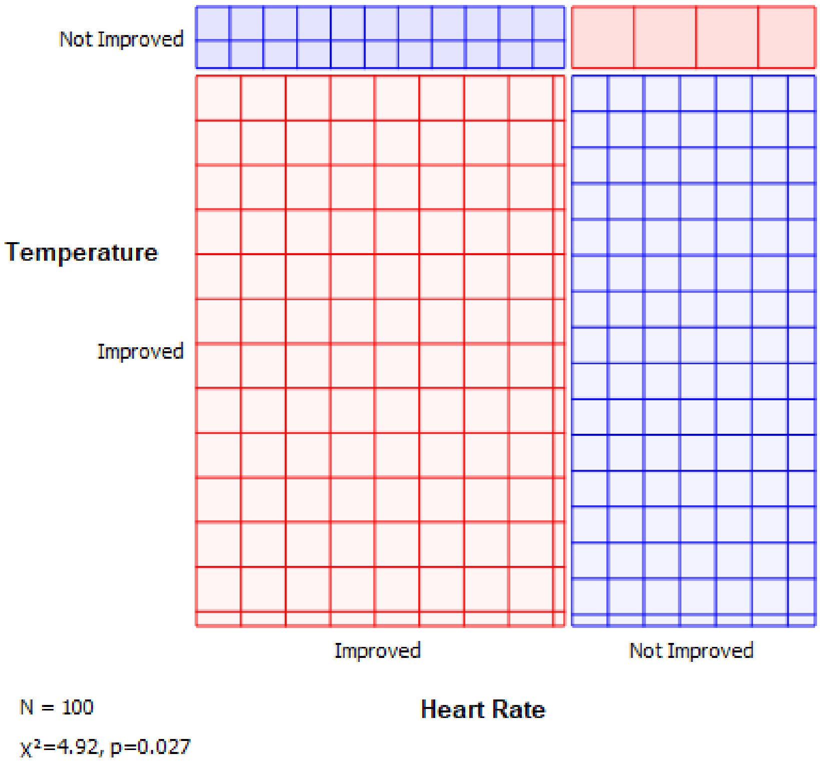

Figure 7. Sieve diagram for the variables heart rate (HR) and temperature (T).

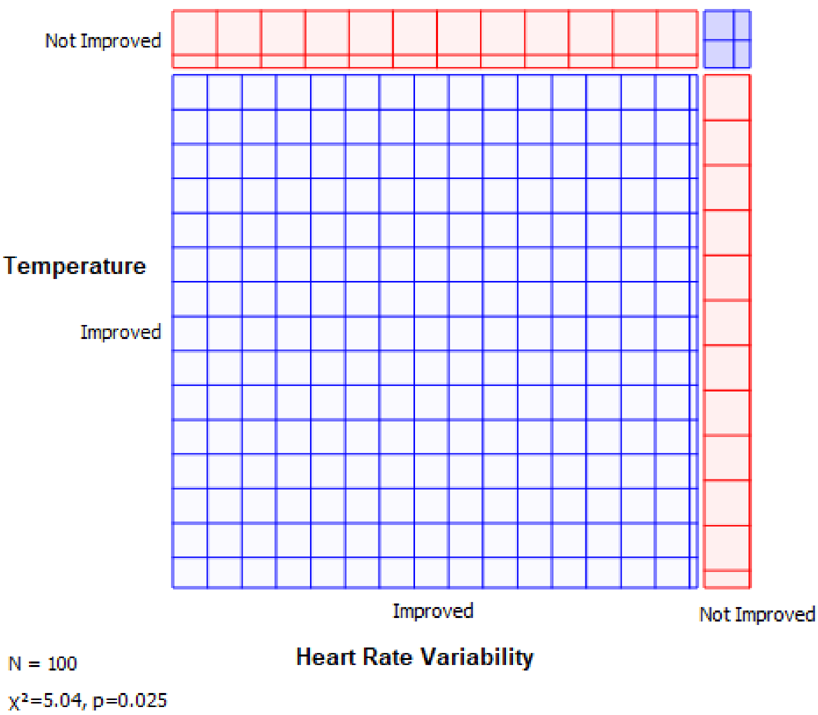

Figure 8. Sieve diagram for the variables heart rate variability (HRV) and temperature (T).

5. Discussion

The analysis and discussion of the results of the experiment with WSNs for monitoring sleep quality and vital signs in the elderly demonstrate significant improvements in several key areas. First, it was demonstrated through paired-sample hypothesis tests that all the metrics measured in the experiment generally improved. Subsequently, the chi-square statistical analysis revealed a substantial improvement in BF and DS among the participants. Specifically, a 68% improvement was observed in breathing frequency, indicating that maintaining optimal levels can significantly enhance the total amount of sleep. Similarly, the deep sleep percentage improved by 68%, underscoring the importance of this sleep phase for overall sleep quality.

Additionally, the experiment demonstrated a notable 70% reduction in snoring among participants, highlighting the importance of controlling this variable for better sleep quality. Although HR improvements were observed in 60% of the cases, this variable did not show a strong enough correlation to be considered a significant factor in sleep quality enhancement. Conversely, HRV emerged as one of the most crucial variables, with a 91% improvement, indicating that higher HRV levels are associated with better sleep quality and longer sleep duration.

OS levels also improved in 59% of the participants, although the correlation with sleep quality was not as strong as for other variables. Nonetheless, higher oxygen saturation levels were linked to improved sleep quality. REMS showed an 85% improvement, demonstrating a direct relationship with increased total sleep hours. Temperature control in the sleeping environment was also found to be critical, as high temperatures negatively impacted sleep duration.

Upon examining the patterns found with the association rules in the top five metrics resulting from the chi-square analysis, the following findings about the occurrence levels of each metric emerged:

- It can be observed that the temperature levels found in the patterns without the sensor network are high and medium-high, while in the patterns found with the use of the sensor network, they are medium-high and medium-low.
- It can be observed that the HRV level found in the patterns without the sensor network is low, while with the sensor network, high and medium-low levels were found.
- It can be observed that the levels of total sleep hours without the sensor network are low and medium-low, while in the patterns found with the use of the sensor network, they are medium-high and high.
- Both snoring and REM sleep present the same levels with and without the sensor network. REM sleep has medium-low and medium-high levels, while snoring has medium-low and low levels.

It is known beforehand through chi-square tests that the five metrics used with the association rules improved significantly. However, improvements in the levels of occurrence in the patterns give us the possible dimension of the improvement. It can be observed that temperature improved by one level (25%) of occurrence in patterns with the sensor network. HRV improved by one and three levels (from 25% to 75%) of occurrence in patterns with the sensor network. Finally, total sleep hours improved by one or two levels (from 25% to 50%) of occurrence in patterns with the sensor network.

The following findings on relevant associations are made:

- Total sleep hours and snoring are inversely associated with and without the sensor network. It can be observed that with the sensor network, the pattern shows that people slept more and woke up less.
- Temperature and snoring are associated with and without the sensor network. It can be observed that, while snoring remains medium-low in the observed patterns, its association with temperature decreased when using the sensor network.
- The HRV and REM sleep metrics are associated with and without the sensor network. Without the sensor network, when HRV is low, REM sleep is medium-low. With the sensor network, HRV can be high or medium-low with medium-high REM sleep. This could indicate that improving HRV improves REM sleep.
- Temperature and total sleep hours are inversely associated with and without the sensor network. It can be observed that with the sensor network, temperature decreased and total sleep hours increased compared to when the network was not used.

On the other hand, there are some observations of relevant relationships in the contingency table analysis:

- As in the association analysis and previous work [4], total sleep time and snoring show a significant relationship.
- As in previous work [4], temperature and heart rate show a significant relationship.

The use of wireless sensor networks for the non-invasive monitoring of sleep quality and vital signs in the elderly has proven to be effective. This study identified key variables, such as breathing frequency, deep sleep, heart rate variability, and REM sleep, as significant factors in improving sleep quality. The findings suggest that WSN technology can provide a reliable and non-intrusive method for caregivers who use the WSN-based intelligent system. This approach offers a promising solution for addressing the unique health challenges faced by the aging population.

6. Conclusions

This research demonstrates significant advancements in the use of WSNs for the non-invasive monitoring of sleep quality and vital signs in elderly individuals. By leveraging the capabilities of WSNs, this study provides a modern and efficient approach to addressing the health challenges faced by the aging population. Key contributions include the implementation of WSNs to continuously monitor various physiological parameters and environmental factors, such as breathing frequency, deep sleep, snoring, HRV, and temperature. The integration of artificial intelligence for data analysis further enhances the effectiveness of the monitoring system, offering personalized health recommendations that improve sleep quality and overall well-being. The results show substantial improvements in several key metrics, highlighting the potential of this technology to significantly enhance the quality of life for elderly individuals. By focusing on non-invasive and continuous monitoring within the home environment, this study not only contributes to the field of geriatric health but also demonstrates the feasibility and scalability of low-cost technologies in providing personalized healthcare solutions. The findings underscore the potential of WSNs to revolutionize elderly care, offering real-time data that support proactive health management and timely interventions, thereby reducing the burden on caregivers and improving the overall quality of life for the elderly.

Moving forward, it is essential to explore the broader implications of this technology, including its adaptability to different living environments and its potential for integration with other health monitoring systems. Future research should also investigate additional environmental variables and sensor types to capture a more comprehensive range of factors that influence sleep quality and vital signs. The results of such research could pave the way for more scalable and adaptable solutions in geriatric health monitoring, thereby contributing to the development of more holistic and effective care strategies for the elderly.

The main limitations of the proposed model in this research include the study's reliance on a single type of wireless sensor network and the fact that specific environmental variables may not capture the full range of factors affecting sleep quality and vital signs in diverse settings. The adaptability of the system to different living environments and varying technological infrastructures also remains untested, posing challenges for its broader application.

Nevertheless, this research represents a significant milestone in geriatric health monitoring, offering an integrated solution to the challenges of aging. The findings underscore the importance of continuous, non-invasive monitoring and the value of personalized health interventions. By advancing the use of WSNs and AI in healthcare, this study paves the way for future innovations in health monitoring technologies, providing a foundation for more effective and efficient healthcare solutions. The insights gained from this research are expected to inform and inspire future studies, driving further advancements in the field of geriatric care and beyond.

This research opens new avenues for future investigation, particularly in exploring the adaptability of WSN technology across diverse living environments and its integration with other health monitoring systems. Further studies could expand on the range of environmental and physiological variables monitored, as well as assess the long-term impact of such technologies on elderly health outcomes. By continuing to refine and adapt these systems, future research can build on the foundations laid by this study, paving the way for more comprehensive and integrated care strategies that address the complex health needs of aging populations.

Author Contributions: C.D.-V.-S. developed the analysis, supervised the research methodology and the approach of this work, prepared the scenario, analyzed the results, and coordinated the overall project. R.A.B. reviewed, interpreted, and drafted the comparison results and tables, conducted the literature review, and assisted with the statistical analysis. R.V. was involved in the formal analysis and manuscript preparation and contributed to the design of the experiments. G.G.-R. made the figures, performed their comparison, conducted the formal analysis, and assisted in data visualization. S.P.-O. and I.H.P.-B. directed some formal concepts, reviewed the manuscript, and provided critical revisions for intellectual content. P.V. contributed to the design and implementation of the wireless sensor network, provided expertise in sensor technology, and assisted with the technical aspects of the study. J.V.-A. was involved in data collection, processed the data for analysis, and assisted in drafting the Discussion Section. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Integrity Code of the Universidad Panamericana, validated by the Social Affairs Committee and approved by the Governing Council through resolution CR 98-22 on 15 November 2022.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are openly available in https://drive.google.com/drive/folders/11HvnLixD9Wm7olIMV9kCfnm2Q0tdg4ym?usp=drive_link [Datos relacionados con el sueño] (accessed on 7 August 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

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