

Perceptions and Acceptability of Sensor-Based Activity Recognition Systems Among Older Adults and Their Families

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Abstract: This paper examines activity recognition systems that use sensor devices with specific activity models. It presents a new system that combines motion, open/close, and ambient sensors with wristband devices and location beacons. Alongside a detailed review of the system, the study also explores the views of two main groups of users: older adults and their family members. Although related studies exist, this research introduces the system and thoroughly analyzes user feedback. An important aspect is the acknowledgment of improvements in sensor-based smart devices, especially in terms of size and subtlety compared to earlier bracelet designs. This study included 40 anonymous participants who tested these system and key factors analyzed include acceptability, safety, peace of mind, privacy, quality of life, autonomy, trust, perceived social support, loneliness, and economic cost. This assessment offers useful insights into how users perceive and accept the system, to understand the main concerns with commonly used devices like cameras and sensors helps identify which devices older adults might be open to using in their routines. These insights are expected to guide the development of future systems that better address user needs.

1 INTRODUCTION

The growing demographic shift towards an aging population presents a formidable challenge in society today (United Nations, 2022), requiring the development of innovative solutions to enhance the well-being of older individuals. In response to this pressing need, Human Activity Recognition Systems (HAR) (Arshad et al., 2022; Bian et al., 2022) have emerged as promising tools with the potential to address diverse health and autonomy-related needs among the elderly.

These systems employ various approaches, with the key determining factor being sensor selection. A wide variety of sensors have been studied for activity recognition (Liu et al., 2020; Fu et al., 2020; Dang et al., 2020), particularly environmental and vision-based sensors. The efficacy and applicability of activity recognition systems hinge significantly on these two sensor types.

On the one hand, environmental sensors, designed

to capture data about the surrounding context, offer insights into activities involving movement or environmental changes (Dang et al., 2020; Yuan et al., 2022). While helpful for recognizing activities without direct visual observation, their limitations include the inability to capture fine details, potentially leading to information loss that might be crucial for accurate identification (Ahad et al., 2020). External factors, such as multi-occupancy, can also cause interference and affect data reliability.

On the other hand, vision-based sensors use cameras or optical devices to capture activities visually (Beddiar et al., 2020), excelling in recognizing actions involving specific movements, gestures, or interactions with objects (Franco et al., 2020; Dang et al., 2020; Ramirez et al., 2021). Despite their ability to provide detailed visual information, they also face challenges, such as dependency on proper illumination, sensitivity to obstructions, and privacy concerns arising from image and video capture (Langheinrich, 2002).

Alternative methods involve wearable devices such as activity bracelets and smartwatches, which extract biometric data from users (Fan and Gao, 2021; Huang et al., 2021).

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Fog nodes are placed near data sources to collect and pre-process data, optimizing transmission to the cloud and reducing network load. They may use lightweight models for initial tasks. The cloud manages then data storage, applying more complex activity recognition models. This division optimizes transmission, ensures flexibility, and enables comprehensive data management.

Numerous proposals have emerged within this domain, aiming to provide effective and non-intrusive solutions for older adults. Examples include the Konekta2 system (Codina, 2022), Beprevent (Ger, 2020), the Noa smart pill dispenser (Inb, 2020), and the ACTIVA system (Montoro Lendínez et al., 2023), each addressing specific aspects of monitoring and support for daily activities.

When comparing state-of-the-art activity recognition systems, several points can be noted. Some approaches require the installation of surveillance cameras and image processing, like the HAR system in Hussain et al. (Hussain et al., 2022), which combines a pre-trained Vision Transformer and recurrent neural networks (LSTM) to capture long-term temporal information. Su et al. (Su et al., 2023) propose a deep learning-based framework for real-time non-contact human activity detection using self-powered sensors. In this work, a multi-layer bidirectional short- and long-term memory (MBLSTM) network is used to process Wi-Fi channel state information (CSI) and recognize human activities. While the system shows very promising results, multi-occupancy is a challenge when using this technique, since it cannot discern several subjects. This is also the case in (Bhavanasi et al., 2023), which uses compact radar sensors for patient activity recognition in hospitals. Conversely, our approach avoids these concerns by using sensors that do not compromise individuals' privacy, along with a system to deal with multi-occupancy.

The success of these HAR systems hinges on user perceptions, particularly those of older adults, and the acceptability of the sensors employed (Camp et al., 2022). Older individuals often face challenges related to mobility, health, and safety (Mottram et al., 2008; Niccoli and Partridge, 2012). To ensure the effectiveness of these solutions, it is crucial to understand the acceptability of different sensor types in activity recognition systems. Thus, the research question guiding this study focuses on the acceptability of sensor types in the activity recognition of older adults, as follows:

Research Question: How acceptable are different sensor types to older adults for activity recognition?

This work aims to address the research question through a comprehensive analysis of the perceptions

held by older adults and their family members regarding sensor-based activity recognition systems. The specific objectives include:

1. **Study Older Adults' Perceptions:** Conduct an in-depth analysis of how older individuals perceive activity recognition systems, with an emphasis on identifying both advantages and disadvantages that these systems may entail for them.
2. **Assess Acceptability:** Evaluate how acceptable activity recognition systems are to older adults, addressing crucial aspects such as trust, security, privacy, and peace of mind.
3. **Evaluate Family Members' Opinions:** Investigate how family members view activity recognition systems, particularly focusing on aspects like security, privacy, usability, and other relevant considerations.

This study will analyze the role of sensors in activity recognition systems in the homes of older adults. The aim is to gain a greater understanding of their needs, since these systems can be used for a wide range of purposes, such as detection of abnormal behaviors (König et al., 2015; Umbricht et al., 2020) or monitoring activities that encourage autonomy.

Identifying the primary concerns around commonly used devices, such as cameras and sensors, is crucial to understand which devices people would be willing to integrate into their daily lives. This understanding will enable a focused effort to develop new systems that capitalize on these findings.

The structure of the paper is as follows: in Section 2, we present a novel sensor-driven connected health system designed to monitor people's activities within their homes. Section 3 presents the methodology used to conduct the analysis. In Section 4, the results from the questionnaires are discussed. Finally, Section 5 sets out the conclusions of the paper.

2 MATERIALS AND METHODS

In this section, we present the activity recognition system used in our study and explain the method followed for our acceptability analysis. This system serves as a basic framework for subsequent evaluation by direct users, older adults, and family members, ensuring they are able to provide a comprehensive assessment and usability feedback.

2.1 System

The architecture of the proposed activity recognition system is illustrated in Figure 1. This figure pro-

vides a visual representation of the system's design and components, offering a better understanding of its structure and functionality.

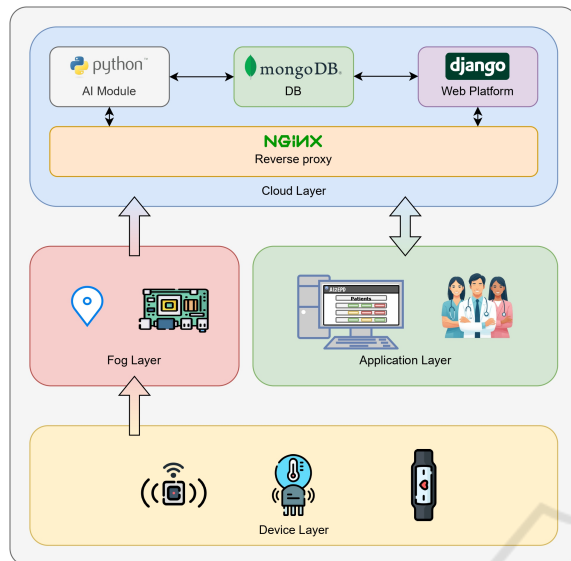


Figure 1: System Architecture.

2.1.1 Device Layer

The device layer comprises various devices that contribute data to the system, including sensors and location devices:

- **Open and Close Sensors.** These sensors use a magnetic field to detect separations between their components. In our system, they are deployed at the main entrance and on containers storing medications for the users. The specific sensor we have deployed is the Aqara Door and Window Sensor, which uses Zigbee technology and has an estimated battery life of two years.
- **Motion Sensors.** Infrared-based motion sensors detect infrared radiation emitted by objects within their field of view. Strategically positioned in areas like bathrooms, communal spaces, and beds, these sensors track residents' movements, providing insights into activities such as sleeping and toileting. The Aqara P1 motion sensor features a sensing angle of approximately 170° and a sensing distance of approximately 7 meters. It works with Zigbee 3.0 wireless connections and has a battery life of up to 5 years. This device, unlike others, allows us to modify the detection range and time, which makes it adaptable to different activities by defining specific detection zones.
- **Temperature and Humidity Sensors.** These sensors monitor ambient conditions like temper-

ature and humidity. They provide data regarding environmental parameters in monitored areas. Within our system, they are deployed in bathing areas to detect changes in related activities. The Aqara Temperature and Humidity Sensor uses Zigbee technology and has a battery life of two years.

- **Location Detection.** To address multi-occupancy scenarios, we adopted the methodology outlined in the ACTIVA system (Montoro Lendínez et al., 2023; Espinilla et al., 2018a; Espinilla et al., 2018b). This method relies on Received Signal Strength Indicator (RSSI) measurements between fixed anchor devices positioned in various rooms and a beacon device carried by the user. Raspberry Pi 4 devices and external Bluetooth 4.0 modules serve as anchor devices, while Mi Band 3 activity bracelets function as beacons. These leverage their Bluetooth connectivity to capture RSSI between anchors, enabling location detection. The activity bracelets have an estimated battery life of 3 weeks.

These sensors have been selected specifically for the activities under monitoring: physical activity, sleep patterns, hygiene routines, and dietary habits.

2.1.2 Fog Layer

The fog layer is a pivotal component within the system, featuring a Raspberry Pi equipped with a Bluetooth adapter and a Zigbee Conbee2 communications module. This central node interconnects various devices distributed throughout the environment. Leveraging the Zigbee protocol, it establishes connections with different sensors positioned throughout the living space. We adopted Zigbee because of its widespread availability in commercial sensors and because it offers extensive communication capabilities coupled with low power consumption, thus rendering it preferable over alternatives such as Wi-Fi (Lee et al., 2007).

These sensors are managed through the Home Assistant platform¹, which allows us to configure and integrate devices operating on different technologies. Upon receiving data within the platform, it is disseminated across a network under the MQTT protocol (through by Mosquitto Broker²) for further processing and transmission to the database.

Regarding location detection, each anchor device publishes its RSSI values relative to the beacon within the MQTT network. When the central node receives

¹<https://www.home-assistant.io/>

²<https://mosquitto.org/>

these values, a location model is run to determine the device's location. The resulting locations are subsequently transmitted to the cloud layer for storage and further processing.

2.1.3 Cloud Layer

The cloud layer is another core element of the system, housing the majority of its components. Comprising four key elements – a database, a reverse proxy, an AI computing module and web platform – this layer orchestrates crucial system functionalities.

- **Database.** MongoDB³, a NoSQL document-based database, has been selected to accommodate the heterogeneous data obtained from various sensors. Its flexible schema aligns well with the diverse nature of the sensor data, meeting the system's requirements effectively.
- **Reverse Proxy.** We chose Nginx⁴ as a reverse proxy because it meets stringent security demands across all system elements, while allowing for enhanced scalability. The system's security is fortified by TLS implementation for inbound and outbound communications, extensive logging for audit purposes, and deployment of attack mitigation techniques, such as DDoS attacks.
- **AI Computing Module.** The AI computing module analyzes user activities and verifies their adherence to predefined activity regimens established by the researchers or healthcare staff, which set out the objectives or healthy habits individuals must uphold (Montagut-Martínez et al., 2022). The module processes daily sensor and location data for each user, leveraging predefined rules to categorize activities. Subsequently, it evaluates whether these activities align with the stipulations outlined in the established regimen.
- **Web Platform.** The web platform, developed under the Django framework⁵, serves as a centralized hub for managing sensors and disseminating information to healthcare personnel. Django's robust toolset and comprehensive library of extensions facilitate agile development.

It is noteworthy that all components operate within containers, leveraging Docker technology to establish a private network, which provides the advantage of enhanced scalability and security. This containerized approach enables the creation of container

replicas to bolster system capacity and ensures isolation from other host system components, improving overall system robustness and resilience.

2.1.4 Application Layer

As previously discussed, the web platform provides comprehensive management functionalities for all system components. Specifically, it allows technical personnel to oversee sensors, anchors, activity bracelets, and residential units within the system. At the same time, healthcare professionals can tailor health or activity regimens to meet the unique needs of individual users. Staff are also able to monitor compliance with these regimens across various time intervals, ranging from days to weeks and months. In addition, they can aggregate data by specifying start and end dates, enabling an effective assessment of users' compliance with predefined activities.

2.1.5 Test Environment

Prior to deploying the system in the homes of the people to be monitored, the system was deployed in a SmartLab. The SmartLab is a testing environment where several technologies are deployed in evaluation for research purposes. At the moment it has a wide variety of sensors and systems, mainly focus on activity recognition. Although the SmartLab presents a testing environment, it is constrained in certain situations. An example of this is the unavailability of running water in the facility and the lack of a shower, having to simulate activities such as brushing teeth, showering and so on, therefore results may vary in real environments. As can be seen in Figure 2, the different elements that conform the system are shown deployed.

3 METHODOLOGY

To conduct this research, a sample of 40 anonymous individuals was recruited on a voluntary basis, each having provided informed consent. The participants were categorized into two distinct groups: a cohort of 20 adults aged between 65 and 82 years, with an equal gender distribution, and another cohort of 20 caregivers or adult family members, aged between 23 and 70 years, predominantly female.

To address the understanding of the system by the participants recruited for our sample group, it is imperative to note that we ensured that they received in-depth explanations of the sensors and devices used along with the methods of data collection and the

³<https://www.mongodb.com/>

⁴<https://www.nginx.com/>

⁵<https://www.djangoproject.com/>



Figure 2: System elements deployed in the SmartLab.

recording of their activities. To ensure that participants understood the implications of the study before giving their informed consent.

Two bespoke instruments were used for data collection: a survey drawn up for older adults and another designed for their family members. The questionnaire directed at older adults, comprising 19 items and three open-ended questions, delved into critical domains such as acceptability, safety, quality of life, personal autonomy, intimacy, privacy, trust, loneliness, perceived social support, and financial investment. The questionnaire targeting relatives of the older adults, encompassing 12 items and 10 short-answer questions, explored similar themes, with the aim of obtaining a complementary perspective from the family members' point of view. The possible answers are Not at all, A little, Moderately, Quite a lot and A lot, depending on how much the person agrees with the question. The questionnaires as well as the results of the questionnaires can be found at the following link: [Perceptions study](#)

The survey was designed based on previous research that explored older adults' perception and acceptance of sensor technology and home health monitoring. The previous studies used as the basis for the design were the following:

- "Elderly persons' perception and acceptance of using wireless sensor networks to assist healthcare" (Steele et al., 2009), which examined how older people perceive and accept the use of wireless sensor networks for healthcare and provided valuable insights into their attitudes and concerns regarding home monitoring technology and their

willingness to adopt it;

- "Perceptions of In-home Monitoring Technology for Activities of Daily Living: Semistructured Interview Study With Community-Dwelling Older Adults" (Camp et al., 2022), which used semistructured interviews to understand older adults' perceptions of in-home monitoring technology for activities of daily living, providing relevant information on their opinions on the usefulness, ease of use and concerns associated with monitoring technology; and
- Statistical Study of User Perception of Smart Homes during Vital Signal Monitoring with an Energy-Saving Algorithm" (Del-Valle-Soto et al., 2022), which analyzed user perception of smart homes during vital sign monitoring with an energy-saving algorithm and was fundamental to understanding how users interact with smart home technology and their expectations in terms of energy efficiency and functionality.

These studies provided a conceptual framework for the design of the survey, allowing us to identify key factors related to the perception and acceptance of monitoring technology in the home. Based on this previous work, the design of the questionnaires focused on critical aspects such as ease of use, perceived usefulness, privacy concerns, and willingness to adopt home monitoring technologies.

Although the hardware configurations may be different from previous studies, the underlying technology remains very similar. As mentioned above, the

sensors and their functionality have been explained in detail so as to ensure that they are thoroughly understood by all participants. This helps to minimize the potential effects that variations in hardware or software could have on subjective opinion, even if environmental factors have not been fully controlled for.

Data collection began with reaching out to participants by telephone, followed by distributing the survey links via the Google Forms platform. Basic demographic information, including age, gender, and marital status, was gathered. This standardized procedure was uniformly applied to both participant groups, ensuring methodological consistency and the acquisition of high-quality data.

4 DISCUSSION

4.1 Older Adult Results

The results of the surveys for older adults provide valuable insights into their perceptions of sensor-based activity recognition systems. The primary aim was to analyze their perspectives on acceptability, safety, quality of life, personal autonomy, privacy, trust, perceived social support, and their views regarding the advantages and disadvantages of such systems.

Regarding acceptability, 25% of participants expressed reluctance to use cameras providing clear footage, while 10% were very willing, and 20% were quite willing. Regarding the installation of thermal cameras, 45% had no objection. With regards to the use of sensors on everyday objects, 75% expressed no reservations. The results revealed a general acceptance of these systems among older adults, with motion and open/closed sensors emerging as the most widely accepted components, which is consistent with previous research (Camp et al., 2022).

Concerning security and quality of life, 45% of the sample would significantly feel safer with the implementation of sensor-based systems. In terms of quality of life and personal autonomy, 35% believed their personal autonomy would substantially increase, while 25% thought it would increase to a considerable extent. Regarding overall quality of life, only 20% anticipated a significant increase. Overall, our survey suggests that sensor-based activity recognition systems enhance personal autonomy and support independent living for older adults, especially when used for medical purposes or emergencies. These findings align with the Steele et al. study (Steele et al., 2009), where participants prioritized timely assistance over data privacy concerns.

On the matter of privacy, 55% of participants felt that sensor-based systems would moderately respect their privacy. Regarding trust, 75% believed these systems could enhance the speed of response in the event of an emergency.

When it came to perceived social support and loneliness, 40% of participants believed they would experience increased social support with the implementation of these systems. Additionally, 50% thought that these systems would moderately help alleviate feelings of loneliness. In terms of peace of mind, our study found that sensor systems provide an increased sense of safety and calmness, consistent with findings by Del Valle et al. (Del-Valle-Soto et al., 2022) on the perceptions of smart home users during monitoring.

Finally, regarding advantages and disadvantages, it is noteworthy that the majority of participants believed these systems would offer peace of mind, security, assistance, and independence. As for the drawbacks, price, lack of privacy, and complexity of use emerged as the most prevalent concerns. Concerns about the cost and usability of these systems remain prevalent among older adults, as seen in our study and supported by previous research by Claes et al. (2015) (Claes et al., 2015).

4.2 Family Survey Results

The results of the survey for family members or caregivers provide additional insights into their perceptions of sensor-based activity recognition systems.

Regarding acceptability, 28.57% of participants expressed a strong willingness to use these systems, and an additional 28.57% are moderately willing. Concerning security and peace of mind, 38.10% of respondents believe that these systems would significantly contribute to providing peace of mind regarding their elderly relatives.

Concerning quality of life, 28.5% of participants believe that use of these systems could substantially enhance autonomy and safety, contributing significantly to an improved quality of life. Regarding privacy, 42.86% of family members express concerns that these systems may not adequately respect their relative's privacy.

In terms of utility, 52.38% of participants believe that these systems would provide a considerable amount of information about their family member's well-being, while 42.86% think it would be highly beneficial if their family member had this type of system. Our study suggests that sensor systems offer peace of mind and utility, although direct supporting research is lacking. However, Camp et al. (Camp

et al., 2022) found that younger participants were more knowledgeable and accepting of activity monitoring systems than older adults.

Opinions regarding home monitoring systems among family members encompass a diverse spectrum. Paramount among concerns is the safeguarding of privacy, with a notable reluctance to install cameras in specific living spaces. At the same time, considerations around convenience, user-friendliness, and the upkeep of these systems are pivotal.

In their answers to the open-ended questions, participants placed significant value on the efficacy, precision, and incorporation of virtual assistants within these systems. In particular, speed of connectivity was considered critical for an effective response in case of emergencies.

In terms of technological preferences, there is a clear preference for sensor-based solutions, followed by cameras and wearable devices.

Financial commitment towards these systems varies, with respondents indicating a willingness to invest between 200 to 4000 euros, alongside an openness to monthly subscription models. However, uncertainty prevails around the matter of pricing.

Regarding information alerts, unanimous preference is observed for urgent notifications via telephone calls and real-time updates through mobile applications. Conversely, periodic reports on the well-being or activities of family members are deemed non-essential by certain respondents.

Connectivity to emergency services is unanimously seen as imperative among participants.

In discussions pertaining to camera-based systems, opinions diverge. While a portion of respondents expresses indifference, the remaining half underscores the necessity for stringent privacy protocols and data management practices.

5 CONCLUSIONS

In this paper, we propose an innovative activity recognition system utilizing a suite of sensors—such as motion detectors, wrist-worn devices, open/close sensors, and location beacons to cover multi occupancy environments. The research explores system’s acceptance, with particular emphasis on reliability and efficiency, offering a nuanced understanding of its practical applications in everyday contexts.

The paper examines perceptions among older adults and their families regarding this technological solution, considering factors like perceived acceptability, usability, and the impact on autonomy, quality of life, and social support. This dual approach

bridges the technical capabilities of the system with the subjective experiences of potential users, providing a well-rounded assessment of the system’s benefits and possible areas for refinement.

The main key findings underscore the necessity of ensuring future designs are guided by user privacy, accessible in terms of ease of use, and financially sustainable. By identifying prevalent concerns—especially around commonly deployed devices like cameras and sensors—this study suggests a pathway toward developing supportive technologies that older adults can trust and rely on. Prioritizing simplicity, privacy, and reliability can lead to solutions that not only offer technological support but also enhance daily living and respect individual preferences, fostering a genuine integration of technology in their routines.

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REFERENCES

- (2020). Beprevent un asiente personal que facilita la vida independiente de los mayores. Available online: <https://www.geriaticarea.com/2017/08/24/beprevent-un-asiente-personal-que-facilita-la-vida-independiente-de-los-mayores/> (accessed on 14 May 2024).
- (2020). Noa smart pill dispense. Available online: <https://inbizi.es/noa/> (accessed on 14 May 2024).
- Ahad, M. A. R., Antar, A. D., and Ahmed, M. (2020). Sensor-based human activity recognition: Challenges ahead. pages 175–189.
- Arshad, M. H., Bilal, M., and Gani, A. (2022). Human activity recognition: Review, taxonomy and open challenges. *Sensors (Basel, Switzerland)*, 22.
- Beddiar, D., Nini, B., Sabokrou, M., and Hadid, A. (2020). Vision-based human activity recognition: a survey. *Multimedia Tools and Applications*, 79:30509 – 30555.
- Bhavanasi, G., Werthen-Brabants, L., Dhaene, T., and Couckuyt, I. (2023). Open-set patient activity recognition with radar sensors and deep learning. *IEEE Geoscience and Remote Sensing Letters*, 20:1–5.

- Bian, S., Liu, M., Zhou, B., and Lukowicz, P. (2022). The state-of-the-art sensing techniques in human activity recognition: A survey. *Sensors*, 22(12):4596.
- Camp, N., Johnston, J., Lewis, M. G., Zecca, M., Di Nuovo, A., Hunter, K., and Magistro, D. (2022). Perceptions of in-home monitoring technology for activities of daily living: Semistructured interview study with community-dwelling older adults. *JMIR aging*, 5(2):e33714.
- Claes, V., Devriendt, E., Tournoy, J., and Milisen, K. (2015). Attitudes and perceptions of adults of 60 years and older towards in-home monitoring of the activities of daily living with contactless sensors: an explorative study. *International journal of nursing studies*, 52(1):134–148.
- Codina, T. (2022). Konekta2, sensorizació intel·ligent de vivendes de persones majors - fundació isocial. innovació en l'acció social. Available online: <https://isocial.cat/es/konekta2-sensoritzacio-intel·ligent-dhabitatges-de-persones-grans/> (accessed on 14 May 2024).
- Dang, L. M., Min, K., Wang, H., Piran, M. J., Lee, C. H., and Moon, H. (2020). Sensor-based and vision-based human activity recognition: A comprehensive survey. *Pattern Recognition*, 108:107561.
- Del-Valle-Soto, C., Nolzaco-Flores, J. A., Del Puerto-Flores, J. A., Velázquez, R., Valdivia, L. J., Rosas-Caro, J., and Visconti, P. (2022). Statistical study of user perception of smart homes during vital signal monitoring with an energy-saving algorithm. *International Journal of Environmental Research and Public Health*, 19(16):9966.
- Espinilla, M., Martínez, L., Medina, J., and Nugent, C. (2018a). The experience of developing the ujami smart lab. *Ieee Access*, 6:34631–34642.
- Espinilla, M., Medina, J., Hallberg, J., and Nugent, C. (2018b). A new approach based on temporal sub-windows for online sensor-based activity recognition. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–13.
- Fan, C. and Gao, F. (2021). Enhanced human activity recognition using wearable sensors via a hybrid feature selection method. *Sensors (Basel, Switzerland)*, 21.
- Franco, A., Magnani, A., and Maio, D. (2020). A multimodal approach for human activity recognition based on skeleton and rgb data. *Pattern Recognit. Lett.*, 131:293–299.
- Fu, B., Damer, N., Kirchbuchner, F., and Kuijper, A. (2020). Sensing technology for human activity recognition: A comprehensive survey. *Ieee Access*, 8:83791–83820.
- Huang, W., Zhang, L., Gao, W., Min, F., and He, J. (2021). Shallow convolutional neural networks for human activity recognition using wearable sensors. *IEEE Transactions on Instrumentation and Measurement*, 70:1–11.
- Hussain, A., Hussain, T., Ullah, W., and Baik, S. (2022). Vision transformer and deep sequence learning for human activity recognition in surveillance videos. *Computational Intelligence and Neuroscience*, 2022.
- König, A., Junior, C. C., Derreumaux, A., Bensadoun, G., Petit, P.-D., Brémond, F., David, R., Verhey, F., Aalten, P., and Robert, P. (2015). Validation of an automatic video monitoring system for the detection of instrumental activities of daily living in dementia patients. *Journal of Alzheimer's disease : JAD*, 44 2:675–85.
- Langheinrich, M. (2002). A privacy awareness system for ubiquitous computing environments. In *UbiComp 2002: Ubiquitous Computing: 4th International Conference Göteborg, Sweden, September 29–October 1, 2002 Proceedings 4*, pages 237–245. Springer.
- Lee, J.-S., Su, Y.-W., and Shen, C.-C. (2007). A comparative study of wireless protocols: Bluetooth, uwb, zigbee, and wi-fi. In *IECON 2007 - 33rd Annual Conference of the IEEE Industrial Electronics Society*, pages 46–51.
- Liu, J., Liu, H., Chen, Y., Wang, Y., and Wang, C. (2020). Wireless sensing for human activity: A survey. *IEEE Communications Surveys & Tutorials*, 22:1629–1645.
- Montagut-Martínez, P., García-Arenas, J. J., Romero-López, M., Rodríguez-Rodríguez, N., Pérez-Cruzado, D., and González-Lama, J. (2022). Feasibility of an activity control system in patients with diabetes: A study protocol of a randomised controlled trial. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy*, pages 2683–2691.
- Montoro Lendínez, A., López Ruiz, J. L., Nugent, C., and Espinilla Estévez, M. (2023). Activa: Innovation in quality of care for nursing homes through activity recognition. *IEEE Access*, 11:123335–123349.
- Mottram, S., Peat, G., Thomas, E., Wilkie, R., and Croft, P. (2008). Patterns of pain and mobility limitation in older people: cross-sectional findings from a population survey of 18,497 adults aged 50 years and over. *Quality of Life Research*, 17:529–539.
- Niccoli, T. and Partridge, L. (2012). Ageing as a risk factor for disease. *Current Biology*, 22:R741–R752.
- Ramírez, H., Velastín, S., Meza, I., Fabregas, E., Makris, D., and Farias, G. (2021). Fall detection and activity recognition using human skeleton features. *IEEE Access*, 9:33532–33542.
- Steele, R., Lo, A., Secombe, C., and Wong, Y. K. (2009). Elderly persons' perception and acceptance of using wireless sensor networks to assist healthcare. *International journal of medical informatics*, 78(12):788–801.
- Su, J., Liao, Z., Sheng, Z., Liu, A. X., Singh, D., and Lee, H.-N. (2023). Human activity recognition using self-powered sensors based on multilayer bidirectional long short-term memory networks. *IEEE Sensors Journal*, 23(18):20633–20641.
- Umbricht, D., Cheng, W.-Y., Lipsmeier, F., Bamdadian, A., and Lindemann, M. (2020). Deep learning-based human activity recognition for continuous activity and gesture monitoring for schizophrenia patients with negative symptoms. *Frontiers in Psychiatry*, 11:574375.
- United Nations (2022). World Population Prospects. Available online: <https://population.un.org/wpp/> (accessed on 14 May 2024).
- Yuan, L., Andrews, J., Mu, H., Vakil, A., Ewing, R., Blasch, E., and Li, J. (2022). Interpretable passive multimodal sensor fusion for human identification and activity recognition. *Sensors (Basel, Switzerland)*, 22.