

Supporting Healthy Aging with Active Assisted Living Technology: From Developing Smart Home Data Ecosystem to Activities of Daily Living Recognition

by
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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contribution

Kang Wang independently authored Chapters 1, 2, 3, and 9 under the supervision of Dr. Plinio P. Morita and Dr. Shi Cao. These chapters were developed specifically for this thesis and were not aimed at publication.

Additionally, this thesis comprises five manuscripts that were for publication. The specific contributions to these manuscripts, except for sole-authored sections, are detailed as follows:

Research presented in Chapter 4:

This chapter is a scoping review study in which Kang Wang was primarily responsible for the research. Kang Wang's contributions included designing the search strategy, identifying search keywords, conducting the search, screening the literature, performing the analysis, drafting the manuscript, and revising it for publication. Shahan Salim assisted in identifying search keywords and screening the papers. Dr. Dmytro Chumachenko contributed to the screening process, analysis, and manuscript writing. Dr. Shahabeddin Abhari provided support in the analysis and writing stages. Dr. Plinio P. Morita, Dr. Moojan Ghafurian, Dr. Shi Cao, and Dr. Zahid A. Butt supervised the manuscript's writing, editing, and revisions. All listed authors contributed to the final article.

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Research presented in Chapter 5:

Kang Wang is the principle contributor to the study detailed in this chapter. Kang Wang was responsible for the ecosystem architecture design, coding implementation for the ecosystem, development of the AAL environment, recruitment of study participants, leading data collection, data modeling, and data analysis. Additionally, Kang Wang was responsible for drafting of the manuscript and revisions for publication. Pedro Miranda from the Ubiquitous Health Technology Lab helped the construction of the AAL environment. Volunteers Kunal Karkhanis and Nicole MacDonald provided assistance in participant recruitment and data collection. Pritthijit Nath contributed to ecosystem development including database construction and data merge. Dr. Jasleen Kaur provided help in the manuscript writing process. Dr. Plinio P. Morita and Dr. Shi Cao supervised the writing, editing, and revision of the manuscript. All listed contributors played essential roles in finalizing the article for publication.

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Research presented in Chapter 6:

Kang Wang is the main contributor of the study presented in this chapter. Kang Wang's responsibilities include the design and construction of the AAL environment, leading participant recruitment, data collection, and independently conducting data modeling and analysis. Kang Wang was responsible for manuscript writing, editing, and revisions for publication. Volunteers Kunal Karkhanis and Nicole MacDonald provided assistance in participant recruitment and data collection. Dr. Jasleen Kaur provided help in the manuscript writing process. Dr. Plinio P. Morita, Dr. Moojan Ghafurian, Dr. Shi Cao, and Dr. Zahid A. Butt supervised the manuscript's writing, editing, and revisions. All listed authors contributed to the final article.

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Research presented in Chapter 7:

Kang Wang is the main contributor of the study presented in this chapter. Kang Wang led the design and construction of the AAL environment, the study design, participant recruitment, data collection, and conducted data modeling and analysis. Additionally, Kang Wang was responsible for drafting, editing, and revising the manuscript for publication. Ayan Dogra provided support in data modeling. Ashish Saragadam, Dr. Jasleen Kaur, Dr. Shahabeddin Abhari, and Dr. Dmytro Chumachenko assisted in manuscript writing. Dr. Plinio P. Morita, Dr. Moojan Ghafurian, Dr. Shi Cao, and Dr. Zahid A. Butt supervised the manuscript's writing, editing, and revisions. All listed authors contributed to the final article.

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Research presented in Chapter 8:

Kang Wang is the lead author of the study presented in this chapter. Kang Wang contributed to conceptualizing and executing the study design and conduction, including constructing

AAL environment, conducting data modeling and analysis. Additionally, Kang Wang was responsible for drafting, editing, and submitting the manuscript for publication. Ashish Saragadam helped with data collection. Dr. Jasleen Kaur, Dr. Plinio P. Morita, Dr. Shi Cao, Dr. Moojan Ghafurian, and Dr. Zahid A. Butt provided critical feedback and assistance in manuscript refinement. All listed authors contributed to the final article.

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Abstract

Background: The aging population is growing rapidly worldwide, posing significant challenges for healthcare systems. This demographic shift demands innovative approaches to address the unique physical, cognitive, and social needs of older adults.. Traditional healthcare systems are often ill-equipped to provide continuous monitoring and support, leading to increased pressure on caregivers and healthcare providers. Active Assisted Living technologies, combined with Artificial Intelligence, present an opportunity to bridge this gap by integrating advanced sensors and analytics into everyday living environments. These technologies can enhance healthcare monitoring, promote independent living, and improve overall well-being for aging populations. The aim of this thesis is to develop and evaluate AI-enhanced AAL systems that address key challenges in aging healthcare. This includes constructing robust data ecosystems for sensor integration, advancing methods for physical indicator prediction, Activities of Daily Living recognition, and ensuring the adaptability of these technologies for real-world applications.

Methods: This thesis employed a multi-phase research methodology, integrating systematic reviews, infrastructure development, and experimental evaluations to advance Active Assisted Living technologies for aging populations.

The research began with a comprehensive scoping review to systematically map the landscape of AI applications in AAL technologies. The review followed the PRISMA methodology, with searches conducted across six databases: PubMed, CINAHL, IEEE Xplore, Scopus, ACM Digital Library, and Web of Science. Studies published over the past decade were considered, resulting in 64 eligible papers that were reviewed and analyzed to identify critical gaps.

Building on these findings, a cloud-native AAL data ecosystem was developed to facilitate the collection, integration, and management of sensor data from commercially available AAL devices. This ecosystem was structured across four layers: perception, transportation, processing, and application. Leveraging cloud computing technologies, the system ensured scalability, interoperability, and real-time data processing. Advanced data acquisition and management protocols were implemented to address challenges related to reliability, security, and compliance with health data standards.

The functionality of the data ecosystem was validated through a heart rate prediction study using contactless monitoring techniques. Forty participants performed 23 predefined daily living activities in a smart home environment equipped with Swidget ambient sensors and Empatica E4 wristbands. Data collected from ambient sensors were analyzed using machine learning models, such as Random Forests, to predict heart rates accurately.

Further research investigated Activities of Daily Living recognition using the same data assets. A proof-of-concept study involving younger adults in controlled smart home environments evaluated the effectiveness of contactless ambient sensors. Machine learning models, such as Adaptive Boosting, Decision Trees, and Gaussian Naive Bayes, were employed to classify daily activities, achieving high accuracy.

To address the challenge of generalizability for Activities of Daily Living recognition among population, a hybrid transfer learning framework was developed. This framework combined Correlation Alignment and Conditional Adversarial Domain Adaptation techniques to adapt models trained on younger adults for application in older populations. Experiments involving 26 healthy older adults were conducted in semi-controlled environments, focusing on less structured activities to simulate real-world conditions.

Results: The scoping review identified critical gaps in the application of AI within AAL technologies, particularly the lack of centralized data ecosystem and real-world experimentation. The developed cloud-native AAL data ecosystem successfully integrated data from multiple commercially available sensors, facilitating seamless data processing and real-time analytics. The heart rate prediction study achieved a high prediction performance with a Mean Absolute Error of 6.023 using the Random Forest model.

The ADLs recognition study, conducted with younger adults in controlled settings, demonstrated an overall accuracy of 0.964 using the Adaptive Boosting model, significantly outperforming wearable sensor-based methods and hybrid modes. The hybrid transfer learning framework further addressed the generalizability challenge by adapting models trained on younger adults in controlled settings to older adults in semi-controlled settings. The hybrid adaptive model achieved an accuracy of 0.576 and an F1-score of 0.538, compared to baseline methods, which achieved only 0.098 in accuracy the most. Additionally, incorporating a small amount of target population data in training enhanced the performance, with accuracy increasing by a maximum of 0.344.

Conclusion: This thesis makes significant contributions to the advancement of AAL technologies on public health monitoring by addressing foundational gaps in data ecosystem development, health indicators prediction, ADLs recognition, and its transferability to older adults in real-world. The research demonstrates the feasibility of AI-enhanced AAL systems to provide reliable, scalable, and inclusive solutions for healthcare monitoring and activity recognition in aging populations. By developing and validating methodologies for real-world application, this work also highlights the potential of these technologies to support public health initiatives. The integration of AAL systems into public health frameworks could enable proactive monitoring, early detection of health risks, and personalized interventions, ultimately improving population-level health outcomes. This thesis lays the groundwork for empowering older adults to live independently, safely, and with improved quality of life, while also supporting caregivers and healthcare providers with actionable insights.

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I also want to thank all the co-authors of the studies presented in this thesis, as well as all my co-authors in our publications. Your efforts, collaboration, and contributions have greatly enriched my work. I am truly thankful for your support and dedication.

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Dedication

Five years ago, I took a leap of faith and left my home in China to pursue the PhD in Canada. It was a journey filled with challenges and sacrifices, as I left behind my family, friends, and everything familiar to me. Along the way, I faced the isolation of the COVID-19 pandemic and endured the long lockdowns in my home country, which made it impossible for me to return home. Yet, through all the hardships, I discovered strength and resilience, and it is to the people who supported me during this journey that I dedicate this thesis.

To my parents, through separated by thousands of miles, your love, encouragement, and support have been my constant source of strength. Our phone calls and video chats kept us connected and reminded me of the values and determination you taught me. Thank you for always believing in me.

To my lover in life, Yijun Pan, your support has been my foundation throughout this PhD journey. You stood by me during the toughest times, helping me in both life and work. I am deeply thankful for your love and the sacrifices you made for me.

To my grandparents, your love have been a cornerstone of my life. Losing you during my PhD journey was one of the hardest things I have ever endured. Not being able to see you one last time still weighs heavily on my heart. I carry the pain of your absence every day, but I believe that you have become the stars in the sky, watching over me every night. This work is my way of keeping your memory alive and honoring everything you meant to me.

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List of Abbreviations

AAL:	Active Assisted Living (or Ambient Assisted Living)
ACC:	Accuracy
Adaboost:	Adaptive Boosting
ADL:	Activity of Daily Living
AI:	Artificial Intelligence
API:	Application Programming Interface
AQI:	Air Quality Index
BADL:	Basic Activity of Daily Living
BPM:	Beats Per Minute
CART:	Classification And Regression Tree
CDAN:	Conditional domain adversarial networks
CNN:	Convolutional Neural Network
CORAL:	Correlation Alignment
CSV:	Comma-Separated Value
CVD:	Cardiovascular disease
DAN:	Domain Adaptation
DBN:	Deep Belief Network
DBSCAN:	Density-Based Spatial Clustering of Applications with Noise
DL:	Deep Learning
DT:	Decision Tree
EDA:	Electrodermal Activity Sensor
FN:	False Negative
FP:	False Positive
GDPR	General Data Protection Regulation
GNB:	Gaussian Naive Bayes
HAR:	Human Activity Recognition
HOASC:	Healthy Older Adults in Semi-Controlled setting
HR:	Heart Rate
HRFLM:	Hybrid Random Forest Linear Model
HTTP:	HyperText Transfer Protocol
HYAC:	Healthy Younger Adults in Controlled setting
IADL:	Instrumental Activity of Daily Living
IoT:	Internet of Things
JSON:	JavaScript Object Notation
KNN:	K-Nearest Neighbor
LSTM:	Long Short-Term Memory
MAE:	Mean Absolute Error
MDI:	Mean Decrease in Impurity
ML:	Machine Learning
MLP:	Multi-Layer Perceptron

MQTT:	Message Queuing Telemetry Transport
NCD:	Noncommunicable Diseases
PCAR:	Permutation-based Change Detection in Activity Routine
PRISMA-ScR:	Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews
PPG:	Photoplethysmography
PSO-BP:	Particle Swarm Optimization Back Propagation
ReactJS:	React JavaScript
REST:	Representational State Transfer
RF:	Random Forest
R ² :	R-squared
RMSE:	Root Mean Squared Error
RTN:	Reverse Transfer Network
SHAP:	SHapley Additive exPlanations
SHT:	Smart Home Technology
SI:	Scatter Index
SQL:	Structured Query Language
SVR:	Support Vector Regression
SVM:	Support Vector Machine
t-SNE:	t-distributed Stochastic Neighbor Embedding
TN:	Ture Negative
TP:	True Positive
UTC:	Universal Time Coordinated
WHO:	World Health Organization
WOS:	Web of Science

Chapter 1 – Introduction

1.1 Introduction

The world is experiencing a significant demographic shift. By 2030, one in six people globally will be aged 60 years or older, and this number is expected to double to 2.1 billion by 2050 [1]. As populations age, all countries face substantial challenges to ensure their health and social systems can effectively support older adults, especially in the context where 80% of older adults will be living in low- and middle-income countries by 2050 [2]. Population aging is often accompanied by increased illness, disability, and dependency, placing additional demands on healthcare systems and creating economic strain. During the last century, the primary health threats were infectious and parasitic diseases, which mainly affected children and infants. However, with advancements in medical technologies, the leading causes of death have shifted to noncommunicable diseases (NCDs), such as cancer, heart disease, and diabetes, which primarily impact older adults [3]. The rising prevalence of NCDs globally has driven up healthcare costs substantially. In Canada, it is estimated that the aging population will result in an 88% increase in medical expenditures by 2040 [4]. In developing countries, the economic burden is also significant, with a reported \$83 billion loss between 2006 and 2015 due to NCDs in older populations [3]. Beyond healthcare expenses, the rising aging population exerts pressure on labor markets, with declines in productivity and an increasing consumption of healthcare resources [5][6].

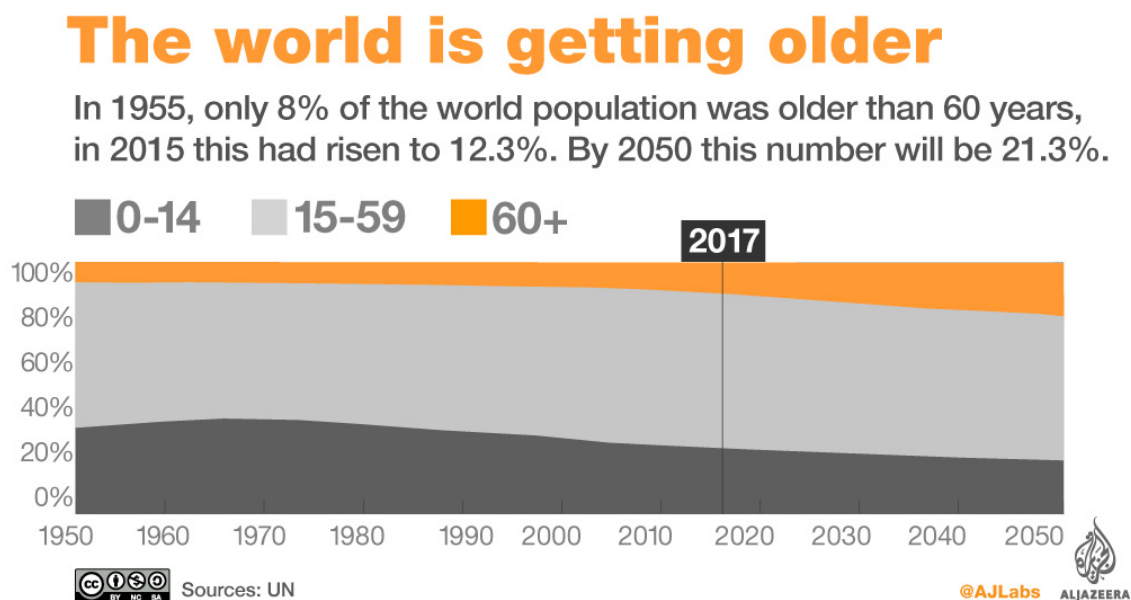


Figure 1. Global Demographic Shift [7]

Most older adults prefer to remain in their own homes as they age, a concept known as “aging in place” [8]. However, many face difficulties with daily activities, especially those with chronic conditions. The current healthcare model overly relies on informal caregivers, such as family members, to provide support for older adults, leading to increased caregiver stress and significant financial and social burdens on healthcare systems [9][10]. This approach also results in a decline in the quality of life for older adults who do not receive

adequate care. The shortage of affordable and accessible professional homecare services further exacerbates the challenges. Recent advances in the Internet of Things (IoT) have led to the development of smart home technologies aimed at assisting older adults with daily activities and monitoring, treating, and managing chronic health conditions [11][12]. These technologies, known as Active Assisted Living (AAL), provide older adults with the resources they need to maintain their independence, safety, and health while remaining in their communities [13][14][15].

The recognition of Activities of Daily Living (ADLs) is a key component of AAL technologies. Daily patterns of living are strongly correlated with physical and cognitive health, and changes in these patterns can serve as early indicators of health issues. For instance, a change in gait speed or balance can reflect cognitive decline and increased fall risk [16], while changes in speech patterns may indicate the onset of Alzheimer's disease or other forms of cognitive decline [17]. AAL technologies use autonomous tracking and ADLs recognition to identify changes in daily routines and potential emergencies, such as falls or sudden health deterioration [18][19]. These technologies enable continuous monitoring and early intervention, providing opportunities for timely healthcare support that can improve health outcomes and maintain the quality of life for older adults.

Despite the progress in consumer-level AAL technologies, widespread adoption has been limited by various challenges [20]. Cost remains a significant barrier, as AAL systems are often expensive for consumers, even though the potential savings would benefit healthcare systems. False alarms and data reliability issues further limit the usability and effectiveness of AAL devices [21]. There is also a lack of incentives for healthcare providers to manage and act on the vast amounts of data produced by these systems. As a result, there is a need to develop low-cost, reliable AAL solutions that are both affordable and effective, ensuring that they can be implemented at scale to support healthy aging worldwide.

The research in this thesis aims to advance the field of healthy aging by presenting the development of a smart home data ecosystem that supports AAL technologies. Specifically, this ecosystem focuses on advancing ADLs recognition, providing older adults with technologies that facilitate independence and improve quality of life. The following chapters detail the development process of this smart home ecosystem, explaining how AAL technologies have been implemented to enable effective ADLs recognition for older adults. This work contributes to the broader public health objective of enhancing the well-being of aging populations by leveraging technology for proactive and responsive health support.

1.2 Structure of the thesis

This thesis is structured as a series of publications, each contributing to the overarching goal of advancing AAL technologies with artificial intelligence (AI) to support healthy aging. The organization of the chapters reflects the logical progression of the research, from identifying gaps and opportunities in the field to developing, implementing, and validating innovative solutions. Each chapter includes a foreword that situates the publication within

the broader context of the thesis, facilitating a seamless transition between studies, and concludes with a discussion section that reflects on the chapter's contributions and introduces to next chapter.

Chapter 1 introduces the thesis, providing structure of the thesis, an overview of the motivation, research context, and significance of leveraging AI and AAL technologies for aging populations. Chapter 2 outlines the research aims, detailing the central research question and breaking it into specific aims. This chapter provides a roadmap for the thesis, connecting the aims to the subsequent studies and explaining how each contributes to answering the overarching research question. Chapter 3 presents the research questions and objectives, further breaking down each aim into actionable questions and sub-objectives that guide the studies presented in the following chapters.

Chapters 4 to 8 present the core research contributions, each corresponding to a peer-reviewed publication or manuscript.

- Chapter 4 is a scoping review that systematically examines the existing literature on AI applications in AAL technologies. This review identifies critical gaps, such as the limited integration of commercial sensors and the lack of frameworks for real-world deployment, which shape the research directions explored in the subsequent chapters.
- Chapter 5 focuses on the development and construction of a cloud-native data ecosystem designed to integrate and process data from commercially available AAL sensors. This chapter demonstrates how such a system can address the identified gaps by enabling seamless data collection, management, and analysis.
- Chapter 6 builds on the data ecosystem by presenting a study that uses it for heart rate prediction. This study highlights the feasibility of leveraging AAL technologies for contactless health monitoring, emphasizing the practical applications of the developed ecosystem in physiological monitoring.
- Chapter 7 explores ADLs recognition using AAL technologies based on the data ecosystem. This proof-of-concept study conducted with younger adults demonstrates the effectiveness of machine learning models in controlled environments, laying the groundwork for adapting these models to older populations.
- Chapter 8 extends the ADLs recognition study to older adults by leveraging transfer learning techniques. This chapter addresses the challenges of generalizing models trained on younger populations to older adults in less controlled environments, providing insights into the adaptability and scalability of AAL systems.

Chapter 9 concludes the thesis with a comprehensive discussion and conclusion. This chapter integrates the findings from all preceding chapters, reflecting on the contributions, limitations, and implications of the research. It also provides a vision for future work, emphasizing the potential for further advancements in AAL technologies to enhance public health and support aging populations.

1.3 Motivation

The motivation for this thesis comes from the pressing global challenge of an aging population and the increasing demand for innovative, scalable solutions to support healthy aging. As the proportion of older adults rises worldwide, healthcare systems are faced with the dual challenge of addressing the complex medical, social, and psychological needs of this demographic while managing the financial and logistical constraints of traditional caregiving models. The development of effective and accessible solutions is essential to empower older adults to live independently, maintain their dignity, and reduce the burden on caregivers and healthcare providers.

ADLs are fundamental to assessing the well-being and functional health of older adults. The ability to perform basic tasks such as bathing, dressing, eating, and moving independently is not only an indicator of health but also directly tied to an individual's quality of life and autonomy. Monitoring these activities in real-time and in a non-intrusive manner can provide valuable insights into changes in health status, enabling timely interventions and preventive care. However, existing solutions for ADLs recognition often rely on wearable devices or self-reported data, which may not be practical or reliable for all older adults due to compliance challenges and physical limitations.

Simultaneously, advancements in AI and AAL technologies present an unprecedented opportunity to address these challenges. By leveraging commercial smart sensors and AI-driven analytics, it is possible to develop contactless, continuous monitoring systems that are not only user-friendly but also demonstrate high accuracy in recognizing daily activities, ensuring reliable data capture for health monitoring and early intervention. However, despite the promise of these technologies, significant gaps remain in their practical deployment. For instance, the current research landscape lacks robust frameworks for integrating diverse data sources into a cohesive ecosystem and adapting AI models to diverse real-world conditions and old populations. Addressing these gaps requires a comprehensive approach that combines technological innovation with an understanding of the unique needs and behaviors of older adults.

This thesis is driven by the vision of creating equitable and scalable AAL solutions that leverage AI to enhance the independence and well-being of older adults. The research aims to explore how commercial smart sensors, when coupled with advanced machine learning techniques, can contribute to healthcare monitoring and ADLs recognition for older adults. This includes addressing key challenges such as the variability in activity patterns among older populations, the limitations of controlled experimental settings, and the scarcity of labeled data for model training. By tackling these issues, this thesis seeks to advance the field of AAL technology, ultimately paving the way for innovative, real-world applications that support aging in place and improve public health outcomes.

1.4 Active Assisted Living and Ambient Assisted living

Active Assisted Living (AAL) and Ambient Assisted Living (AAL) are two closely related terms often used interchangeably in the field of aging healthcare technology. While “Active”

emphasizes technologies that actively engage users to perform tasks or enhance their abilities, “Ambient” focuses on systems seamlessly integrated into the environment, providing unobtrusive monitoring and support for daily living. These two perspectives are inherently interconnected, as effective AAL systems often combine both active engagement and ambient integration to provide comprehensive support. In this thesis, both terms are used across different chapters to reflect the varied focus of individual studies. To ensure consistency and clarity, the abbreviation “AAL” is used as a unified term to encompass both concepts.

AAL represents an innovative approach to supporting the health, independence, and well-being of older adults by utilizing advanced technologies [22]. AAL aims to create a safe and supportive environment that allows aging individuals to maintain their quality of life while continuing to live in their homes, often referred to as “aging in place” [8]. As the aging population grows, the importance of AAL technologies in facilitating healthy and independent living becomes increasingly evident.

AAL encompasses a diverse set of technologies, including smart home sensors, IoT devices, and AI systems. These technologies work together to detect health-related issues and provide real-time interventions [23]. By integrating smart sensors, AAL systems can collect data on movement, vital signs, environmental conditions, and other factors critical to an individual's well-being [24]. Motion detectors, pressure sensors, wearable devices, and environmental monitors are examples of the types of sensors used to track health and activity patterns [24]. The information collected through these sensors is processed by AI algorithms that analyze behavioral patterns, detect anomalies, and provide alerts for potential health risks [25].

AAL technologies enhance the overall quality of life for older adults by supporting both physical and cognitive health [26]. For example, AAL systems can provide reminders for medication, suggest activities that promote physical exercise, and offer cognitive training games to keep the mind active [27][28]. These personalized interventions, guided by data collected in real-time, help in maintaining a balanced and healthy lifestyle. By providing older adults with user-friendly interfaces—such as voice commands or mobile applications—AAL systems empower individuals to manage their health actively and independently [29].

The benefits of AAL extend to caregivers and healthcare professionals as well [30]. AAL systems enable caregivers to remotely monitor the well-being of older adults, reducing the burden of constant physical presence while providing peace of mind [31]. In addition, healthcare providers can access valuable health data collected by AAL systems to make informed decisions regarding an individual's care [32]. This data-driven approach facilitates better coordination between healthcare services and home-based care, ultimately enhancing the continuity and quality of care.

Despite its promise, the adoption of AAL technologies faces several challenges. The high cost of devices, concerns regarding privacy and data security, and difficulties in integrating these systems with traditional healthcare infrastructure [33], and challenges in real-world implementation and effective integration with AI for healthcare monitoring [34] are among the barriers to widespread adoption. Addressing these issues is crucial to creating effective AAL solutions that support the health and well-being of older adults on a larger scale.

1.5 Activities of Daily Living recognition

Activities of Daily Living include basic routine tasks, such as eating, bathing, dressing, and moving around the home, which people typically perform independently [35]. In the context of elderly healthcare, accurately recognizing these activities is essential for assessing and monitoring the health of older adults. ADLs recognition is a specific part of human activity recognition that plays an important role in understanding the abilities and limitations of aging populations [36]. This monitoring provides important information for healthcare providers and caregivers, allowing for sustained independent living and timely intervention. By understanding the specific needs of older adults, healthcare systems can offer a more personalized level of care, which can lead to improved overall health outcomes and a better quality of life for older individuals [37].

ADLs recognition is particularly valuable because it directly reflects the functional status of an individual. Being able to perform these basic tasks independently is a key indicator of an older adult's ability to live without continuous assistance, which significantly affects their quality of life [38]. Therefore, recognizing and understanding changes in these activities is crucial. Small declines in the ability to perform ADLs can be early signs of broader health issues, such as mobility problems, cognitive impairment, or the onset of chronic conditions [39]. By closely monitoring these changes, healthcare providers can take preventive actions to slow or manage the decline, ensuring that older adults receive the support they need before problems escalate.

Integrating ADLs recognition with AAL technologies using AI greatly improves the ability to monitor these activities in a discreet and continuous way. AI algorithms analyze data collected from various sensors used in smart home environments, including motion detectors, wearable devices, environmental sensors, and more advanced pressure and door sensors, to track daily routines accurately [40]. Motion detectors can provide insights into the physical activity of individuals, while wearable devices often monitor vital signs, such as heart rate and body temperature, which help in assessing health conditions more comprehensively [41]. Environmental sensors, such as temperature and humidity sensors, are crucial for monitoring living conditions, which can affect an older adult's well-being [42]. Pressure sensors placed on beds or chairs can help in understanding sleep patterns or time spent resting, which are key indicators of health [43]. Door sensors can be used to track movement within different areas of the home, helping to identify potential issues like reduced mobility or social isolation [44].

Such continuous monitoring is crucial for detecting small changes in activity patterns that may indicate emerging health concerns, such as reduced mobility, increased risk of falls, or other health-related issues [45]. For example, if pressure sensors detect that an individual is spending significantly more time in bed, this may be an early indication of fatigue, depression, or other health problems [46]. Similarly, a gradual decrease in the frequency of certain activities, such as bathing or dressing, could indicate increasing difficulty with physical movement or a decline in motivation, which might be linked to depression or cognitive issues [47]. Early identification of these changes allows caregivers and healthcare professionals to intervene promptly, thereby preventing potential complications before they worsen.

In addition, AI-enhanced ADLs recognition plays an important role in advancing personalized healthcare. By accurately understanding an individual's daily activity patterns and specific needs, AAL technologies can adjust environmental conditions—such as lighting, temperature, and recommended daily activities—to improve the well-being and comfort of older individuals [48]. This level of personalization is made possible by AI's learning capabilities, which adapt interventions based on collected data, ensuring that the responses remain relevant and effective. For example, if a decrease in physical activity is detected, the system can recommend light exercises or activities that are suitable for the individual's health status [49]. This adaptive approach ensures that the interventions provided are not only timely but also aligned with the evolving needs of the individual, promoting a higher level of personalized care.

Beyond monitoring individual activities, ADLs recognition extends the capabilities of AAL systems to provide a comprehensive understanding of behaviors and interactions with the environment [50]. The detailed insights provided by AI-driven AAL technologies enable healthcare providers to develop tailored interventions that address specific needs, significantly improving the quality of care. For instance, monitoring an individual's sleep patterns and adjusting the environment to improve sleep quality can have a significant impact on overall health [51]. Additionally, recognizing patterns of social isolation or reduced engagement in activities can prompt timely interventions to enhance social interaction and mental well-being, addressing both physical and emotional health [52].

AI-driven ADLs recognition also facilitates improved communication and coordination between healthcare providers, caregivers, and older adults. By providing detailed and continuous insights into an individual's ability to perform daily tasks, all stakeholders can stay informed about the person's current status and evolving needs [53]. This enhanced communication ensures that any decline in health can be addressed collaboratively, with input from all parties involved. For instance, family members can be informed about changes in activity patterns, which helps them provide additional support, while healthcare professionals can adjust treatment plans as needed [54]. This coordinated approach to care significantly improves the quality of support that older adults receive and reduces the risk of health emergencies.

Additionally, ADLs recognition using AI empowers older adults by giving them greater control over their own health. By recognizing specific activities of daily living, AI systems can provide personalized feedback through user-friendly interfaces [55], encouraging individuals to engage in healthy behaviors and make informed decisions about their daily routines [56]. For instance, an AI system can provide reminders for medication or suggest hydration breaks, all informed by ADLs recognition data that monitors routine activities [57]. By using insights from ADL recognition to offer targeted suggestions, these systems not only promote physical health but also enhance a sense of independence and self-efficacy among older adults.

1.6 Machine Learning and Deep Learning methods

With the increasing availability of complex and diverse datasets generated from smart home systems and wearable technology, advanced machine learning (ML) techniques have become crucial for analyzing and deriving valuable insights from such data. ML and deep learning (DL) leverage computational models that learn from data patterns to solve specific tasks. In this thesis, both ML and DL techniques are employed to address different aspects of health monitoring and activity recognition. Recent advancements in data availability, algorithmic improvements, and computational efficiency have significantly contributed to the effectiveness of these techniques in health applications [58].

The methods selected for this thesis research are informed by a scoping review presented in Chapter 4, which highlighted the prevalence and success of these approaches in current studies. By selecting these commonly used methods, this thesis aims to ensure consistency with existing best practices in the domain of healthy aging and activity monitoring.

The general ML techniques used in this thesis can be broadly categorized into two main tasks: classification and regression [59].

- **Classification:** Classification is a type of supervised learning that involves training a model to recognize and assign labels to new input data based on patterns observed during training. In this thesis, classification models are used to recognize ADLs from sensor data collected in the smart home environment.
- **Regression:** Regression is another supervised learning task where the goal is to predict a continuous outcome based on input features. In this thesis, regression is used to validate the smart home data ecosystem for health monitoring. A pilot study was conducted using data collected from the AAL environment to predict physical health indicators, specifically heart rate. This regression task helps demonstrate the effectiveness of the data ecosystem in monitoring and providing insights into the physical health of older adults.

The following sections provide an overview of the ML and DL methods employed in this thesis.

1.6.1 Support Vector Machines and Support Vector Regression

Support Vector Regression (SVR) is a powerful supervised learning algorithm derived from the foundational principles of Support Vector Machine (SVM) [60], which are commonly used for classification tasks. SVR adapts these principles to solve regression problems, where the objective is to predict continuous values rather than discrete classes [61].

To understand SVR, it is helpful to start with a brief overview of how SVM works. SVM aims to find an optimal hyperplane that separates data points belonging to different classes. In two-dimensional space, this hyperplane is a line (Figure 2(a)), whereas in higher dimensions, it becomes a plane or a hyperplane. The goal of SVM is to identify the hyperplane that maximizes the margin between different classes, providing the best possible separation of the data.

SVR, on the other hand, seeks to find a hyperplane that can predict a continuous output with minimal error. Unlike SVM, which focuses on maximizing the margin between classes, SVR defines a margin of tolerance (often denoted as epsilon) around the hyperplane (Figure 2(b)). The objective is to ensure that the predicted values lie within this margin of tolerance, while simultaneously minimizing the model's complexity. The data points that lie outside this margin are known as support vectors, and these points play a crucial role in determining the regression function.

One of the key features of SVR is the use of kernel functions, which allow it to model complex, non-linear relationships effectively. By mapping the input data into a higher-dimensional feature space, kernel functions—such as linear, polynomial, and radial basis function kernels—enable SVR to capture intricate patterns in the data. The choice of kernel function is critical, as it directly impacts the model's ability to generalize and accurately predict the target variable.

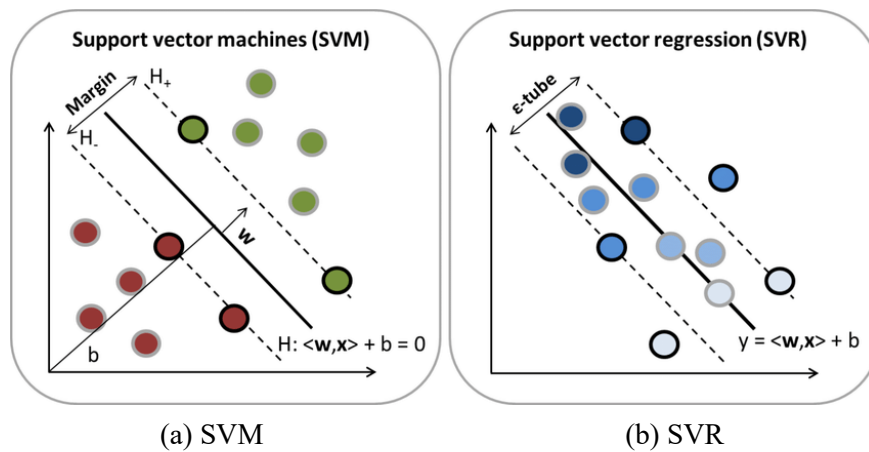


Figure 2. SVM and SVR [342]

1.6.2 K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a simple, yet effective supervised learning algorithm used for both classification and regression tasks [62][63]. In this thesis, KNN is utilized for both classification and regression tasks.

The KNN algorithm works by identifying the 'k' nearest data points in the feature space to make a prediction about a new data point. In classification, KNN assigns a class to the new data point based on the majority class among its 'k' nearest neighbors. In regression, KNN predicts the value of the new data point by averaging the values of its 'k' nearest neighbors. The distance between data points is typically calculated using metrics such as Euclidean distance, which helps determine the similarity between data points.

KNN is a non-parametric algorithm, meaning it does not assume any underlying distribution of the data. This makes KNN particularly useful for sensor data from smart homes, where the distributions can be complex and difficult to model. The selection of an appropriate 'k' value is crucial for the performance of the KNN algorithm. For example, in Figure 3, if the $k = 3$, the data point is classified into Class B, while if $k = 6$, the data point belongs to Class A. In addition, a small value of 'k' makes the model sensitive to noise, leading to overfitting, while a large value of 'k' may result in overly smooth predictions and potentially underfitting.

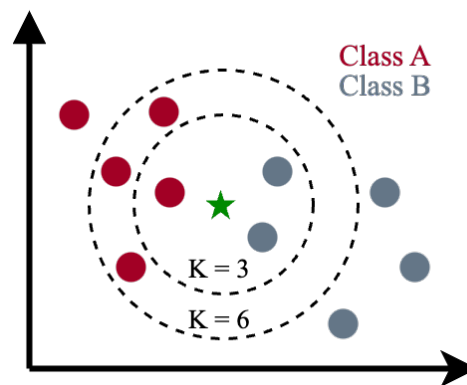


Figure 3. KNN [343]

1.6.3 Decision Tree

Decision Tree (DT) are widely recognized as one of the most interpretable and intuitive machine learning algorithms [64]. It can be used for both classification and regression tasks.

A Decision Tree consists of nodes and branches that represent decisions or outcomes based on certain conditions. At each internal node of the tree, a decision is made by evaluating a specific feature of the input data, with branches representing possible outcomes of that decision. This process continues until a terminal (leaf) node is reached, which provides the final prediction. In the case of classification, the leaf node represents the class label, while in regression, it represents a predicted numerical value.

Feature selection for splitting nodes is a critical component of DTs. The feature to split on is determined based on criteria such as impurity or information gain [65]. Impurity measures the degree of disorder or impurity within a dataset, and the goal is to minimize this impurity at each split to create more homogeneous branches. Information gain, on the other hand, measures the reduction in entropy, aiming to maximize the separation between classes by selecting features that provide the most significant improvement in homogeneity. By evaluating all available features using these criteria, the DT selects the feature that results in the most informative split, ensuring that the resulting branches are distinct and meaningful.

For example, consider a simplified scenario where the task is to classify activities such as ‘walking’ or ‘sitting’ based on features like room temperature or humidity. The DT starts by evaluating the feature that provides the best split between different activities (e.g., temperature level). Depending on the value of this feature, the data is divided into different branches, and the next feature is evaluated until a final classification is made at the leaf nodes. This recursive partitioning of the data allows DTs to effectively model non-linear relationships between input features and output labels.

1.6.4 Random Forest

Random Forest (RF) is an ensemble learning method that builds upon the foundational concepts of DT by constructing multiple trees and aggregating their predictions to achieve better accuracy and generalization [66]. RF is used in this thesis for both classification and regression tasks.

The RF algorithm works by creating a collection of DTs, each trained on a random subset of the data. This subset is generated using a process known as bootstrap sampling, where samples are drawn from the original dataset with replacement. Additionally, at each split in the tree, only a random subset of the features is considered for splitting. This combination of random sampling of data points and random selection of features helps to reduce the correlation among individual trees, thereby improving the overall robustness of the model.

In classification tasks, RF predicts the class label by aggregating the majority vote from all the individual DTs in the ensemble. For regression tasks, the prediction is made by averaging the numerical values predicted by each DT. This aggregation process helps to mitigate the risk of overfitting, which is a common issue with individual Decision Trees, especially when they grow too deep.

The strength of RF lies in its ability to handle high-dimensional datasets with many features and its resilience to noise [67]. By averaging the predictions of multiple DTs, RF achieves greater stability and accuracy, as individual errors are likely to be canceled out in the ensemble. This characteristic makes RF particularly suitable for analyzing complex sensor data from smart home environments, where noise and variability are common.

Another key advantage of RF is its ability to provide estimates of feature importance, which can offer valuable insights into the relationships between input features and the target variable [68]. Feature importance is determined by evaluating how much each feature contributes to reducing the impurity across all trees in the forest. In this thesis, feature importance analysis is used to identify which factors are most influential in predicting ADLs and physical health indicators, providing further interpretability and guiding the development of targeted interventions for healthy aging.

1.6.5 Adaptive Boosting

Adaptive Boosting (AdaBoost) is an ensemble learning algorithm that builds upon the foundational concepts of DT and shares a similar rationale with RF as it aims to improve the performance of weak classifiers by combining them into a strong classifier [69]. In this thesis, AdaBoost is used for classification tasks, specifically for recognizing ADLs from sensor data collected in smart home environment

The AdaBoost algorithm works by training a sequence of weak learners, typically DTs with a shallow depth (often referred to as decision stumps). During each iteration, the algorithm assigns weights to the training data points, giving higher weights to those that were misclassified in previous iterations. This weighting mechanism ensures that subsequent classifiers focus more on the difficult cases, thus improving the model's ability to accurately classify the entire dataset.

Once all the weak learners are trained, AdaBoost combines their predictions using a weighted majority vote for classification. The final model is a weighted sum of all the individual classifiers, where each classifier's weight is determined based on its performance. This iterative process of training and weighting results in a model that is highly effective at reducing bias and variance, leading to improved generalization.

In the context of ADLs recognition, AdaBoost is particularly useful for its ability to handle complex, non-linear patterns in the sensor data. By focusing on the misclassified instances, AdaBoost creates a more robust model that can effectively distinguish between different activities, even when the data contains noise or variability. This characteristic is crucial for smart home environments, where sensor readings can be influenced by various factors such as changes in lighting, temperature, or movement artifacts. Similar to RF, AdaBoost leverages multiple models to create a stronger overall predictor, but unlike Random Forest, it focuses sequentially on the mistakes made by the previous models, thereby enhancing its adaptive capacity.

1.6.6 Gaussian Naive Bayes

Gaussian Naive Bayes (GNB) is a probabilistic learning algorithm based on Bayes' theorem, commonly used for both classification and regression tasks [70]. In this thesis, GNB is employed for regression and classification task.

The GNB algorithm assumes that the features are normally distributed and calculates the probability of an outcome based on the conditional distributions of the features given a target variable. For classification, GNB calculates the posterior probability of each class based on the conditional distributions of the features and assigns the class with the highest posterior probability. In the case of regression, GNB models the relationship between the predictor variables and the continuous target variable by estimating the posterior probability, thereby providing predictions in the form of expected values. The assumption of normality makes GNB particularly suitable for situations where the underlying data distribution is approximately Gaussian, which simplifies the learning process and makes the algorithm computationally efficient. In this thesis, when using GNB, it does not assume any specific network structure or joint probability distribution among the predictors. Instead, it assumes that each predictor contributes independently to the outcome, conditioned on the target variable.

One of the main advantages of GNB is its simplicity and computational efficiency. Since GNB makes strong independence assumptions between features, it is less prone to overfitting compared to more complex models, particularly when dealing with high-dimensional data. This is beneficial for the smart home sensor data used in this research, where computational resources may be limited, and the simplicity of the model allows for faster predictions.

1.6.7 Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is a type of artificial neural network that is commonly used for both classification and regression tasks. In this thesis, MLP is employed for regression task. The use of MLP allows for capturing complex, non-linear relationships between the input features and the target variable, making it particularly suitable for health-related applications [71].

As a part of deep learning neural network, an MLP consists of multiple layers of neurons, including an input layer, one or more hidden layers, and an output layer. Each neuron in a layer is connected to every neuron in the subsequent layer through weighted connections, and each connection is associated with a weight that determines the strength of the influence of one neuron on another. The learning process involves adjusting these weights to minimize the difference between the predicted output and the actual target value, typically using an optimization algorithm such as stochastic gradient descent and a backpropagation process.

In the context of this thesis, the MLP is used to predict heart rate by modeling the relationships between various environmental and physiological factors, such as temperature, humidity, motion, and other relevant features collected from the AAL environment. By using multiple hidden layers and non-linear activation functions, MLP is able to learn complex representations of the data, enabling it to accurately predict the target variable even in the presence of intricate and non-linear relationships between the input features.

One of the main strengths of MLP is its flexibility and ability to approximate any continuous function given sufficient data and an appropriate architecture. This makes MLP a powerful tool for regression tasks in smart home environments, where the relationships between sensor data and health indicators may be highly non-linear. The deep architecture of MLP enables it to capture subtle interactions between input features, which is essential for accurate health monitoring.

In the next chapter, research aims that guide this thesis will be discussed.

Chapter 2 – Research Aims

The growing global demographic shift towards an aging population presents unique challenges and opportunities for healthcare monitoring and management. Smart home technologies, especially those integrated within AAL environments, have emerged as pivotal tools in supporting healthy aging. This thesis explores the potential of these technologies to enhance the quality of life and independence of older adults through advanced data analysis and machine learning techniques.

2.1 Research question

The central question guiding this research is: *How can AAL technologies coupled with AI support healthy aging, particularly in healthcare monitoring?*

To address this broad inquiry, the thesis is structured around three major aims that progressively build upon one another, demonstrating the application of AAL technologies from foundational data ecosystem construction to practical health monitoring implementations, particularly in daily activity recognition.

2.2 Research aims

2.2.1 Aim 1: Identify existing integrations of Artificial Intelligence with Active Assisted Living

The first aim of this research is to thoroughly assess the current landscape of AI applications within commercially available AAL technologies that support older adults aging at home. This involves a detailed examination of existing studies to outline how AI is currently being utilized in AAL settings, identify potential research opportunities that could further enhance these integrations, and pinpoint significant gaps in the literature. The goal is to provide a comprehensive overview of how AI-enhanced AAL technologies can better support the elderly, particularly in home environments, by improving their functionality and responsiveness to the unique challenges faced by this demographic. This aim sets the stage for subsequent innovation and development in the field by clarifying the state of the art and directing attention to areas ripe for further research and application.

2.2.2 Aim 2: Construct and demonstrate a smart home data ecosystem capable of interpreting Activities of Daily Living

The second aim of this thesis is to construct a robust smart home data ecosystem that serves as the foundation for collecting, managing, and analyzing data from a wide array of AAL sensors. This centralized infrastructure ensures reliable, scalable, and secure data collection. It is essential for the downstream analysis and ensures that the data captured are reliable, scalable, and secure. By establishing this infrastructure, the research lays the groundwork for sophisticated data processing and analysis that supports following health monitoring applications. In addition, to validate its functionality and demonstrate its practical use in healthcare monitoring, a specific study, such as heart rate prediction through AAL should be conducted, highlighting its potential in supporting contactless physiological monitoring.

2.2.3 Aim 3: Recognize Activities of Daily Living based on the data ecosystem

The final aim is subdivided into two critical components:

- **3a. Develop and validate machine learning models for ADLs recognition in controlled environments**

This part of the research develops and tests machine learning models for ADL recognition using data collected from young adults. Serving as a proof of concept, it aims to demonstrate the feasibility and effectiveness of these models within a controlled environment.

- **3b. Optimize ADLs recognition for older adults using domain transfer learning**

This aim seeks to optimize the recognition of ADLs for older individuals in less controlled environments by applying domain transfer learning. By adapting models initially developed for young adults in controlled settings, we enhance their performance for older adults, whose living situations are typically more variable. This method improves model accuracy and adaptability, making it better suited for real-world applications in elderly care.

To effectively explore the main research question, which is how AAL solutions, particularly those enhanced with AI, can support healthy aging, a thorough scoping review was conducted. This review assessed the integration of AI in commercially available AAL systems, identifying prevalent applications and significant research gaps. By focusing on commercially available devices, this review aimed to guide the proposed solutions are feasible for real-world implementation. Crucially, the insights gained from this review directed the focus of subsequent research studies and explicitly informed the development of the research aims, guiding this thesis to conduct studies that can address gaps and needs identified in the literature.

The scoping review revealed a significant gap in the availability of centralized data ecosystems for collecting, storing, and managing data from AAL environments. Most existing studies rely on direct data acquisition from devices, which limits the scalability and depth of data analysis. This discovery led to the formulation of the Aim 2: to develop a robust smart home data ecosystem that enhances the capability of AAL systems to handle heterogeneous datasets efficiently.

Additionally, the review noted that a substantial body of research focuses on ADLs recognition using AI and AAL technologies, emphasizing its importance for the aging population. This observation shaped the Aim 3, which is twofold. Initially, the aim involves using young adults in controlled environments to develop and validate machine learning models that achieve high performance—this phase acts as a proof of concept. Subsequently, the successful models are adapted and applied to older adults in less controlled environments, enhancing the applicability and effectiveness of these solutions in real-world settings typical of our target demographic.

Each of these aims not only addresses a specific component of the overall research question but also builds upon the previous to create a comprehensive understanding of how AAL

technology can be optimized for elderly care. The implementation of these aims will provide a detailed insight into the practical benefits and challenges of deploying smart home technologies for health monitoring, highlighting the potential for significant public health impacts.

Chapter 3 – Research Questions and Objectives

This chapter outlines the specific research questions that guide each objective stemming from the goals established in Chapter 2. By detailing these questions, this chapter deepens our understanding of how each aim is systematically explored and addressed throughout the thesis. This approach ensures that every element of the research is clearly defined, providing a comprehensive roadmap for the investigations that follow.

3.1 Scoping review on the landscape of AI application with AAL for older people

The initial aim focuses on assessing the application of AI in AAL technologies using commercially available devices in real-world settings. This comprehensive review sets the foundation for identifying how AI technologies can enhance healthcare monitoring for older people.

- **RQ1:** How are AI methods currently used in the AAL context to assist healthcare monitoring for older adults?
- **RQ2:** How are AAL environments constructed using commercially available sensors in real-world settings?
- **RQ3:** What type of information are AAL technologies collecting, and how can it help to generate valuable outcomes?
- **RQ4:** What are the strengths of existing research, and what gaps need to be addressed to uncover opportunities for future research?

These questions aim to identify effective strategies and notable gaps in current research, directing subsequent development and application phases in this thesis. These questions have been answered in Chapter 4.

3.2 Development of AAL data ecosystem

The second objective revolves around developing a cloud-native data ecosystem for AAL sensors. This ecosystem aims to optimize the utility of AAL sensors integrated with cloud technologies, enhancing healthcare monitoring for elderly populations. The development focuses on constructing a system that not only supports real-time monitoring but also ensures the security and reliability necessary for handling sensitive health data. Furthermore, the functionality and utility of the ecosystem are demonstrated through its application in specific studies, such as heart rate prediction, which exemplify its potential in practical healthcare scenarios.

- **RQ1:** How can cloud-native technologies enhance the integration and utility of AAL sensors in elderly healthcare monitoring?
- **RQ2:** What are the key challenges and solutions in developing a secure, real-time remote monitoring system with AAL sensors?
- **RQ3:** How can the developed cloud-native AAL sensor ecosystem be validated through specific applications, such as heart rate prediction, to improve healthcare monitoring for the elderly?

Answers to these questions will contribute to the construction of a high-performing, scalable, and secure data ecosystem, ensuring that the technologies developed can support advanced healthcare monitoring applications. These questions have been answered in

Chapter 5 and 6.

3.3 ADLs recognition

The final aim is divided into two phases: a proof-of-concept study with young adults (section 7.2.4.3.1 has outlined the rationale for selecting this group), and an application of transferring model performance to older adults in less controlled environments.

- **Phase 1 – proof of concept with young adults:**
 - **RQ1:** Can AAL sensors, coupled with AI, effectively recognize ADLs in a controlled environment?
 - **RQ2:** What recognition performance can machine learning models achieve, and what features are most important?
- **Phase 2 – validation with older adults in less controlled situation:**
 - **RQ1:** How does the performance of machine learning models, developed in controlled environments with young adults, transfer to the situation that with older adults in less controlled environments?
 - **RQ2:** Can the high performance achieved with young adults be successfully transferred to older adults using advanced deep learning models, and if so, how?

These questions guide the exploration of ADLs recognition capabilities within AAL frameworks, focusing initially on establishing baseline performance with young adults before adapting these methodologies to address the complexities encountered with older adults. These questions have been answered in Chapter 7 and 8.

Chapter 4 – Advantages and Challenges for Integrating AAL

Technology for Public Health Monitoring for Aging Population

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4.1 Foreword

The aging population presents significant challenges and opportunities for healthcare systems globally. As life expectancy increases, so does the need for sustainable, effective healthcare interventions that support aging individuals in maintaining independence and quality of life. One of the critical challenges is the effective integration of technology into daily care routines that can adaptively support the elderly in their preferred living environments without compromising their autonomy or safety.

AAL technologies, enhanced by AI, have emerged as promising solutions to support the elderly in their homes. However, the real-world application of these technologies is fraught with challenges, including the need for technological adaptability, ethical considerations, and user-friendly designs that accommodate the aging population's diverse needs. Due to these complexities, there is a pressing need for a comprehensive exploration of how AI can be effectively implemented within AAL technologies. This scoping review, which forms a crucial part of this thesis, addresses these issues by exploring the integration of AI in AAL technologies, focusing particularly on their deployment in real-world settings using commercially available devices.

This study was motivated by the ongoing need to understand and improve how AI technologies can be seamlessly integrated into the daily lives of older adults to enhance their safety, health, and overall well-being. By focusing on AI's role in commercially available AAL technologies, this review addresses a gap in current research, which often overlooks the practical implementation challenges and opportunities in real-world settings.

The relevance of this research is underscored by the rapid advancements in AI and its potential to significantly enhance AAL technologies. This can make these tools more adaptive, responsive, and user-friendly, thus more effective in real-life applications. However, integrating these advanced technologies into everyday use involves overcoming significant technological, ethical, and practical challenges.

The primary aim of this comprehensive scoping review was to map out the current landscape of AI applications within AAL settings, identify existing gaps in the literature, and provide a foundation that guides the subsequent studies presented in this thesis. By systematically analyzing the current state of research, this review not only highlights the

potential of AI to transform the lives of the aging population—ensuring they live more independently and with greater dignity—but also reveals key areas where further research is needed. These gaps form the basis for the research directions pursued in this thesis, providing clarity on where contributions can be most impactful.

This scoping review serves as the groundwork for the studies presented in this thesis. By identifying existing gaps and aligning them with the research objectives, the review provides clear guidance for the subsequent work, ensuring that the research contributes effectively to advancing AAL technologies.

4.2 Application of Artificial Intelligence in Active Assisted Living for Aging Population in Real-world Setting with Commercial Devices – A Scoping Review

4.2.1 Overview

Background

The aging population is steadily increasing, posing new challenges and opportunities for healthcare systems worldwide. Technological advancements, particularly in commercially available Active Assisted Living devices, offer a promising alternative. These readily accessible products, ranging from smartwatches to home automation systems, are often equipped with Artificial Intelligence capabilities that can monitor health metrics, predict adverse events, and facilitate a safer living environment. However, there is no review exploring how Artificial Intelligence has been integrated into commercially available Active Assisted Living technologies, and how these devices monitor health metrics and provide healthcare solutions in a real-world environment for healthy aging. This review is essential because it fills a knowledge gap in understanding AI's integration in Active Assisted Living technologies in promoting healthy aging in real-world settings, identifying key issues that require to be addressed in future studies.

Objective

The aim of this overview is to outline current understanding, identify potential research opportunities, and highlight research gaps from published studies regarding the use of Artificial Intelligence in commercially available Active Assisted Living technologies that assists older individuals aging at home.

Methods

A comprehensive search was conducted in six databases—PubMed, CINAHL, IEEE Xplore, Scopus, ACM Digital Library, and Web of Science—to identify relevant studies published over the past decade from 2013 to 2024. Our methodology adhered to the PRISMA extension for scoping reviews to ensure rigor and transparency throughout the review process. After applying predefined inclusion and exclusion criteria on 825 retrieved articles, a total of 64 papers were included for analysis and synthesis.

Results

Several trends emerged from our analysis of the 64 selected papers. A majority of the work (39/64, 61%) was published after the year 2020. Geographically, most of the studies originated from East Asia and North America (36/64, 56%). The primary application goal of Artificial Intelligence in the reviewed literature was focused on activity recognition (34/64, 53%), followed by daily monitoring (10/64, 16%). Methodologically, tree-based and neural network-based approaches were the most prevalent Artificial Intelligence algorithms used in studies (32/64, 50% and 31/64, 48% respectively,). A notable proportion of the studies (32/64, 50%) carried out their research using specially designed smart home testbeds that simulate the conditions in real-world. Moreover, ambient technology was a common thread (49/64, 77%), with occupancy-related data (such as motion and electrical appliance usage logs) and environmental sensors (indicators like temperature and humidity) being the most frequently used.

Conclusion

Our results suggest that Artificial Intelligence has been increasingly deployed in the real-world Active Assisted Living context over the past decade, offering a variety of applications aimed at healthy aging and facilitating independent living for the older adults. A wide range of smart home indicators were leveraged for comprehensive data analysis, exploring and enhancing the potentials and effectiveness of solutions. However, our review has identified multiple research gaps that need further investigation. First, most research has been conducted in controlled testbed environments, leaving a lack of real-world applications that could validate the technologies' efficacy and scalability. Second, there is a noticeable absence of research leveraging cloud technology, an essential tool for large-scale deployment and standardized data collection and management. Future work should prioritize these areas to maximize the potential benefits of Artificial Intelligence in Active Assisted Living settings.

Keywords: Active Assisted Living, Ambient Assisted Living, Smart Home, Remote Healthcare Monitoring, Aging, Older Adults, Real-world Deployment, Artificial Intelligence, Machine Learning, Internet of Things, Independent Living, Commercial Sensors

4.2.2 Introduction

4.2.2.1 Background

Globally, we are observing an unprecedented demographic shift characterized by a marked increase in the aging population [72]. According to World Health Organization projections, the segment of individuals aged 60 and above is set to surge to over 2 billion by 2050, marking a double increase from the figures reported in 2015 [1]. The observed upsurge is not limited to high-income economies but is also pronounced in low and middle-income countries. This demographic transition presents many challenges, encompassing an amplified burden on healthcare systems, the imperative for age-suited housing, and the escalating demand for older people-focused services and supportive care solutions [73]. Interestingly, the majority of the older adults prefers 'aging in place' – a concept representing the desire of individuals to maintain residence within their current homes or

communities, regardless of changes in age, financial status, or ability [74]. Nonetheless, in the absence of sufficient supportive structures, aging in place can prove to be a challenging endeavor, posing risks including intensified social isolation, health deterioration, and reduced autonomy [75]. Consequently, there is an increased demand for innovative solutions designed to support independent living for older individuals, all while ensuring their health, safety, and overall quality of life are upheld.

An innovative response to this exigency is embodied by the concept of Active Assisted Living (AAL), which harnesses the power of technological advancements to support seniors with routine tasks and healthcare needs. Integrating Artificial Intelligence (AI) into AAL methodologies presents a particularly transformative opportunity, offering the potential to efficiently and effectively address the complex needs of an increasingly aging society, such as interaction, activity assistance, activity recognition, health monitoring, and rehabilitation [76]. The genesis of AAL marks a significant milestone in the domain of older adults' care and assistance. AAL emerges from an intersection of healthcare, social sciences, and information technology disciplines, proposing an inventive approach to enhancing the quality of life for senior individuals [77]. It underpins the creation of environments that support aging in place, offering the older adults with a variety of health conditions a means to uphold their independence and life quality while ensuring their health and safety needs are robustly addressed. When examining the foundational elements of AAL, it is evident that multiple critical components contribute to its composition. Specifically, AAL encompasses a range of assistive technologies, sensor-driven systems, and service-oriented architectures [78]. All components are synergistically integrated to offer personalized and context-aware care for the older population. The significance of these technologies transcends mere functional support, addressing the socio-emotional dimensions of aging as well [79]. In addition, the utilization of commercially available devices makes AAL technologies more accessible and often more cost-effective than traditional healthcare solutions [80], as these products are designed for mass-market appeal and are, therefore, often less expensive than specialized medical devices. Furthermore, commercial devices usually undergo rigorous testing and quality assurance to meet consumer expectations, resulting in an advantage of reliability. Their user-friendly interfaces and seamless integration with existing devices, such as smartphones and tablets, encourage higher adoption rates among the older demographic.

The application of AI in the context of AAL can redefine how support is provided to the aging population [76]. It can facilitate the development of more accurate health monitoring systems [40], predict potential health risks [81], and provide personalized support to individual needs [82]. AI can enable AAL systems to evolve with changing user requirements, ensuring consistent and relevant support. One of the most significant contributions of AI to AAL lies in its potential to alleviate the pressure on healthcare systems by using assistive technologies to deliver timely intervention and cognitive activity support [83]. The global demographic shift towards an aging population has resulted in a considerable strain on healthcare services. This pressure is evident in increased healthcare costs, heightened demand for healthcare professionals, and the need for more specialized

care facilities. AI deployment within AAL can help counter these challenges by facilitating more effective health monitoring, predictive analytics for timely interventions, and automated assistance for daily tasks. As a result, AI-powered AAL systems have potentials for reducing the need for hospitalizations, lowering healthcare costs, and allowing healthcare professionals to focus on more critical cases [84]. Simultaneously, AI applications within AAL have substantial implications for enhancing the quality of life for seniors [85]. AI can facilitate a more personalized, user-centric approach to older people's care by catering to each individual's unique needs and preferences. Through its capabilities for learning and adapting, AI can understand a user's habits, preferences, and health status, thereby enabling a personalized approach to care that considers each individual's specific needs and circumstances. Consequently, seniors can maintain greater independence and autonomy, leading to a more fulfilling and dignified aging experience. AI's ability to predict potential health issues before they become severe can enhance the preventive aspect of healthcare for older adults [86]. By detecting changes in an individual's behavior or health indicators, AI-powered AAL systems can alert the user and their caregivers about potential health risks. This proactive approach to healthcare could result in more timely interventions, thereby improving health outcomes and possibly extending healthy life expectancy.

4.2.2.2 Related work

In the domain of AI-powered AAL systems, a large amount of primary research have focused on activity recognition and health monitoring through advanced data analysis, which has led to significant breakthroughs. Innovative approaches in HAR using wearable sensors have shown promising results. Cheng et al. [87] introduced the Contrastive Supervision for HAR method, which marks a leap forward by utilizing time series data augmentations and contrastive learning, thereby enhancing classification accuracy without additional computational demands. Similarly, the ProtoHAR framework developed by authors [88] represents a stride in personalized federated learning, addressing the challenges of non-independent and identically distributed data in HAR tasks, ensuring privacy while boosting accuracy and convergence speed. Xu et al. [89] proposed an approach that integrates channel attention with multi-frequency analysis demonstrates substantial improvements in activity recognition by exploiting the full spectrum of frequency components. Moreover, in order to decrease the computation cost, Bu et al. [90] implemented a dynamic inference method focuses on crucial temporal intervals, optimizing computational efficiency in activity recognition. Furthermore, Channel-Equalization-HAR, with its channel equalization technique, addresses 'channel collapse' happened on heterogeneous sensor signal, improving recognition performance efficiently [91]. However, these studies share a common limitation in the activity recognition domain: the reliance on public datasets rather than primary data, which may impact the generalizability of the findings. Expanding into the health monitoring domain, the study [92] explored cognitive impairment detection in older adults through appliance usage patterns, highlighting the potential of unobtrusive monitoring but noting the challenge of distinguishing individual behaviors in multi-occupant homes. Meanwhile, the exploration of AAL technology via the Internet of Medical Things for monitoring Type-2 diabetic patients showcases the use of glucose oxide sensors and DenseNet-169 model analysis, presenting a novel method for

real-time monitoring with the caveat of needing further validation for practical application [93].

In addition, researchers have extensively examined the application of AI, smart home environments, and AAL technologies for remote healthcare monitoring by conducting literature review, particularly in the context of aging populations [94][95][96][97][98][99][100][101]. Yeap et al. [94] conducted a review centered on HAR in AAL environments. This review highlighted the significance of strategically placing unobtrusive sensors and optimizing sensor combinations to enhance recognition accuracy. Furthermore, challenges in implementing activity recognition, such as lacking standard communication methods for diverse IoT sensors, were outlined. Addressing the limitations of rustic feature extraction in HAR, Ramanujam et al. [102] conducted a comprehensive review of deep learning techniques for recognition system using smartphone and wearable sensors. The study discussed Convolutional Neural Networks, Long-Short Term Memory models, and hybrid models, assessing their performance, efficiency, and capacity to identify complex activities. It also explored benchmark datasets and the challenges associated with multi-model fusion. Ethical and privacy considerations are pivotal, as highlighted by Zhu et al. [103] in their scoping review on smart home technologies tailored for older adult care. The findings underscored prevalent concerns surrounding privacy, autonomy, safety, fairness, and the potential reduction of human interaction. A systematic review from Gochoo et al. [104] emphasized the escalating challenges in data privacy and security concerning in-home technology adoption. The review identified various technical approaches to make the environment more comfortable for older people to live. However, the authors pointed out the special need for a comprehensive system for patient safety and data privacy in smart homes. Furthermore, Sapci et al. [97] reviewed innovative technologies in healthcare for older adults, spanning assisted living tools, remote monitoring technologies, artificial intelligence-driven solutions, and robotic systems. While these technologies hold potential to enhance independence and healthcare outcomes among older adults, the review noted a lack of appropriate reference standards and critical appraisal for these technologies. In a systematic review, Lussier et al. [105] assessed smart home sensor technologies' effectiveness for early detection of mild cognitive impairment in older adults. The review includes seventeen studies that focused on monitoring everyday life activities to assess functional performance. The findings suggested that smart home technologies can detect changes in daily routines associated with cognitive impairment, potentially aiding clinicians in older adults' care. However, challenges were found in real-time ongoing assessments and monitoring more complex activities.

4.2.2.3 Objective

The objective of this scoping review is to map the state-of-knowledge about integration of AI in AAL context that has been constructed by commercially available devices and used to support older people aging in place. Based on the research objectives, we generated the following research questions (Textbox 1), which guided us to conduct this scoping review.

Textbox 1. Research questions

- **RQ1:** How are AI methods currently used in AAL context to assist healthcare monitoring for seniors?
- **RQ2:** How are AAL environments constructed using commercially available sensors in real-world?
- **RQ3:** What type of information are AAL technologies collecting, and how can it help to generate valuable outcomes?
- **RQ4:** What are the strengths of existing research, what research gaps need to be addressed to uncover opportunities for future research?

To answer the research questions, a scoping review following the PRISMA methodology guidelines was conducted. This review focuses on exploring and charting the current corpus of knowledge about AI applications within AAL. This work will help shape the future path of care for older people and independent living.

4.2.2.4 Main contribution

Although numerous review papers have explored AI's application in AAL and home care, our paper sets itself apart by:

- Focusing on AAL environments constructed in real-world settings, rather than those simulated in laboratories or confined to theoretical discussions. This approach provides critical insights into the practical challenges and implementation guidance that emerge only in real-world contexts, offering a more comprehensive understanding of the effectiveness and scalability considerations essential for AAL solutions' success.
- Examining commercially available devices used within the AAL platform, including specific brands, thus offering a tangible guide for stakeholders interested in the practical deployment of AAL technologies. This level of detail not only facilitates replication studies and encourages the adoption of effective AAL technologies but also highlights the current market's technological advancements, providing a unique and valuable perspective on leveraging market-driven innovations to support the aging population.

The main contribution of this scoping review include:

- This scoping review paper provides a pioneering examination of the integration of AI technologies within AAL frameworks. It identifies and categorizes AI models that are optimally suited to address a spectrum of healthcare-related challenges for the aging population. By detailing the application of AI in activities recognition, behavior pattern modeling, and personalized healthcare solutions for the old individuals, this review illuminates the transformative potential of AI in gerontechnology.
- We present an in-depth analysis of the technological infrastructure required to construct effective AAL environments. This includes a focused exploration of commercially available devices and technologies that form the construction of AAL solutions, providing a practical and replicable model for both academic and industry stakeholders. This contribution is pivotal in bridging theoretical research with the practical application of AAL solutions in real-world settings.

- The review methodically dissects the nature of information captured by AAL systems and the consequential value derived from this data. It highlights how AAL technologies utilize collected data to support predictive analytics, recognition tasks, and implement proactive health management strategies. This analysis not only reveals the current capabilities of AAL systems in managing and leveraging data but also proposes frameworks for enhancing data utility for aging care.
- Through a critical evaluation of the current integration of AI within AAL solutions, this review identifies several critical limitations within the current landscape of AAL and AI integration. It highlights the need for uncovering participants' demographic information in studies, and also the refinement of AI models and the adoption of more advanced AI learning strategies such as federated learning, continuous learning, and contrastive learning to address the complexities of AAL solutions. The scarcity of open datasets emerges as a significant challenge, indicating a pressing need for addressing data scarcity and advocating for the creation and sharing of open datasets. Furthermore, the review identifies data heterogeneity, resulting from the diverse types of data involved in AAL solutions, as a hurdle for consistent and effective analysis. Additionally, the limited utilization of cloud technologies in existing studies is pinpointed as a factor that restricts computing resources, suggesting a potential area for expansion to enhance computational capabilities in AAL research.

4.2.3 Methods

4.2.3.1 Review protocol

This scoping review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) framework [106], ensuring transparency and methodological rigor in order to comprehensively explore the research questions while minimizing bias. By following the PRISMA-ScR framework, we systematically conducted the search, selection, and analysis of relevant studies. The review protocol involved six key steps: 1) defining research objectives and requests; 2) conducting a comprehensive literature search across multiple academic databases; 3) screening titles and abstracts to assess study eligibility; 4) conducting full-text screening to determine final inclusion based on predetermined criteria; 5) extracting relevant information from selected studies; 6) collecting, summarizing, charting, and reporting the results. The following sections will present our information sources, search strategy, eligibility criteria, article selection process, and data extraction and charting procedures.

4.2.3.2 Information sources

The search for relevant literature was conducted across six different databases, including PubMed, CINAHL, IEEE Xplore, Scopus, ACM Digital Library, and Web of Science (WOS). These databases were chosen for their comprehensive coverage of various disciplines, which aligns with the scope of studies included in this review. PubMed and CINAHL were chosen to encompass articles in healthcare disciplines, while the inclusion of IEEE Xplore and ACM Digital Library was motivated by their strong emphasis on engineering, technology, and computer science literature, in which AAL relevant literature

can be found. Scopus and WOS were included to ensure broad coverage across multiple disciplines.

4.2.3.3 Search strategy

The search was conducted on February 12th, 2024, using a predefined set of search keywords and their corresponding synonyms. The primary search keywords included “smart home”, “elderly”, “artificial intelligence”, and “real-world”. To enhance the search strategy and capture a broader range of relevant literature, an extensive list of synonyms for each keyword was also included. The complete list of search keywords and their corresponding synonyms can be found in Table 1. These keywords were derived from previous review articles focusing on AAL, AI, healthy aging, and real-world [76][80][101][107][108][109].

To accommodate the search requirements of different databases, search terms were modified accordingly. All databases were searched using title, abstract, and keywords, except for PubMed, where title, abstract, and MeSH terms (“internet of things”, “self-help devices”, “aged”, and “artificial intelligence”) were searched. The search was limited to studies published within the last 10 years, specifically from January 1st, 2013, to the date of the search (February 12th, 2024). Search strings were designed by a liaison librarian from the University of Waterloo, who possesses extensive experience in literature search methodologies. Detailed search strings for each database are provided in Appendix A. The search process was also conducted under the guidance of the librarian.

Table 1. Search keywords and synonyms

Keywords	Synonyms
Smart home	Smarthome; Ambient Intelligence; Active Assisted Living; Ambient Assist*; Assist* Environment, IoT, Internet of Things
Elder*	Older people; senior*, aging; older adult*, geriatric
Artificial Intelligence	Machine Learning; Deep Learning; Neural Network*
Real-world	Home; house

4.2.3.4 Eligibility criteria

The inclusion and exclusion criteria were established to ensure the selection of relevant studies for this scoping review. Articles should primarily concentrate on the integration of AI methods within the AAL environment. In addition, only peer-reviewed journal articles or conference papers written in English were included, while book chapters, online articles, and magazines were excluded. Review articles were also excluded to prioritize studies presenting original research. Studies were required to collect and analyze primary data instead of relying on public datasets.

Additionally, our scoping review does not restrict the age of participants in studies, meaning we included studies that did not exclusively involve older participants. This decision was driven by our recognition that while some studies might not directly involve older individuals, the methodologies and interventions they propose can be relevant and

potentially beneficial for the aging population. Furthermore, our search keywords were intentionally designed to prioritize papers related to aging, ensuring that the content and objectives of these studies align with our research goals. Thus, even in the absence of older participants in some studies, the potential applicability of their proposed methods to the aging population justified their inclusion in our review.

Given the objective of this scoping review, which focuses on the application of AI on older people in real-world settings using commercially available AAL technologies, our focus was on studies that utilized such devices. We excluded studies that solely relied on voice sensors, robots, smartphones, or cameras. However, if the experimental environment encompassed a combination of AAL devices and other IoT devices, those studies were included. Additionally, articles evaluating prototypes developed by the authors themselves were excluded. Furthermore, the studies had to be conducted in real-world settings. By “real-world”, we do not strictly refer to individual residences. Our criteria encompass homes, nursing homes, or long-term care facilities involving participants. We also considered studies that established a smart home testbed in an experimental home environment or any space designed to mirror a residential unit. Such settings provide basic living space and furniture, and they fulfill the context of real-world. However, we excluded studies based solely on simulations or those conducted in simple lab environment without replicating a normal living environment. Lastly, the included articles needed to employ AI methods for conducting quantitative data analysis tasks, as our review aimed to objectively assess measurable outcomes from AI models and AAL related metrics, which are best represented through quantitative data. A detailed description of the eligibility criteria can be found in Table 2.

Table 2. Eligibility criteria for including and excluding articles in the scoping review

Inclusion criteria	Exclusion criteria
Articles focus on using AI methods to evaluate AAL interventions	Book chapters, online articles, and magazines
Peer-reviewed journal papers and published conference papers	Articles based on literature reviews
Articles written in English	Article not written in English
Articles published after January 1 st , 2013	Studies use secondary or open datasets
Studies using primary data	Studies use prototype sensors
Studies using commercially available sensors	Studies construct AAL settings based on voice sensors, robots, smartphones, or cameras
Studies using quantitative data analysis methods	Studies not use participants to evaluate the AAL interventions
Studies involve participants in real-world AAL settings (e.g., living-like testbeds, individual residence, nursing homes, communities)	Studies conducted in experimental laboratories

4.2.3.5 Selection process

We used Covidence as the screening tool to facilitate the review process. All search results (n=1420) from the databases were imported into Covidence, allowing for automated removal of duplicates (n=595). The screening process started with title and abstract screening, during which ineligible articles (n=825) were identified and excluded based on the information provided in the titles and abstracts. Subsequently, a full-text screening was conducted on 228 articles to further exclude articles (n=164) that did not meet the eligibility criteria. From this process, a final set of articles (n=64) was filtered for subsequent data extraction. Three researchers were involved in the screening process in all steps, with each paper being reviewed by two researchers. Decision votes were given from two researchers independently. An article's outcome was determined only if both researchers provided identical votes. In the event of a conflict, the final decision was made by the third researcher.

4.2.3.6 Data extraction, charting and analysis

Three researchers independently extracted, organized, and summarized the data on included articles (n=64) using Microsoft Excel. Each researcher was assigned an equal number of articles to ensure consistency. Regular meetings and discussions were conducted throughout the data extraction process to address any questions or uncertainties that arose. To guide the data extraction, a specific form was developed based on the research questions. Textbox 2 displays the key data items included in the form, along with their corresponding descriptions.

The extracted data were then organized and summarized using tables, figures, and narrative synthesis. The findings and characteristics of the included studies were synthesized and presented in the Results section, providing a comprehensive overview of the existing literature.

Textbox 2. Data items textbox

Article Identification

- Title, authors, and DOI number of the articles.

Publish year

- Year of publication.

Study country

- The country where the study was conducted.

Study goal

- The aim or objective of the study, which also highlights the application of AI models.

Study site

- The type of site where the study took place, such as home or long-term care facility.

Study duration

- The duration or time period of the experimental session.

Data acquisition method

- The methods used for data collection, such as direct transmission from devices, API, MQTT, etc.

Data type

- Numeric or signal data.

Data size

- The number of sample points or data points collected.

Participant information

- Information about participants, including number of participants, their gender, age, and any relevant disease or health conditions.

ADLs

- The specific ADLs that were performed during the experimental session.

Technology

- The type of technology used, whether it is ambient, wearable, or a hybrid approach.

Sensor information

- Details about the sensor used, including the type, name, location, number, brand, and price.

AAL system

- Whether the constructed AAL systems are cloud-based data ecosystems, especially where the data is stored and processed (i.e. cloud or local).

AI methods

- The AI algorithms or methods used for data analysis.

Findings & limitations

- A summary of the findings from the study and any limitations or constraints encountered.

4.2.4 Results

4.2.4.1 Overview

In this section, we present the results of our scoping review, including the article screening and reviewing process, characteristics of selected studies, as well as charts and tables addressing the proposed research questions. Please note that a study can span multiple classifications and appear in different groups simultaneously. For example, a study may involve participants from various age groups. Therefore, in our presentation of the results, a paper is categorized under each group it is eligible. Consequently, the total count of articles in a chart or table may exceed the actual number of articles included. However, for calculating percentages, we consistently use the total number of articles (64) as the denominator, as we want to illustrate the proportion of total articles corresponding to each specified group.

Figure 4 depicts flowchart based on PRISMA-ScR framework. The flowchart outlines the systematic process used to identify, screen, and review eligible articles for inclusion in this scoping review. Initially, a total of 1420 articles were identified from six databases. Following the removal of 595 duplicate articles, 825 unique articles remained. The subsequent step involved screening the titles and abstracts, resulting in the exclusion of 597 articles that were identified as irrelevant to the focus of this scoping review. This left 228 articles for full-text review. Finally, after the full-text review, an additional 164 articles were excluded for not meeting the predefined criteria, resulting in 64 eligible articles for inclusion in the data analysis.

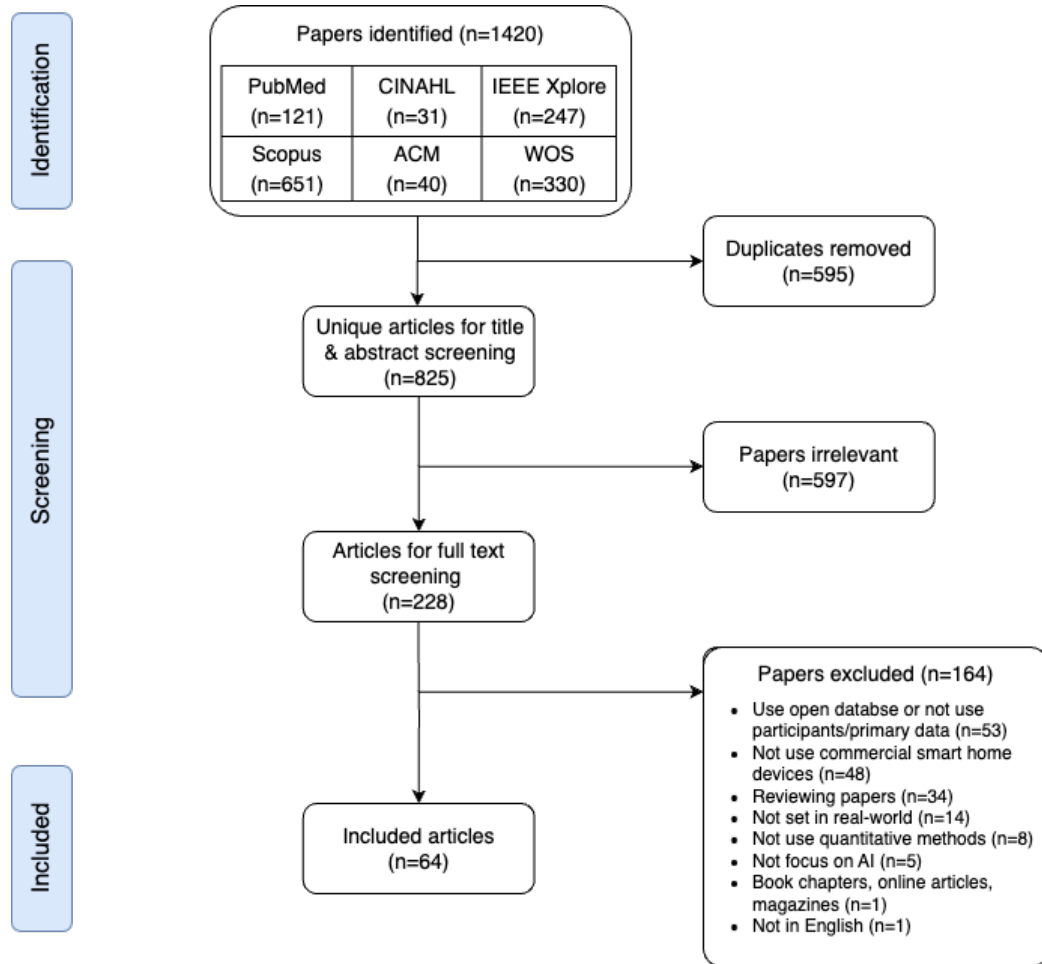


Figure 4. Study selection using PRISMA flowchart

Publication year, country, and participants' age

The scoping review examined scholarly articles published between January 2013 and February 2024, ranging in a 11-year timeframe. However, since no eligible articles were found in 2013 and 2014, Figure 5 only plots the years from 2015 to 2024 (same for all other results in this paper). Figure 2 illustrates a steady increase in scholarly output over the years. Notably, more than half of articles (39/64, 61%) were published from 2020 onward. In 2015 and 2016, 4/64 (6%) articles were published each year, while the subsequent year, 2017, witnessed a rise to 7/64 (11%) articles. However, the year 2018 experienced a decline with only 4/64 (6%) articles. The following years witnessed a rebound, with 6/64 (9%) articles published in both 2019 and 2020. Particularly, there was a considerable increase in research activity in 2021 and 2022, with 9/64 (14%) and 14/59 (22%) articles published respectively. Despite this surge in 2022, there was a downturn in 2023, with the number of published articles falling to 8/64 (13%) for the year. Although there were only 2/64 (3%) articles published up to the date of search in 2024, it is expected that more articles will be published later in the year. Figure 6 shows the distribution of published articles across different countries. The United States and Japan exhibited the highest publication rates, with both country contributing 9/64 (14%) articles. Canada and South Korea followed closely behind, with publishing 7/64 (11%) and 6/64 (9%) articles, respectively. China, Spain, and the UK each contributed 5/64 (8%) articles, with India and Italy followed by contributing

4/64 (6%) and 3/64 (5%) articles, respectively. Australia, Iran, and Sweden each published 2/64 (3%) articles. Additionally, five countries, including Brazil, Germany, France, Czech Republic, and Belgium, published a single article each (1/64, 2%). Results show that North America and East Asia are leading in the number of works, followed by European countries. Other areas show less focus on this field. Participants' age distribution is also investigated in this scoping review, shown in Figure 7. Based on the classification provided in [110], the age range was categorized into four groups: child population (aged 0-14 years), young population (aged 15-47 years), middle-aged population (aged 48-63 years), and older adult population (aged over 63 years). Among the included studies, 23/64 (36%) articles concentrated on participants aged over 63 years old. However, it is notable that more than one-third studies (25/64, 39%) did not provide specific information regarding the age of their participants or other demographic information. Studies involving young population were moderately represented (15/64, 23%), while fewer articles (6/64, 9%) included middle-aged population. There is 1/59 (2%) study included children as participants, where the research was conducted in households with both children and young participants.

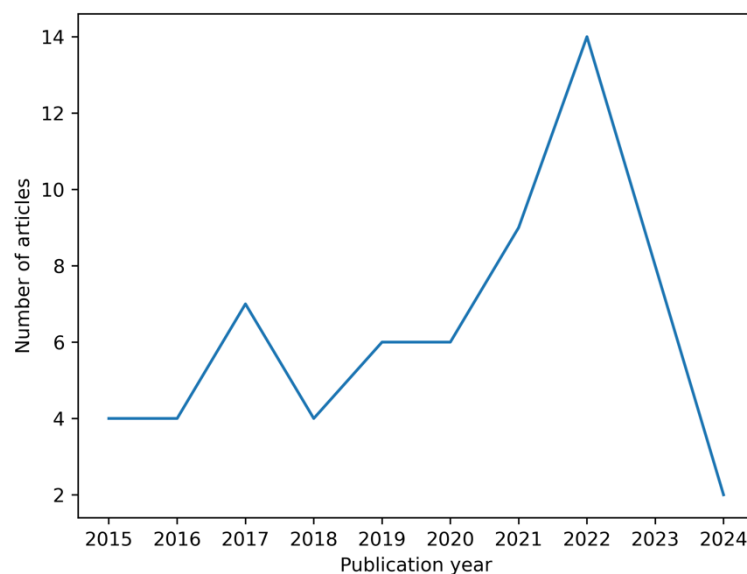


Figure 5. Number of publications per year (up to the last search time-February 17th, 2024)

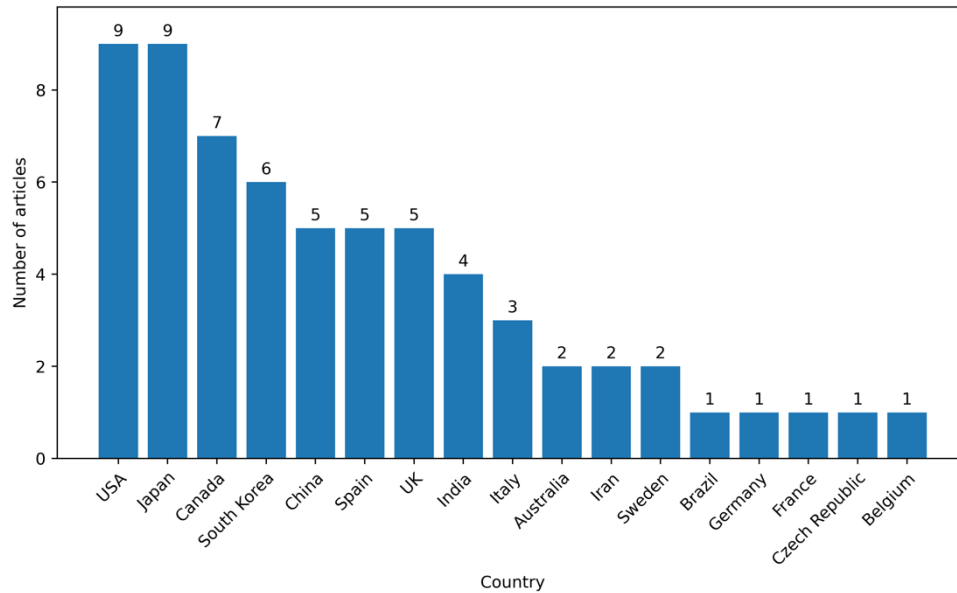


Figure 6. Number of publications from each country

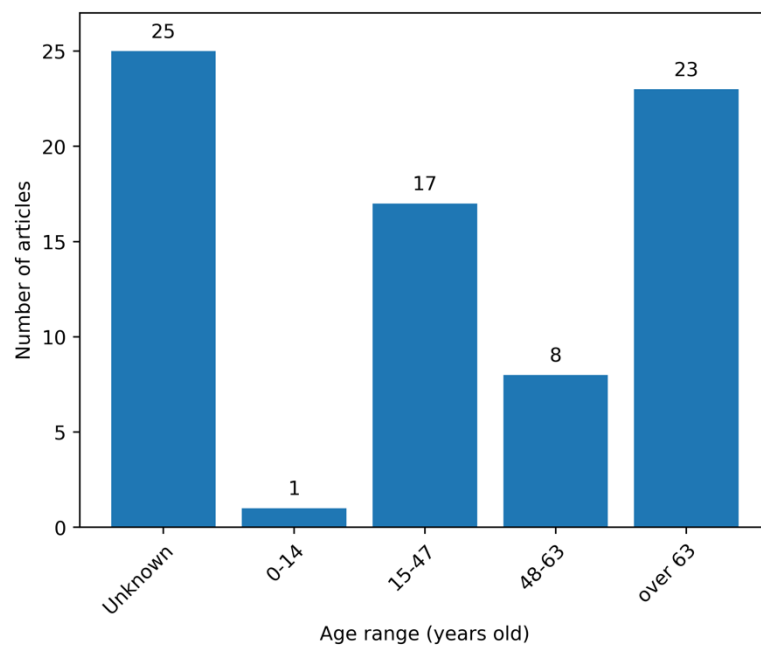


Figure 7. Number of publications by participants age

4.2.4.2 RQ1 – AI applications in AAL

Subsections within this section will detail the findings related to Research Question 1: How are AI methods currently being utilized in the AAL context to support healthcare monitoring for seniors? We will present the applications of the studies reviewed, the learning strategies employed in the models, and the specific AI algorithms used in these studies.

Application of the studies

The included articles have a range of applications, which we have categorized into five types and organized them by year (Figure 8). Firstly, Demonstration studies aim to

showcase the relationships between AAL indicators and health indicators. Secondly, Monitoring studies focus on observing and tracking inhabitants' living or activity routines to construct behavior patterns. Thirdly, Recognition studies aim to identify or classify individuals' ADLs using AAL sensors. Fourthly, Prediction studies aim to forecast indicators such as clinical scores [111] or mood levels [112]. Lastly, Detection studies revolve around identifying negative events, such as anomaly activities, falls, or dementia. Among the identified goals (as shown in Table 3), recognition turns out to be the most prevalent goal, which was pursued in 34/64 (53%) studies. There is a considerable decline observed in the number of articles focused on monitoring and detection, with each category comprising only 10/64 (16%) and 9/64(14%) articles, respectively. Following this, 8/64 (13%) articles were identified with the aim of prediction. Demonstration, on the other hand, appears to be the least common goal, with a limited number of studies (6/64, 9%) focusing on it.

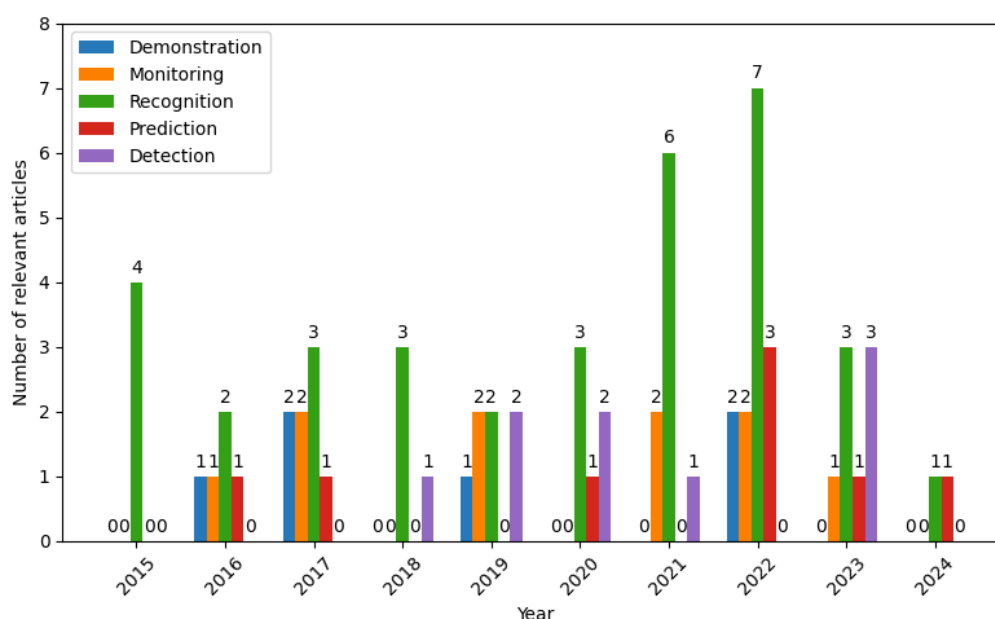


Figure 8. Study applications by year

Table 3. Applications of studies

Goal	Studies	Number of studies
Demonstration	[112][113][114][115][116][117]	6
Monitoring	[118][119][115][120][121][122][123][124][125][126]	10
Recognition	[127][128][129][130][131][132][133][134][135][136][137] [138][139][140][141][142][143][144][145][146][147][148] [149][150][151][36][152][153][154][155][156][157] [158][159]	34
Prediction	[111][160][161][162][120][163][164][165]	8
Detection	[118][166][167][168][169][170][171][172][173]	9

Artificial Intelligence algorithms

In this section, our exploration is centered around the application of AI algorithms within the studies under review, particularly in relation to achieving the objectives of these studies. It has been observed that several studies leverage AI algorithms not only in the data modeling phase but also during data preprocessing [115][156][157][158][165]. In presenting our findings, we have focused specifically on the AI algorithms applied in the data modeling phase. The rationale for this approach is rooted from our aim to highlight the direct impact of AI on the analytical outcomes, decision-making processes, and insights derived from the data.

According to learning approach, Artificial Intelligence algorithms can be classified into four types [76], including supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning. We categorized the included studies into these four types. Notably, we did not identify any studies utilizing semi-supervised or reinforcement learning; hence, our results only present for supervised learning and unsupervised learning, as detailed in Table 4. Only 6/64 (9%) studies use unsupervised learning, whereas 58/64 (91%) studies use supervised learning. This disparity is anticipated, as choice of learning approach depends on the research objective or application. Typically, supervised learning caters to tasks like regression and classification, serving purposes such as prediction, recognition, and demonstration. On the other hand, unsupervised learning is more suited for tasks like dimensionality reduction, clustering and outlier/anomaly detection, with aims primarily revolving around monitoring and detection. The trend in learning strategies over the years (Figure 9) indicates that supervised learning has maintained steady and growing interest. However, this trend also serves as a reminder of the need to incorporate more innovative and advanced unsupervised learning models into research.

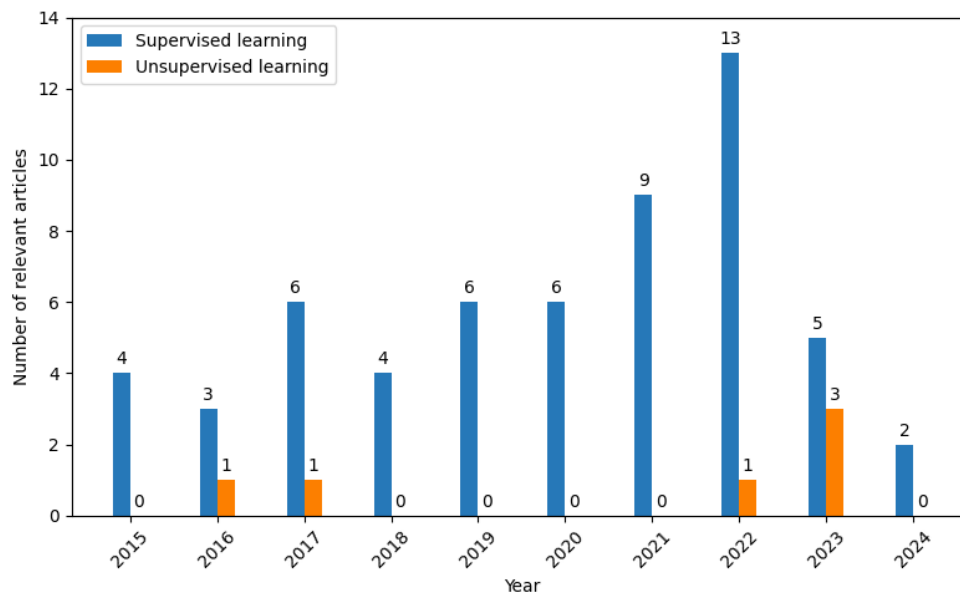


Figure 9. AI learning strategies by year

Table 4. Artificial Intelligence algorithms used grouped by learning approach

Learning approach	Description	Studies	Number of studies
Supervised learning	Refers to the process where a model is trained on a labeled dataset to make predictions or infer mappings, it can be used in prediction and regression tasks; some common models are linear regression, decision trees, and neural networks.	[36], [111], [112], [113], [114], [116], [117], [118], [119], [120], [121], [122], [124], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [172], [173]	58
Unsupervised learning	Refers to the process where a model identifies patterns and structures in unlabeled data, it can be used in tasks such as clustering, dimensionality reduction, and anomaly detection; some common models are k-means clustering, hierarchical clustering, and principal component analysis.	[115], [123], [125], [126], [156], [171]	6

Table 5 provides details of the AI algorithms employed in the studies reviewed, including those used for comparative analysis. The analysis revealed several categories of algorithms, which were summarized from study [76]. The definition of each algorithm type is also given in Table 5. Among the used AI algorithms, tree-based and neural network-based approaches being the most prevalent, appearing in 32/64 (50%) and 31/64 (48%) studies, respectively. The extensive utilization of these approaches demonstrates their effectiveness in handling complex ADLs related data and extracting meaningful patterns. Linear-based algorithms were utilized in 24/64 (38%) studies, suggesting their continued relevance for modeling relationships between factors (e.g., the study by B. Lin et al. [113] explored the relationship between ADLs and air quality). Bayesian-based algorithms were employed in 13/64 (20%) studies, while distance-based algorithms were utilized in 18/64 (28%) studies. Finally, 1/64 (2%) studies fell into the “Other” category, as the authors developed a novel AI approaches of their own for detecting abnormal behavior changes. Figure 10 illustrates the algorithms used over the years, showing that traditional machine learning methods have remained steady, while novel neural network approaches are attracting increasing interest.

In addition, the models employed within studies under each type exhibit considerable diversity. Within the linear-based category, Support Vector Machine (SVM) emerges as the most prevalent model, appears in 23/64 (36%) studies, trailed by Linear Regression in 4/64 (6%) studies and Logistic Regression in 3/64 (5%). For the tree-based category, 29/64 (45%) studies use Random Forest model, while 12/64 (19%) studies utilize the Decision Tree. Other tree-based models include the Classification And Regression Tree (CART) (2/64, 3%), AdaBoost (4/64, 6%), Gradient Boost (2/64, 3%), J48 (1/64, 2%), and XGBoots (1/64, 2%). Within Bayesian-based category, the Naïve Bayes model leads with 7/64 (11%) appearances, followed by the Hidden Markov Model (3/64, 5%). Among distance-based models, K-Nearest Neighbors appears in 14/64 (22%) studies, followed by K-Means algorithm (4/64, 6%), while Density-Based Spatial Clustering of Applications with Noise (DBSCAN) appears in just 1/64 (2%) study. Turning to the second popular algorithm type, which is neural network-based, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) occupied the first two places, and each was utilized in 10/64 (16%) and 12/64 (19%) studies, respectively, while Multilayer Perceptron (MLP) appears in 9/64 (14%) studies. Other frequently used neural network-based models include the Recurrent Neural Network (5/64, 8%), Deep Neural Network (2/64, 3%), Gated Recurrent Unit (2/64, 3%), Artificial Neural Network (2/64, 3%), Fully Connected Neural Network (1/64, 2%), Residual Neural Network (1/64, 2%), Particle Swarm Optimization Back Propagation Neural Network (PSO-BP Neural Network)(1/64, 2%), and CNN-Autoencoder (1/64, 2%). There is one (1/64, 2%) study that categorized in the ‘other’ type, because it is a novel machine learning algorithm that proposed by Dawadi et al. [115]. Authors not only introduced a novel concept termed the “activity curve”, designed to depict the daily routines of individuals, but also proposed a “Permutation-based Change Detection in Activity Routine (PCAR)” algorithm, which can be used to detect changes in behavioral routines by comparing activity distributions derived from the activity curve using a two-sample permutation test.

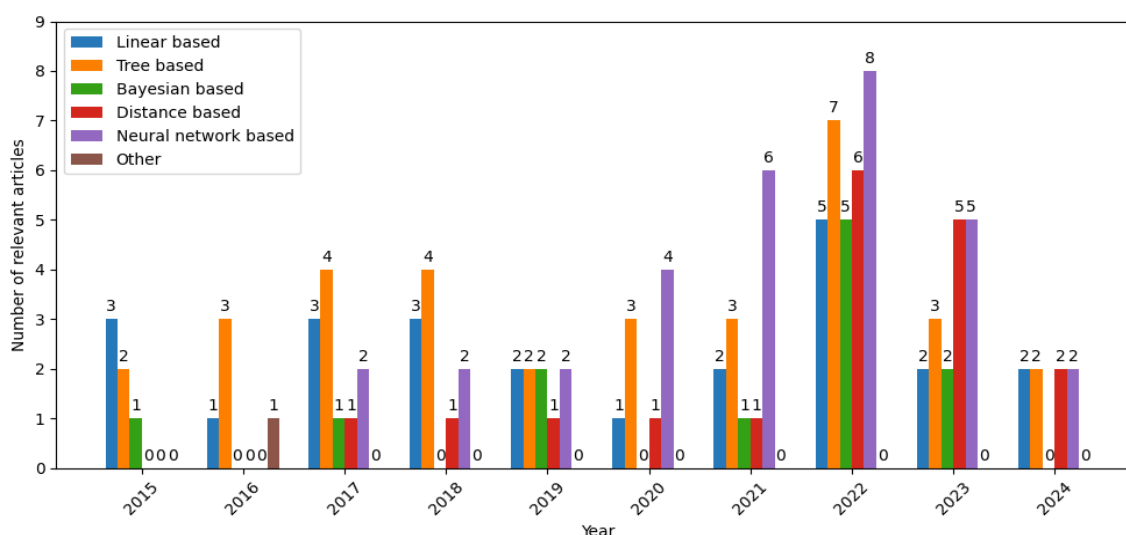


Figure 10. Algorithm types by year

Table 5. Artificial Intelligence algorithm types used for data modeling

Algorithm types	Definition	Models	Number of studies	Total number of studies
Linear-based	Using models to establish relationships between input and output variables through linear equations or hyperplanes.	Logistic Regression [147], [165], [172]	3	24 ([129], [130], [113], [131], [132], [111], [137], [138], [168], [143], [144], [160], [119], [147], [148], [122], [170], [172], [164], [158], [173], [165], [117], [159])
		Linear Regression [113], [111], [138], [168]	4	
		SVM [129], [130], [131], [132], [111], [137], [138], [168], [143], [144], [160], [119], [147], [148], [122], [170], [172], [164], [158], [173], [165], [117], [159]	23	
Tree-based	Using models to make decisions and predict outcomes by splitting data into hierarchical structures resembling trees.	Random Forest [127], [128], [130], [113], [131], [133], [111], [134], [135], [168], [141], [142], [143], [145], [160], [146], [162], [147], [148], [116], [170], [152], [163], [172], [157], [164], [173], [165], [159]	29	32 ([127], [128], [130], [113], [131], [132], [133], [111], [134], [135], [138], [168], [141], [142], [143], [145], [160], [146], [162], [147], [148], [116], [170], [152], [124], [163], [172], [157], [164], [173], [165], [159])
		Decision Tree [130], [131], [132], [138], [141], [142], [160], [116], [124], [172], [164], [173]	12	
		CART [128], [116]	2	
		AdaBoost [128], [130], [160], [170]	4	
		Gradient Boost [147], [157]	2	
		J48 [113]	1	
		XGBoost [165]	1	
Bayesian-based	Using models to predict outcomes based on prior knowledge and	Hidden Markov Model [127], [169], [114]	3	13 ([127], [130], [131], [138], [169], [160], [114],
		Naïve Bayes [130],	7	

	observed data, updating probabilities through Bayes' theorem.	[138], [160], [148], [157], [158], [173]		[148], [112], [125], [157], [158], [173])
		Bayesian Network [131], [112]	2	
		Gaussian Mixture Model [125]	1	
Distance-based	Using models to classify or cluster data points based on their proximity or distance to one another in a feature space.	K-Nearest Neighbors [128], [132], [136], [138], [143], [160], [147], [148], [172], [157], [164], [158], [173], [165]	14	18 ([128], [132], [136], [138], [143], [160], [147], [148], [123], [171], [125], [172], [126], [157], [164], [158], [173], [165])
		K-Means [123], [171], [125], [126]	4	
		DBSCAN [125]	1	
Neural network-based	Using models to process and transform input data through interconnected layers of nodes, inspired by the structure of the human neural networks.	CNN [127], [167], [140], [147], [148], [121], [149], [150], [36], [153]	10	31 ([127], [131], [118], [166], [167], [139], [140], [168], [142], [169], [143], [144], [160], [161], [147], [120], [148], [121], [149], [150], [151], [36], [170], [153], [154], [155], [172], [156], [157], [164], [159])
		LSTM [127], [118], [139], [144], [161], [148], [151], [36], [153], [154], [157], [159]	12	
		Fully Connected Neural Network [127]	1	
		MLP [131], [168], [143], [160], [148], [170], [172], [164], [159]	9	
		Recurrent Neural Network [166], [169], [161], [154], [159]	5	
		Artificial Neural Network [142], [120]	2	
		Deep Neural Network [160], [121]	2	
		Residual Neural Network [36]	1	

		Gated Recurrent Unit [161], [154]	2	
		PSO-BP Neural Network [155]	1	
		CNN-Autoencoder [156]	1	
Other	Novel AI models proposed by authors.	PCAR [115]	1	1 ([115])

4.2.4.3 RQ2 - Real-world AAL environments

This section presents results relevant to Research Questions 2: How are AAL environments constructed using commercially available sensors in real-world? It details the integration with cloud services, the configurations of study settings, the technologies employed, and the commercial devices utilized.

Integration of cloud

The scoping review explored how the included studies constructed the AAL systems, particularly focusing on whether they integrated cloud mechanisms into their AAL structure, thus creating cloud-based data ecosystem. The integration of cloud technology has the potential to revolutionize healthcare delivery and enhance the practicality of AAL systems. Cloud-based AAL systems offer several advantages over traditional localized systems. They can store and process vast amounts of data from numerous sources, enabling more comprehensive care. Additionally their scalability allows them to accommodate increasing numbers of devices without significant hardware upgrades. Moreover, cloud techniques address security and privacy concerns, making AAL systems more confidential and secure. As shown in Table 6, approximately one-third of the included studies (20/64, 31%) use cloud mechanism in their AAL systems, while 44/64 (69%) studies did not. Those studies that employed cloud mechanisms demonstrated various ways of integration, including data storage [168][172], data transmission [146], and cloud computing [136][164][172]. Figure 11 displays the yearly trend of cloud integration in studies. Despite peaking at 7/64 (11%) in 2022, the overall adoption of cloud technology remains relatively low.

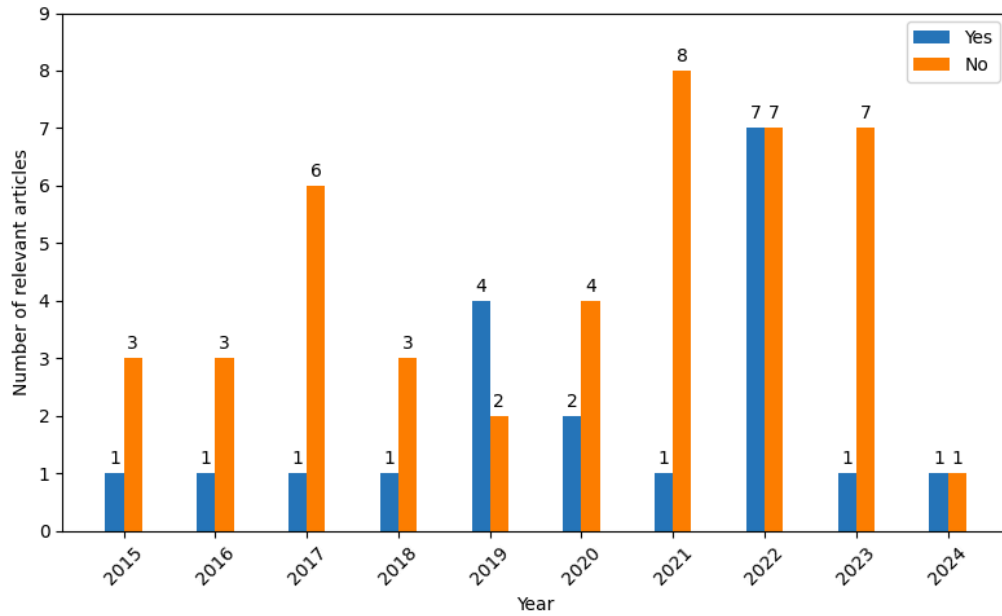


Figure 11. Cloud technology usage by year

Table 6. Cloud based AAL system

	Studies	Number of studies
Yes	[118], [132], [136], [137], [138], [139], [169], [143], [160], [119], [146], [162], [148], [152], [124], [154], [163], [172], [164], [165]	20
No	[127], [128], [129], [130], [113], [131], [133], [111], [134], [166], [167], [135], [140], [168], [141], [142], [144], [145], [161], [114], [147], [115], [120], [121], [116], [149], [150], [151], [112], [36], [122], [170], [153], [123], [171], [125], [155], [156], [126], [157], [158], [173], [117], [159]	44

Settings

The scoping review identified studies conducted in various settings that utilized smart homes and AAL interventions (Table 7). Among the included studies, a significant number utilized smart home testbeds, with 32/64 (50%) studies specifically conducted in controlled environments designed to simulate real-world smart home settings. These testbeds were equipped with basic rooms and equipment for daily living. Additionally, 25/64 (39%) studies were conducted in common homes with real-world residential settings in an uncontrolled manner. Only 4/64 (6%) studies were identified in a nursing home setting, and moreover, 3/64 (5%) study was found in a hospital setting. The results emphasize the prevalence of research conducted in smart home testbeds, followed by common homes. The limited representation of nursing homes and hospitals suggests a potential research gap

in exploring the application of AAL interventions in these settings. Figure 12 illustrates the evolution of study settings over the years. There has been an increase in studies conducted in common home environments, peaking at 8/64 (13) in 2022, whereas the use of testbeds has seen a decline.

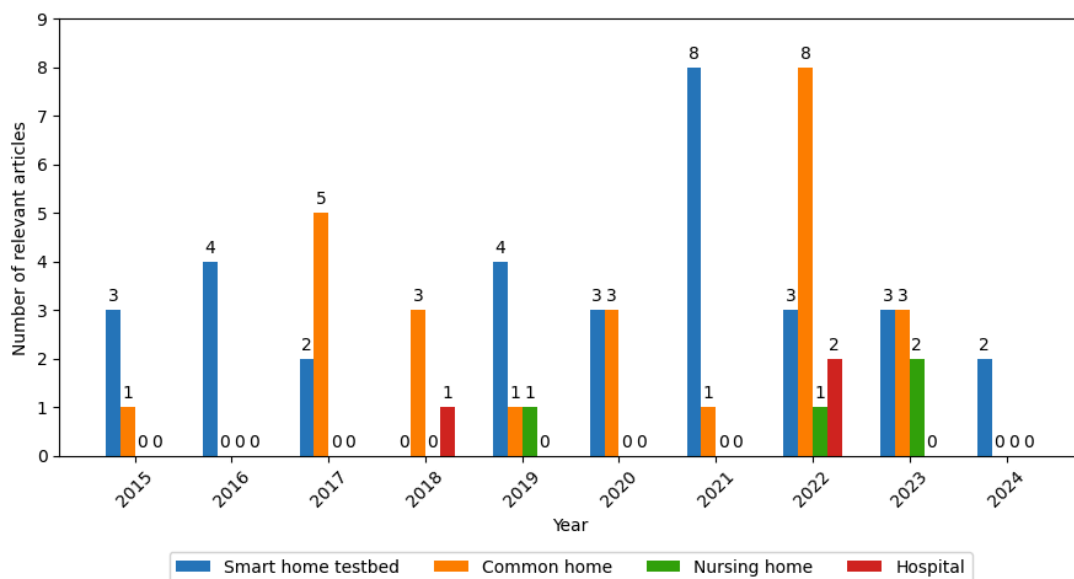


Figure 12. Study settings by year

Table 7. Study settings

	Studies	Number of studies
Smart home testbed	[127], [128], [129], [118], [133], [111], [166], [167], [135], [136], [137], [138], [140], [141], [142], [169], [144], [145], [161], [146], [114], [147], [115], [151], [36], [122], [152], [153], [156], [164], [158], [173]	32
Common home	[130], [113], [131], [132], [134], [139], [168], [143], [160], [119], [162], [120], [148], [121], [149], [112], [170], [123], [171], [125], [154], [163], [126], [157], [117]	25
Nursing home	[116], [124], [155], [172]	4
Hospital	[150], [165], [159]	3

Device technologies

The included articles identified three types of device technologies: ambient, wearable, and hybrid technology (Table 8). Ambient technology encompasses electronic devices that are contactless, sensitive, and responsive to the presence of individuals within an environment, which is getting growing interest (Figure 13). Wearable technology, on the other hand,

involves electronic accessories designed to be worn on the body, allowing for the tracking of daily activities and personal health metrics. Hybrid technology represents the integration of these two distinct technologies. Among the used technologies, ambient technology was the most commonly used, appearing in a total of 49/64 (77%) studies. This widespread adoption and extensive exploration of ambient technology in AAL-related research highlights its prominence in the field. Conversely, wearable technology was only present in 4/64 (6%) studies, indicating its limited utilization. Additionally, the hybrid technology, which combines ambient and wearable approaches, was evaluated in 11/64 (17%) articles, showing its potential for integrated monitoring solutions.

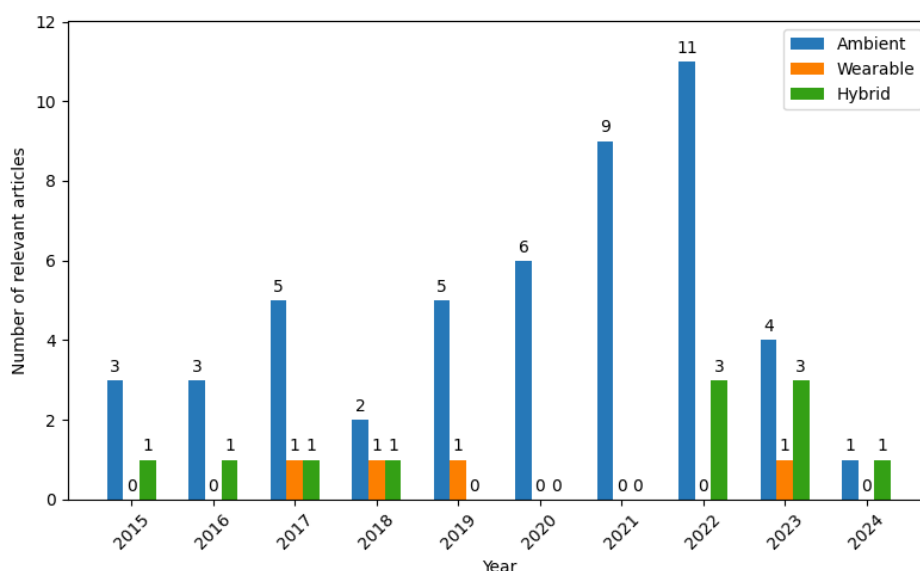


Figure 13. AAL technologies by year

Table 8. Device technologies

Technologies	Studies	Number of studies
Ambient	[127], [128], [129], [113], [118], [133], [111], [134], [166], [167], [135], [136], [137], [139], [140], [168], [141], [142], [169], [143], [144], [160], [119], [161], [146], [114], [162], [147], [115], [120], [148], [121], [116], [149], [150], [151], [36], [122], [170], [152], [153], [123], [124], [171], [125], [156], [158], [173], [165]	49
Wearable	[138], [157], [117], [159]	4
Hybrid	[130], [131], [132], [145], [112], [154], [163], [155], [172], [126], [164]	11

Device type, sensors, and brand

Results in Table 9 present a diverse range of devices and sensors utilized in the included studies. categorized into five groups: environmental sensors, occupancy sensors, power sensors, physical sensors, and others. Figure 14 shows a sustained use of environmental, occupancy, and power sensors, alongside an increasing focus on emerging technologies like radar and Wi-Fi sensors in AAL research. Among the environmental sensors, temperature sensors were the most prevalent, featured in 20/64 (31%) studies, followed by humidity sensors in 13/64 (20%) studies, and air quality sensors in 8/64 (13%) studies. Occupancy sensors, specifically passive infrared motion sensors, were the most widely deployed, appearing in 34/64 (53%) studies. Magnetic/latch/contact door sensors were also frequently used and appeared in 24/64 (38%) studies. Power sensors, notably power meters and light sensors, were used in 8/64 (13%) and 13/64 (20%) studies, respectively. Physical sensors, often employed to monitor vital signs or gait information, had limited usage, with only 3/64 (5%) studies utilized blood pressure meters and oximeters, while 2/64 (3%) studies made the use of multi-parametric belts, Polysomnography device, weight scales, and gait sensors. Only 1/64 (2%) study reported the use of glucometer.. Additionally, other novel technologies, such as UWB radar, Wi-Fi router, ultrasonic sensors, and LiDAR sensors, were found in 12/64 (19%), 7/64 (11%), 5/64 (8%), and 1/64 (2%) study, respectively. Smart watch is also commonly used in studies, appearing in 10/64 (16%) articles.

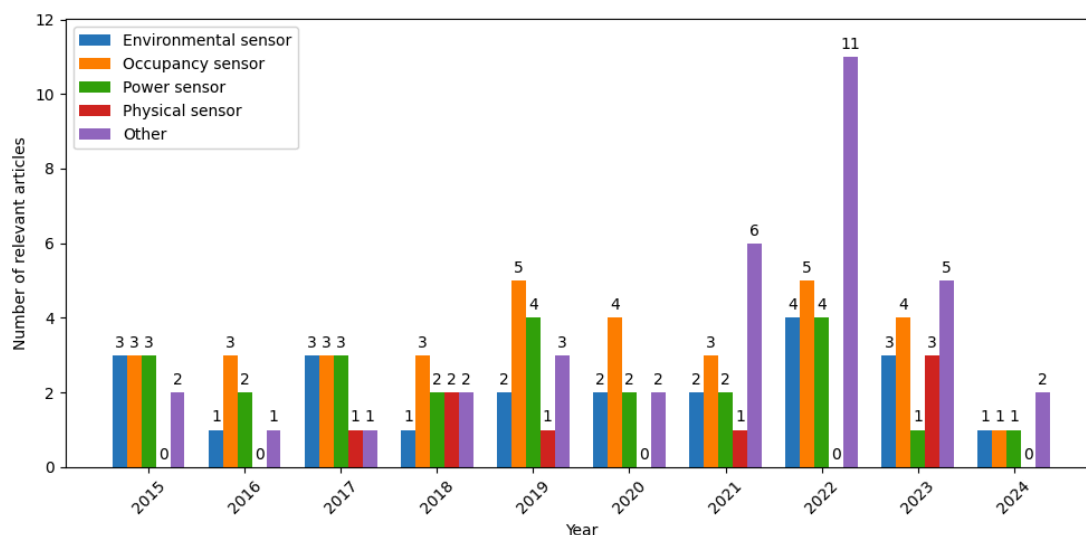


Figure 14. Device type used by year

Table 9. Device information

Type	Device/Sensor	Studies	Brand of Products	Number of studies
Environmental sensor	Temperature sensor	[111], [113], [130], [133], [137], [139], [140], [141], [119], [161], [162], [120], [116], [122], [171],	SHiB [111][113][119][130], AIRMAR WX200 [113], KNX [120], Aqara [122], Fibaro	20

		[125], [154], [163], [155], [164]	[125][171], Swidget [164]	
	Humidity sensor	[133], [139], [140], [141], [161], [120], [116], [171], [125], [154], [163], [155], [164]	Omron 2JCIE-BL01 [139], KNX [120], Fibaro [125][171], Swidget [164]	13
	Air quality sensor	[113], [132], [135], [137], [120], [116], [155], [164]	LiCOR [113], LGR [113], TECO [113], Teledyne [113], SNAP [132], ECHONET Lite [135], KNX [120], Swidget [164]	8
	Thermostat	[132]	Not specified	1
	Luminosity sensor	[137], [139], [154], [163]	Omron 2JCIE-BL01 [139], Xiaomi [154]	4
	Atmospheric pressure sensor	[139], [163]	Omron 2JCIE-BL01 [139]	2
	Gas sensor	[112], [122]	Xiaomi [122]	2
	Noise/sound sensor	[139], [161], [120], [163], [155]	Omron 2JCIE-BL01 [139], KNX [120]	5
Occupancy sensor	Passive Infrared motion sensor	[130], [113], [118], [132], [133], [111], [134], [135], [136], [137], [139], [140], [168], [169], [160], [119], [161], [146], [114], [162], [115], [116], [151], [112], [122], [170], [123], [171], [125], [154], [163], [172], [126], [164]	SHiB [111][113][119][130] [170], ECHONET Lite [135], Panasonic [139], Senba [160], Rohm [146], Xiaomi [122], FIBARO [123], Fibaro [125][171], Aqura [154], Lifelog [172], Swidget [164]	34
	Magnetic/latch /contact door sensors	[130], [113], [118], [133], [111], [134], [136], [139], [140], [168], [141], [169], [119], [161], [146], [114], [115], [122], [170], [171], [125], [163], [126], [164]	SHiB [111][113][119][130] [170], Rohm [146], Xiaomi [122], Fibaro [125][171], Aqura [154], Swidget [164]	24
	Bed/mat	[118], [134], [136],	Not specified	8

	presence/pressure sensor	[137], [140], [168], [122], [126]		
	Debitmeter/faucet/water flow sensor	[134], [141], [114], [122]	Not specified	4
Power sensor	Power meter	[129], [132], [141], [145], [151], [112], [122], [152]	PZEM-004T [122], RATOC Systems [152]	8
	Light sensor	[130], [113], [118], [132], [111], [135], [140], [169], [119], [162], [122], [171], [125]	SHiB [111][113][119][130], ECHONET Lite [135], IKEA [122], Fibaro [125][171]	13
	Smart plug/outlet	[133], [140], [114], [122], [171], [154], [164]	Xiaomi [122], Fibaro [171], Xiaomi [154], Swidget [164]	7
	Electric sensor	[134]	Not specified	1
	Smart switch	[112], [164]	Swidget [164]	2
Physical sensor	Multi-parametric belt	[132], [138]	Zephyr Bioharness 3.0 [132], Zephyr HXM [138]	2
	Oscillometric blood pressure meter	[132], [155], [126]	Taidoc TD3128B [132]	3
	Oximeter	[132], [155], [126]	Onyx Nonin 9560 [132]	3
	Glucometer	[132]	Taidoc TD4277 [132]	1
	Polysomnography device	[117], [159]	Xltek Trex HD [117], Compumedics E-64 [159]	2
	Body weight scale	[132], [126]	Taidoc TD2555B [132]	2
	Motion/gait capture sensor (IMU)	[142], [161]	Xsens MVN [142]	2
Other	Wireless/Wi-Fi router	[127], [131], [166], [144], [147], [149], [158]	Tp-link archer c20 [127], Asus RT-AC86U [144], Optronix RL821GWV [147], ESP 32 [158]	7
	UWB radar	[128], [167], [143], [148], [149], [150], [36], [153], [124], [156], [173], [165]	Novelda XeThru [36][124][128][153][156][167], Sharp DC6M4JN3000	12

			[143][148], Decawave MDEK1001 [149]	
	Ultrasonic sensor	[129], [132], [141], [145], [151]	TAG [129], Dragon [141][151]	5
	Vibration sensor	[130], [133], [154]	SHiB [130], Xiaomi [154]	3
	Smart watch	[131], [145], [121], [112], [154], [163], [172], [157], [164], [159]	Sony smart watch 3 [131], LG Watch Urbane [145], Apple Watch series 6 [121], Xiaomi's Mi Band-3/4 [112][154], Fitbit Alta [163], Lifelog [172], Microsoft [157][159], Empatica [164]	10
	Accelerometer	[117]	GENEActiv [117]	1
	LiDAR sensor	[133]	Not specified	1
	Speaker	[118], [126], [169]	Amazon Echo Show [126]	3

4.2.4.4 RQ3 - Data, indicators, and valuable outcomes

The results presented in this section address the Research Question 3: What type of information are AAL technologies collecting, and how can it help to generate valuable outcomes? We outline the indicators used in each study, the AI algorithms employed, the achievements of the models, and the conditions indicated, as summarized in Table 10.

Table 10 reveals a diverse range of indicators used in AAL environments, spanning indoor temperature, motion detection, door/window status, electrical power usage, ultrasonic signals, air quality metrics, and physiological signals such as heart rate and gait. These indicators serve as inputs to various AI algorithms, ranging from SVM, Random Forest, and Decision Trees, to more advanced methods like CNN, LSTM networks, and Deep Neural Networks. The capabilities of these models are extensive, covering areas from ADLs recognition (24/64, 38%), behavior pattern modeling (8/64, 11%), and cognitive health assessment (1/64, 2%) to abnormal behavior detection (8/64, 11%), fall detection (3/64, 5%), sleep quality monitoring (3/64, 5%), indoor position recognition (1/64, 2%). Over time, the scope of health conditions monitored has expanded significantly, with a notable emphasis on comprehensive healthcare monitoring for aging population. This includes monitoring specific conditions such as cognitive impairment (4/64, 6%), Alzheimer's disease (2/64, 3%), dementia (5/64, 8%), and facilitating stroke rehabilitation (1/64, 2%), as well as general healthcare monitoring (49/64, 77%).

Table 10. Indicators, AI models, model capabilities

Year	Study	Sensor measurement	AI algorithms	Model outputs/	Health conditions
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				capabilities	monitored
2015	[129]	Electrical power consumption readings; Ultrasonic signal	SVM	ADLs recognition	General healthcare monitoring on old individuals
2015	[130]	Indoor temperature; Presence or absence of motion or movement; Open or close status of door/window; On/off state of the light; Vibration level	SVM; Random Forest; Decision Tree; AdaBoost; Naïve Bayes	ADLs recognition & pattern comparison	Cognitive impairment; Parkinson
2015	[137]	Indoor temperature; Quality indicators of air (e.g., AQI, CO ₂ , PM, CH ₄); Illuminance value; Presence or absence of motion or movement; Presence or absence of pressure on the sensor	SVM	Home state prediction	General healthcare monitoring on old individuals
2015	[141]	Indoor temperature; Indoor humidity; Open or close status of door/window; Flow rate of fluid; Electrical power consumption; Ultrasonic signal	Random Forest; Decision Tree	ADLs recognition	General healthcare monitoring on old individuals
2016	[111]	Indoor temperature; Presence or absence of motion or movement; Open or close status of door/window; On/off state of the light	Linear Regression; SVM; Random Forest	Cognitive health clinical score prediction	Cognitive impairment
2016	[145]	Electrical power consumption; Ultrasonic signal; 3-axis acceleration data	Random Forest	ADLs recognition	General healthcare monitoring on old individuals
2016	[146]	Presence or absence of motion or movement; Open or close status	Random Forest	ADLs recognition	General healthcare monitoring

		of door/window			on old individuals
2016	[115]	Presence or absence of motion or movement; Open or close status of door/window	PCAR	Behavior pattern modeling & abnormal behavior detection	General healthcare monitoring on old individuals
2017	[113]	Open or close status of door/window; On/off state of the light	Linear Regression; Random Forest; J48	Relationship evaluation between behavior and air quality	General healthcare monitoring on old individuals
2017	[131]	Wi-Fi signal (i.e. channel state information); 3-axis acceleration data	SVM; Random Forest; Decision Tree; Bayesian Network; MLP;	Indoor position recognition	General healthcare monitoring on old individuals
2017	[135]	Quality indicators of air (e.g., AQI, CO ₂ , PM, CH ₄); Presence or absence of motion or movement; On/off state of the light;	Random Forest	ADLs recognition	General healthcare monitoring on old individuals
2017	[120]	Indoor temperature; Indoor humidity; Quality indicators of air (e.g., AQI, CO ₂ , PM, CH ₄); Sound level	Artificial Neural Network	Room occupancy detection	General healthcare monitoring on old individuals
2017	[152]	Electrical power consumption;	Random Forest	ADLs recognition	General healthcare monitoring on old individuals
2017	[123]	Presence or absence of motion or movement;	K-Means	Behavior pattern modeling	Cognitive impairment
2017	[117]	Electroencephalogram ; heart rate; 3-axis acceleration data	SVM;	Sleep classification	Sleep quality monitoring
2018	[132]	Quality indicators of air (e.g., AQI, CO ₂ ,	SVM; Decision Tree; K-Nearest	Health status	General healthcare

		PM, CH ₄); Body weight; Indoor temperature and humidity; Presence or absence of motion or movement; Electrical power consumption; On/off state of the light; ECG; respiration signals; heart rate; breathing rate; acceleration, activity level; posture; Blood pressure readings; Blood oxygen saturation level; Blood glucose level; Ultrasonic signal	Neighbors	monitoring	monitoring on old individuals
2018	[134]	Presence or absence of motion or movement; Open or close status of door/window; Presence or absence of pressure on the sensor; Flow rate of fluid; Electrical signal and output voltage	Random Forest	Behavior pattern modeling	Mild cognitive impairment Alzheimer's disease
2018	[170]	Presence or absence of motion or movement; Open or close status of door/window	SVM; Random Forest; AdaBoost; MLP	Symptoms score prediction	Alzheimer's disease
2018	[159]	Electroencephalogram , heart rate; 3-axis acceleration data	SVM; Random Forest; LSTM; MLP; Recurrent Neural Network	Sleep stage classification	Sleep quality monitoring
2019	[118]	Presence or absence of motion or movement; Open or close status of door/window; Presence or absence of pressure on the sensor; On/off state of the light	LSTM	Behavior pattern modeling & Abnormal behavior detection	General healthcare monitoring on old individuals but specifically for isolated

					older people
2019	[138]	ECG; respiration signals; heart rate; breathing rate; 3-axis acceleration data; activity level; posture	Linear Regression; SVM; Decision Tree; Naïve Bayes; K-Nearest Neighbors	ADLs recognition	General healthcare monitoring on old individuals
2019	[169]	Presence or absence of motion or movement; Open or close status of door/window; On/off state of the light;	Hidden Markov Model; Recurrent Neural Network	Behavior pattern modeling & Abnormal behavior detection	General healthcare monitoring on old individuals
2019	[119]	On/off state of the light	SVM	Behavior pattern modeling	General healthcare monitoring on old individuals
2019	[116]	Indoor temperature; Indoor humidity; Quality indicators of air (e.g., AQI, CO ₂ , PM, CH ₄); Presence or absence of motion or movement;	Random Forest; Decision Tree; CART	Behavior pattern modeling & Abnormal behavior detection	General healthcare monitoring on old individuals
2019	[151]	Presence or absence of motion or movement; Electrical power consumption; Ultrasonic signal;	LSTM;	ADLs occurrence time prediction	General healthcare monitoring on old individuals
2020	[128]	Radar signal	Random Forest; CART; AdaBoost; K-Nearest Neighbors;	ADLs recognition	General healthcare monitoring on old individuals
2020	[166]	Wi-Fi signal (i.e. channel state information)	CNN; Recurrent Neural Network	Fall detection	General healthcare monitoring on old individuals
2020	[139]	Indoor temperature; Indoor humidity; Illuminance value;	LSTM	ADLs recognition	General healthcare monitoring

		Atmospheric pressure value; Sound level; Presence or absence of motion or movement; Open or close status of door/window;			on old individuals
2020	[140]	Indoor temperature; Indoor humidity; Presence or absence of motion or movement; Open or close status of door/window; Presence or absence of pressure on the sensor; On/off state of the light; Power consumption and usage log of an outlet	CNN	ADLs recognition	General healthcare monitoring on old individuals
2020	[168]	Presence or absence of motion or movement; Open or close status of door/window; Presence or absence of pressure on the sensor	Linear Regression; SVM; Random Forest; MLP	Abnormal behavior detection	General healthcare monitoring on old individuals
2020	[162]	Indoor temperature, Presence or absence of motion or movement; On/off state of the light;	Random Forest	Users' well-being prediction	General healthcare monitoring on old individuals
2021	[127]	Wi-Fi signal (i.e. channel state information)	Random Forest; Hidden Markov Model; CNN; LSTM; Fully Connected Neural Network	ADLs recognition	General healthcare monitoring on old individuals
2021	[133]	Indoor temperature; Indoor humidity; Presence or absence of motion or movement; Open or close status of door/window; Power consumption and usage log of an outlet; Vibration level;	Random Forest	Early-stage dementia classification	Dementia

		LiDAR signal			
2021	[167]	Radar signal	CNN	Fall detection	General healthcare monitoring on old individuals
2021	[136]	Presence or absence of motion or movement; Open or close status of door/window; Presence or absence of pressure on the sensor	K-Nearest Neighbors	ADLs recognition	General healthcare monitoring on old individuals
2021	[142]	Gait signal	Artificial Neural Network	Gait identification	General healthcare monitoring on old individuals
2021	[144]	Wi-Fi signal (i.e. channel state information)	SVM; LSTM	ADLs recognition	General healthcare monitoring on old individuals
2021	[121]	3-axis acceleration data	CNN; Deep Neural Network	Body skeleton tracking & hand keypoints detection	Stroke patient rehabilitation
2021	[36]	Radar signal	Residual Neural Network	ADLs recognition	General healthcare monitoring on old individuals
2021	[122]	Indoor temperature; Presence or absence of motion or movement; Open or close status of door/window; Presence or absence of pressure on the sensor; Flow rate of fluid; Electrical power consumption; On/off state of the light;	SVM	Mood classification (i.e., pleasure, sleepiness, contentment)	General healthcare monitoring on old individuals

		Power consumption and usage log of an outlet			
2022	[143]	Radar signal	SVM; Random Forest; K-Nearest Neighbors; MLP	ADLs recognition	General healthcare monitoring on old individuals
2022	[160]	Presence or absence of motion or movement	SVM; Random Forest; Decision Tree; AdaBoost; Naïve Bayes; K-Nearest Neighbors; MLP; Deep Neural Network	Dementia risk classification (high and low)	Dementia
2022	[114]	Presence or absence of motion or movement; Open or close status of door/window; Flow rate of fluid; Power consumption and usage log of an outlet	Hidden Markov Model	ADLs recognition	General healthcare monitoring on old individuals
2022	[147]	Wi-Fi signal (i.e. channel state information)	K-Nearest Neighbors; CNN	ADLs recognition	General healthcare monitoring on old individuals
2022	[148]	Radar signal	CNN; LSTM; MLP	ADLs recognition	General healthcare monitoring on old individuals
2022	[149]	Wi-Fi signal (i.e. channel state information); Radar signal	CNN	ADLs recognition	General healthcare monitoring on old individuals
2022	[150]	Radar signal	CNN	ADLs recognition	General healthcare monitoring on old individuals
2022	[112]	Concentration of a	Bayesian	Probabilisti	General

		specific gas; Presence or absence of motion or movement; Electrical power consumption; On/off state of the switch; 3-axis acceleration data	Network	c relationship evaluation between ADLs and mood	healthcare monitoring on old individuals
2022	[153]	Radar signal	CNN; LSTM	ADLs recognition	General healthcare monitoring on old individuals
2022	[124]	Radar signal	Decision Tree	Human presence & posture detection	Elderly wandering
2022	[125]	Indoor temperature; Indoor humidity; Presence or absence of motion or movement; Open or close status of door/window; On/off state of the light	Gaussian Mixture Model; K-Means; DBSCAN	Anomaly sleep pattern detection	Parkinson; Dementia
2022	[154]	Power consumption and usage log of an outlet; Vibration level; 3-axis acceleration	LSTM; Recurrent Neural Network; Gated Recurrent Unit	ADLs recognition	General healthcare monitoring on old individuals
2022	[163]	Indoor temperature; Indoor humidity; Illuminance value; Atmospheric pressure value; Sound level; Presence or absence of motion or movement; Open or close status of door/window; Heart rate	Random Forest	Stress level classification	General healthcare monitoring on old individuals
2022	[165]	Radar signal	Logistic Regression; SVM; Random Forest; XGBoost; K-	COVID-19 infection classification	COVID-19

			Nearest Neighbors		
2023	[161]	Indoor temperature; Indoor humidity; Sound level; Presence or absence of motion or movement; Open or close status of door/window; Gait signal	LSTM; Recurrent Neural Network; Gated Recurrent Unit	ADLs recognition & location recognition & start time prediction	General healthcare monitoring on old individuals
2023	[171]	Indoor temperature; Indoor humidity; Presence or absence of motion or movement; Open or close status of door/window; On/off state of the light; Power consumption and usage log of an outlet	K-Means	Outlier detection	General healthcare monitoring on old individuals
2023	[155]	Indoor temperature; Indoor humidity; Quality indicators of air (e.g., AQI, CO ₂ , PM, CH ₄); Sound level; Blood pressure readings; Blood oxygen saturation level	PSO-BP Neural Network	Health status score prediction	General healthcare monitoring on old individuals
2023	[172]	Presence or absence of motion or movement; 3-axis acceleration data	Logistic Regression; SVM; Random Forest; Decision Tree; K-Nearest Neighbors; MLP	Abnormal behavior detection	Dementia
2023	[156]	Radar signal	CNN-Autoencoder	ADLs recognition	General healthcare monitoring on old individuals
2023	[126]	Presence or absence of motion or movement; Open or close status of door/window;	K-Means	Behavior pattern modeling	Dementia

		Presence or absence of pressure on the sensor; Blood pressure readings; Blood oxygen saturation level; Body weight			
2023	[157]	3-axis acceleration data	Random Forest; Gradient Boost; Naïve Bayes; K-Nearest; LSTM	ADLs recognition	General healthcare monitoring on old individuals
2023	[173]	Radar signal	SVM; Random Forest; Decision Tree; Naïve Bayes; K-Nearest Neighbors	Fall detection & post-fall breath rate prediction	General healthcare monitoring on old individuals
2024	[164]	Indoor temperature; Indoor humidity; Quality indicators of air (e.g., AQI, CO ₂ , PM, CH ₄); Presence or absence of motion or movement; Open or close status of door/window; Power consumption and usage log of an outlet; On/off state of the switch; Steps, Heart rate	SVM; Random Forest; Decision Tree; K-Nearest Neighbors; MLP	Heart rate prediction	General healthcare monitoring on old individuals
2024	[158]	Wi-Fi signal (i.e. channel state information)	SVM; Naïve Bayes; K-Nearest Neighbors	Respiration classification	General healthcare monitoring on old individuals

4.2.5 Discussion

This section presents the key findings derived from the scoping review, which aim to address the four research questions proposed earlier. Furthermore, we conduct a comparative analysis of these findings with other relevant review articles in the field.

4.2.5.1 RQ1. How are AI methods currently used in AAL context to assist healthcare monitoring for seniors?

The sharp increase in AAL research, especially from 2020 onwards, as highlighted in our results, is evidence of the growing recognition of AI's transformative potential in this domain. Our review identified that supervised learning is the most popular learning approach among the included studies, a trend closely aligned with their application objectives. The prevalent use of supervised learning in these studies can be attributed to its direct applicability in situations where predictions or classifications are essential, and where labeled data is available. In the context of supervised learning, ground truth labels are usually obtained from human experts, manual annotation, or specified sensors capable of delivering precise measurements. For example, Cook et al. [130] used experimenters to label activity data, while Rad et al. [112] engaged three psychologists for the annotation process. Lin et al. [113] utilized instruments to measure accurate air quality metrics. As our findings also indicate, the predominant adoption of tree-based and neural network-based AI methodologies showcases the confidence in these techniques to proficiently manage the complex data associated with Activities of Daily Living (ADLs). This trend is further demonstrated by studies such as the one by M. Jovanovic et al., which underscores the increasing reliance on advanced AI models in AAL systems [76]. The review paper by Zinno et al. [174] approved that machine learning can be used as a powerful and reliable tool in AAL, especially fuzzy c-means, k-means, ANN, KNN, SVM, decision trees and random forest. Similarly, Ramanujam et al. [102] discusses the automatic extraction of features for classification of human activities using CNN, LSTM and ConvLSTM.

Our scoping review underscores the diverse role of AI within AAL. From augmenting the accuracy of daily activity recognition to proactively forecasting potential health challenges and devising individualized healthcare monitoring solutions, AI proves pivotal in the advancement of AAL. Similarly, Lussier et al. [105] and Yeap et al. [94] analyzed AI tools for activity recognition. Hela et al. [175] reviewed AI approaches for anomaly detection in smart homes. Yebda et al. [176] looked at risk situation detection in AAL. The adaptability of AI-powered AAL systems to the ever-evolving needs of users, especially older adults, is a testament to the technology's versatility and forward-thinking approach.

The potential of AI to proactively detect health concerns marks a transformative approach in geriatric care. As revealed in our study, AI-integrated AAL systems have the capacity to provide early detection of health risks to users by monitoring AAL sensors' data from an individual's behavior or health signs. Such early detection prioritizes preventative measures over reactionary treatments, signifying a transformative phase in healthcare. As emphasized in our findings, this proactive approach has the potential to markedly improve health outcomes and prolong the healthful lifespan of older people.

4.2.5.2 RQ2. How are AAL environments constructed using commercially available sensors in real-world?

To answer Research Question 2, we discuss our results in terms of what technologies were used to construct the AAL environment and what settings were usually used to deploy these

technologies.

Technologies

In results, we find a discernible trend toward utilizing ambient technology in AAL research. One primary rationale for this trend lies in the direct health implications of monitoring environmental parameters such as temperature, humidity, light levels, and air quality. For instance, fluctuations in these metrics have tangible impacts on individuals with health conditions like asthma, allergies, or skin disorders. Moreover, ensuring optimal conditions through ambient sensing can substantially improve sleep quality [177], a fundamental aspect of holistic health. Additionally, especially in the context of healthcare for older population, variations in ambient conditions might serve as early indicators of potential accidents or challenges faced by senior residents. There are several studies that use hybrid technology which combines ambient and wearable devices. This fusion of technologies aims to provide a comprehensive assessment of both the environment and the individual. Wearable devices continuously monitor personal metrics, offering insights into the individual's physiological responses. When integrated, the data from both sources can provide a real-time feedback loop, allowing for immediate interventions when necessary. The synergy of these technologies, as highlighted in studies [132][154], promises not only improved health outcomes but also paves the way for more personalized and adaptive health monitoring solutions in smart living environments.

Study Settings

A study by Grant D et al. supports the view that testing in real conditions is vital for the effective application of AAL solutions [178]. Our results indicate that four main types of real-world settings were used to implement the AAL environment: mainly smart home testbeds, then actual homes, nursing homes, and hospitals. The controlled testbed environments, designed to simulate real-home settings, play a pivotal role in the initial testing and refinement of AAL solutions. They offer a controlled environment where variables can be manipulated to improve the efficacy and robustness of AAL systems before their deployment in uncontrolled settings. A study by Sepasgozar S. et al. underscores the importance of such testbeds, highlighting their role as a bridge between theoretical research and real-world application [179]. However, as highlighted in our results, the limited representation of certain settings, such as nursing homes and hospitals, presents an area for future exploration, ensuring that the benefits of AAL can reach all areas of healthcare for older people.

AAL infrastructure development spectrum

To provide a clear view of how the AAL solutions have evolved over the past 11 years, we have re-organized the results concerning cloud integration, study settings, device technology, and devices types by year from earliest to the most recent. Our analysis reveals a spectrum of AAL development over these years. 1) The adoption of cloud computing in AAL studies has been limited, despite a notable increase in 2022. This observation implies that while the potential advantages of cloud computing are recognized, its integration into AAL solutions has yet to become a standard practice. 2) Over time, the settings for AAL

studies have evolved from controlled smart home testbeds to common home environments. Although smart home testbeds remain a popular choice, the shift towards common homes highlights a move to more realistic and generalizable research outcomes. This transition suggests that AAL technologies are maturing, with researchers increasingly confident in testing these systems in everyday living scenarios. 3) The trend in device technology used in studies points to a preference for ambient technology solutions. Ambient devices provide unobtrusive monitoring, which is crucial for user acceptance and long-term adoption in AAL systems. 4) The consistent use of environmental, occupancy, and power sensors shows the crucial role in AAL infrastructures. They are essential for monitoring living conditions, detecting presence, and managing energy consumption, which contribute to the ADLs recognition [140], behavior pattern modeling [134], and anomaly detection [118]. The growing interest in ‘other’ novel sensors, such as radar and Wi-Fi, indicates their growing popular for application like fall detection [173] and indoor localization [131].

4.2.5.3 RQ3. What type of information are AAL technologies collecting, and how can it help to generate valuable outcomes?

To address Research Question 3, this section leverages the findings presented in Table 10. Our discussion focuses on the correlation between the indicators used, the AI models applied, and the outcomes achieved, highlighting their relevance to specific healthcare monitoring conditions.

The analysis of AI model usage patterns, as revealed in Table 10, indicates a preference for traditional machine learning models such as Random Forest and SVM when analyzing numerical data. Conversely, advanced deep learning models (CNN, LSTM, etc.) are favored for processing signal data. The selection of AI models is also driven by the specific learning objective: tasks aimed at classification often employ classification models, while those focused on pattern recognition or anomaly detection typically utilize clustering models.

The utilization of occupancy and power consumption data in smart homes can offer insights into residents' health and behaviors. Behavioral patterns, detected from occupancy data, can be signals of significant disruptions in the daily routines of residents, potentially highlighting underlying health concerns and detecting anomaly behaviors [115][123][134][118][169][119][116][126]. For instance, irregularities in power consumption patterns in bedrooms may suggest sleep disturbances [125], while prolonged periods of inactivity might signal broader health or psychological challenges [180]. Such data also lends itself to understanding physical activity levels, with reduced occupancy in areas like home gyms possibly indicating declining physical engagement. Cognitive health, especially in older populations, can be assessed by noting frequent and uncharacteristic occupancy in specific zones of the home [130][111][134][123][181]. Combined with other health metrics, this data provides a comprehensive view of an individual's well-being, underscoring the importance of smart homes in health monitoring [132][162].

Furthermore, the utilization of environmental data is underpinned by several reasons,

especially when considering healthcare monitoring in smart homes. Firstly, the integration of environmental data with individual health metrics can serve as an early detection mechanism for potential health issues [133]. For instance, deviations in normal air quality coupled with alterations in a resident's sleep pattern may be indicative of emerging respiratory issues [132][182]. Additionally, such data can be pivotal in the management of chronic illnesses. Diseases like asthma or allergies often have environmental triggers, and continuous monitoring can both alert inhabitants and adjust the internal environment to mitigate risks [183]. Moreover, the long-term accumulation and analysis of this data can offer invaluable insights into the broader effects of environmental conditions on health, proving beneficial not just for individual inhabitants but potentially informing larger public health strategies.

In addition, physical vital signs like heart rate, body temperature, and blood pressure can complement environmental, occupancy, and power usage data in smart homes. When combined, these metrics can link physiological responses to specific environmental or behavioral events, enhancing our understanding of an individual's health. For instance, worse cardiovascular events might be observed concurrently with an increase in room temperature or prolonged kitchen activity, hinting at potential stressors or health-related events [163][184]. Similarly, a decrease in movement as detected by occupancy sensors, paired with abnormal vital signs, could raise concerns about a resident's physical or emotional well-being [122][185]. Such integrative monitoring promotes timely health interventions and a more proactive approach to well-being.

Last but not least, the integration of innovative sensor technologies, such as radar and Wi-Fi signals, for ADLs recognition has seen a significant rise. The transition to advanced AI models, especially deep learning, in the reviewed studies, reflects a strategic move to harness the capabilities of these models in interpreting complex, high-dimensional data for the feature extraction and pattern recognition [36][124][127][128][131][143][144][147][148][149][150][153][156][158][165][166][167][173]. The indicators from these signals enable the detection and monitoring of movements without contact, offering efficient delivery of personalized healthcare monitoring for aging population.

4.2.5.4 RQ4. What are the strengths of existing research, what research limitations need to be addressed to uncover opportunities for future research?

Current main challenges

In the evolving landscape of AI in AAL for the aging population, our review highlights several persistent challenges. Firstly, data scarcity remains a fundamental hurdle, undermining efforts to develop robust AI models due to the limited availability of comprehensive and diverse datasets. Among the studies we reviewed, only 4/64 (6%) studies [127][149][122][126] provide open access to their data. The scarcity of pertinent data has led some researchers [87][158] to explore data augmentation methods as a workaround. While this approach can yield effective models, it still limits researchers' capacity to test and improve AI algorithms under varied and complex conditions.

Another significant issue identified is class imbalance, as noted in several papers from our review [122][143][148][170]. This imbalance occurs when certain activities or health events are vastly more represented in the data than others, leading AI models to become biased towards these majority classes. Such biases decrease the models' ability to recognize rarer, yet crucial, events critical for the old population's safety and well-being.

Moreover, data heterogeneity presents another layer of complexity (Table 10), arising from the use of a wide range of devices, each producing data in different formats. Addressing this challenge is vital for comprehensive healthcare monitoring and has prompted the adoption of various techniques [88] to manage the diversity of data sources.

Lastly, the constraint of limited computational resources impacts the development and testing of AI models, particularly as more studies employ complex deep learning methods. This limitation calls for the design of efficient algorithms and optimization techniques [90][91] to fully leverage the available computational power, ensuring the most insightful outcomes from AI applications in AAL.

Current research strengths, limitations, and future opportunities

Our scoping review reveals several research strengths that highlight the utility of AI technologies in practical AAL applications. Firstly, an increasing trend in research (as shown in Figure 2) not only indicates growing interest but also underscores the urgency of leveraging innovative technologies to meet the complex needs of the aging population. The peak of this research activity was in 2022 with 14 studies published that year. Despite a recent downward trend, we anticipate a resurgence in interest. Secondly, AI applications within AAL range from demonstration and monitoring to recognition, prediction, and detection tasks. Notably, more advanced deep learning models (Figure 7) have been effectively utilized for ADLs recognition, behavior pattern modeling, cognitive health assessment, abnormal behavior detection, fall detection, sleep quality assessment, and indoor positioning. These achievements highlight the models' ability to meet diverse healthcare monitoring requirements for seniors. Thirdly, there is an evident shift towards the use of contactless and ambient technologies in recent studies (Figure 10). These technologies, involving devices that do not require direct contact with the individual, offer unobtrusive monitoring. Lastly, the testing and deployment of more AAL solutions in real-world domestic settings represent a critical move from laboratory environments to everyday practical use (Figure 9). This transition to real-world deployments presents the feasibility and effectiveness of AI-driven AAL solutions in actual living conditions.

Despite these encouraging results, the review also identifies substantial research gaps, emphasizing the need for further investigation in this area. The existing literature serves as a foundational basis, but the observed gaps and omissions indicate significant opportunities for future research aimed at developing more impactful, reliable, and generalizable solutions in the domain of AAL.

One of the most critical gaps we identified is the omission of demographic information on

participants, especially their age data, in a great number of studies (25/64, 39%). Given that age can be a fundamental variable that can greatly influence the interpretation and generalizability of study results and, not including age data reduces the transparency and replicability of the research [186]. Age information can significantly influence the outcomes of studies and their applicability across different population segments [187]. This oversight not only reduces the overall quality of the research but also limits our understanding of how AAL solutions may perform across diverse age groups. Thus, it is crucial for future research in this area to prioritize the inclusion and reporting of age data. Apart from age, the exclusion of other demographic details in reviewed studies, such as gender, ethnicity, socioeconomic status, and educational background, hinders our ability to assess the inclusivity and diversity of the research. This limitation is critical, as the effectiveness and appropriateness of AAL technologies may vary significantly across different demographic groups, potentially leading to solutions that do not fully address or even overlook the specific needs of various subpopulations within the older adult demographic.

In addition, we also observed the age bias among participants. As shown in Figure 4, while it is promising that 23/64 (36%) studies in our review included participants over the age of 64, there is a concerning trend: 17/64 (27%) studies utilized a younger participant cohort aged between 15 and 47 years. This trend toward younger participants in research intended for AAL solutions, which are specifically designed for aging population, can significantly undermine the development of technologies that accurately address the unique needs, preferences, and limitations of older adults. Such practices not only skew the research focus away from its intended population but also raise questions about the effectiveness and suitability of proposed AAL solutions for older adults. Furthermore, this bias raises ethical concerns about equity and inclusivity, contributing to a digital divide within the aging population by developing technologies that may not be accessible or user-friendly for all older adults [188]. While the solutions proposed in studies aim to benefit older individuals, the findings still highlight the imperative need for more studies that focus explicitly on aging participants to fully comprehend the effectiveness and limitations of AI in AAL for this demographic. Focusing on the intended user group—older adults—will not only make the research more relevant but will also likely yield insights that are directly beneficial for improving the quality of life among the aging population [189].

Another key limitation observed in the existing literature is the scarcity of studies providing open-access datasets that are used in their studies. Only 4/64 (6%) studies [122][126][127][149] provide their dataset. This absence is particularly concerning given that open datasets serve as a cornerstone for scientific advancement. It is acknowledgeable that there are several challenges associated with making datasets publicly available, such as privacy concern, ethics, and technical challenges [190][191]; however, providing open access to datasets has multiple benefits that can substantially propel the field of AAL forward. Firstly, open datasets facilitate replicability, allowing other researchers to validate and build upon previous findings, thus ensuring the robustness and reliability of scientific discoveries. Secondly, open data enables broader collaborations and interdisciplinary

research, accelerating the pace of innovation and enabling more comprehensive analyses that may yield new insights. Thirdly, open datasets allow for meta-analyses, which can pool data from multiple studies to provide higher statistical power and more generalized conclusions.

We also observed a dominant reliance on traditional supervised and unsupervised learning methodologies in current AAL research. This trend points to a notable gap: the insufficient explore of advanced machine learning methods such as federated learning, continuous learning, contrastive learning, and self-supervised learning. Through the recent studies, federated learning has been showcased in study [88], demonstrating its capability to enhance privacy and personalization in HAR, particularly addressing the challenge of data heterogeneity. Another study [192] highlights the importance of continuous learning within dynamic smart environments, especially when adapting new activities. The application of contrastive learning, as shown in study [87] highlights its ability in utilizing unlabeled data for improving classification accuracy, an advantage for real-world practical deployment. Similarly, study [193] underlines the effectiveness of self-supervised learning in extracting meaningful features from ambient sensor data, emphasizing its utility in conditions with limited labeled data. To bridge this gap, future studies should explore these cutting-edge technologies to overcome current limitations and unlock new potentials in AAL applications, thereby ensuring more robust, adaptive, and efficient healthcare solutions for the aging population.

Additionally, in our scoping review, we observed a significant trend: a large portion of the research, nearly half, was conducted within the confines of smart home testbeds. While these testbeds attempt to replicate typical home environments, discrepancies may still exist when comparing them to actual residences. Findings derived from them may not necessarily be generalizable to the larger population. This is because studies often lack validation within broader community settings. On the other hand, there's a notable underrepresentation of studies centered around nursing homes and hospitals, indicating a potential research gap. Aloulou et al. [194] underscored this discrepancy, emphasizing the need for studies to bridge the divide and ensure that AAL solutions are both versatile and universally applicable.

Another common limitation that we found from the studies is the sparse use of cloud technology. As is shown in Table 6, less than a third of studies (20/64, 31%) involve cloud technology to operate data collection, management, and computation. This represents a missed opportunity given the numerous advantages that cloud technology can offer in the realm of AAL. As is identified in a review by Cicirelli et al. [24], to solve the processing constraints in AAL systems, a cloud computing framework should be brought in to fulfill the systems' requirements for collecting data regarding all aspects of daily life. In AAL contexts, utilizing cloud technology facilitates large-scale deployment, enabling an expansive reach in data storage and analytics, which is essential for long-term healthcare monitoring to the well-being of the aging population. Moreover, the automated nature of cloud technology streamlines operations, providing a timely and efficient decision-making

process. Additionally, its standardized platform promotes seamless system integration and uniform data analysis methods, enhancing interoperability and adaptability without compromising service quality, thereby offering a less intrusive approach for healthcare monitoring in AAL environments. Current barriers to implementing cloud technology in AAL systems primarily include concerns regarding data privacy and security [195], expense consideration [196], and the data management support [197] associated with migrating to cloud-based solutions. Alternative approaches to mitigate these barriers include adopting hybrid cloud models that combine the flexibility and scalability of cloud computing with the control and security of on-premises solutions. This balanced approach not only addresses privacy and security challenges by allowing sensitive data to be processed locally but also offers a cost-effective solution by leveraging cloud resources for broader, less critical computational needs. Additionally, utilizing blockchain technology can further enhance data management with its secure, decentralized capabilities, ensuring data integrity and privacy, addressing security concerns.

Another notable concern arising from our scoping review is the predominant tendency to collect data directly from devices in AAL systems. While direct data collection may offer the advantage of simplicity, it exposes the system to several significant drawbacks, particularly in terms of security and data quality, making the data vulnerable to unauthorized access and tampering. This can be a critical concern, especially when dealing with sensitive health information of an aging population. Moreover, data quality may also be compromised through this method, given the absence of built-in validation processes and data filters that more secure protocols would generally provide. To address these challenges, future studies should consider employing advanced and reliable data collection protocols, such as Application Programming Interfaces (APIs) or Message Queuing Telemetry Transport (MQTT) [198]. These protocols not only offer robust cyber security measures but also ensure higher data quality through built-in validation mechanisms. APIs and MQTT protocols are widely regarded as reliable and secure methods for data transmission, crucial for ensuring the integrity and utility of data in AAL applications.

4.2.6 Limitations

This scoping review has several limitations that should be taken into account when interpreting the findings. First, the review was confined to six databases, including PubMed, CINAHL, IEEE, Scopus, ACM, and Web of Science. While these databases are comprehensive and widely used in academic research, the limitation to these platforms may result in the omission of relevant studies indexed in other databases, potentially leading to a less exhaustive overview of the available literature. Second, the language scope of the review was limited to studies published in English. As a result, studies published in other languages were not included, which could potentially introduce a language bias and exclude valuable contributions from non-English speaking researchers, also affecting the numbers related to published articles from each country. Third, despite our efforts on using comprehensive and inclusive keywords in the search strategy, it is possible that relevant studies not containing these specific terms were overlooked, thus limiting the breadth of studies captured. Lastly, as with any literature review, the process of article selection and

data extraction was subject to human error and subjective judgment. Despite employing rigorous methodologies and multiple reviewers to mitigate this limitation, the possibility of inadvertently missing eligible studies or making interpretative errors cannot be completely ruled out.

4.2.7 Conclusions

The landscape of AI in AAL is vibrant, showing encouraging prospects for improving the quality of life among the aging population. This scoping review synthesizes the current state of AI applications in terms of their models and goals in AAL, particularly focusing on the integration with commercially available smart home sensors, as gleaned from relevant studies. Our key findings indicate the following: (1) AI has been employed in a diverse range of applications, targeting various objectives such as recognition, monitoring, and detection; (2) a variety of AI methodologies have been utilized to achieve these objectives, with neural network and tree-based models emerging as the most prevalent; (3) a wide range of smart home devices, ranging from environmental to physical sensors, have been incorporated in these studies; and (4) the majority of these studies have been conducted in smart home testbed environments. Gaps were identified and discussed related to 1) the absence of participants' demographic information; 2) the lack of open-access datasets; 3) an excessive number of testbed trials; 4) the non-utilization of cloud technology; and 5) the absence of a standardized data collection method. These findings adequately address our four research questions and illuminate current research gaps, revealing opportunities for future investigation. Overall, the integration of AI technologies with AAL is revolutionizing the support framework for older adults aging in place; however, substantial efforts are required to make these advancements into practical, real-world applications.

4.2.8 Acknowledgment

Authors would like to express gratitude to Rebecca Hutchinson, the Liaison Librarian for Computer Science at University of Waterloo who provided assistance in designing the search queries and guiding the search strategy for this scoping review. Authors would also like to acknowledge Kristopher Espiritu for his assistance with the paper screening and data extraction processes.

4.3 Discussion

This scoping review has provided a comprehensive examination of the integration of AI in AAL technologies for the aging population, revealing critical advancements and several significant research gaps. The review not only highlighted these gaps but also clearly indicated the research directions necessary for advancing the field. Based on these findings, the subsequent studies within this thesis have been carefully designed to address these identified gaps and extend the existing body of knowledge. Each study presented in this thesis directly responds to these gaps, aiming to demonstrate how advanced AI applications can enhance AAL technologies, thereby improving the quality of life and care for elderly populations.

4.3.1 Thesis studies guided by scoping review

This scoping review highlights key gaps and challenges, which guides the path for the studies in this thesis. It is outlined as follows:

4.3.1.1 Centralized data ecosystem and cloud technology integration

The review exposed a significant gap in the utilization of centralized data ecosystems, particularly those based on cloud technologies, revealing a considerable missed opportunity given the scalability, accessibility, and efficiency benefits of cloud technology in AAL applications. In response, this thesis includes a study in Chapter 5 on the development of a cloud native remote monitoring data ecosystem for the aging population, utilizing commercial AAL sensors. This ecosystem not only enhances data collection, management, and computational processes but also serves as a foundational element for subsequent studies within this thesis, offering a robust framework for scalable and effective elderly care.

4.3.1.2 Pilot study on validating the AAL data ecosystem

Building directly on the infrastructure developed in Chapter 5, a pilot study is conducted to validate the functionality and effectiveness of the created AAL data ecosystem. Detailed in Chapter 6, this study focuses on heart rate prediction based on the AAL ecosystem. The scoping review highlighted the lack of existing studies focused on the prediction of physical indicators such as heart rate within AAL environments, particularly through entirely contactless means. This thesis addresses this significant gap by being the first to explore heart rate prediction using a totally contactless AAL approach. The pilot study not only validates the system but also pioneers its potential for broader health monitoring applications, showcasing the practical application and reliability of the system in real-world settings.

4.3.1.3 Enhancing Activity of Daily Living recognition with contactless solutions

Reflecting the findings from the scoping review, where a majority of studies focused on ADLs recognition, this area is highlighted as an important research domain. This thesis acknowledges the significance of ADLs recognition and decides to advance it by introducing a novel contactless AAL approach. Chapter 7 introduces a novel contactless AAL approach, marking a distinct shift from traditional methods that often rely on direct sensor contact. This study involves young adults and is designed as a proof-of-concept to demonstrate the feasibility and effectiveness of using contactless sensing technologies for ADLs recognition.

4.3.1.4 Advancing ADLs recognition in older adults

Building on the successful proof-of-concept study involving young adults in previous chapter, Chapter 8 leverages advanced domain transfer learning methods to extend the robust recognition performance to older adults in a less controlled activity situation. This phase of the study significantly progresses towards real-world applicability, employing data collection in less controlled settings that mirror everyday life for older adults more like in real-world. The successful application of domain transfer learning allows for significant

reductions in the need for extensive labeled data from older populations, which is often challenging and costly to obtain. By leveraging labeled data from younger individuals and adapting it for older adults, this approach facilitates more efficient deployment of AAL based health monitoring.

4.3.2 Other gaps addressed in this thesis

In this thesis, the studies also addressed following limitations that identified in the scoping review of current research.

Real-world application in study sites

Another noted deficiency is the limitation of study sites, with many studies not conducted in genuine real-world settings. In response, the studies detailed in this thesis are situated in a real-world environment at a Research Aging Institution in Waterloo. This setting provides a realistic and practical backdrop for testing and validating the proposed AAL solutions, ensuring their applicability and effectiveness in actual use scenarios.

Addressing participant age bias

The review identified a participant age bias where some studies targeted at the aging population predominantly used younger adults, potentially skewing results and applicability to the intended demographic. To address this discrepancy, our research incorporates a balanced participant pool that includes both young and older adults. Initially, a proof-of-concept study was conducted with young adults, which was then extended to incorporate older adults. This strategy not only validates the applicability of the AAL systems for the intended aging population but also facilitates the adaptation and optimization of monitoring performance across different age groups using advanced methodologies.

Advanced analysis techniques

Furthermore, to enhance the performance and adaptability of AAL systems, this thesis incorporates advanced deep learning techniques, specifically domain transfer learning. This approach has been employed to transfer the successful monitoring performance observed in young adults to older adults, thereby achieving effective and personalized remote monitoring across different age groups.

Chapter 5 – Development of a Remote Monitoring Data Ecosystem for Aging

Kang Wang, Pritthijit Nath, Jasleen Kaur, Shi Cao, and Plinio P. Morita. (published). "Cloud Native Remote Monitoring Data Ecosystem for Aging Population based on Commercial AAL Sensors," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Jul. 2023, doi: <https://doi.org/10.1109/embc40787.2023.10340481>.

5.1 Foreword

Building upon the comprehensive insights gathered from the scoping review in the previous chapter, which highlighted the transformative potential of AI in AAL contexts, this chapter shifts the focus to the practical implementation of an AI-driven AAL solution. The study presented here aims to bridge the gap between theoretical research and real-world applications by developing a robust, cloud-based ecosystem for monitoring the health and well-being of older adults.

The scoping review emphasized the need for AAL solutions that can be effectively deployed in real-world settings, particularly emphasizing the integration of a centralized data ecosystem and the use of cloud technology. Recognizing this need, the current study focuses on creating a comprehensive remote monitoring system that leverages commercially available AAL sensors. By utilizing off-the-shelf devices, this study aims to demonstrate the feasibility and accessibility of implementing AAL technologies in practical scenarios, making them more readily adoptable by older adults and their caregivers.

The cloud-based architecture of the proposed ecosystem is a key innovation that addresses the scalability and data management challenges identified in the scoping review. By harnessing the power of cloud computing, the researchers have developed a flexible and extensible platform that can efficiently collect, store, process, and analyze the vast amounts of heterogeneous data generated by diverse AAL sensors. This cloud-centric approach enables seamless integration of multiple data sources, facilitating comprehensive monitoring and personalized insights for each individual user.

The ecosystem incorporates a wide array of sensors, including ambient devices for tracking indoor environmental conditions, occupancy patterns, and activity levels, as well as wearable sensors for capturing vital physiological data. This multifaceted approach allows for a holistic assessment of older adults' health status and daily functioning, providing a rich context for detecting anomalies, identifying trends, and supporting proactive interventions.

This chapter also includes a pilot study to validate the effectiveness of the proposed cloud-based AAL ecosystem. The study examined the relationship between motion sensor data and physical activity levels, as measured by step counts, in a group of participants

performing daily living activities. This demonstrates the ecosystem's ability to effectively capture and analyze activity data in real-world settings.

The development of this cloud-based AAL ecosystem serves as a foundation for subsequent studies presented in this thesis. By establishing a robust and flexible infrastructure for data collection, storage, and analysis, this ecosystem enables the exploration of various aspects of AI-driven eldercare, paving the way for future studies on heart rate prediction and activity recognition.

5.2 Cloud Native Remote Monitoring Data Ecosystem for Aging Population based on Commercial AAL Sensors

5.2.1 Overview

In the recent years, Active Assisted Living technologies used for autonomous tracking and activity recognition have started to play major roles in geriatric care. From fall detection to remotely monitoring behavioral patterns, vital functions and collection of air quality data, AAL has become pervasive in the modern era of independent living for the elderly section of the population. However, even with the current rate of progress, data access and data reliability has become a major hurdle especially when such data is intended to be used in new age modelling approaches such as those using machine learning. This paper presents a comprehensive data ecosystem comprising remote monitoring AAL sensors along with extensive focus on cloud native system architecture, secured and confidential access to data with easy data sharing. Results from a validation study illustrate the feasibility of using this system for remote healthcare surveillance. The proposed system shows great promise in multiple fields from various AAL studies to development of data driven policies by local governments in promoting healthy lifestyles for the elderly alongside a common data repository that can be beneficial to other research communities worldwide.

Clinical relevance - This study creates a cloud-based smart home data ecosystem, which can achieve the remote healthcare monitoring for aging population, enabling them to live more independently and decreasing hospital admission rates.

5.2.2 Introduction

Our planet is currently facing a demographic milestone: the aging population worldwide is increasing at an unprecedented rate and it could reach an extreme higher level in the future. In 2010, the World Health Organization (WHO) released a report on Global Health and Aging which stated that around 524 million individuals were over 65 years old, and it was projected that this number could rise to 1.5 billion by 2050 [199]. Aging presents various difficulties for individuals, caregivers, healthcare providers, and governments. Population aging is accompanied by more illness, disability, and dependency, and chronic diseases such as dementia, depression, and diabetes, showing to be caused by lack of physical activity [200]. One major reason for fatal injuries among older adults, leading to hospitalization, is the rise in falls. According to a study presented in [201], it is estimated that 40% of those admitted will not be able to live independently and around 25% will pass

away within a year. An analysis of a survey conducted by the UK Disabled Living Foundation found that more people worry about losing independence (49%) than dying (29%) as they grow older [202]. Recent studies also indicate that a significant number of older adults desire to grow old in their homes [203], where they will require the support of caregivers or medical professionals for monitoring or assistance. Therefore, it is crucial to create new tools and technologies to aid senior individuals aging in place [204].

Recent improvements made in the Internet of Things (IoT) space have enabled the usage of smart home monitoring devices to enhance independent living for senior citizens by providing the resources and support for enabling to feel more independent, secure and healthy lifestyles in society [13][14][15]. Assisted living, which is normally the go to care model, has resulted in lower quality of life and higher costs to the Canada's healthcare system [9][10], while IoT technology aims to bring a smarter and more supportive way of helping seniors in their latter years. The rise of Active Assisted Living (AAL) technology, such as autonomous tracking and activity recognition, have not only been quite beneficial but have also become an important basis for detecting changes in daily patterns and identifying emergency situations [205][206]. In geriatric care where falls are an essential problem, Kumar et al. [207] proposed a unified IoT based general architecture that aids all different types of sensing devices with intercommunication to provide fall avoidance or when fall occurs, performs effective fall detection and raises the alarm for immediate medical assistance. Akhila et al. [208] came up with an IoT enabled health monitoring system to remotely monitor pulse rate, temperature, electrocardiogram, and air quality for the healthcare of senior patients and to help them take necessary precautions. Outside the domain of developing system architectures, Ramachandran et al. [209] proposed a network channel using V-TDMA technology to assist in providing continuous and reliable data transmission from wearable systems without compromising mobility.

In behavioral analysis, numerous studies have been performed in the past that analyzed patterns in living and physical behavior and linked them with cognitive changes. Özdemir et al. [16] showed that changes in gait speed or balance can have the ability to represent a change in cognition that subsequently increase the probability of a fall. Fredericks et al. [17] showed that speech pattern changes can indicate onset or early stages of degenerative conditions such as Alzheimer's. Actionable insights from behavioral analysis coupled with AAL technology [210][211] promises extensive technological developments that can be presented forward to improve geriatric care technologically. However, even in the midst of rapid progress, the access to data, especially for those which are suitable as input data for machine learning algorithms to power various recognition systems, have always been regarded as important challenges for any practitioner developing low-cost and permanent AAL solutions capable of large-scale deployments.

As a possible solution to the above challenges, in this paper, a remote monitoring data ecosystem aimed specifically at using AAL sensors to improve independent living for seniors is presented in this paper, with extensive discussions covering different technical aspects and major implementation details. The structure of the paper is presented as follows: The

section on Implementation describes the methodology adopted consisting of the four system layers along with the important technologies used. The section on Results explicates the remote monitoring interface and a case study using the data ecosystem and posits relevant discussions along with any new future system-wide extensions that might enhance the developed ecosystem.

5.2.3 Implementation

5.2.3.1 System architecture

The proposed cloud (Microsoft Azure) based data ecosystem provides an accessible platform for real-time sensor data derived from different AAL type sensors deployed in the monitoring room, specifically made for simulating the everyday activities of elderly citizens in the community. The current work environment consists of a Ubuntu 20.04 LTS based Azure Standard B1ms virtual machine with 2 GB RAM and 1 vCPU; a MySQL database in version 5.7 with 2 vCores, 4GB RAM and 100GB storage; a Azure Blob in version 1.2. Coding languages and libraries used in this project include Python, PHP, Pandas, and NumPy, etc.

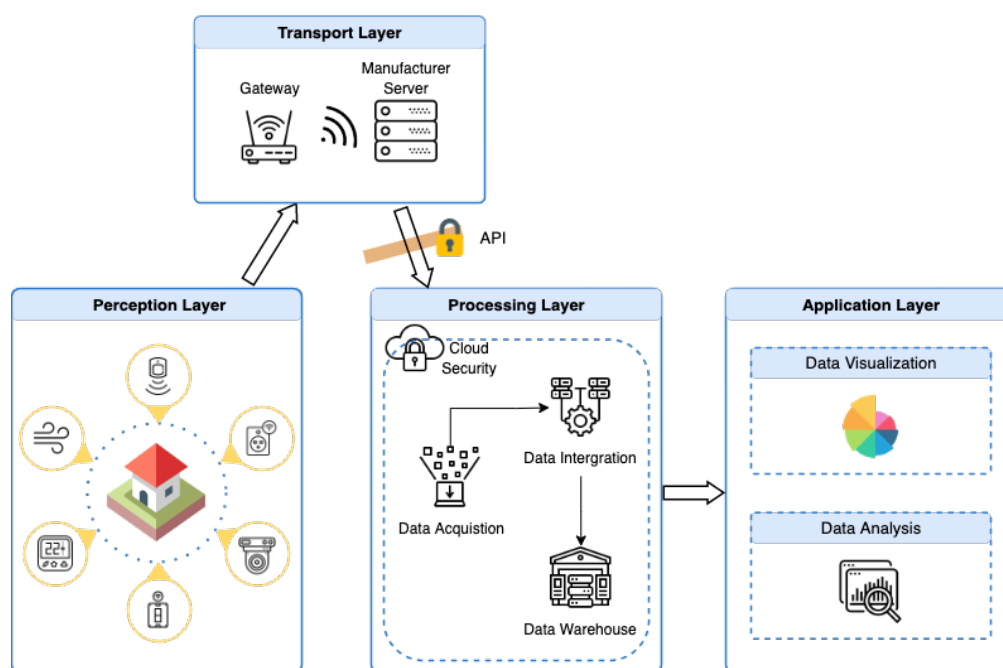


Figure 15. Smart home data ecosystem structure

The proposed data ecosystem is a four-layer IoT system, which consists of a perception layer, a transport layer, a processing layer, and an application layer. The scripts comprising the processing engine in processing layer acquire the data from perception layer, after the data is uploaded from devices to manufacturers' servers through a transport layer. The data flow from the sensor manufacturers' servers to Ubiquitous Health Technology Lab (UbiLab)'s data processing engine and subsequent storage in Azure Blob and MySQL Database. The entire system architecture is depicted schematically in Figure 15.

5.2.3.2 Perception layer

The perception layer, which serves as the information source for the data ecosystem, also

constitutes the device layer. It comprises of IoT wireless sensors, specifically, environmental sensors in the case of a smart home ecosystem that continuously monitor indoor conditions. The perception layer of proposed data ecosystem was deployed in a real-world environment, which is the Research Institution for Aging in Waterloo. To keep track of the physical indicators of older individuals, wearable devices are also integrated into the ecosystem. Our proposed ecosystem encompasses the following sensors, as depicted in Table 11.

Table 11. Deployed smart home sensors

Layer	Devices	Data information	
Layer 1 Swidget	Smart outlets	Usage log	Power consumption
	Smart switch	Usage log	Power consumption
	Air quality sensor	AQI Air pressure Temperature	Humidity eCO ₂ bVOC
	Temp+Hum+Motion	Temperature Humidity	Motion occupancy
Layer 2 Ecobee	Thermostat	Temperature	Humidity
	Motion sensor	Temperature	Motion occupancy
	Door contactor	Door/cabinet usage log	
Wearable	Empatica e4	HRV BVP	Skin temperature
	Fitbit sense	HR	Steps

5.2.3.3 Transport layer

The transportation layer functions as a link between the perception layer and the data server, with the gateway acting as a terminal to collect temporary data from the sensors and transmit it back to the data server. In the proposed ecosystem, as commercial devices are utilized, device manufacturers restrict direct access to the gateway, thereby not allowing the data to be sent directly to a personal data server. For security purposes, they only permit the data to be uploaded to their own data server, resulting in additional steps if a third party wishes to access the data.

The gateway utilized within the ecosystem is equipped with compatibility for the current widely used wireless communication protocols, including Wi-Fi, Z-Wave, and Zigbee [212]. As the most commonly used smart home communication technology, these protocols have advanced features concerning security, interoperability, and connectivity.

The security feature is the primary concern as it preventing sensitive information from being hacked during the transmission. Each of the protocols has encryption and authentication mechanisms to ensure that smart home sensors can be securely connected to the gateway through these communication networks [213].

Interoperability ensures that devices from various manufacturers can operate in concert in a dependable manner. Wi-Fi is compatible with all Wi-Fi devices, Z-Wave enables interconnection between different Z-Wave devices, while the most recent 3.0 version of Zigbee allows for seamless interoperability between a wider range of devices, regardless of their functional domains [214].

The connectivity capability determines the number of devices that can be interconnected in the mesh network. Each protocol has the capability to support a specific number of nodes, sufficient to support a smart home mesh network. Wi-Fi has the capacity to connect 250 access points, Z-Wave has the capability to support 232 nodes, and Zigbee provides the most extensive support with a capacity to connect 65,000 devices at one time [212].

5.2.3.4 Processing layer

The processing layer constitutes a central component of the ecosystem. All activities within the processing layer occur on the cloud server. The processing layer is responsible for tasks such as data collection, pre-processing of data, and data storage.

Authentication

In the proposed data ecosystem, to minimize the redundant authentication procedures for smart home devices from different vendors, a unified authentication platform was developed to enhance the compatibility of the ecosystem when incorporating additional devices, provided they use the OAuth standard for authentication [215]. The use of a unified authentication platform can also reduce the risk of privacy breaches. The platform comprises a front-end and a back-end. The front-end is used to display the necessary PIN code for the authentication process, while the back-end is responsible for communicating with API endpoints and requesting the necessary tokens for authentication. The communication workflow between the platform and API points is depicted in Figure 16.

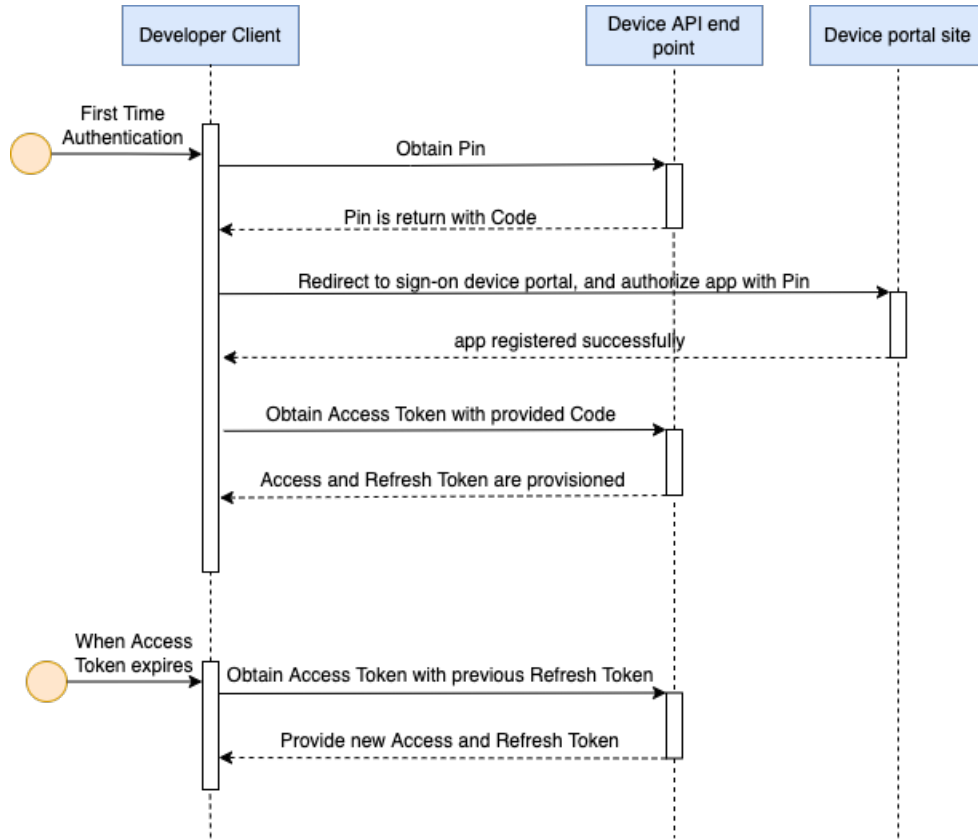


Figure 16. Authentication flow between end points

Data fetch

After the successful authentication, the platform can send a data fetch request to the API in manufacturers' servers. The data fetch from the manufacturers' servers occurs in two phases i.e., Device Data Extraction and Download Data Dump. The UbiLab processing engine collects the necessary sensor ids, location data, and component information through a private API request during the Device Information Extraction phase. The location information and component information provide results about the specific location (for example, bathroom, kitchen, living room, etc.) and monitored parameters (for example, humidity, air quality, temperature, pressure, etc.), respectively. The sensor ids correspond to the identification codes for a specific AAL sensor installed inside the monitoring room. Based on the device ID, site ID, component ID, start date, and end date, a specified REST endpoint is requested over HTTP in the Download Data Dump phase, producing rows of sensor data as a JSON response. Depending on how many components are available for a particular sensor, JSON data corresponding to each component ID is obtained, aggregated, and given to the next step of the data flow for additional processing.

Data pre-processing

In the Data pre-processing phase, the retrieved data is processed through several steps. The dataset is initially searched for rows with missing data, and if any are identified, these rows are discarded. Secondly, for ease of temporal reference and further analysis, the timestamp (which was initially in Unix Epoch) has been changed to Universal Coordinated Time (UTC). Thirdly, for operational flexibility, the data is transformed from a CSV format into

a suitable Pandas data frame. The data frame is then duplicated into a Raw and a Processed form, and sent to the next stage for storage purposes. As shown in Figure 17, the processed copy goes through an additional stage of row merging based on the switch data present. Data exploration showed that the raw data had rows that might be divided into sets based on the next occurrence of switch data. The set contained alternate rows with data for several columns that could be combined into a single row with the timestamp of the first row.

TS	deviceId	hostId	room	outlet_1_avg	outlet_1_on	temp	humi	aq_iaq	aq_tvoc	aq_co2
2022-03-31 5:06:55	24a160749b98	zyilxsmabyGA77Fk0zy	Living Room	0	1					
2022-03-31 5:07:07	24a160749b98	zyilxsmabyGA77Fk0zy	Living Room			16.41	26.27			
2022-03-31 5:07:08	24a160749b98	zyilxsmabyGA77Fk0zy	Living Room					595.63	1000	5956.29

TS	deviceId	hostId	room	outlet_1_avg	outlet_1_on	temp	humi	aq_iaq	aq_tvoc	aq_co2
2022-03-31 5:06:55	24a160749b98	zyilxsmabyGA77Fk0zy	Living Room	0	1	16.41	26.27	595.63	1000	5956.29

Figure 17. Merge rows in neighboring timestamps

Data storage

For the data storage stage, two different types of cloud storage facilities are availed for extra redundancy. The “Raw” (unmerged) data frame is saved as a JSON Blob under Azure Blob Storage as it can store unstructured and semi-structured data, while the “Processed” (merged) data frame is connected to a Azure managed MySQL database for data analytics purposes. If in an unplanned scenario, due to data error, the additional merge stage fails, as a fallback, data can be retrieved from the Blob Storage. Both of the storage schema is secure and scalable. They provide security measures such as access control lists and shared access signatures or firewalls for controlling access to data. They also implement encryption for data both during storage (encryption-at-rest) and transfer (encryption-in-transit) to ensure the security of the data. Additionally, both Blob and MySQL services in Azure Cloud are highly scalable and allow users to easily increase or decrease the amount of storage they need as their data storage requirements change.

5.2.3.4 Application layer

The application layer is the top layer of this data ecosystem. It is tasked with presenting a user-friendly interface that facilitates interaction with interconnected smart home devices and healthcare monitoring services. This interface, which is implemented as a web-based application, enables a wide range of functions such as data visualization, human activity recognition, behavior pattern analysis, and abnormal behavior detection. The front-end of this interface is built using the ReactJS framework, while the back-end is implemented using JavaScript. The back-end provides the capability to discover and control devices, receive notifications, and access real-time data and services, which are then reflected on the front-end. In addition, the application layer also provides extraordinary opportunities to explore different AI models and novel data fusion techniques to be trained on the cloud based on collected database to improve the sensitivity of healthcare monitoring services.

5.2.3.5 Pilot study design

A preliminary investigation was conducted to assess the correlation between motion counts and steps utilizing the proposed data ecosystem and aimed to verify its viability in monitoring and tracking individuals' step counts utilizing smart motion sensors.

A total of 40 participants was involved in the study (23 male and 17 female aged between 18 and 34 years old). After obtaining consent, each participant was instructed on how to wear the Fitbit. During the experiment, participants were asked to perform basic daily living activities under researchers' instructions. Such daily living activities include cooking, eating dinner, going to sleep, and taking showers, etc. Fitbit measured participants' steps during the session, while motion devices recorded motion data through passive infrared sensors at the same time. One whole session for a participant could up to three hours while the data time interval is 1 minute. After cleaning the data and opting out incompleteness data, we obtain 36 individual's data. As the data is not normally distributed, the Spearman correlation test was chosen as the test tool for evaluating the association. The experimental procedures in this study were approved by Research Ethical Board of the University of Waterloo under ORE #43843.

5.2.4 Results

In this section, we present the remote monitoring interface at the application layer, analyzing its functions from device control, data access, data visualization. In addition, the results of pilot study was presented to confirm the usability of proposed ecosystem on healthcare remote monitoring.

5.2.4.1 Remote monitoring interface

Here is a presentation of the developed remote monitoring interface of data ecosystem in application layer. As is shown in the Figure 18, three major function components are covered in the dashboard, providing a simple way to discover and manage connected devices, including the ability to view and control their current state, set preferences, and configure device settings. Additionally, this interface can collect and manage data from devices, including real-time data and historical data that can be used to gain insights into behaviors.



Figure 18. Remote monitoring interface

5.2.4.2 Pilot study results

The Spearman correlation coefficient is $r = 0.76$ (range 0.71-0.82; $n=36$; $P<.001$), which suggests that there is a strong association between motion counts and steps. A visual inspection using one subject's example data to determine the alignment is shown in Figure 19. A clear trend alignment is illustrated in the Figure 5., and increased number of steps was accompanied by increased motion. Specifically, when participants performed movement activities in the room, which was indicated by more steps taken, higher levels of activation of motion sensors were observed. During periods of inactivity where fewer steps were recorded, the motion sensors also showed no or minimal activation. If there were several motion counts but with zero steps, it could attributed to sleep or sedentary behavior.

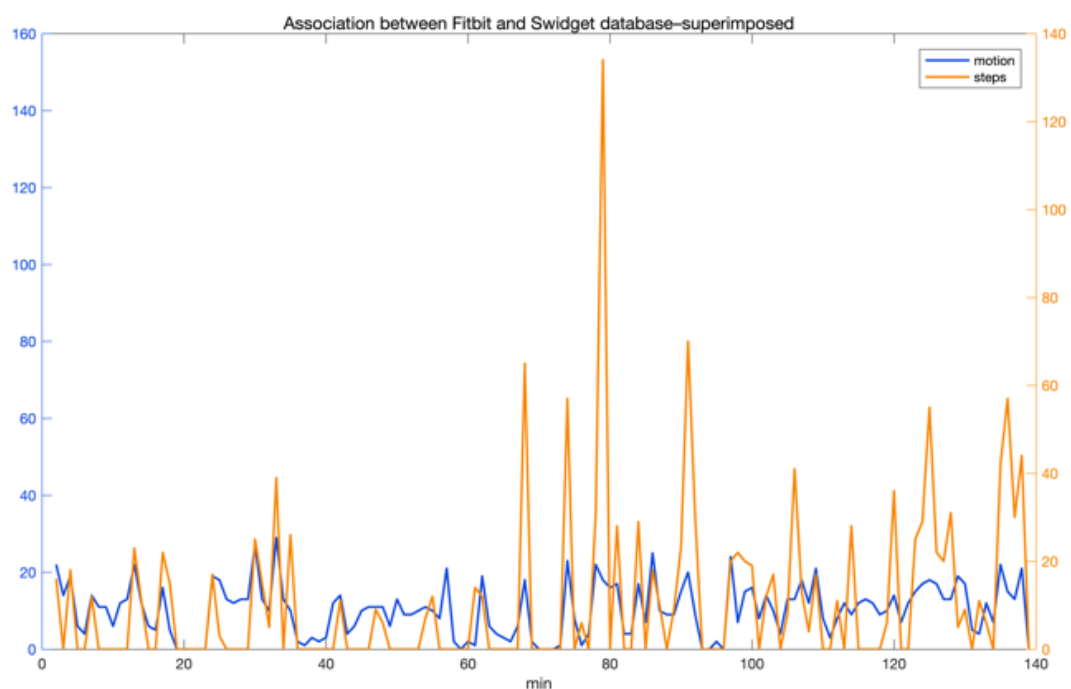


Figure 19. One subject data superimposed between steps and motion

5.2.5 Conclusion

The data ecosystem in its current form plays an integral platform to onboard multiple AAL-based IoT sensors that have the capability to assist in analyzing local conditions as well as sensing motion of indoor participants. High granular multi-source indoor sensor data fused using big data approaches [216] can be used as model input in several deep learning-based methodologies for generating valuable and actionable insights. Coupled with a real-time dashboard, which readily gives the status of several sensors laid out in a monitored indoor environment, the ecosystem can function as a control center of several geriatric studies where motion-related data can be studied and modelled using different machine learning techniques, which can, among other things, help in anomaly detection, change in behavioral patterns, and sleep habits, etc. From a research standpoint, the data ecosystem is capable of empowering studies in multiple fields ranging from effective behavioral monitoring in AAL supported residential environments to developing data driven policies supporting local governments in urban infrastructure and health planning that aim to promote healthy lifestyles in the elderly populations. Being a generalized system that can be customized based on the nature of the targeted application, the ease of data sharing forms an effective component that will enable other research communities around the world to perform directed studies and understand various living and lifestyle patterns.

The limitation of this study is participants' age group in our pilot study is different from our target population. However, the primary goal of this pilot study is to validate the feasibility of this ecosystem. In the further study, we will integrate more AAL sensors into this ecosystem such as vibration sensor to fulfill different monitoring requirements.

5.3 Discussion

With the successful implementation of the cloud-native remote monitoring data ecosystem, as detailed in this chapter, a robust platform that can support a wide range of studies has been developed, focusing on enhancing the quality of life for the aging population. This data ecosystem not only allows for the continuous monitoring of various health and environmental parameters but also enables the integration of advanced analytical techniques to extract meaningful insights from collected data.

The ecosystem serves as a foundational element for subsequent studies presented in this thesis. By establishing a reliable and adaptable infrastructure for data collection and analysis, it provides a base from which various aspects of elderly care can be explored. The studies that follow build upon the data and insights generated by this ecosystem, whether through improving ADLs recognition techniques or advancing health indicator predictions. Each of these studies relies on the robust data collection, data processing and management capabilities established here, showcasing the ecosystem's critical role in enabling more targeted and effective research.

Chapter 6 - Heart Rate Prediction with Contactless Active Assisted

Living Technology: A Smart Home Approach for Older Adults

Kang Wang, Shi Cao, Jasleen Kaur, Moojan Ghafurian, Zahid A. Butt, and Plinio P. Morita. (published) "Heart rate prediction with contactless active assisted living technology: a smart home approach for older adults," Frontiers in artificial intelligence, vol. 6, Jan. 2024, doi: <https://doi.org/10.3389/frai.2023.1342427>.

6.1 Foreword

Following the successful establishment of a cloud-native remote monitoring data ecosystem, this chapter progresses our exploration into its practical applications. Specifically, it focuses on the development and validation of non-invasive, smart home-based methods for predicting heart rates among older people—a demographic significantly impacted by cardiovascular diseases.

The need for this study arises from two aspects. First, it serves to validate the capabilities of the newly developed AAL ecosystem in a practical setting, ensuring that the infrastructure not only supports but enhances the functionality of health monitoring technologies. More critically, this research addresses a conspicuous gap identified in our comprehensive scoping review—the lack of application of AAL technologies in predicting vital physical health indicators such as heart rate. This absence is notable in the field, where the potential for AAL to contribute significantly to preventive healthcare has not been fully explored. By filling this gap, the study aims to pioneer the use of AAL systems in facilitating real-time, non-intrusive heart rate monitoring, setting a precedent for future innovations in elder care technology.

Heart rate is a vital health indicator, closely linked to cardiovascular health and overall wellness. Accurate and timely heart rate monitoring can lead to early detection of potential health issues, allowing for swift medical intervention and better management of chronic conditions. Consequently, heart rate prediction plays a crucial role in enhancing the quality of life and extending the independence of older adults.

This chapter is dedicated to implementing and evaluating several machine learning techniques to predict heart rates using contactless technologies integrated within our AAL system. These methods promise to provide a non-intrusive solution for continuous health monitoring, minimizing the discomfort and compliance issues associated with traditional monitoring devices.

By exploring these advanced predictive models, this study aims to validate the effectiveness of the AAL ecosystem in a setting that closely mimics real-life conditions. The outcomes are expected to offer valuable insights into the utility of non-intrusive monitoring solutions, emphasizing the practical benefits and scalability of such technologies in real-world AAL applications.

6.2 Heart Rate Prediction with Contactless Active Assisted Living Technology: A Smart Home Approach for Older Adults

6.2.1 Overview

Background

As global demographics shift towards an aging population, monitoring their heart rate becomes essential, a key physiological metric for cardiovascular health. Traditional methods of heart rate monitoring are often invasive, while recent advancements in Active Assisted Living provide non-invasive alternatives. This study aims to evaluate a novel heart rate prediction method that utilizes contactless smart home technology coupled with machine learning techniques for older adults.

Methods

The study was conducted in a residential environment equipped with various contactless smart home sensors. We recruited 40 participants, each of whom was instructed to perform 23 types of predefined daily living activities across five phases. Concurrently, heart rate data were collected through Empatica E4 wristband as the benchmark. Analysis of data involved five prominent machine learning models: Support Vector Regression, K-nearest neighbor, Random Forest, Decision Tree, and Multilayer Perceptron.

Results

All machine learning models achieved commendable prediction performance, with an average Mean Absolute Error of 7.329. Particularly, Random Forest model outperformed the other models, achieving a Mean Absolute Error of 6.023 and a Scatter Index value of 9.72%. The Random Forest model also showed robust capabilities in capturing the relationship between individuals' daily living activities and their corresponding heart rate responses, with the highest R^2 value of 0.782 observed during morning exercise activities. Environmental factors contribute the most to model prediction performance.

Conclusions

The utilization of the proposed non-intrusive approach enabled an innovative method to observe heart rate fluctuations during different activities. The findings of this research have significant implications for public health. By predicting heart rate based on contactless smart home technologies for individuals' daily living activities, healthcare providers and public health agencies can gain a comprehensive understanding of an individual's cardiovascular health profile. This valuable information can inform the implementation of personalized interventions, preventive measures, and lifestyle modifications to mitigate the risk of cardiovascular diseases and improve overall health outcomes.

Keywords: Active Assisted Living, Smart Home, Heart Rate Monitoring, Healthy Aging, Non-intrusive Healthcare Monitoring, Aging in Place, Machine Learning

6.2.2 Introduction

6.2.2.1 The impact of aging population and the need for Active Assisted Living

The world is currently experiencing a significant demographic shift, characterized by a rapid increase in the aging population. This demographic milestone is projected to reach unprecedented levels in the coming years [217]. Advancements in healthcare and living standards have led to an increase in the lifespan of individuals, resulting in a significant rise in the proportion of the older individuals within the global population [218]. In 2022, the world wide population of individuals aged 65 years or older is more than 770 million, which means more than one in ten people are older adults [219]. Eastern and South-Eastern Asia are home to the largest number of older adults who are 65+ years old, accounting for approximately 260 million individuals, followed by Europe and Northern America with over 200 million older individuals, representing the highest percentage of older adults (more than 17 percent) [217]. These numbers are projected to increase over the next three decades, with an estimated 1 in 6 people worldwide being aged 65 years or over by 2030, and this figure is expected to double to 1.5 billion individuals by 2050. Especially in low and middle-income countries, where 80% of older adults are projected to reside, healthcare challenges may be significant [1].

Chronic non-communicable diseases, including heart diseases, cancer, and chronic respiratory diseases, often accompany the process of aging [220]. These conditions require specialized healthcare services that monitor various health indicators, including physical activity, heart rate, blood pressure, and sleep quality [221]. Active Assisted Living (AAL) technology, i.e., technology that aims to maintain older adults' living independence using technology advancements, has emerged as a promising solution to address the healthcare needs of the aging population. By embedding reliable devices and sensors within a house, AAL creates a "smart home" environment [222]. When coupled with Artificial Intelligence (AI), Smart Home Technologies (SHTs) has the potential to assist with daily functions in the home and monitor, treat and manage chronic health conditions [12]. Moreover, smart homes can allow caregivers to provide better healthcare for older adults and even reduce their reliance on caregivers [223]. Smart home devices can continuously capture health-related information in an unobtrusive manner, thereby enabling safer independent living for the older adults [224]. The integration of SHTs with AI offers the potential to constantly observe, model, and understand human behavior, as well as identify early warnings for interventions [225]. Compared to other Internet of Things (IoT) technologies, such as wearables, SHTs do not require older individuals to carry it all day, which can be inconvenient or easily forgotten, particularly for those individuals living with dementia [226].

6.2.2.2 Heart Rate Prediction and its Importance in Cardiovascular Health Monitoring

Cardiovascular diseases (CVDs), also known as heart-related diseases, stand as the leading cause of death worldwide. In 2019 alone, CVDs accounted for 17.9 million deaths, representing 32% of all global deaths [227]. These devastating consequences are particularly prevalent in low- and middle-income countries, where limited access to healthcare services hinders early detection and treatment [228]. As individuals age, the

prevalence of CVDs increases, with the aging population being more susceptible to these diseases compared to younger individuals [229]. A report from Benjamin et al. [230] indicated that 40% of individuals aged between 40 and 59 have CVDs, while more than 70% of older adults aged 60 and above were affected by CVDs. Heart Rate (HR) serves as a key risk factor for CVDs and has been found to have a strong positive association with cardiovascular morbidity and mortality [231]. Consequently, accurate and timely prediction of heart rate can greatly contribute to the early detection and prevention of cardiovascular events, thereby improving overall cardiovascular health outcomes.

6.2.2.3 Current challenges and objectives

Despite the significant potential of SHTs and AI in predicting heart rate and enhancing cardiovascular health monitoring, there are several challenges that need to be addressed. Existing literature primarily focuses on wearable devices and IoT technologies for health monitoring, which often rely on user compliance and can be burdensome for older adults [232]. Furthermore, the application of SHTs in predicting heart rate has been limited to specific contexts or necessitates the combination of wearable technologies, rendering it impractical for daily living scenarios. Therefore, the objective of this research paper is to investigate the feasibility of utilizing SHTs, coupled with AI, for heart rate prediction in an unobtrusive manner within an active assisted living environment. The paper aims to bridge the existing gap in research and contribute to the development of a comprehensive and practical solution for predictive monitoring of heart rate in real-world scenarios, addressing the limitations of wearable devices and current monitoring approaches. The objectives assume that smart home indicators, such as motion sensors and power consumption, can observe activity patterns and their correlation with changes in HR and studies whether such correlation exists.

6.2.2.4 Overview and paper structure

The increasing prevalence of cardiovascular diseases among the aging population highlights the urgent need for reliable indoor heart rate monitoring. This study leverages the potential of smart home technologies to address the need, proposing a contactless, machine learning-based solution for heart rate prediction. This paper is organized as follows: Section 1, the Introduction, introduces the topic and outlines the current challenges in the field. Section 2, Related Work, reviews relevant literature to provide an overview of the state-of-the-art in using smart home technology for heart rate prediction. Section 3, Materials and Methods, describes the devices used for the study, along with the deployment of the smart home environment. This section also details the methodology employed in the study. Section 4 presents the Results and Findings, where the analyses performed are reported. Finally, Section 5 discusses the implications of these findings, acknowledging the limitations of the current study and suggesting potential areas for future research.

6.2.3 Related work

This section presents an overview of previous research conducted in the field of heart rate prediction using IoT technology, machine learning, and smart home approaches for older adults. Lin et al. [233] have explored the use of IoT technology to monitor cardiovascular

events. They provided a comprehensive overview of sensor advancements capable of monitoring various physiological signals associated with CVDs. However, most of these sensors require attachment to the body. To address the limitations associated with inconvenience to carry of traditional health monitoring devices, Xiao et al. [234] developed an intelligent wearable bracelet that can monitor heart rate during sports and provide real-time alerts for abnormal records. Similarly, David Chung Hu et al. [235] proposed an intelligent monitoring system by integrating temperature sensors, pulse sensors, and accelerometers to measure the vital signs in older adults. The system demonstrated high accuracies, exceeding 90%, in measuring body temperature, pulse rate, and fall detection. Through the comparison of pulse rates during various activities, the study revealed substantial variations in heart rate across different activities. Ali et al. [236] developed a wearable sensor prototype for heart rate and body temperature monitoring, achieving a low deviation of 2% compared to commercially available devices. Al Rasyid et al. [237] integrated body temperature sensor and pulse oximeter sensor into a wireless body sensor network to monitor various vital signs. This study identified a limitation related to the distance threshold (20 meters) between the body-attached sensors and the server receivers, and the greater distance, the more data loss. Alnaggar et al. [252] utilized Eulerian Video Magnification for non-contact heart rate and respiration rate extraction from video signals using camera. Although the proposed architecture are effective in extracting heart rate estimation from facial recordings, they face limitations with high-frequency noise, varying light conditions, motion, and raise privacy concerns, making it less suitable for daily living monitoring. The integration of AI techniques enables researchers to gain deeper insights from heart-related data and predict cardiovascular events. Dami & Yahaghizadeh [238] proposed a deep learning method called LSTM-DBN, combining Long Short-Term Memory (LSTM) and Deep Belief Network (DBN) to detect arterial events with superior performance compared to other methods, such as Logistic Regression, Random Forest (RF), and Recurrent Neural Network. Mohan et al. [239] introduced a hybrid machine learning model, HRFLM, which combined RF and Linear Model to predict cardiovascular diseases with a high accuracy of 88.7%. Wang & Gao [240] developed a real-time heart rate monitoring system for athletes using wearable devices and deep learning techniques, achieving accurate heart rate prediction and activity classification in volleyball plays. Additionally, IoT based SHTs have been widely utilized in indoor healthcare and assisting older adults in aging in place [241]. Adib et al. [242] utilized ubiquitous sensing technologies to remotely monitor vital signs using a wireless sensing technology called Vital-Radio, achieving a high accuracy of 99% for breathing and heart rate measurements. However, the performance of this method is limited by large body movements, as it primarily relies on detecting chest motion. In studies [253] and [254], the authors utilized Wi-Fi technology to monitor vital signs by detecting physiological movements that affect channel state information. However, this technology also has limitations in accurately detecting high heart rates or breathing rates during periods of excessive movement. Scalise et al. [243] developed a smart home network with heterogeneous health sensors to monitor cardiovascular situations in older adults, while Pham et al. [244] presented a cloud based smart home environment for comprehensive homecare services for older adults.

Despite the advantages of wearable devices in terms of accuracy and non-invasiveness, challenges related to their adoption and user compliance exist. Wearable devices heavily rely on participants' willingness to wear them, and some individuals such as older adults with dementia may forget to wear them regularly, leading to incomplete data and reduced healthcare monitoring quality [226]. Additionally, concerns regarding the use of unfamiliar devices in research studies and the discomfort associated with wearing them for extended periods can create resistance among users, especially older adults. Sensor burden and user discomfort have been identified as critical issues that need to be addressed in wearable sensor monitoring solution [245].

However, current research exhibits a gap in the ability to monitor heart rate information using smart home technologies alone, without the need for additional wearable devices, which is more practical for daily living contexts. The primary contribution of this research is achieving precise heart rate prediction and enabling cardiovascular healthcare monitoring for different activities within the context of daily living without requiring additional involvement from individuals.

The scientific novelty of this study is demonstrating the adaptability of machine learning techniques to heterogeneous smart home indicators for indoor heart rate monitoring. Furthermore, the application novelty lies in exploring the potential of smart home technology to unobtrusively monitor heart rate for general surveillance, addressing the limitations of existing approaches.

6.2.4 Materials and methods

6.2.4.1 Devices

AAL devices

Through the collaboration with smart home manufacturer Swidget, this study can acquire diverse smart home sensors and have access to their data repository through Application Programming Interfaces (APIs). The Swidget concept focuses on the adaptability and integration of smart home technologies. Their smart devices operate based on installing modular sensors into reconfigured common electrical devices such as outlets, on-off switches, and dimmers, which makes these devices unobtrusive, ensuring zero-effort from users. Moreover, these sensors are integrated directly into electrical circuits, meaning they do not have batteries. This ensures that they can be powered reliably for an extended period of time, without the concern of depleting battery life, provided there are no power outages. In this study, we paired smart outlets and smart switches with (1) air quality module sensors, (2) temperature and humidity sensors, and (3) passive infrared motion module sensors, which create four configurations in total. In addition, door contact sensors were also installed in the environment.

Wearable devices

The purpose of using wearable device here was to collect the HR data, serving it as the benchmark when comparing with the predicted HR values. Consequently, it requires that the selected wearable device should be reliable and accurate. Empatica E4 wristband was

selected as the HR measuring tool. Its accuracy has been validated by the study from [246], which demonstrated that Empatica E4 is a practical and reliable device for collecting HR data. Empatica E4 can measure the HR value with a sample rate of 1 HZ. In addition to HR, Empatica E4 is also equipped with an electrode, a photoplethysmography, a skin temperature, and a 3-axis accelerometer, from which electrodermal activity, blood volume pulse, and skin temperature can be measured. Through the Empatica Manager application, Comma-Separated Values (CSV) files containing raw HR data can be downloaded from the devices.

6.2.4.2 AAL environment

A smart home environment was constructed in an apartment unit in the Research Institution for Aging in Waterloo (see Figure 20), with each device being assigned an ID. This apartment unit is composed of a kitchen, a living room, a bedroom, and a bathroom, which is decorated with necessary furniture to fulfill individuals' daily living requirements. The smart home environment was designed to be a sensor-rich space aiming to capture as many Activities of Daily Living (ADLs) as possible. According to locations of electrical devices in the room, we replaced original switches and outlets with Swidget intelligent devices and paired them with four types of environmental sensors.

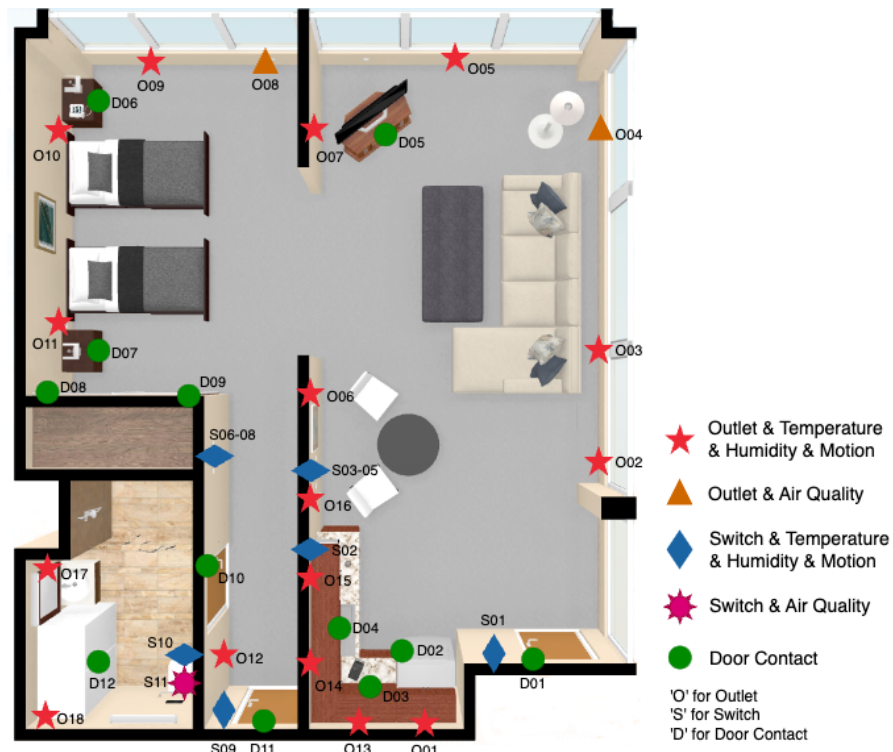


Figure 20. AAL environment

When placing motion sensors in the environment, we followed the optimized sensor placement principles stated in [247], considering the detection range of Swidget motion sensor is 3 meters, including 1) coverage: making sure the sensor has a wide enough field of view to detect movement in the area we want to monitor; 2) placement: mounting the sensor at a height of around 7 feet to ensure it can detect movement across a room; 3) false

alarms: positioning the sensor away from areas that is covered by furniture, such as behind sofa or bed, but areas where movement is likely to occur naturally to reduce false alarms. Door contact sensors were attached on each door, closet, and drawer to capture open/close events. Similarly, to get more accurate and comprehensive environmental data, we placed multiple temperature & humidity sensors and air quality sensors in different rooms. Additionally, we placed more sensors in the areas where these parameters are more likely to change, such as the kitchen, and the bathroom.

In order to better capture the ADLs happening in the room, we recruited five volunteers during the design phase to perform potential activities in the room, assisting us to iteratively test and adjust the locations and numbers of sensors.

6.2.4.3 Study

ADLs scenarios

The ADLs scripts in this study was generated by following the principles in [248]. They cover basic ADLs and instrumental ADLs as well as single activities, posture-oriented, and movement-oriented activities, involving all spaces in the room, which can be representative for an individual's ADLs that happen within days. Each orientation requires different efforts from individuals and under each of them, we developed four to five scenarios to ensure the coverage of comprehensive ADLs.

Textbox 3 indicates that the activities designed for the different scenarios share similarities but different levels of activities, which can cause changes in heart rate. By repeating similar activities, a larger and more diverse dataset can be collected, which aids the machine learning model in distinguishing between various activities and heart rate patterns, thereby improving the robustness and accuracy of the models.

Textbox 3. ADLs scenarios

- | |
|---|
| <ol style="list-style-type: none"> 1. Phase 1. Single activities <ul style="list-style-type: none"> ● Scenario 1. Arriving home ● Scenario 2. Eating dinner ● Scenario 3. Sleep ● Scenario 4. Cooking ● Scenario 5. Going out 2. Phase 2. Posture-oriented <ul style="list-style-type: none"> ● Scenario 1. Reading on sofa ● Scenario 2. Completing a puzzle ● Scenario 3. Reading on bed ● Scenario 4. Meal time ● Scenario 5. Bathroom job 3. Phase 3. Movement-oriented <ul style="list-style-type: none"> ● Scenario 1. Tidying a room ● Scenario 2. Morning exercise ● Scenario 3. Taking shower ● Scenario 4. Wandering in rooms |
|---|

4. Phase 4. Basic ADLs
 - Scenario 1. Cleaning rooms
 - Scenario 2. Changing footwear
 - Scenario 3. Prepare meal
 - Scenario 4. Make up
5. Phase 5. Instrumental ADLs
 - Scenario 1. Arriving home from groceries
 - Scenario 2. Cleaning kitchen
 - Scenario 3. Emptying garbage
 - Scenario 4. Morning routine
 - Scenario 5. Wrap up things

Participants

Recruiting participants for this study posed several challenges unique to the COVID-19 pandemic, especially with respect to our target population of older adults who are more vulnerable to infection. Consequently, we recruited students from the University of Waterloo as participants using convenience sampling. A total of 40 participants took part in the study, comprising 17 males and 23 females. The participants' mean age was 24 years, ranging from 18 to 39 years. Written informed consent was obtained from all participants before they took part in the study. To safeguard their privacy and confidentiality, participant information was de-identified. In order to minimize the bias arising from this age group difference, we instructed participants to simulate being seniors and engage in activities at a slower pace than their usual speed. The ethics of the study were reviewed and approved by the Research Ethics Office of the University of Waterloo under the ORE #43843.

Procedure and data collection

Prior to the experiment, participants were asked to provide their informed consent and complete a questionnaire that was designed to collect demographic information. Subsequently, the researchers escorted participants to the smart home environment, where they were oriented to the locations of labeled sensors, appliances, and furniture. Additionally, participants were requested to wear Empatica E4 wristbands to generate benchmark heart rate data.

During the experiment, facilitators observed participants' activity performance through cameras in the room next to the apartment unit while delivering activity instructions to participants via a phone. Activity instructions were delivered in sequence by phases and scenarios to participant and no further instructions were provided unless participants asked for specific assistance. One minute transition time was allotted between each scenario, in order to reset all activated sensors. An observer documented activity information, including start and end timestamps, using an annotation sheet. Sensor readings were collected, formatted, and stored in the cloud database via our smart home data ecosystem. Only one participant was tested at a time, and each experiment session lasted approximately three hours.

Data pre-processing & summary

After performing data cleaning and excluding datasets from incomplete participants, a total of 28 participants' data remained available for further analysis. The data collected from the participants originated from two distinct sources, each with its own sampling rate. The smart home data gathered through 41 sensors shown in Figure 1 had a granularity of 30 seconds, while the HR data was recorded by the Empatica wristband at a rate of one measure per second. There is no missing data in the dataset, thereby eliminating the need for data imputation.

In the preprocessing stage for smart home data, we integrated data from different smart home sensors into a unified dataset. This integration involved structuring parameters from each sensor into individual columns within a single dataset. Consequently, each column in this dataset corresponds to a specific sensor parameter, facilitating ease of analysis and interpretation. Moreover, we ensured the synchronization of data across different sensors, leveraging the uniform timestamps and intervals recorded by each device. The synchronization process involved aligning data points from different sensors that shared the same timestamp.

To ensure compatibility between these datasets for HR prediction tasks, a methodical preprocessing approach was implemented for HR dataset, beginning with the synchronization of their timestamps. Let t_{home} represent the starting timestamp of the smart home dataset, and t_{HR} represent the corresponding starting timestamp in the Empatica dataset. The alignment process involves matching these starting points such that $t_{home} = t_{HR}$. Following this synchronization, the HR data was resampled to align with the 30-second granularity of the smart home data. This was achieved by calculating the average HR over every 30-second intervals, starting from t_{HR} . So for each 30-second interval in the smart home dataset, the corresponding $\overline{HR}_{30s}$ computed, ensuring that the HR data is in sync with the smart home data.

In this study, each sensor recorded data for various features (see Appendix B) during the experiment session. To ensure the accuracy and reliability of the data, we incorporated a one-minute transit time between each experimental scenario. It is essential to clarify that data from these transition times were not included in our analysis. During these transit periods, participants were inactive, allowing the sensors to reset to their initial state. This approach was crucial to mitigate any potential carryover effects from one scenario to the next. Consequently, it resulted in approximately 270 data instances per parameter for each participant. These instances represent a time series within each scenario, with each data point corresponding to a 30-second interval. However, it should be noted that these time series are not continuous between scenarios because of transition time. When aggregating data across all subjects, the final dataset comprised over 7500 sample points. Figure 21 illustrates the total number of data instances collected from all subjects for each scenario, along with the average time duration (seconds) spent by subjects in each scenario.

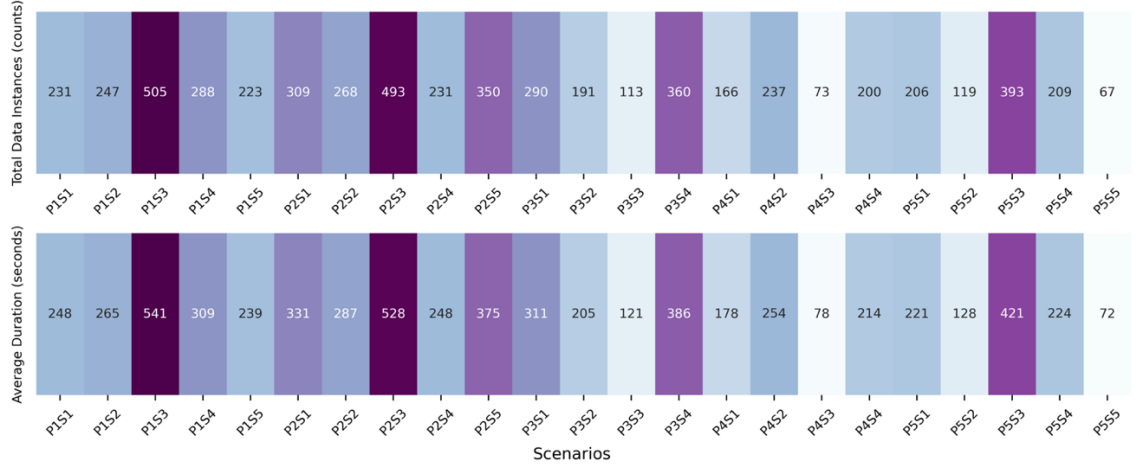


Figure 21. Total number of data instances and average time duration for each scenario

Additionally, in the feature extraction process, we utilized parameters from each sensor, acquired through APIs at 30-second intervals, as individual features. This approach means that each sensor parameter was treated as a distinct feature. Specifically, for extracting temperature and humidity feature, we divided the environment into five separate rooms and extracted these parameters independently for each room. We selected sensors located in each specific room, and the room's temperature and humidity features were determined by averaging the readings from these sensors. Consequently, each participant's dataset comprised 137 features (Appendix B) related to smart home indicators, and all of these features were utilized in the data analysis. These features encompassed a wide range of factors, including but not limited to motion occupancy, temperature, humidity, air quality, switch log, and energy consumption gather from each of the sensors in the environment. The inclusion of these smart home indicator-related features added depth and richness to the dataset, enabling a comprehensive analysis of the participants' living environment and activity patterns.

Machine Learning models and evaluation metrics

In this study, five classical machine learning models were selected to perform the prediction task. These models included Support Vector Regression (SVR), K-nearest neighbor (KNN), RF, Decision Tree (DT), and Multilayer Perceptron (MLP). Furthermore, to evaluate the performance of prediction models, several commonly-used metrics were used, which are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), , R-squared (R^2), and Scatter Index (SI). These metrics comprehensively assess different aspects of model performance. Their equations are as follow:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\bar{y}_i - y_i)^2}$$

$$SI = \left(\frac{RMSE}{\frac{1}{n} \sum_{i=1}^n \hat{y}_i} \right) \times 100\%$$

Where y_i is true value, $\bar{y}_i$ is the mean of true value $\hat{y}_i$ is the predicted value.

Specifically, RMSE calculates the square root of the average squared differences between predicted values and the actual values, while MAE measures the average absolute difference between predicted values and true values. R^2 indicates how well the predicted values from the model fit the observed data, ranging from 0 to 1. SI provides a normalized measure of prediction error. A lower value of SI indicates better performance of the model. If the SI value is less than 10%, it indicates a good model performance [249].

Evaluation setup

The data was process and analyzed on a Linux server (16GB RAM) with Ubuntu v22.04.3 operation system. Python v3.10.12 was used as the programming language to complete the data analysis task, along with its corresponding libraries such as Pandas v2.0.3, Matplotlib v3.5.1, and Numpy v1.21.5. Machine learning models were constructed based on the Scikit-learn v1.2.1 framework.

6.2.5 Results

6.2.5.1 HR data summary visualization

Overall HR data distribution

The distribution of heart rate data for all participants and activities is illustrated in Figure 22.

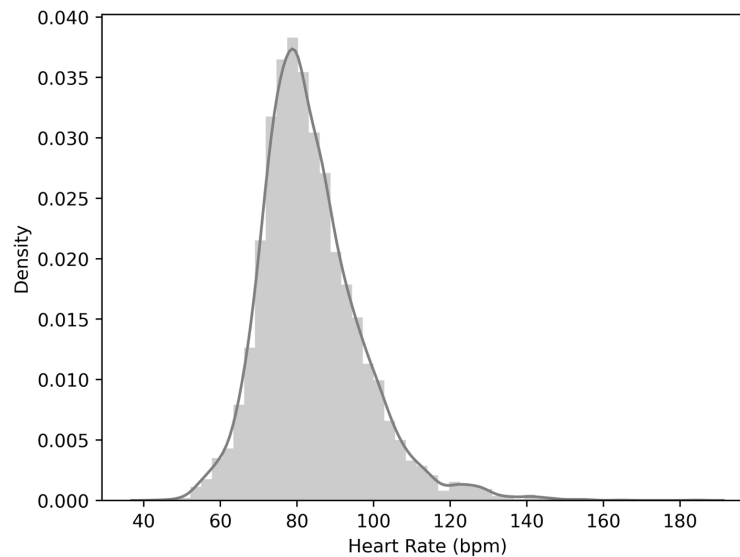


Figure 22. Heart rate distribution

The majority of observations are concentrated around 80 beats per minute (bpm), which is commonly associated with typical resting heart rate. This suggests that a major portion of the data corresponds to individuals in a relaxed state, aligning with common indoor activities. A smaller proportion of instances is observed around 50 bpm, likely indicating periods of low activity intensity. The distribution of heart rate values also includes a proportion of samples ranging from 120 to 150 bpm, capturing instances of elevated heart rate during physical exercise scenarios.

This wide range of heart rate values reflects a spectrum of activity intensities within the set scenarios, from light to moderate and vigorous levels, highlighting the body's adaptive physiological responses to different forms of physical exertion. The distribution of the heart rate data appropriately reflects different activity intensities, providing a solid foundation for prediction analysis and ensuring the reliability and interpretability of prediction models [250].

HR data distribution by scenarios

In this section, we analyzed the distribution of heart rate data in various scenarios (Figure 23) using boxplots to gain insights into physiological responses associated with different daily life scenarios. Each box represents a specific scenario, and the upper (or lower) whisker extends to the maximum (or minimum) data points within 1.5 times the height of the box from box top (or bottom). Data points outside of the whisker are considered as outliers, which have been excluded from the analysis. The thick line within the box represents the median, while the box itself represents the interquartile range between 25th and 75th percentiles, capturing the middles 50% of the data. This visualization provides insights into the spread or dispersion of the dataset.

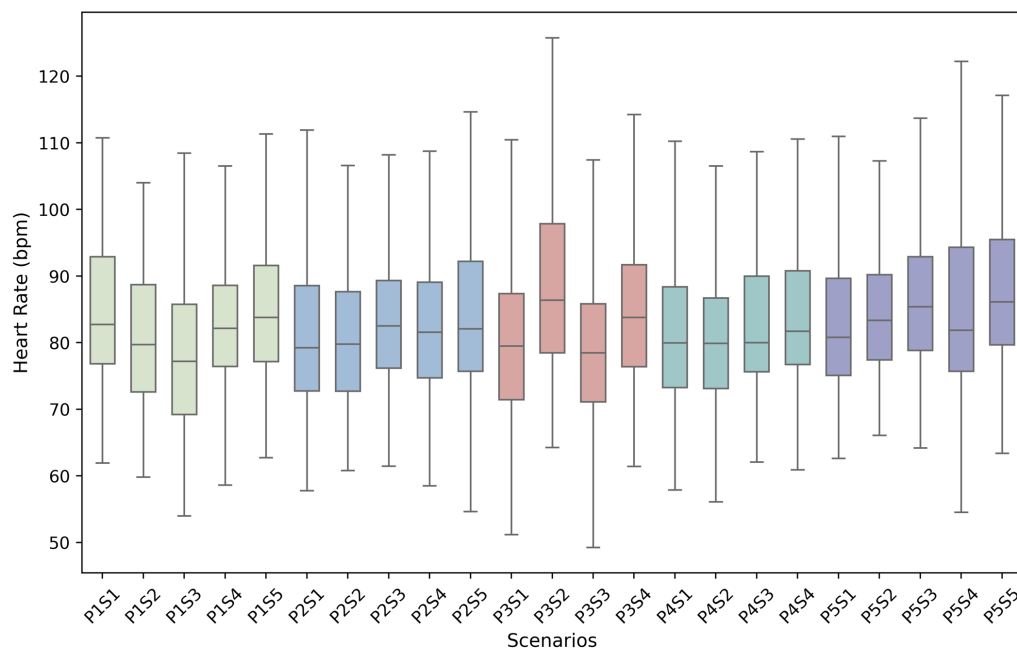


Figure 23. Heart rate data distribution on different scenarios (P stands for phase and S stands for scenario)

The figure illustrates the heart rate data distributions across various scenarios, revealing some variation among them. However, the differences observed are not excessively pronounced and align with typical daily living situations. These fluctuations in heart rate are expected based on the nature of the performed activities. Phase 2, which comprises posture-oriented activities with minimal movement, exhibits a relatively stable data distribution across different activities. These activities typically involve low physical exertion, resulting in heart rates that remain within a relatively narrow range. The majority of heart rate data in Phase 2 falls between 70-90 bpm, indicating a consistent and moderate level of cardiovascular demand. Conversely, Phase 3 includes movement-oriented activities that require individuals to exert energy, resulting in considerable variability in heart rate data distribution across scenarios. The range of heart rate values for Phase 3 activities seems to be wider compared to other phases. Notably, the morning exercise scenario (P3S2) displays the highest heart rate distribution, with values exceeding 120 bpm, which may indicate the significant cardiovascular demands associated with this activity. Phase 1, encompassing a range of single activities including sleep, also exhibits noticeable variations in heart rate data. During sleep (participants only lied down rather than in actual sleep), heart rates tend to decrease due to the body's relaxation and decreased metabolic demands, resulting in the lowest recorded heart rate during this phase approaching approximately 50 bpm. On the other hand, Phases 4 and 5 show similar and consistent heart rate distributions. These distributions exhibit a notable right-skewed pattern, indicating that the majority of activities in these phases result in heart rates higher than the median value. This suggests increased cardiovascular demands during these activities. In other words, these activities generally involve more intense physical exertion, causing a higher cardiovascular response compared to the median level.

6.2.5.2 Heart rate prediction

Different models

The whole dataset was initially shuffled and divided into an 8:2 ratio for training and testing, respectively. During the training phase, the training dataset was further divided into five equal subsets to facilitate 5-fold cross-validation. In this process, each of the five subsets, in turn, served as a validation set while the remaining four subsets were used for training. This process aided in parameter tuning, identifying the optimal model, and enhancing the reliability and generalizability of the predictive models. Each model was constructed through the Scikit-learn framework. The main optimized hyperparameters for each model were set as follows, which was operated by grid search [251] from different combinations of parameters: SVR (rbf kernel, $c=5$); KNN ($k=8$); RF ($n_trees=200$, $max_depth=12$); DT ($max_depth=9$); MLP ($max_iter=350$). The detailed performance is shown in Table 12.

Table 12. Evaluation results for five machine learning models

	SVR	KNN	RF	DT	MLP
RMSE	9.217	9.495	8.124	10.469	11.327
MAE	6.954	7.227	6.023	7.814	8.588

R^2	0.277	0.281	0.594	0.099	0.237
SI (%)	13.14	11.52	9.72	9.98	13.60

The results presented in the table confirm the feasibility of utilizing smart home indicators for heart rate prediction, as demonstrated by the performance of the five machine learning models with a mean MAE value of 7.321. Among the evaluated models, RF achieved the best performance in terms of MAE, with a value of 6.023. This indicates that RF achieved the lowest average prediction error for the heart rate value compared to the other models. Additionally, RF also exhibited the lowest RMSE (8.124) and the highest R^2 value (0.594), indicating superior accuracy and goodness of fit. KNN and SVR also performed reasonably well, with RMSE values of 9.495 and 9.217, respectively. Both models showed similar MAE values, with KNN at 7.227 and SVR at 6.954, suggesting comparable average prediction errors and accuracy. In contrast, DT and MLP exhibited higher RMSE and MAE values, indicating greater prediction errors compared to the other models. DT achieved the lowest R^2 value of 0.099, indicating a weaker fit between predicted and actual heart rate values. MLP also had a relatively low R^2 value of 0.237, suggesting a moderate fit to the actual data. When considering the SI, which provides an overall measure of model performance, RF achieved the lowest value of 9.72%, followed by DT (9.98%), KNN (11.52%), SVR (13.14%), and MLP (13.60%). It is worth noting that a SI below 10% is considered good for model performance in regression tasks [249]. Based on their performance, RF outperformed the other models, demonstrating the lowest prediction deviation, highest accuracy, and the lowest SI, while KNN and SVR also showed competitive performance. DT and MLP, on the other hand, exhibited relatively weaker performance compared to the other models. Overall, the evaluation results indicate that leveraging smart home indicators with machine learning models can be a promising approach for heart rate prediction.

Different phases & scenarios

To gain insight into the prediction performance across different phases and scenarios, we conducted a separate evaluation for each of the 23 predefined activity scenarios (Textbox 3). The results, obtained using the RF model, are presented in Figure 24 and Table 2. Figure 24 combines the SI line chart with the R^2 bar chart, enabling a comprehensive comparison of model's performance across different phases and scenarios, and facilitating an understanding of the relationship between R^2 and SI for each scenario. Table 13 provides detailed results for all evaluation metrics, serving as reference for interpretation. Results from them demonstrate that the machine learning models, particularly RF model, exhibited moderate to good prediction accuracy for heart rate values in various orientated phases and scenarios.

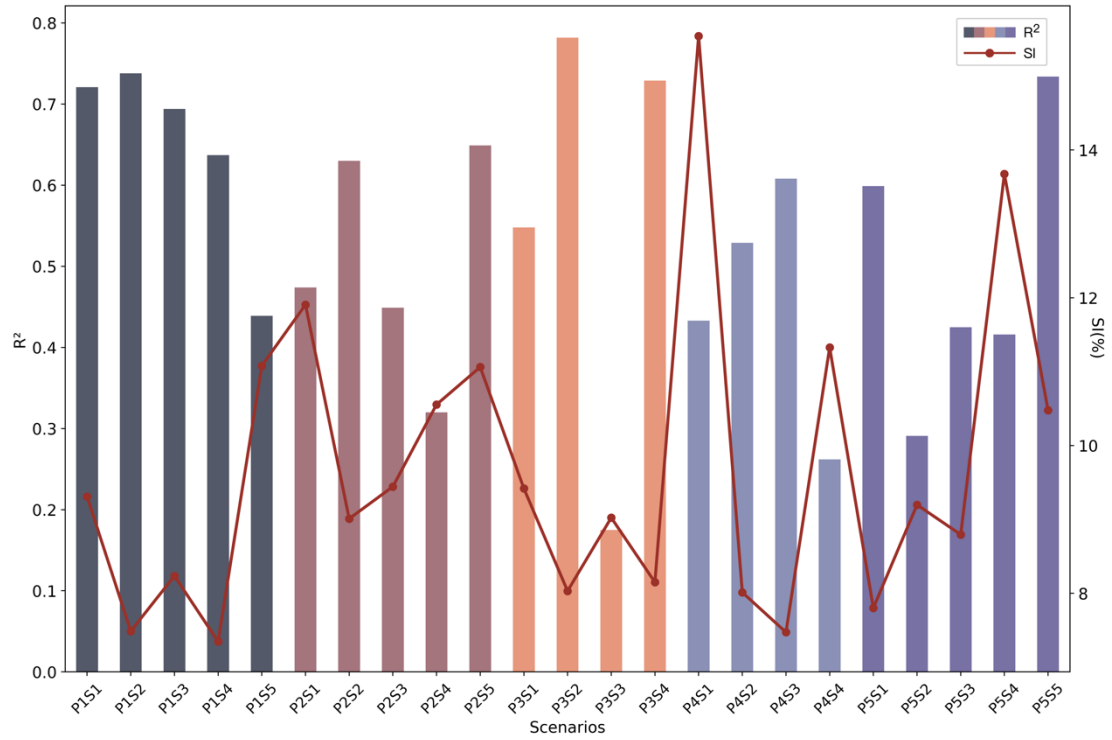


Figure 24. RF performance for different scenarios

Table 13. Detailed results on phases and scenarios based on RF

		Scenario1	Scenario2	Scenario3	Scenario4	Scenario5	Avg
Phase1	RMSE	7.974	5.987	6.583	6.154	9.560	7.252
	MAE	6.152	4.560	4.447	4.894	6.643	5.339
	R²	0.721	0.738	0.694	0.637	0.439	0.646
	SI (%)	9.31	7.48	8.23	7.34	11.08	8.68
Phase2	RMSE	9.811	7.414	7.923	8.856	9.473	8.695
	MAE	7.051	5.214	5.682	6.048	7.352	6.269
	R²	0.474	0.630	0.449	0.320	0.649	0.504
	SI (%)	11.90	9.01	9.44	10.55	11.06	10.39
Phase3	RMSE	7.369	7.202	7.596	6.413		7.145
	MAE	5.755	5.028	5.740	4.903		5.357
	R²	0.548	0.782	0.175	0.729		0.559
	SI (%)	9.41	8.03	9.02	8.15		8.65
Phase4	RMSE	13.340	6.383	6.058	9.336		8.779
	MAE	8.543	4.530	4.922	7.210		6.301
	R²	0.433	0.529	0.608	0.262		0.458
	SI (%)	15.54	8.01	7.47	11.32		10.58
Phase5	RMSE	6.493	7.506	7.573	11.937	9.561	8.614
	MAE	4.637	5.800	5.813	8.478	7.632	6.472
	R²	0.599	0.291	0.425	0.416	0.734	0.493
	SI (%)	7.80	9.19	8.79	13.67	10.47	9.98

Phases

The analysis of evaluation results provided valuable insights into performance of the RF model across different phases. The model demonstrated its strong performance in Phase 3, which includes movement-oriented activities. In this phase, the RF model achieved the lowest RMSE (7.145) and the second lowest MAE (5.375), indicating higher precision and accuracy in predicting heart rate values for such activities. In contrast, Phase 4, representing basic ADLs, had the highest RMSE value of 8.779 among the phases, followed by Phase 2 (8.695). Phase 5 exhibited the highest MAE value of 6.472, followed by Phase 4 (6.301). Despite this, the RMSE and MAE values across all phases are within a reasonable range, indicating a generally acceptable level of prediction accuracy.

In terms of the R^2 scores, three out of five phases (Phase 1, Phase 2, and Phase 3) achieved R^2 scores consistently exceeding 0.5, while the other two phases approached 0.5. Particularly, Phase 1 achieved the highest R^2 score (0.646), closely followed by Phase 3 with a R^2 score of 0.559. Similarly, when considering SI values, three out of five phases (Phase 1, Phase 3, Phase 5) achieved SI values below 10% with the remaining two slightly exceeding this threshold. The lowest SI is observed in Phase 3 with 8.65%, closely followed by Phase 1 at 8.68%.

Scenarios

Further analysis of individual scenarios within each phase revealed notable variations between activities. Among the different scenarios, Phase 1 Scenario 2 (P1S2) involving eating dinner exhibited the lowest RMSE (5.987), closely followed by P4S3 which pertains to meal preparation. On the other hand, the highest RMSE was observed on P4S1, associated with tasks of cleaning rooms. Additionally, the model demonstrated strong performance in terms of MAE during Phase 3 with minimal variance ranging from 4.903 to 5.755. Notably, P3S2 (morning exercise) and P3S4 (wandering in rooms) achieved low MAE values of 4.903 and 5.028, respectively. Furthermore, P1S3 obtained the lowest MAE with 4.447 while P4S1 recorded the highest MAE with a value of 8.543.

In terms of R^2 scores. The highest R^2 score of 0.78 was observed for the morning exercise scenario (P3S2). Similarly, the scenario of wandering in rooms (P3S4) exhibited a relatively high R^2 score. However, the scenario of taking a shower (P3S3), which lacked sensor coverage in the shower area, recorded the lowest R^2 score of 0.17. This disparity highlights the impact of sensor availability on the predictive accuracy of heart rate during specific activities. For SI score, which measures the variability of the predicted values around the true values, the RF model showed good performance with a majority of the scenarios having an SI score of less than 10%. However, some scenarios had higher SI scores, with the highest being 15.54% for cleaning rooms (P4S1). Moreover, model performed moderately well in Phase 1, with the lowest SI score of 7.34% observed for cooking (P1S4). Even though taking shower had the lowest R^2 score, its SI score was only 9.02%.

Sensor and feature importance

To determine which sensors and features most significantly influence heart rate prediction, based on RF model, we utilized the Mean Decrease in Impurity (MDI) metric to quantify

the relative importance of each feature. We identified the top 20 features that significantly impact heart rate prediction, as illustrated in Figure 25.

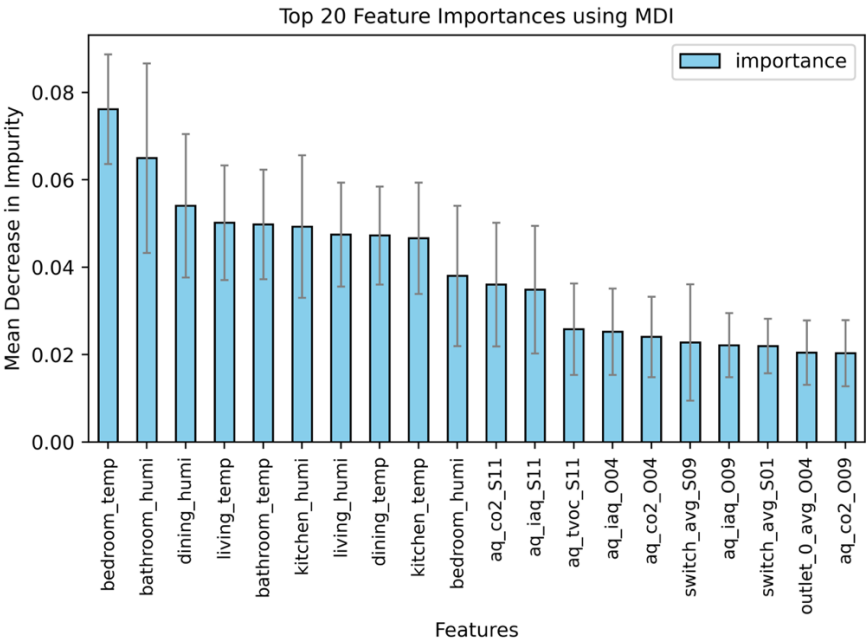


Figure 25. Feature Importance using MDI based on RF model

Figure 25 illustrates that features related to temperature and humidity in all five rooms prominently dominate the feature importance hierarchy, with the top ten spots occupied by these variables. Specifically, temperature readings in the bedroom is the most influential feature, achieving the highest MDI value of 0.76. The humidity level in the bathroom follows closely, marked as the second most critical feature with an MDI value of 0.65.

Subsequently, air quality-related features, as measured by relevant sensors, including CO₂ levels, Air Quality Index, and Total Volatile Organic Compounds, occupy seven of the next ten spots in feature importance. The sensors monitoring these parameters were strategically positioned in key home areas such as the living room (sensor O04), bedroom (sensor O09), and bathroom (sensor S11).

Moreover, the analysis reveals that features associated with the use patterns of switches and electrical outlets at specific locations also contribute significantly to the model's predictive performance. For instance, switch sensors S01 in the living room and S09 outside the bathroom, which were frequently interacted with by participants, proved to be influential.

These findings highlight the critical role of sensors monitoring environmental conditions like temperature, humidity, and air quality in impacting the model accuracy for heart rate prediction. This is consistent with the results from Ren et al. [184], which suggest a strong correlation between these environmental factors and heart rate response, implicating their impact on cardiovascular health.

6.2.6 Discussion

6.2.6.1 Principal findings

The principal findings of this study demonstrate the potential and feasibility of using machine learning methods in predicting HR based on AAL technologies. All machine learning models employed in the study achieved favorable prediction results, with the RF model standing out as particularly noteworthy. Its capabilities in capturing the relationship between daily living activities and heart rate responses can make it a promising tool for accurate heart rate prediction in the future.

Furthermore, the study suggested that the performance of the RF model varied depending on the specific daily living activities being performed. A common knowledge we can take from the results is that activities that involved more indoor movement and triggered multiple sensors within the smart home environment resulted in higher prediction performance. On the other hand, activities involving static positions or posture changes showed comparatively lower prediction performance. These findings emphasize the importance of constructing an AAL environment with an adequate number of smart home devices, enhancing higher prediction performance.

6.2.6.2 Public health perspective

The findings of this research have valuable implications for public health. Accurately predicting heart rate based on contactless smart home technologies during individuals' daily living activities enables healthcare providers and public health agencies to gain a comprehensive understanding of an individual's cardiovascular health profile. This valuable information can inform the implementation of personalized interventions, preventive measures, and lifestyle modifications to mitigate the risk of cardiovascular diseases and improve overall health outcomes. By monitoring heart rate fluctuations using non-intrusive AAL technology, public agencies can detect early signs of cardiovascular issues, provide timely interventions, and allocate resources more efficiently to address cardiovascular health challenges at both the individual and population levels, reducing the burden of chronic diseases and improving the well-being of older adults.

6.2.6.3 Novelty

This study contributes to the existing research by addressing the limitations of previous studies that primarily focus on wearable devices and IoT technologies, which may be burden for some older adults. Unlike other studies [234][235][236][237], this research investigates the feasibility of utilizing contactless smart home technologies alone, without the need for additional wearable devices, making it more practical for daily living contexts. Even when compared to studies that also monitor heart rate in a contactless manner [242][252][253][254], this study demonstrates distinct advantages. Firstly, it is not limited by large body movements since it does not rely on detecting chest or other physiological motions. This makes the proposed solution particularly effective in daily living scenarios. Secondly, there are fewer privacy concerns as it does not require visual monitoring. Lastly, the proposed solution exhibits environmental robustness, overcoming challenges such as high-frequency noise and variable lighting conditions that can affect other systems. By

leveraging AI techniques, this study provides an advanced approach that unobtrusively monitors heart rate within an AAL environment, thus bridging the existing gap in research. The integration of contactless smart home technologies and machine learning algorithms enables heart rate monitoring without relying on user compliance, overcoming the challenges associated with wearable devices.

6.2.6.4 Limitations and future work

It is crucial to acknowledge the limitation of this study, which is the age range of the sample population. The participants in our study primarily consisted of young individuals, and it is important to recognize that physiological responses and behaviors may differ among different age groups, causing the bias in studies results. Another limitation is the fixed order for ADLs in the experiment, which may not accurately reflect real-world scenarios and some previous activities could potentially impact HR response during subsequent activities. Furthermore, the dataset for our analysis was limited to evaluable data from only 28 subjects, a sample size that is not sufficient for a comprehensive analysis of robustness. While these data provide useful preliminary insights, this limitation in sample size constrains the generalizability of our findings.

Despite these limitations, our study still represents a notable advancement in utilizing SHTs as a valuable tool for healthcare monitoring, demonstrating the feasibility and potential effectiveness of using contactless smart home technology for heart rate monitoring. To further strengthen the validity and applicability of our findings, future research will address these limitations by evaluating with a larger group of participants and including a more representative sample of older adult participants. In addition, further study will be conducted in real-world in an uncontrolled settings to evaluate impacts of numbers and locations of smart home sensors to prediction performance, exploring optimal configuration of sensors in a AAL environment.

6.2.6.5 Conclusions

The results of this study highlight the promising potential of utilizing contactless SHTs coupled with machine learning techniques for accurate heart rate prediction during individuals' daily living activities within AAL environments. Integrating contactless SHTs into individuals' living environments facilitates a convenient and unobtrusive method for tracking variations in heart rate during different activities. This approach not only addresses common issues such as user compliance and sensor burden found in traditional systems but also assist individuals to discern the diverse impacts of various activities on their heart rate, fostering a more engaged and informed approach to personal health monitoring. This integration of technology into the daily lives of older adults enables unobtrusive monitoring of their cardiovascular health, providing valuable insights for healthcare providers and public health officials. The approach can be further integrated into the UbiLab AAL Data Ecosystem, providing comprehensive indoor healthcare surveillance for older adult population.

6.3 Discussion

The implementation and validation of the heart rate prediction models using the data collected from the data ecosystem not only represent significant advancements in AAL technologies but also serve as a crucial pilot study. This study has successfully demonstrated the AAL's capacity for predicting heart rates using contactless methods. By addressing a critical gap identified in the scoping review, this pilot study showcases the potential of AAL technologies to enhance preventive healthcare for older individuals. It validates that the AAL solution can effectively integrate with AI to deliver reliable and non-intrusive health monitoring solutions.

Looking ahead, the technologies and methodologies developed and validated in this chapter lay a robust foundation for subsequent studies within this thesis. The successful application of these AI-enhanced health monitoring techniques sets a precedent for further exploration and refinement of AAL technologies in later chapters.

Chapter 7 – Activities of Daily Living Recognition – A proof-of-concept Study

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7.1 Foreword

Building upon the previous chapter's demonstration of heart rate prediction using contactless AAL technology, this chapter shifts focus to the recognition of ADLs for older adults. The previous study validated the practical application of the AAL data ecosystem for physiological monitoring. However, physiological metrics like heart rate provide only a partial view of an individual's health. To fully support aging populations, it is essential to expand monitoring capabilities to include daily functional activities. Recognizing ADLs is a key component of assessing the overall health, independence, and quality of life of older adults. The study presented in this chapter is also based on the data ecosystem developed before.

ADLs recognition plays a crucial role in understanding the capabilities and needs of older individuals, providing direct insights into their ability to perform essential activities independently. These activities, such as bathing, dressing, eating, and moving around the home, are fundamental to maintaining autonomy and quality of life. A decline in the ability to perform these tasks often signals the onset of health issues or functional decline, necessitating timely intervention. Therefore, accurately recognizing ADLs is critical for enabling early intervention and support, helping older adults maintain their independence.

This chapter acts as a proof-of-concept study to explore the extension of the AAL system to include ADLs recognition using non-intrusive, contactless sensors. Leveraging the cloud-native data infrastructure from the previous chapter, we collect and analyze ambient data from a smart home environment to infer daily activities. By utilizing AI-driven techniques, the system aims to recognize and classify various ADLs, providing a more holistic approach to health monitoring and personalized care for older adults.

A significant aspect of this study is its focus on contactless monitoring, which is particularly important for older adults who may find wearable devices cumbersome. Contactless AAL sensors, such as motion detectors and environmental sensors, offer a zero-effort solution for monitoring daily activities without requiring active participation. This ensures continuous data collection, which is essential for detecting subtle changes in behavior or activity patterns that may indicate emerging health issues, thereby supporting proactive and personalized eldercare.

7.2 A Contactless Method for Recognition of Daily Living Activities for Older Adults Based on Ambient Assisted Living Technology

7.2.1 Overview

Background

During demographic shifts towards an older population, healthcare systems face increased demands, highlighting the need for innovative approaches that facilitate supporting older adults' well-being and safety. This study aims to demonstrate the effectiveness of zero-effort Ambient Assisted Living technology in recognizing daily activities of older adults via machine learning algorithms by comparing with wearable technology.

Methods

Conducted in a smart home environment equipped with a comprehensive range of non-intrusive sensors, the study involved 40 participants, during which they were instructed to perform 23 types of predefined daily living activities, organized in five phases. Data from these activities were concurrently captured by both ambient and wearable sensors. Analysis was performed using five machine learning models: K-Nearest Neighbours, Decision Trees, Random Forest, Adaptive Boosting, and Gaussian Naive Bayes.

Results

Ambient sensors, especially using the AdaBoost model, demonstrated high accuracy (0.964) in activity recognition, significantly outperforming wearable sensors (best accuracy 0.367 with Random Forest). When fusing data from both sensor types, the accuracy slightly decreases to 0.909. Despite spatial overlap challenges, ambient sensors accurately recognize activities across various room settings with accuracies all above 0.950. Feature importance analysis reveals that climatic, electrical, and motion-related features are crucial for model classification.

Conclusion

This study showcases the efficacy of Ambient Assisted Living technology in recognizing daily indoor activities of older adults. These findings have implications for public health, highlighting Ambient Assisted Living technology's potential to support older adults' independence and well-being, offering a promising direction for future research and application in smart living environments.

Keywords: Ambient Assisted Living, Smart Home, Human Activity Recognition, Contactless Monitoring, Aging Independent Living, Internet of Things, Machine Learning

7.2.2 Background

The phenomenon of population aging represents one of the most significant demographic shifts of the 21st century, with profound implications for health and social systems worldwide [1][255][256][257]. Aging is a complex biological process characterized by the accumulation of molecular and cellular damage over time, leading to a gradual decrease in physical and mental capacities and an increased risk of disease and death [255][256]. The

global demographic landscape is shifting towards an older population at an unprecedented pace [1]. In 2020, the number of individuals aged 60 years and older surpassed the number of children under five years of age for the first time in history [1]. By 2030, it is projected that one in six people worldwide will be aged 60 years or over, with the population of older adults increasing from 1 billion in 2020 to 1.4 billion [1]. This trend is expected to continue, with the global population of those aged 60 years and older doubling to 2.1 billion by 2050 [1]. Moreover, the number of individuals aged 80 years and older is anticipated to triple between 2020 and 2050, reaching 426 million [1]. Such demographic shift presents profound challenges for healthcare systems, demanding transformative approaches to manage the increasing burden of chronic diseases, long-term care, and geriatric care [258]. The strain on healthcare resources necessitates innovative strategies, including a holistic, personalized approach to healthcare, emphasizing preventive measures, adaptive care models, and innovative technologies to meet older adults' diverse and evolving health needs [258]. Overcoming these challenges demands a paradigm shift in healthcare policies, infrastructure, and delivery systems to ensure comprehensive, efficient, and sustainable healthcare for an ageing population [258][259][260][261]. These challenges underscore the need for innovative healthcare monitoring solutions that facilitate aging in place [258][259][260][261]. The importance of indoor human activity recognition (HAR) lies at the intersection of technological innovation and the enhancement of individual well-being [24][260][261][262]. In an era where intelligent environments are increasingly integrated into daily life, the ability to accurately and non-intrusively recognize human activities within indoor spaces holds considerable significance [24][260][261][262]. This capability offers multifaceted advantages, ranging from optimizing home automation systems to facilitating personalized healthcare monitoring for the aging population [24][260][261][262]. By utilizing advanced sensing technologies and artificial intelligence, indoor HAR contributes to creating intelligent living spaces that adapt to older adults' needs and preferences [24][260][261][262]. Additionally, it plays a pivotal role in healthcare, providing valuable insights into daily routines, detecting anomalies, and offering a non-intrusive means of assessing overall well-being. As we progress towards a more interconnected and technologically driven world, indoor HAR becomes paramount in fostering convenience, safety, and improved quality of life [24][260][261][262].

Traditional indoor healthcare solutions, such as the application of wearable devices for HAR, have gained prominence for their potential in monitoring individuals' daily activities [263][264][265][266][267][268]. Wearables, ranging from fitness trackers to smartwatches, are portable and convenient for collecting valuable data on movement, heart rate, and other vital signs [263][264][265][266][267][268]. However, these solutions have their weaknesses. Wearable devices heavily rely on user compliance, and consistent wear patterns or device removal can result in complete or accurate data collection [263]. Moreover, the discomfort associated with continuous wear may lead to user reluctance and impact the overall effectiveness of these solutions [263]. These devices also primarily track data related to the individual's activities and physiological states, often overlooking the context in which these activities occur [263]. This oversight is critical because the environment plays a significant role in health and well-being, influencing everything from

physical activity levels to mental health status. By focusing predominantly on individual metrics, wearable sensors may not capture the full picture of an individual's health needs and capacities, especially in the context of their unique living environments [263]. These weaknesses underscore the need for alternative and more comprehensive approaches to indoor healthcare solutions that address these limitations for a more holistic understanding of human activity [24][263].

Ambient Assisted Living (AAL) technology, in contrast, offers a more non-intrusive approach to monitoring and supporting the health and independence of older adults [24][76]. This technology encompasses systems and devices integrated into the environment, such as motion sensors, contact sensors, and smart home devices, which can passively and continuously collect data on an individual's activities via their interactions with their environment [24][76]. In AAL systems, the data collected by ambient sensors is processed using machine learning algorithms, designed to sift through the data, extracting and learning from patterns associated with various activities of daily living (ADLs) [24][76]. By identifying these patterns, the system can distinguish between different activities, such as cooking, sleeping, or walking. This process involves techniques such as feature extraction, where specific characteristics of the data are identified as relevant to certain activities, and classification, where these features are used to categorize the activity type [24][76]. Through continuous learning and adaptation, these machine learning models become increasingly adept at recognizing a wide array of human activities within diverse environmental contexts, thus facilitating accurate and responsive AAL systems [24][76]. This approach allows for the recognition of daily living activities in a more comprehensive manner, considering not just the individual's actions but also the context in which these actions take place, all while eliminating the need for active user engagement and compliance, operating unobtrusively and without causing discomfort to older adults [24][76][263].

AAL technologies have demonstrated significant benefits in enhancing the independence and well-being of older adults, contributing to a more sustainable healthcare system. For instance, an IoT-aware AAL system implemented by Mainetti et al. [298] for older population care showed promise in emergency response and health monitoring, providing timely alerts and remote monitoring capabilities that enhance the safety and health management of older adults. A study [299] conducted under the UK Department of Health's Whole System Demonstrator program highlighted benefits of AAL technologies, including a 15% decrease in accident-related hospital visits, a 14% reduction in hospital bed days, a 20% drop in emergency admissions, and an impressive 45% decrease in mortality rates. Similarly, the Veterans Health Administration in the US implemented a nationwide home telehealth program [300] which, upon analysis of quality and performance from 17025 patients, revealed a 25% decrease in bed days of care, a 19% reduction in hospital admissions, and an average satisfaction score of 86% post-enrollment [300]. The economic impact of AAL technologies in healthcare is potentially substantial, though concrete evidence on their current financial effects remains limited because AAL is still emerging and requires time for widespread adoption to demonstrate full economic benefits. However,

early evidence from passive monitoring systems, which are considered the first generation of AAL technologies, provides insights into AAL's economic impact [303]. For instance, a six-month home telemonitoring program [304] for chronic obstructive pulmonary disease patients resulted in savings of \$343 per patient. Similarly, a telecare system [305] for diabetes patients showed savings of \$1065 per patient per year. In addition to these early findings, projected economic impacts for AAL technologies are also promising. According to recent projections, passive monitoring technologies could save approximately \$425 per member per month compared to standard care, leading to annual savings of \$5069 per person and over \$5.1 million for a group of 1000 individuals [303]. Furthermore, a report by Lewin [301] suggests that the cost of equipping a smart home for assisted living could decrease from \$2500 to \$250 by 2030, making these technologies more accessible and economically viable for a broader population. Additionally, older adults have shown enhanced user satisfaction and increased adoption to AAL technologies, as evidenced by a survey conducted in the study [302].

Ultimately, the HAR capabilities of AAL technology play a crucial role in the early detection of anomalies in daily activities [24][76][269]. This early detection system is instrumental in identifying potential health issues before they escalate into more serious conditions [24][76][269]. By leveraging this technology to monitor deviations from normal activity patterns, AAL systems can promptly alert healthcare providers or family members, facilitating timely intervention [24][76][269]. Such an approach not only enhances the well-being and safety of older adults but also contributes to a more sustainable healthcare system by potentially reducing the need for emergency medical services and hospital admissions [24][76][259][269]. Furthermore, by providing a framework for remote monitoring, AAL technologies enable older adults to maintain their independence and age in place, reducing reliance on physical human assistance [24][76][259][269]. This not only helps to preserve the dignity and quality of life of the elderly but also alleviates the growing pressure on caregiving services [24][76][259][269]. As such, AAL technologies emerge as pivotal components in the evolution of indoor healthcare monitoring, offering a comprehensive solution that addresses the multifaceted challenges associated with an aging population [24][76][259][269]. By promoting proactive health management and supporting the autonomy of older adults, AAL systems exemplify a forward-thinking approach to enhancing geriatric care and optimizing healthcare resources.

This research aims to explore the efficacy of AAL technology in HAR compared to wearable sensors and assessing the potential to enhance ambient sensor performance with wearable sensor data. The overall goal is to advance the understanding of HAR by leveraging different ambient sensor types, contributing to the ongoing evolution of technology in indoor healthcare monitoring to support an aging population.

7.2.3 Related works

Recent research has thoroughly investigated the use of AAL and wearable devices for the monitoring and recognition of human activities [260][283].

7.2.3.1 Applications of AAL sensors in activity recognition

Studies in this domain have explored various types of AAL sensors to accurately capture a wide range of activities. For example, the depth camera technology utilized by Yeung et al. [270], demonstrates a pioneering application in monitoring patient mobility within Intensive Care Unit settings. Through the development of a specialized convolutional neural network-based (CNN-based) computer vision algorithm, this technology has shown great promise in accurately detecting and classifying patient movements and interactions with healthcare personnel. The successful implementation of this approach highlights the potential of depth sensor-based systems in enhancing patient care, especially for activity movement detection. Similarly, Singh et al. [271] employed a comparable technique in their research, leveraging depth sensor technology to monitor hand hygiene practices in a hospital setting. By installing depth sensors across one hospital unit, the researchers developed a CNN model to detect hand hygiene dispenser usage with high accuracy. Their work further demonstrates the efficacy of such technologies in offering a continuous, objective activity monitoring system. Apart from depth camera technology, acoustic sensors are also widely used. Sim et al. [272] used acoustic sensors and proposed Reasoning By Similarity and Reasoning By Elimination strategies to accurately classify daily activities within smart home settings based on sound patterns. These AI algorithms, developed to mimic human cognitive processes, leverage sound-based activity recognition to distinguish between various household tasks such as eating, drinking, and utensil usage. This innovative approach offers a non-invasive method for ADL monitoring without relying on invasive monitoring techniques such as cameras.

However, the integration of camera-based and acoustic sensor technologies in real-world applications within the domain of smart environments and activity recognition raises significant privacy concerns [273]. As cameras can capture sensitive visual information and acoustic sensors can capture confidential conversation.

Other types of AAL sensors, such as environmental, electrical, and motion sensors, are frequently combined by researchers to enhance activity recognition systems without significantly impacting user privacy. Cook et al. [130] combined environmental sensors and motion sensors with machine learning algorithms to effectively differentiate between the activity patterns of older adults with normal functioning, those with Parkinson's disease, and those with mild cognitive impairment. This integrated approach, achieving up to 97% accuracy, illustrates the effective capability of such sensor-based systems to monitor and analyze the effects of various health conditions on daily living activities. Further, Delaine et al. [114] combined motion sensors and electrical sensors with a mathematical framework for a priori performance estimation, focusing on ADLs recognition through Activities–Actions–Events decomposition. This innovative approach, utilizing metrics such as participation counters and distinguishability, aims to enhance the precision of smart home ADL recognition systems. By predicting the effectiveness of sensor configurations in distinguishing between similar activities, their work lays the groundwork for optimizing smart home instrumentation, ensuring more accurate and efficient monitoring of resident behaviors.

Although these sensors provide valuable data such as indoor environment, energy usage, and resident movement, without directly capturing personal identifiable information or private conversations, they still face the limitation of requiring an optimized sensor network for effective deployment [274]. This optimization is crucial for balancing the comprehensiveness of monitoring with the practicality and cost-effectiveness of the sensor infrastructure, ensuring that the system is both sensitive to similar ADLs and scalable to different living environments.

7.2.3.2 Application of wearable sensors in activity recognition

Wearable device-based systems, utilizing technologies like fitness trackers, accelerometers, and heart rate monitors, have been widely adopted for their capability to recognize resident activities [268]. These systems have become particularly valuable in aging healthcare, where continuous health monitoring is crucial. For instance, Albargi et al. [157] proposed a BeautyNet framework, leveraging wrist-worn accelerometer data with an LSTM-autoencoder-based classifier, identifies various hand activities with high accuracy rates exceeding 90% in both controlled and uncontrolled settings. This method provides significant advancements in recognizing delicate hand movements. Furthermore, Ramos et al. [154] utilized wearable devices equipped with gyroscopes, accelerometers, and photoelectric sensors, alongside advanced deep learning models such as Recurrent Neural Networks, Long Short-Term Memory, and Gated Recurrent Unit models, to precisely recognize daily activities of residents in a smart home. This innovative integration achieves high accuracy rates for activity recognition, providing a comprehensive understanding of residents' habits, which is crucial for enhancing elderly care and lifestyle monitoring in smart living environments.

Additionally, wearable sensors can be effectively integrated with AAL sensors to enhance the recognition of ADLs. Nakagawa et al. [145] utilized smartwatch, smartphone, and indoor positioning ultrasonic sensors in combination with Random Forest classifiers to enhance ADLs recognition in smart homes. By incorporating acceleration data from wearable devices, they improved recognition accuracy by 12%. Their method addresses privacy concerns and broadens the range of recognizable activities, including cooking, sleeping, and dining, without intrusive monitoring, marking a significant advancement in real-time, efficient ADLs recognition technologies.

However, the requirement for persistent wearing and the relative intricacies of wearable devices can lead to considerable hindrance, resulting in diminished adherence and usability issues in older adults [275]. These challenges include physical discomfort, cognitive burden associated with device management, and potential technological intimidation, which may particularly affect this demographic. Moreover, beyond usability issues, the dependence on wearable devices for activity recognition in older adults faces additional limitations, including the need for frequent charging, which may be overlooked or found burdensome by some elderly individuals, leading to gaps in data collection [215]. Furthermore, the challenge of using wearable sensor systems to adapt to the varied behaviors and

environments of older people is significant. Such devices may not fulfill the diverse physical and health conditions within the elderly population, further complicating widespread adoption.

7.2.3.3 Comparison between AAL and wearables in activity recognition

We compare the use of AAL and wearable technologies in activity recognition, focusing on the aspects of activities tracked, deployment settings, recognition performance, and performance metrics.

The two types of sensors vary in their ability to detect different activities. Wearable sensors are highly effective in capturing metrics directly related to the user's physiological states or physical movements. For instance, these sensors are good at monitoring body posture-related activities, such as standing up, bending, or transitioning between positions, or detecting changes in physical parameters like heart rate, which are often critical for health and fitness applications [345]. Their close contact with the user ensures precise measurements of body-centric data, providing a high level of accuracy for individual-specific tasks. In contrast, AAL technologies are designed for passive and continuous monitoring within the environment, making them particularly suitable for capturing contextual and spatial activities [283]. For example, AAL sensors are good at recognizing stationary or environmental behaviors, such as monitoring room occupancy, detecting movement patterns within a space, or determining whether certain objects are in use [346].

Regarding the settings in which these technologies are deployed, AAL systems are typically integrated into homes where they offer continuous monitoring without disrupting daily life, ideal for passive observation of daily routines and emergency situations [283]. Wearables, however, offer the advantage of portability, functioning effectively both indoors and outdoors, which supports a broader range of activities including structured exercises and outdoor mobility [283][288].

In indoor environments, wearables often provide sufficient data to effectively recognize activities due to their direct contact with the user. This direct measurement offers advantages in terms of accuracy, user-friendliness, and non-intrusiveness [286]. However, challenges such as incorrect usage, comfort concerns, and maintenance issues like charging can compromise data quality. A hybrid approach combining both wearable and AAL technologies may mitigate these drawbacks by ensuring consistent data quality, even when the wearable is used incorrectly or forgotten [286].

Both technologies are evaluated using similar metrics due to the multi-class classification nature of human activity recognition tasks. Accuracy, precision, recall, and F1-score are commonly employed to assess how effectively AAL and wearable sensors identify and classify various activities. These metrics provide a comprehensive view of each technology's effectiveness in accurately monitoring the activities they are designed to track [285][287].

7.2.3.4 Current challenges

Despite the progress made in utilizing AAL and wearable sensors for activity recognition, several challenges remain. One of the primary concerns is the balance between accuracy and privacy, especially with AAL sensors that monitor individuals within their living spaces. As noted by [273], there is a need for systems that respect user privacy while still providing comprehensive monitoring. Wearable sensors, while offering detailed data, often face challenges related to user compliance, battery life, data incompleteness, and data overload [215], limiting their practicality for long-term monitoring. Additionally, both AAL and wearable sensor systems struggle with the adaptability to diverse user behaviors and environments, highlighting the need for more flexible and personalized approaches in sensor-based activity recognition.

In addition, there is considerable variation in the choice of sensor platforms (i.e., wearable or AAL) for indoor activity recognition across current studies [276]. Each type of sensor brings unique advantages to the specific activities they are able to monitor. This presents a complex decision-making process for researchers and practitioners aiming to implement effective and user-centric activity recognition solutions.

7.2.3.5 Contribution of the study

This study proposes an innovative contactless AAL solution for indoor activity recognition, utilizing machine learning methods. As a proof of concept, we demonstrate the viability of using AAL sensors to recognize daily activities in a controlled environment. We also conduct a comparison with wearable sensors to establish a baseline for performance. Furthermore, this research explores whether combining these two types of sensors can improve the recognition performance.

This study makes several key contributions:

- 1) It demonstrates the ability of AAL technology to achieve high accuracy in recognizing ADLs while maintaining privacy, as these AAL sensors are non-intrusive and do not collect sensitive information.
- 2) By embedding sensors into power outlets and switches, our solution can overcome the limitations associated with wearable sensors, particularly concerns related to battery life. This innovation ensures continuous operation without the risk of power failures.
- 3) The findings offer valuable insights into sensor selection, not only between wearable and AAL sensors, but also identifying the most impactful types of AAL sensors for indoor activity recognition.
- 4) This study serves as a proof of concept for using our AAL sensor solution to recognize daily activities in controlled settings, establishing a solid foundation for future work that can further evaluate the system's effectiveness in real-world environments.

7.2.3.6 Research questions

This study poses the following research questions:

- 1) How does the performance of activity recognition using ambient sensors compare to wearable sensors, and can integrating both sensor types enhance recognition accuracy?

- 2) How does spatial overlap of ADLs affect recognition performance with ambient sensors?
- 3) Which features related to AAL sensors contribute most significantly to the accuracy of activity recognition?

7.2.4 Methods

7.2.4.1 Materials

7.2.4.1.1 Devices

Ambient devices

In this research, our smart home setup integrates sensor technologies from Swidget Corporation. Unlike traditional smart home systems that rely on a central hub and connected devices, which can quickly become outdated due to rapid tech advances, the key feature of our smart home solution is the replacement of existing electrical outlets and light switches in the house with smart outlets and switches, equipped with smart hub function. At the same time, using separate, swappable inserts equipped with smart home sensors to add smart features.

Specifically, we have equipped our smart home environment with Swidget's intelligent outlets and switches. Additionally, we utilized three types of Swidget's sensor inserts to monitor indoor environmental conditions: one for air quality assessment, the second one for the concurrent measurement of temperature and humidity, and the third one for motion detection. The data frequency for all sensors is every 30 seconds. Their detailed features are shown in Table 14.

Table 14. AAL sensor information

Devices	Parameter information		Specification
Smart outlet	Usage log	Power consumption	Binary data (0/1) for usage log; Power consumption's unit is W (watt)
Smart switch	Usage log	Power consumption	Binary data (0/1) for usage log; Power consumption's unit is W (watt)
Air quality sensor	Air Quality Index (AQI)	eCO ₂	AQI index: 0-500; eCO ₂ : 400-6000ppm
	Air pressure	bVOCs	Air pressure: 300-1100hPa; bVOCs: 0-1000 ppb
Temperature & Humidity sensor	Indoor temperature		-10 °C – 40 °C
	Indoor humidity		0 - 100%
Motion sensor (passive infrared sensor)	Motion occupancy		3 meters range; 120 degrees

The choice of sensors used in this study was guided by a prior scoping review conducted by Wang et al. [283]. This review identified the types of sensors most commonly used in

AAL applications for ADLs recognition. Specifically, the review highlighted occupancy sensors, environmental sensors, and power sensors as being the most effective for activity recognition in smart home environments. These sensors were selected not only because they are widely deployed and proven to be effective in tracking movement, environmental conditions, and device usage, but also because they provide a well-balanced approach to achieving comprehensive insights into daily activities.

Wearable device

In this research, we aim to evaluate the effectiveness of contactless smart home sensors in identifying daily living activities and to compare this capability with that of wearable sensors. Another goal is to determine if smart home sensors can mitigate the inconvenience associated with continuous wear of wearable devices. To ensure a robust comparison, we chose the Empatica E4 wearable sensor as a benchmark. There are 4 sensors that embedded in Empatica E4, they are 3-axis accelerometer, Photoplethysmography (PPG), Electrodermal Activity Sensor (EDA), and Infrared Thermopile. Their detailed features are shown in the Table 15.

The Empatica E4 is a medically certified device capable of recording various physiological signals, and it has gathered recognition in numerous applications. Multiple studies have attested to its accuracy and reliability in activity recognition, leveraging both its raw accelerometer motion data and integrated physiological features [277]. When combining with advanced machine learning algorithms, the Empatica E4 can offer even more precise insights into a user's range of activities [278].

These advancements emphasize the device's reliability for using it as a benchmark for activity recognition.

Table 15. Empatica sensor features

Sensor	Data	Unit	Frequency	Function
3-axis accelerometer	Accelerometer from X, Y, Z axis	1/64g	32 Hz	Capture motion activity
PPG	Heart rate	beat/minute	1 Hz	Capture cardiovascular features
	Blood Volume Pulse	μV	64 Hz	
	Interbeat Interval	N/A	N/A	
EDA	EDA data	Microsiemens (μS)	4 Hz	Derive features related to emotion, stress, and excitement
Infrared Thermopile	Skin temperature	Celsius	4 HZ	Capture skin temperature

7.2.4.1.2 AAL environment

An apartment within the Research Institution for Aging located in Waterloo was outfitted to serve as a smart home setting, as depicted in Figure 26. This particular unit includes basic living spaces such as a bedroom, bathroom, living room, and kitchen, all furnished adequately to meet the everyday needs of its residents.

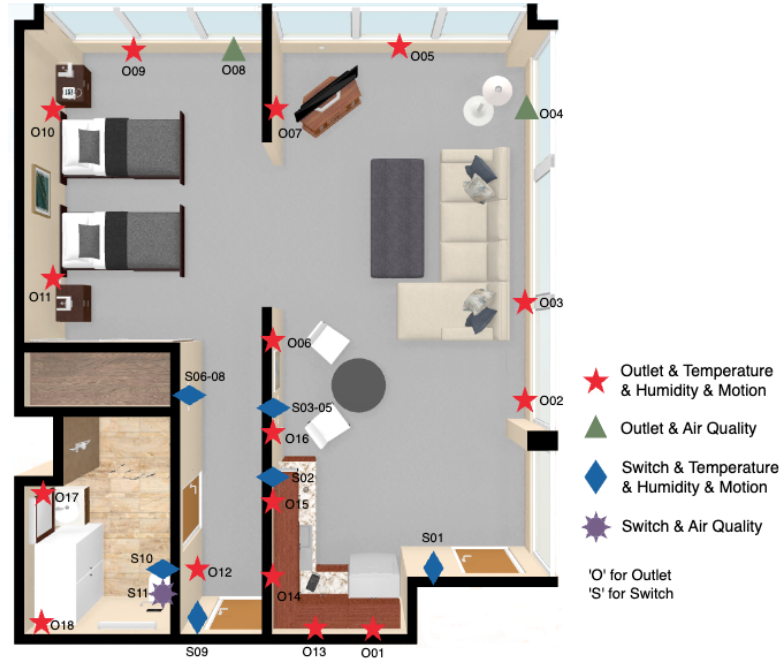


Figure 26. AAL environment

Constructing this smart home involved setting up an environment enriched with necessary smart home sensors, aiming to maximize data capture from daily activities. Specifically, we replaced the standard switches and outlets throughout the apartment with Swidget's smart outlets and switches, which provided us with the necessary infrastructure to host a variety of insert sensors. The selection of specific insert sensors was strategically tailored to the unique characteristics of each space and the activities typically performed therein. The strategic selection of sensor types to be paired with these hubs was influenced by both unique characteristics of each space and the activities typically performed therein. For example, we installed a higher concentration of temperature and humidity sensors in the kitchen to capture the environmental fluctuations, especially those induced by cooking activities that can easily affect temperature and humidity. The living room and bathroom were each equipped with an air quality sensor, chosen for their high occupancy and potential exposure to moisture and chemical emissions, respectively. Motion sensors were attached to each smart outlet and switch to provide extensive activity detection coverage across the apartment. This deployment approach resulted in a robust sensor network comprising 17 smart outlets, 6 smart switches, 23 motion sensors, 23 temperature and humidity sensors, and 2 air quality sensors.

7.2.4.2 Activities of Daily Living

The proficiency of elderly individuals in executing ADLs serves as a critical measure of their self-sufficiency and functional independence. The ADLs used in this study are described in Table 3. In adherence to the methodologies outlined in [248], our creation of

ADL scripts concentrated on five distinct categories: foundational familiarization activities, posture adaptation activities, movement integration activities, basic ADLs (BADLs), and instrumental ADLs (IADLs). These scripts encompass the variety of activities within an individual's daily space, thus providing a comprehensive simulation of daily activity patterns. Each ADL category is designed to challenge specific cognitive and physical abilities, ensuring a broad representation of daily life activities. For each category, we have defined four to five scenarios to represent these ADLs.

Specifically, phase 1 aims to introduce basic tasks and acclimatizing participants to experimental test bed. For phase 2, the emphasis is on performing tasks that require changes in posture and body positioning, with a specific focus on how one adapts their body to comfortably complete various tasks. Phase 3 incorporates tasks that necessitate more significant movement around the home. It stresses the integration of movement with daily activities, enhancing mobility and functional reach. Phase 4 is centered on BADLs that are crucial for independence, such as cleaning and meal preparation. Lastly, phase 5 focuses on IADLs, which represent more complex activities that are vital for living independently but are not necessarily related to basic self-care. Refer to Table 16 for specific details of each scenario of each phase.

Table 16. ADLs performed by participants

Categories	Name of Scenarios	Description
Phase 1 - foundational familiarization	Scenario 1 - "Arriving home"	Participant opens the door from outside using their key, locks the door from inside, and turns on switch 01 to illuminate the space. They proceed to the bathroom, turn on switch 10, and wash their hands with soap for 30 seconds before rinsing. After turning off the faucet and drying hands, they turn off the light (switch 10) and exit, closing the door behind them. They head back to the living room, turn on the living room lamp, retrieve the remote from drawer 4, and turn on the TV. After placing the remote back into drawer 4 and closing it, they pick a teacup and a glass. Sitting on the couch, they mimic drinking for 1 minute before placing the teacup on the glass table. They then wait seated on the couch for 1 minute as a transition.
	Scenario 2 - "Eating dinner"	Participant retrieves a bowl of food from the middle shelf of the fridge, opens the microwave, and places the bowl of food inside. They set the microwave for 30 seconds and wait. Once the microwave finishes, they close it, retrieve a fork/spoon from drawer 2, and walk towards the dining room. They pull the chair from the dining table closer to the couch, sit,

		and mimic eating for 2 minutes. Afterwards, they stand up, push the chair back, and return the bowl into the fridge. The transition involves sitting on another chair for 1 minute.
	Scenario 3 - “Sleep preparation and sleep”	Participant enters the bathroom, turns on switch 9, which is outside the bathroom. They then turn on switch 10, closing the door behind themselves. They pick up a toothbrush, apply toothpaste, and mimic brushing teeth for 1 minute before rinsing and washing the toothbrush. They then wash their face for 30 seconds, dry it with a paper towel, and step onto the weighing scale before stepping off and turning off switches 9 and 10. They enter the bedroom, walk towards the bed, turn off the bedroom lamp, and lie on the bed in a simulated sleep position for 5 minutes. The transition allows them to use their phone if they wish, for 1 extra minute before sleep.
	Scenario 4 - “Cooking”	Participant enters the kitchen and turns on switch 02. They retrieve a vegetable (potato) from the fridge's first shelf, open the faucet to wash the vegetable, then close the faucet. They dry the vegetable with a paper towel, dispose of the towel in garbage bin in Cabinet 10, and then get a knife from drawer 2. They cut the vegetable on a cutting board from drawer 3 for 30 seconds, place the slices on a pan, and season them with salt and pepper from cabinet 3. After cooking (2 minutes), they wash the knife, board, and other utensils in the sink and dry them, putting everything back into their respective drawers and cabinets. They remain where they are for a 1-minute transition.
	Scenario 5 - “Going out”	Participant enters the bedroom, opens the closet, and mimics the process of getting dressed by sequentially putting on a shirt, pants, belt, and jacket. They close the closet, enter the bathroom, turn on the light switch 10, and mimic styling hair for 30 seconds, followed by applying makeup/moisturizer/sunscreen for 1 minute. Exiting the bathroom, they close the door behind them, enter the living room, retrieve the remote from drawer 4, and turn off the TV. They also turn off the living room lamp and switch 02, place the

		remote back into drawer 4, and transition by standing by the door for 1 minute.
Phase 2 - posture adaptation	Scenario 1 - "Reading on the sofa"	Participant picks up a magazine from the glass table and sits on the sofa in the living room to read for 3 minutes. They change postures while sitting; at 45 seconds, they lean on the sofa arm, at 1 minute 30 seconds lean forward on knees, and at 2 minutes lean backwards. After reading, they put the magazine back on the glass table, adjust to lay down on the sofa, shifting around for 1 minute, changing sides, sit up, and place feet onto and off the ottoman for 30 seconds. Transition includes sitting on the couch for an additional minute.
	Scenario 2 - "Completing a puzzle"	Participant retrieves a puzzle from cabinet 14, which is designated as the TV rack, and ensures the cabinet door is securely closed afterward. They then proceed into the dining room, where they illuminate the space by activating switch 05. A dining room chair, positioned closest to the couch, is pulled out to be used. The participant takes a moment to sit still on the chair for one minute, possibly to prepare mentally for the task ahead. The puzzle-solving process begins shortly thereafter, with the participant adjusting their posture at various intervals: leaning forward at the 45-second mark and leaning backward at 1 minute and 15 seconds, all the while making adjustments to their legs for added comfort. This routine is maintained for a total of 2 minutes. During this period, a puzzle piece is accidentally dropped but promptly retrieved by the participant. Upon completion of the puzzle activity, the pieces are methodically returned to their box. The participant stands, tucks the chair back into its original position, and turns off switch 05, reverting the dining room to its initial state. The puzzle box is then placed back into cabinet 14. The activity concludes with the participant transitioning to the living area, where they take a moment to sit on the couch for one minute, marking the end of the sequence.
	Scenario 3 - "Meal preparation"	Participant enters the kitchen and turns on switches 01 and 02. They collect ingredients for a meal (pepper, mushroom) from the fridge and gather utensils: a bowl from cabinet 4, a knife from drawer

		2, and a cutting board from drawer 3. They cut vegetables for 2 minutes, changing postures once 1 minute has passed, asking a participant to drop a piece of pepper on the ground, and pick it up and place in the garbage (cabinet 10). Vegetables are placed in a bowl, and any remnants back into the fridge. They get a pan from cabinet 8, spatula from drawer 1, and cook the ingredients on a pretend stove, shifting weight between feet for 1 minute while cooking. The cooked vegetables are transferred into a bowl, and dirty dishes are placed into the sink. The participant dries dishes, puts away clean dishes, cutting board, and utensils back into their respective places. Transition includes staying by the door for 1 minute.
	Scenario 4 - “Reading in the bedroom”	Participant enters the bedroom, retrieves a magazine from drawer 5, turns on the bedside lamp, and sits down on the bed. They place a pillow against the wall for support to sit up on the bed and read the book for 2 minutes, adjusting positions while seated for comfort. Then they lie down on the bed to read, marking positions (45 seconds mark lay on your back, at 1:30 minutes on the stomach). After reading, they put the magazine back into drawer 5, unplug the phone from the charger, and turn off the bedside lamp. Transition includes standing up in the bedroom for 1 minute.
	Scenario 5 - “Bathroom job”	Participant enters the bathroom, turns on switches 9 and 10, closes the bathroom door, lifts the toilet lid, sits on the toilet for 2 minutes, and flushes. They step into the shower area, mimic showering actions for 2 minutes like washing arms, legs or shaving. After stepping out, they mimic drying the body with a towel for 30 seconds. They turn off switch 10, exit the bathroom, close the door behind them, and turn off switch 9. Transition includes waiting in the hallway for 1 minute.
Phase 3 - movement integration	Scenario 1 - “Waking up & morning exercise”	Participant starts lying on the bed and changes postures while lying on the bed before sitting on the bed side. They turn on the bedroom lamp, walk out of the bedroom, walk to the living room, and turn on the TV using the remote from drawer 4, which they return after use. The participant then jogs

		around the living room for 1 minute. The transition includes sitting on the couch for 1 minute.
	Scenario 2 - “Taking a shower”	Participant walks towards the bathroom, turns on switch 09, enters, and closes the door behind them. They turn on the bathroom light with switch 10 and step into the shower area, mimicking the act of turning on the faucet while facing the faucet, turning back to the faucet, and mimicking washing arms and legs for 2 minutes. They turn off the faucet, get out of the shower with a towel, dry off, turn off the bathroom lights with switches 09 and 10, exit the bathroom, and close the door. Transition involves waiting in the hallway for 1 minute.
	Scenario 3 - “Tidying”	Participant walks to the living room, retrieves a crumpled paper from the TV rack, turns on switch 01 in the kitchen, and throws the paper into the trash in cabinet 10. They obtain a broom beside a table, sweep in front of the cabinet area for 1 minute, return the broom beside the table, and turn off switch 01. They walk back to the dining room and pull the chair (the one closest to the couch) back into position. Transition includes sitting on the chair for 1 minute.
	Scenario 4 - “Going to sleep”	Participant sits on the sofa for 1 minute, stands from their sitting position, walks around the living room for 1 minute, grabs the remote from drawer 4, turns off the TV, returns the remote, and turns off the living room lamp. They walk to the bedroom, walk to the bed side, turn off the bedroom lamp, close the blinds, sit on the bed, lie on the bed, and change positions on the bed for 3 minutes. Transition involves staying still in bed for 1 more minute.
Phase 4 - BADLs	Scenario 1 - “Cleaning rooms”	Participant enters the living room, turns on switches 03 and 04, removes pillows from couch and vacuum (beside the TV) into outlet and on. They vacuum the sofa and floor for 1 minute, turn off the vacuum, unplug, and organize the pillows onto the couch. Switches 03 and 04 are then turned off. The transition involves sitting on the couch for 1 minute.
	Scenario 2 - “Meal-time”	Participant enters the kitchen and turns on switches 02 and 01, gets a plate of food in the fridge (continues from phase 1) and places the bowl from

		the cabinet 4 and plate on the counter. They grab a spoon from drawer 2 and transfer the food from the plate to the bowl using the spoon, then take the bowl of food and spoon and place it on the dining table. They turn on switch 05, pull out the chair closest to the couch, sit, and mimic eating for 2 minutes, get up from chair and tuck it in. The spoon and plate are placed into the garbage (or empty into the garbage) and the bowl back into the fridge. Switches 01, 02, and 05 are turned off. The transition is to stay where you are for 1 minute.
	Scenario 3 - “Changing footwear”	Participant enters the bedroom, turns on the light 06, walks over to drawer 7 and pretends to grab a new pair of socks, removes shoes from feet, sits on the bed, and removes socks on feet. They then change into a new pair of socks, put shoes back onto feet, and turn off switches 06 and 07. Transition includes staying in the bedroom for 1 minute.
	Scenario 4 - “Bathroom visit”	Participant walks towards the bathroom, turns on switch 9, enters the bathroom, and turns on switch 10, closes the door behind. They lift the toilet lid, sit on the toilet for 2 minutes, stand up from the toilet and flush. Walking to the sink, they turn on the faucet, wash hands for 30 seconds, turn off the faucet and dry hands using paper towel, dispose of the paper towel when done. They then turn off switch 10 and leave the bathroom, closing the door behind, and turn off switch 9. Transition involves waiting in the hallway for 1 minute.
Phase 5 - IADLs	Scenario 1 - “Arriving home and organizing groceries”	Participant stands outside the apartment for 1 minute with a grocery bag in hand, then enters, closes the door behind them, and turns on switch 01. They walk to the kitchen, place the grocery bag on the kitchen floor, and unload groceries, placing them into the fridge, cupboard, or cabinets for 2 minutes. Once done, grocery bags are placed in cabinet 09. Transition includes waiting in front of the fridge for 1 minute.
	Scenario 2 - “Cleaning kitchen”	Participant washes dishes until they are clean, returns bowl and spoon to cabinet 4 and drawer 2 respectively. They sweep the kitchen floor for 1 minute, put broom back into place, get the vacuum cleaner, and vacuum for 1 minute, then put the

		vacuum cleaner back. They get a mop, mop the kitchen for 1 minute, and return the mop to its place. The participant then grabs a kitchen cloth, wipes down the counter area for 1 minute, and sits on the chair closest to the kitchen for the transition time of 1 minute.
	Scenario 3 - “Emptying garbage”	Participant opens cabinet 10, picks up the garbage bag, closes the door, and leaves the bag outside. They then replace the garbage bag with a new one, close the cabinet door, and wash hands using soap. After drying hands with paper towel, they dispose of the towel in the garbage bin in cabinet 10. Transition includes waiting in the kitchen for 1 minute.
	Scenario 4 - “Morning routine”	Participant walks towards the bathroom, turns on switch 09, enters the bathroom, turns on switch 10, closes the door behind them, and puts toothpaste onto toothbrush. They brush teeth for 1 minute, rinse brush, wash face for 30 seconds, turn off faucet, and dry hands and face with paper towel before disposing of it. They comb hair/apply makeup for 1 minute, step onto the weighing scale, then off again. The participant turns off switches 10 and 09 and waits in the hallway for 1 minute as a transition.
	Scenario 5 - “Wrap up things for going out”	Participant turns on bedroom lamp, ensures all items needed are gathered, and walks around the house as if collecting things. They turn off all switches that are on, turn off the lamps if they are on, and leave the apartment, closing the door behind them.

7.2.4.3 Study trial

7.2.4.3.1 Participants

The study was conducted during the constraints of the COVID-19 pandemic. We initially aimed at older adults. However, adjustments in participant recruitment strategies were necessary due to restricted access to older adults either in public or in long-term care residences. This measure was crucial to protect this vulnerable group and minimize the spread of infection. Consequently, an alternative sampling method was employed. We engaged adult students from the University of Waterloo to participate in the study by distributing flyers across the campus and leveraging the university's internal participants pool.

This decision raised ethical considerations, but they are justified on several reasons. Primarily, the use of adult students significantly reduced the risk to older adults, who are notably more vulnerable to severe outcomes from COVID-19. Maintaining the continuity of research during the pandemic was crucial, and with stringent public health restrictions preventing access to older populations, adult students provided a viable alternative that allowed scientific inquiry to proceed. This shift was ethically approved by the University of Waterloo's Research Ethics Office under the reference number ORE #43843, ensuring that all research activities conformed to high ethical standards. Adult students are capable of providing informed consent and fully understanding the risks and benefits involved in their participation, which supports the ethical integrity of their inclusion. While there are differences between the behaviors of older adults and younger individuals, the preliminary data collected from adult students can still offer valuable insights into the usability and effectiveness of the technologies being tested. Additionally, all necessary measures were taken to mitigate health risks to these participants, including health screenings, social distancing measures, and psychological support, aligning with the most stringent public health guidelines to ensure their safety during the study.

During the recruitment, a preliminary screening, facilitated by a detailed questionnaire, was implemented to determine their ability to independently perform ADLs—a prerequisite for inclusion. In the questionnaire, we listed questions to determine their eligibility based on specific inclusion and exclusion criteria. The inclusion criteria focused on the ability to perform ADLs independently, the absence of any conditions that could hinder mobility, and the willingness to adhere to study protocols. Participants also needed to demonstrate the ability to understand and follow instructions. The exclusion criteria included any inability to comply with study protocols, including COVID-19 safety measures. Following this initial screening, our study's cohort was established, consisting of 40 individuals: 17 men and 23 women, with an age distribution of 18 to 39 years and a mean age of 24 years. In order to ensure privacy, all personal data were anonymized. To address the age-related bias inherent in our younger cohort, participants were instructed to adapt their activity pace to reflect a range of behaviors observed among older adults. This adaptation included simulating scenarios where an older adult might have a reduced pace in completing tasks, instead of assuming a uniform slowdown among all activities and participants. We acknowledge this simulation can still cause bias. Simulating such behaviors may lead to psychological impacts, including increased stress or a temporary reduction in self-efficacy, as participants adapt to the restricted activity levels typical of older adults. Furthermore, physically mimicking aging-related conditions might result in unnatural body mechanics, potentially causing discomfort or strain. From a data integrity perspective, these simulations could introduce biases, as younger participants might not accurately represent the variability and complexity of older adult behaviors. Ethically, we ensure that all simulations are performed with the utmost respect for both the participants and the conditions being emulated, and participants are fully briefed on their roles, with psychological support provided to address any adverse effects. Continuous monitoring during the study helps mitigate any physical or emotional consequences, ensuring that the research remains both ethical and scientifically valid.

This research ethical ramifications were acceptable based on the rationale that collecting data from young adults could still yield insights into the validity of the daily activity recognition algorithms being tested. Additionally, this setup provides an opportunity to compare algorithm performance across different age groups, potentially offering broader applicability and understanding of the technology's effectiveness.

7.2.4.3.2 Procedure and data collection

Before initiating the experimental procedures, participants were required to provide written consent and complete a demographic survey. They were then introduced to the smart home environment, familiarized with its sensor-equipped appliances, spaces, and furniture. In addition, Empatica E4 was worn by participants on their preferred wrist to collect continual physiological data while they performed ADLs.

During the experiment, the participants' activities were monitored via cameras from a separate observation room, with activity instructions were delivered via a phone. The sequence of activities was carefully planned and corresponding to the phases and scenarios. Participants proceeded without additional guidance unless explicitly requested. A one-minute intermission was allowed between scenarios for the purpose of resetting sensors. An observer documented the start and end times of each activity, noting these on a log sheet to aid in data annotation and labeling. Sessions were conducted individually, with each scenario lasts around five minutes and the whole duration is approximate two hours.

Data from ambient devices were collected through the UbiEco cloud-based big data pipeline [279]. Specifically, raw sensor data was acquired through the manufacturer's Application Programming Interface (API) channel, followed by re-formatting and secure storage within an Azure cloud MySQL database. Data from the wearable sensors were collected via the Empatica Manager application, which enables the extraction of raw Empatica E4 data into CSV files.

7.2.4.3.3 Data cleaning and pre-processing

Prior to analysis, all data collected from ambient sensors and wearable devices was rigorously cleaned and pre-processed to ensure its reliability and validity. It is important to clarify that these devices do not perform any data processing, standardization, or cleaning tasks themselves; they solely function as data collection tools. We acquire raw data from these devices through the manufacturer's API, and all subsequent data processing steps are conducted locally on our servers. The details of the data attributes are presented in Tables 1 and 2.

Our dataset primarily consisted of numeric data, such as temperature and humidity levels from ambient sensors, alongside data from wearable devices, and binary data representing occupancy information.

To facilitate comparison and integration of data from various sources, we standardized the measurement scales and formats. For example, temperature readings from different sensors

were unified to the same scale (e.g., degrees Celsius). We also synchronized timestamps across different sensors to ensure temporal alignment, maintaining consistent data granularity across measurements from each sensor type.

For numeric data, outliers were identified and removed using z-scores, which helped eliminate data points that deviated significantly from the majority, ensuring the robustness of our dataset. For binary data, we used contextual analysis and logical checks to detect anomalies. Contextual analysis helped flag unrealistic rapid state changes, while logical checks uncovered inconsistencies, such as contradictory occupancy states during non-operational hours or discrepancies across logically related sensors.

Missing values in numeric data were imputed using the mean of the available data points at the same attribute, offering a straightforward yet effective approach to maintain continuity in time series data. For binary data, we utilized a logical imputation method based on the mode or the most frequent value, thereby preserving the binary nature of the data.

Given the placement of multiple temperature and humidity sensors within the same room, we observed high correlations between these readings. To address this redundancy and reduce data complexity, we unified the temperature and humidity readings from multiple sensors within the same room by calculating the mean of all sensor readings, thereby creating a single representative value for each environmental parameter per room.

7.2.4.4 Flexible window mapping for sensor fusion

In the data analysis phase, we internally fused data from AAL sensors and wearable sensors, respectively. We also integrated these two heterogeneous sensors together to explore the performance of hybrid data on activity recognition tasks. Current studies on sensor fusion typically concentrate on data integration within homogeneous sensor environments, either focusing solely on AAL technologies or on wearable sensors. However, this may not be suitable for our situation that involves heterogeneous sensors. In this paper, inspired by the concept of flexible window techniques [292], we here propose an innovative flexible window mapping method that allows for the temporal alignment of heterogeneous sensors with differing frequencies. This method dynamically adjusts the time windows for data aggregation from each sensor, ensuring that corresponding data points are accurately aligned.

The rationale for using the flexible window mapping method extends to its adaptability to diverse data rates from ambient and wearable sensors, which enhances the quality of data integration by allowing precise control over window sizes and shifts according to the specific characteristics of the data [289]. This adaptability is crucial for maintaining data fidelity, particularly in environments where timing and sequence of events are critical for accurate analysis. Moreover, by enabling a more accurate alignment of data from different sensors, this method enhances the overall quality of the integrated dataset. Better alignment leads to more reliable analysis outcomes, as the data more accurately reflects the

synchronized activities and environmental conditions recorded by the diverse sensor systems [290]. Furthermore, accurate temporal alignment is critical for the validity of any subsequent analyses performed on the fused dataset. Misalignments can mislead findings, particularly in activity recognition studies where timing and sequence of events are crucial [291]. Lastly, designed to be scalable and flexible, this approach can be adjusted for different experimental needs and is applicable across various research contexts involving multiple sensor systems.

Let us define a set $W = \{w_1, w_2, w_3, \dots, w_n\}$ where each w_i represents a dynamic flexible window designed to map data attributes from both ambient and wearable sensors onto a unified temporal scale. The cardinality of the set N , corresponds to the number of data attributes we aim to synchronize. For each window w_i , it encompasses a subset of data points, represented by $X = \{x_1, x_2, x_3, \dots, x_{s_i}\}$, where each x_j corresponds to a data value within the time frame defined by w_i , and s_i is the size of window, which is determined by a function $f(f_i, t)$ that takes into account the frequency f_i (Hz) of the data attribute it maps and a targeted time unit t (seconds) for analysis, defined as:

$$s_i = f(f_i, t) = f_i \times t$$

This function ensures that each window w_i contains an integer number of data points corresponding to the least common multiple of the sampling rates involved, adjusted to the temporal resolution t .

The time frame T is defined as a set of discrete time units $T = \{t_1, t_2, t_3, \dots, t_m\}$ where t_j corresponds to the j -th time unit for which data alignment is required. Within each window w_i , we collect the series of data values X , which are subject to analysis. The mapping of these values over the desired time frame T can be represented as:

$$M_i(T) = \{X \mid X = \{x_1(t_j), x_2(t_j), x_3(t_j), \dots, x_{s_i}(t_j)\}, \forall t_j \in T\}$$

Here, $x_k(t_j)$ is the k -th data value in window w_i for the j -th time unit t_j . The function $M_i(T)$ effectively aligns the various data points within the temporal scope of the study.

Once mapped, the feature extraction process is applied to the dataset within each window w_i , extracting feature information from the sequence of data points X . To progress through the dataset, window w_i slides to the next subset of data with a stride length l , which may vary depending on the desired overlap between consecutive windows:

$$w_i(n+1) = w_i(n) + l = w_i[a, a + s_i - 1] = w_i[a + l, a + s_i + l - 1]$$

Where $w_i(n)$ is current window and $w_i(n+1)$ is next step window. $w_i[a, a + s_i - 1]$ denote the start and end indices of current window. The stride length l can be adjusted to allow for the analysis of data with more granularity (with $l < s_i$ for overlapping windows) or with broader strokes (with $l = s_i$ for non-overlapping windows).

By adopting this flexible window mapping method, our study is equipped to handle and analyze data from sensors with varying frequencies, ensuring temporal alignment and enabling robust activity recognition across different sensor modalities.

7.2.4.5 Feature extraction

In this study, for combining the datasets, we standardized the data collection frequency by adopting the ambient sensors' 30-second sampling rate, the highest granularity among the sensors we evaluated. This decision was made to synchronize the datasets, thereby maintaining the ambient data's resolution while aligning the wearable sensor data accordingly.

For the features of ambient sensor data, we utilized the raw data attributes retrieved via API as features. We assigned each sensor with an ID. We employed the proposed flexible window mapping method for wearable sensor feature extraction and sensor fusion. Thus, some key parameters we chose when using this method are $t = 30s$, $l = s_i$ for non-overlapping, where s_i can be calculated using t and frequency (Hz) associate with each sensor. The Empatica E4 provides seven data attributes at varying frequencies. For each of these attributes, we independently align them to a 30-second granularity over seven windows, totaling $N = 7$ windows. Within each window, both features from time-domain and frequency-domain were extracted. Specifically, we obtained 15 time-domain features including mean, minimum, maximum, median, standard deviation, mean absolute deviation, median absolute deviation, interquartile range, counts above and below mean, energy, skewness, kurtosis, and signal magnitude area. After performing the Fourier Transform, we extracted additional 3 features including mean, max, and standard deviation from the frequency domain. These features can effectively capture various aspects of the data distribution and dynamics, revealing critical characteristics relevant to the monitored activities.

The label feature is associated with the ADLs. We assigned each ADL (Table 3) one of 23 unique scenario labels, such as P1S1 (stands for Phase1 Scenario1), to facilitate model predictions. These labels were annotated on the ambient data and the wearable data based on the activity logs recorded during the study sessions. A comprehensive table detailing these features can be found in Table 17.

Table 17. Features table

Category	Feature	Description
Ambient sensors	<i>Outlet_0_on_01-18</i>	18 features Binary data reflecting the on/off states of the upper ports as captured by outlet sensors designated as O01 to O18.
	<i>Outlet_1_on_01-18</i>	18 features Binary data reflecting the on/off states of the lower ports as captured by outlet sensors designated as O01 to O18.
	<i>Outlet_0_avg_01-18</i>	18 features Continuous data reflecting the energy usage of the upper ports as captured by outlet sensors designated as O01 to O18.

	<i>Outlet_1_avg_01-18</i>	18 features Continuous data reflecting the energy usage of the lower ports as captured by outlet sensors designated as O01 to O18.
	<i>switch_avg_S01-S11</i>	11 features Continuous reflecting the energy usage of switch sensors designated as S01 to S11.
	<i>living_temp</i>	10 features Measurement of temperature and humidity across five rooms.
	<i>living_humi</i>	
	<i>kitchen_temp</i>	
	<i>kitchen_humi</i>	
	<i>dining_temp</i>	
	<i>dining_humi</i>	
	<i>bedroom_temp</i>	
	<i>bedroom_humi</i>	
	<i>bathroom_temp</i>	
	<i>bathroom_humi</i>	
	<i>motion_01-23</i>	23 features Binary data reflecting the occupancy states from 23 passive infrared sensors.
	<i>aq_co2_O04</i>	9 features Measurement of air quality related parameters from 3 environmental sensors.
	<i>aq_iaq_O04</i>	
	<i>aq_tvoc_O04</i>	
	<i>aq_co2_O09</i>	
	<i>aq_iaq_O09</i>	
	<i>aq_tvoc_O09</i>	
	<i>aq_co2_S11</i>	
	<i>aq_iaq_S11</i>	
	<i>aq_tvoc_S11</i>	
Wearable sensors	<i>Mean</i>	Mean magnitude of the array, $\bar{x} = \frac{\sum x_j}{s_i}$
	<i>Min</i>	Minimum. The smallest value in the array, $\min(X)$
	<i>Max</i>	Maximum. The biggest value in the array, $\max(X)$
	<i>Median</i>	The median value in the array
	<i>SD</i>	Standard Deviation of the array, $\sigma = \sqrt{\frac{1}{s_i} \sum_{j=1}^{s_i} (x_j - \bar{x})^2}$
	<i>MeanAbsDev</i>	Mean Absolute Deviation, $\frac{1}{s_i} \sum_{j=1}^{s_i} x_j - \bar{x} $

	<i>MedAbsDev</i>	Median Absolute Deviation, $\frac{1}{s_i} \sum_{j=1}^{s_i} x_j - \text{median}(X) $
	<i>IQR</i>	Interquartile Range. $IQR = Q_3 - Q_1$
	<i>SamplesAboveMean</i>	Number of values above the mean
	<i>PositiveCount</i>	Number of positive values
	<i>NegativeCount</i>	Number of negative values
	<i>Energy</i>	Sum of the squared magnitudes of values $\sum_{j=1}^{s_i} x_j^2$
	<i>Skewness</i>	Asymmetry of values' distribution, $\frac{s_i}{(s_i-1)(s_i-2)} \sum_{j=1}^{s_i} \left(\frac{x_j - \bar{x}}{\sigma}\right)^3$
	<i>SMA</i>	Signal Magnitude Area. To measure the accumulated magnitude of values, $\frac{1}{s_i} \sum_{j=1}^{s_i} x_j $
	<i>Kurtosis</i>	Shape of the values' distribution, $\frac{1}{s_i} \sum_{j=1}^{s_i} \left(\frac{x_j - \bar{x}}{\sigma}\right)^4 - 3$
	<i>Mean_fft</i>	Mean magnitude after applying Fourier Transform on to the array
	<i>Max_fft</i>	Maximum after applying Fourier Transform on to the array
	<i>SD_fft</i>	Standard Deviation after applying Fourier Transform on to the array
Label	<i>Activity Label</i>	Label category that associated with each daily living activity, such as P1S1.

7.2.4.6 Data summary & analysis flow

After the data cleaning process and the exclusion of participants with incomplete records, the datasets from 28 participants were retained for analysis. On average, the ambient dataset for each participant contains approximately 270 data instances, cumulating in over 7532 instances for the entire dataset. The number of data instances of each activity label is shown in Figure 27. The wearable sensor dataset matches this granularity, and same for the combined dataset. Regarding dataset dimensionality, the ambient dataset contains 125 features, the wearable dataset has 126 features, and the combined dataset includes 251 features.

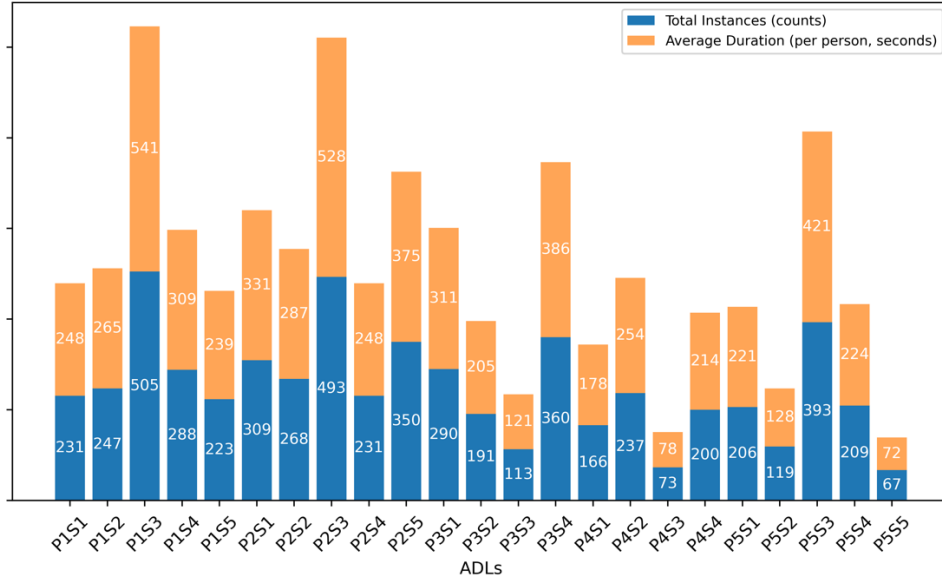


Figure 27. Number of data instances and average duration per ADL

In the data analysis phase, the modeling procedure for machine learning algorithms involves splitting the dataset into an 80:20 ratio, where 80% constitutes the training set and the remaining 20% serves as the testing set. Within the training set, a 5-folder cross validation approach was employed to optimize the model's configuration. To elaborate, this method involves dividing the entire training dataset into five distinct subsets. Each subset is used once as a validation set while the other four subsets form the training set. This process is repeated five times, with each of the five subsets used exactly once as the validation data. This method can enhance the robustness of the model evaluation process. It ensures that each segment of the dataset is used both for training and validation, which helps prevent model overfitting and provides a well-rounded assessment of performance across varied data. Furthermore, to fine-tune the model's hyperparameters, a grid search method was utilized. Once the optimal model with its best-performing set of hyperparameters was identified through cross-validation, it was then re-assessed on the testing set to determine the final performance metrics.

7.2.5 Results

7.2.5.1 Models & evaluation metrics

7.2.5.1.1 Model selection

In this study, we address the challenges of multi-class activity recognition within AAL environments, characterized by the complexity and multidimensionality of sensor data. Traditional statistical methods often struggle to effectively manage the volume and diversity of data, particularly when dealing with large, unstructured datasets and non-linear relationships between variables [284]. These methods are inadequate for adapting to the varied and dynamic nature of AAL data, making it difficult to classify activities accurately. In contrast, machine learning algorithms are good at these settings. Their inherent ability to reveal hidden patterns in complex data without requiring manual re-operation allows them to continuously improve and adapt as they process more information. This capability is critical in AAL environments, where the behavior patterns and activity levels of residents

can show considerable variability. Moreover, the use of machine learning in this context directly supports our research objectives of developing an efficient, reliable multi-class activity recognition system that can operate autonomously within the diverse ecosystem of an AAL environment.

Given this justification, we strategically selected five widely used machine learning models that are particularly suited for multi-class activity recognition within the context of AAL technology [283]. This selection was informed by their demonstrated effectiveness in similar applications, as highlighted by the review [283]. Each was selected for its unique strengths in addressing the challenges of activity recognition within AAL environments. These models are:

K-Nearest Neighbours (KNN) [293]: KNN was chosen for its robust capability in handling multi-class problems and its effectiveness in environments where relationships between data points are non-linear. This model is good at recognizing patterns based on similarity measures, which is particularly valuable in AAL settings where activities often differ only slightly from one another. KNN helps improve our understanding of how minor variations in activity data can be effectively captured and classified, advancing our scientific knowledge of behavior pattern recognition.

Decision Tree (DT) [294]: DT are beneficial for AAL applications as they provide clear criteria for activity classification, facilitating the understanding of what features are most influential in determining activity types. This is crucial for identifying specific activities that require particular interventions or monitoring. This model contributes significantly to the field by improving our understanding of feature relevance and decision-making processes in complex activity recognition scenarios.

Random Forest (RF) [295]: Random Forest enhances classification accuracy and robustness by aggregating the results of individual trees. This model addresses overfitting—a common issue in complex AAL datasets—and is good at managing datasets with numerous predictor variables. This capability makes it particularly well-suited for our dataset, which contains heterogeneous data. By effectively managing complex datasets and enhancing the accuracy of activity classification, Random Forest not only meets the operational demands of AAL environments but also provides insights into managing data complexity and variability.

Adaptive Boosting (AdaBoost) [296]: It is chosen for its ability to improve the accuracy of the classification by combining multiple weak classifiers into a strong classifier. AdaBoost is particularly effective in scenarios where there is an imbalance in the activity data. This model incrementally adjusts the focus on misclassified instances, making it ideal for improving activity recognition performance in AAL systems.

Gaussian Naive Bayes (GNB) [297]: It is employed for its efficiency and speed in making predictions. GNB assumes independence between predictors. It is particularly

advantageous in AAL settings where the calculation of probabilities for many classes (activities) is required. While GNB provides a baseline for performance comparison against more complex models, it also offers critical insights into the probabilistic relationships within AAL data, facilitating faster and more efficient activity classification.

7.2.5.2 Metrics selection

To assess the performance of the selected machine learning models, we employed four commonly used metrics in human activity recognition tasks [285], providing a comprehensive understanding of models' efficacy. These include Accuracy (ACC), Precision, Recall, and F1-Score. These metrics comprehensively capture the effectiveness of the models [285]. Detailed definitions of each metric and justifications for their use are provided below.

Accuracy measures the overall correctness of the model across all activity classifications, calculated as the ratio of correctly predicted observations (both true positives and true negatives) to the total observations:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

Accuracy is beneficial as it provides a straightforward indicator of how often the model correctly identifies all types of activities, which is crucial for ensuring that the model is generally reliable across a diverse set of activities.

Precision assesses the accuracy of the positive predictions for each specific activity, calculated as the ratio of true positives to all predicted positives:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Precision is particularly important in multi-class activity recognition where it is crucial to minimize false positives for specific activities, ensuring that each detected activity is indeed correct and thus reducing the noise in activity alerts or triggers.

Recall measures the model's ability to correctly identify all instances of a particular activity, calculated as the ratio of true positives to all actual positives:

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

Recall ensures that the model captures as many instances of each specific activity as possible. High recall is essential for activities that have significant consequences if missed, such as monitoring critical activities in healthcare or security settings.

F1-score provides a balance between Precision and Recall for each activity, calculated as the harmonic mean of Precision and Recall:

$$\text{F1-score} = 2 \times ((\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}))$$

The F1-Score maintains a balanced approach between catching as many instances of an activity as possible (Recall) and ensuring those instances are accurately classified (Precision), especially in environments where both false positives and false negatives carry significant costs.

(TP is True Positive, FP is False Positive, FN is False Negative, and TN is True Negative.)

7.2.5.3 Evaluation setup

We conducted our analysis on a Linux server running Ubuntu v22.04.3, equipped with 16GB RAM, to ensure stable and efficient data processing. The software stack included Python v3.10.12, along with essential libraries: Pandas v1.3.5, Matplotlib v3.5.1, Numpy v1.21.5, etc. For the machine learning framework, we utilized Scikit-learn v1.3.2.

7.2.5.4 Compare wearable vs. ambient vs. combined (hybrid)

In this study, we treated the combined data as the hybrid solution. We conducted a comparative analysis of machine learning algorithms on different sensor data sources. Results are shown in Figure 28.

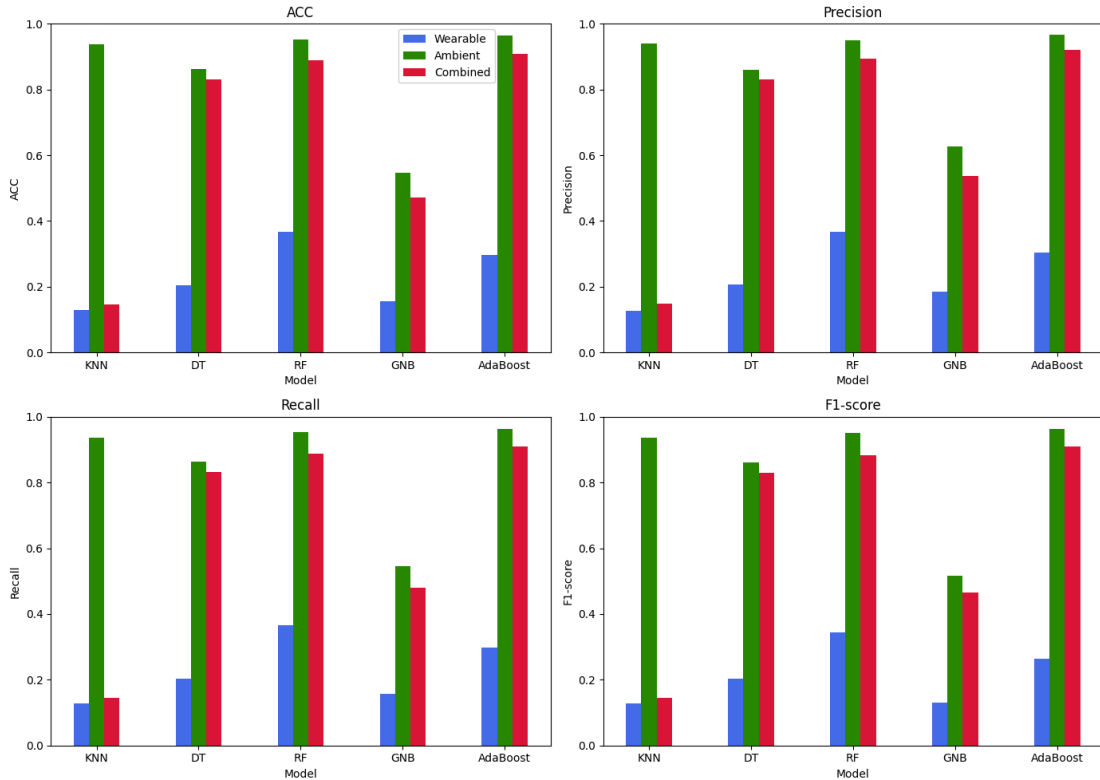


Figure 28. Comparative analysis on three datasets

As demonstrated in Figure 3, ambient sensor data consistently yields high accuracy and reliability in activity recognition tasks across all models. AdaBoost exhibited superior performance across the ambient and combined dataset. Conversely, on wearable sensor data, there is a significant decrease in performance, with all models' accuracy are less than 0.4, even though RF achieved the best performance. In the combined dataset, we did not observe a significant improvement in performance; rather, there was a decrease across all models compared to their performance on the ambient dataset. Specifically, the KNN model not only failed to improve but also exhibited a substantial decline in performance compared to its performance with ambient data. Even the AdaBoost model experienced a slight reduction in effectiveness on the combined dataset. Detailed performance results for the models are presented in Tables 18.

Evaluating models that utilize only wearable sensor data uncovers significant limitations in their ADL recognition capabilities. The RF model, while the most accurate within this subset, only achieves a low accuracy of 0.367. This figure is notably inferior compared to its performance on ambient data, underscoring the restrictive expressiveness of wearable data for this application. The KNN model fares even worse, with an accuracy of merely 0.129, further highlighting the inherent challenges of wearable data. In contrast, ambient data enables models to perform exceptionally well, with the DT and AdaBoost models also demonstrating this discrepancy by exhibiting very low recall (0.204 and 0.297, respectively) and precision (0.206 and 0.303, respectively) when using wearable data.

Conversely, the application of machine learning models to ambient sensor data dramatically enhances performance. The AdaBoost model attains an accuracy of 0.964 and a same F1-score (0.964), indicating a well-balanced precision-recall trade-off. RF model follows to records a high accuracy of 0.953, reflecting the superior effectiveness of ambient data for ADLs recognition. The DT model also shows significant improvement in performance (e.g., 0.659 improvement in accuracy) from the wearable to the ambient dataset. Models like KNN and GNB also see significant gains, with precision and recall values that underscore the viability of ambient sensors for complex activity recognition tasks.

When applied to the combined dataset, the models exhibited a decrease in performance rather than an improvement. Despite maintaining a relatively high accuracy of 0.909, the AdaBoost model did not outperform its results with ambient-only data, a trend that was consistent across other performance metrics. Most notably, the KNN model experienced the greatest decline upon incorporating wearable data, with its accuracy dropping to 0.146. Similarly, both the DT and GNB models demonstrated a moderate decrease in performance, for instance, with their F1-scores decreasing from 0.860 to 0.830 and 0.516 to 0.466, respectively. The RF model also encountered a similar decrease in its performance.

These results reinforce the notion that data from ambient sensors alone may provide sufficient information for the recognition of ADLs. With the selection of an appropriate model, such as the AdaBoost algorithm, the recognition performance can be exceptionally high, suggesting that the added complexity of integrating wearable data may not always be necessary for accurate ADLs recognition.

Table 18. Model performance results on three datasets

		ACC	Precision	Recall	F1-score
Wearable sensor dataset	KNN	0.129	0.126	0.129	0.127
	DT	0.204	0.206	0.204	0.204
	RF	0.367	0.366	0.367	0.344
	GNB	0.157	0.186	0.157	0.131
	AdaBoost	0.296	0.303	0.297	0.265
	KNN	0.937	0.940	0.937	0.936
	DT	0.863	0.861	0.863	0.860

Ambient sensor dataset	RF	0.953	0.951	0.953	0.950
	GNB	0.546	0.627	0.546	0.516
	AdaBoost	0.964	0.966	0.964	0.964
Combined dataset	KNN	0.146	0.148	0.146	0.145
	DT	0.832	0.831	0.832	0.830
	RF	0.889	0.893	0.889	0.884
	GNB	0.472	0.537	0.479	0.466
	AdaBoost	0.909	0.920	0.909	0.909

7.2.5.5 Different phases & scenarios

To efficiently utilize our research resources and maintain a focused analysis, the previous section assessed the overall performance of each machine learning model across all datasets using the metrics. This preliminary evaluation allowed us to identify the most effective model, which we then subjected to a more detailed analysis on all scenarios. However, to ensure completeness and maintain transparency, we have included the results of all models across all scenarios in Appendix C.

Based on the best performed model on each dataset, we conducted a detailed analysis on recognition performance across phases and scenarios. We have charted the precision, recall, and F1-score for each scenario across the three datasets and have illustrated the outcomes in their respective confusion matrices.

In the evaluation on the wearable sensor dataset, the models' performance was generally suboptimal across various scenarios (Figure 29). This was particularly apparent in scenario P4S3, where the model's precision, recall, and F1-score values were all zero, indicating incorrect predictions for every instance in this scenario. Overall, precision scores were relatively low; most did not exceed 0.5, with only one scenario (P3S3) reaching a precision of 0.6. This is resulted from the model correctly identifying only 6 samples out of 23 data samples, as the confusion matrix shown in Figure 30 confirms. Additionally, the analysis uncovered significant fluctuations in performance across different activities. For instance, the scenario labeled P1S3 exhibited relatively better recognition performance, with precision at 0.42, recall at 0.62, and F1-score of 0.50. In contrast, scenarios such as P5S1 and P4S1 obtained much weaker results. P5S1 achieved a mere 0.20 in precision, a recall of 0.10, and a F1-score of 0.13, while P4S1 recorded even lower rates with a precision of 0.17, recall of 0.09, and a F1-score of 0.12. This variation highlights the difficulty in maintaining consistent recognition performance throughout the different scenarios and activities presented in the dataset.

Although the overall performance of wearable sensors for activity recognition is relatively low, certain scenarios demonstrate fair performance. Specifically, in P1S3 (“sleep preparation and sleep”), the RF model correctly classified 63 out of 101 samples. In P2S3 (“meal time”), the model achieved the highest recall of 0.75, with 74 out of 99 samples correctly recognized and a F1-score of 0.47. In P3S2 (“taking a shower”), the model recorded a precision of 0.38, recall of 0.47, and a F1-score of 0.42.

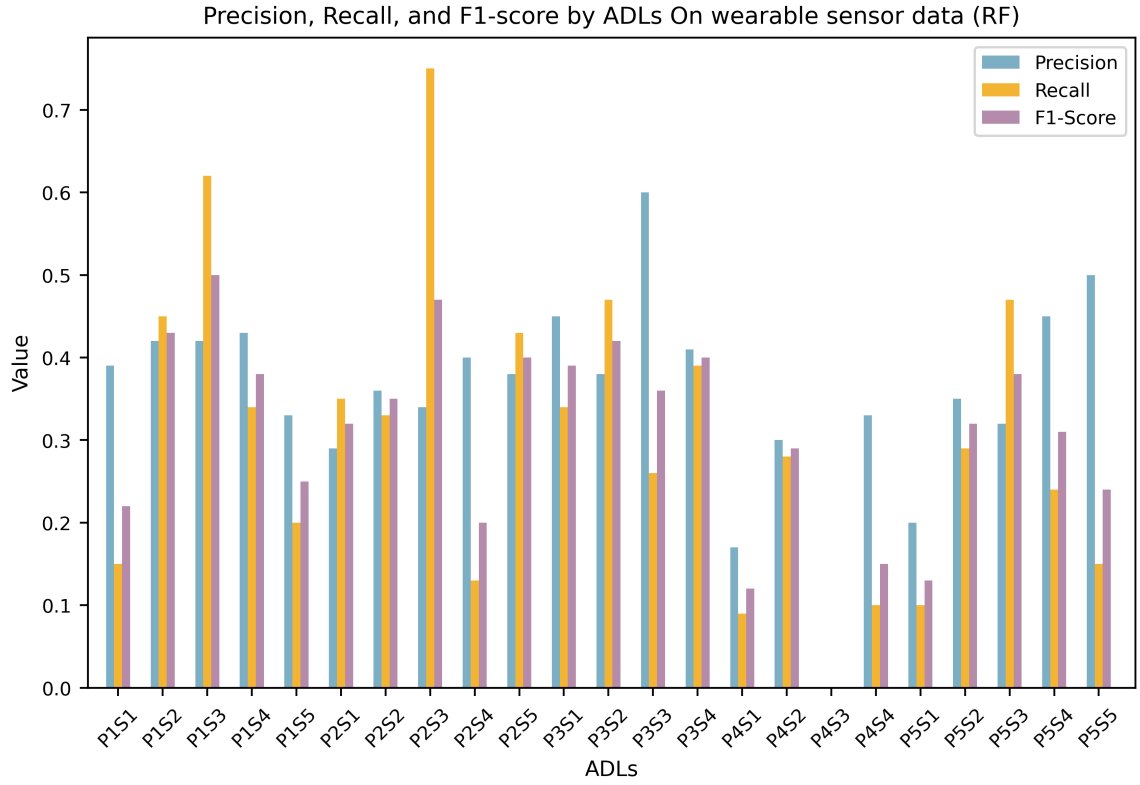


Figure 29. Best performed model's (RF) performance by scenarios and on wearable data

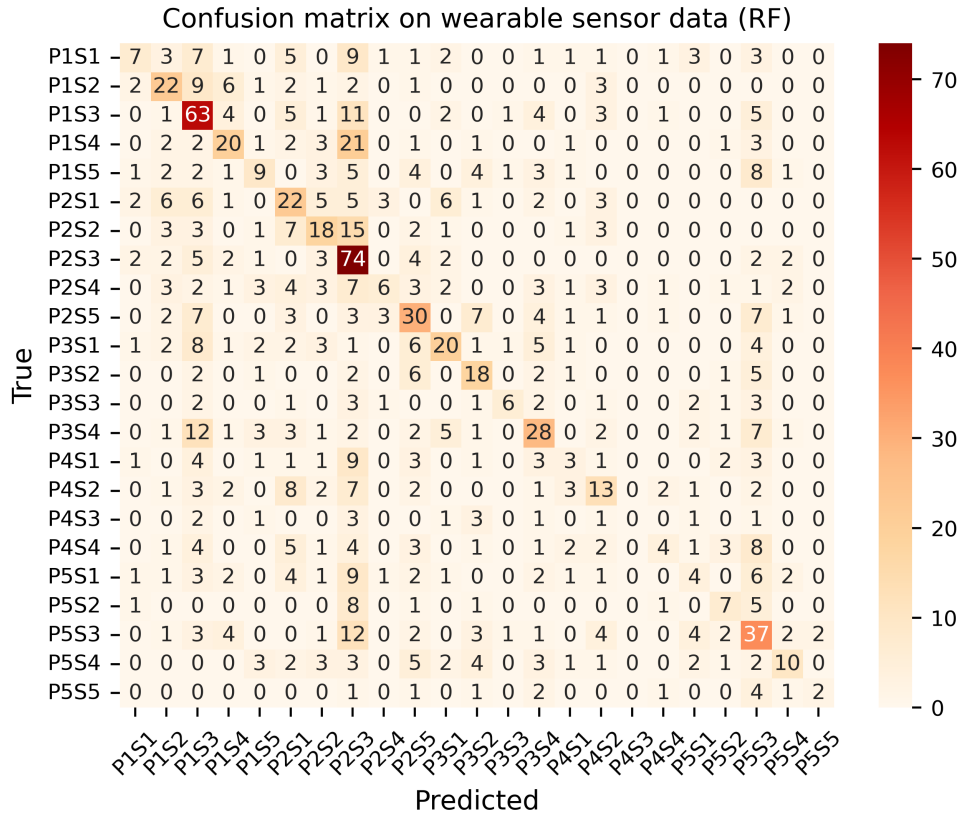


Figure 30. Best performed model's (RF) confusion matrix on wearable data

In the evaluation on the ambient sensor dataset, the model achieved strong performance, particularly in terms of precision, as is shown in Figure 31 . A majority of the precision values (20 out of 23) exceeded 0.9, with the other three values ranging between 0.85 and 0.90. The lowest precision value is 0.85, which is on the scenario P5S2, yet this value is still considered relatively high. Notably, the model achieved a perfect precision score of 1 in twelve different scenarios. The recall values have same trend, with the majority (20 out of 23) over the 0.9 mark. The lowest recall values were observed in scenarios P5S5 and P5S2, with 0.62 and 0.71 respectively. An analysis of the confusion matrix (Figure 32) revealed that for P5S5, out of the total 13 data instances, 8 samples were correctly predicted, while 5 samples were miss classified to P5S3, P5S1, and P3S1. Similarly, in P5S2, 17 instances were accurately classified, but 7 instances were misclassified as P5S3 and P5S1. This misclassification could be attributed to the similarity between the activities in these scenarios. The F1-scores provided insight into the balance between precision and recall, with the model achieving scores above 0.9 in 20 scenarios, between 0.8 and 0.9 in one scenarios, and only two scenario falling below 0.8. Overall, the model's performance in Phase 5, though slightly lower compared to other phases, was still relatively high. The average values for precision, recall, and F1-score in Phase 5 were 0.93, 0.83, and 0.86, respectively, highlighting the effectiveness of the model in handling data from the ambient sensor dataset.



Figure 31. Best performed model's (Adaboost) performance by scenarios on ambient data

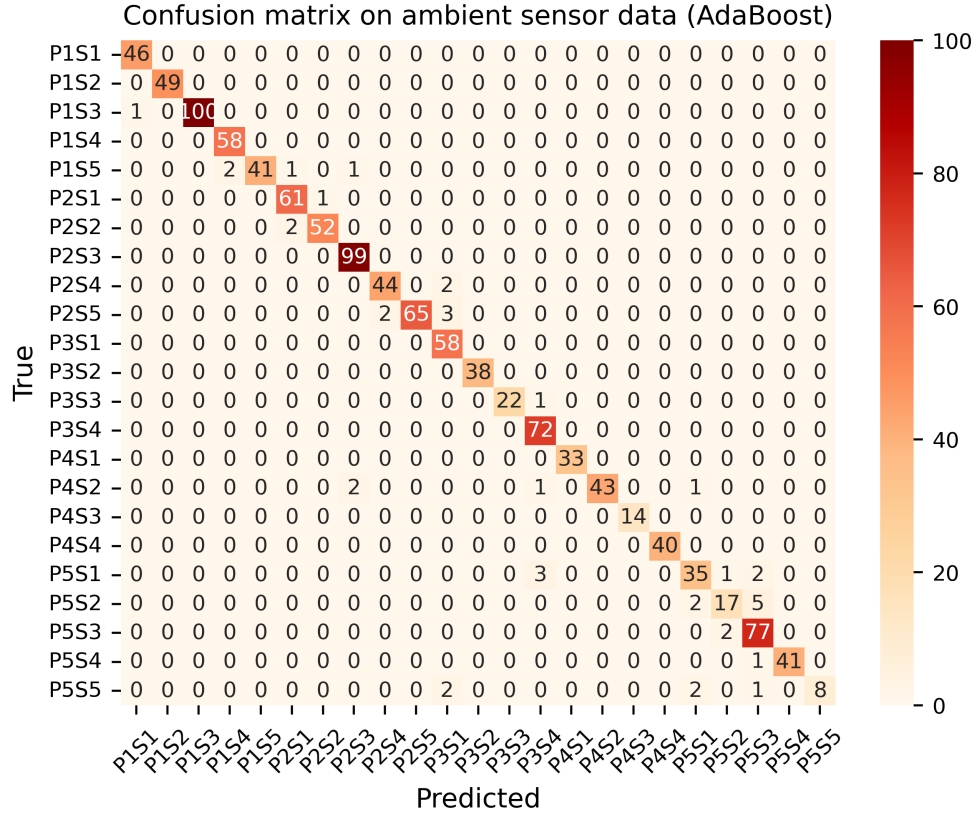


Figure 32. Best performed model's (Adaboost) confusion matrix on ambient data

The analysis of the combined dataset showed positive but slightly diminished results compared to the ambient-only dataset, which presented that integrating wearable data would not improve activity recognition performance. This was particularly apparent when comparing the outcomes from the ambient and combined datasets using the AdaBoost model (Figure 33). In some scenarios, performance was comparable across both datasets. For example, in activity P3S2, each dataset achieved exceptional accuracy, with both registering a perfect precision of 1. The recall rates were also high, at 1 and 0.95 respectively, resulting in F1-scores over 0.95. This pattern was observed in several other activities as well. For instance, in scenarios P4S1 and P4S3, the model attained a precision of 1 in both datasets, and notably, in P4S3, it achieved a score of 1 across all three metrics.

However, the overall performance on the combined dataset did not surpass that on the ambient dataset. In the combined dataset, precision exceeded 0.9 in only 18 of 23 scenarios, with the lowest precision observed in P3S4 at 0.64. A similar trend was noted in recall and F1-score metrics. The confusion matrix for the combined dataset is presented in Figure 34. In comparison to the confusion matrix shown in Figure 32, it also can be observed that the performance on the combined dataset is worse than that achieved using the ambient dataset alone.

These findings indicate that integrating wearable data for activity recognition may not significantly enhance performance and can, in fact, diminish it. The results have shown that

using ambient data alone was more effective for accurately classifying and recognizing a range of human activities than the combined dataset.

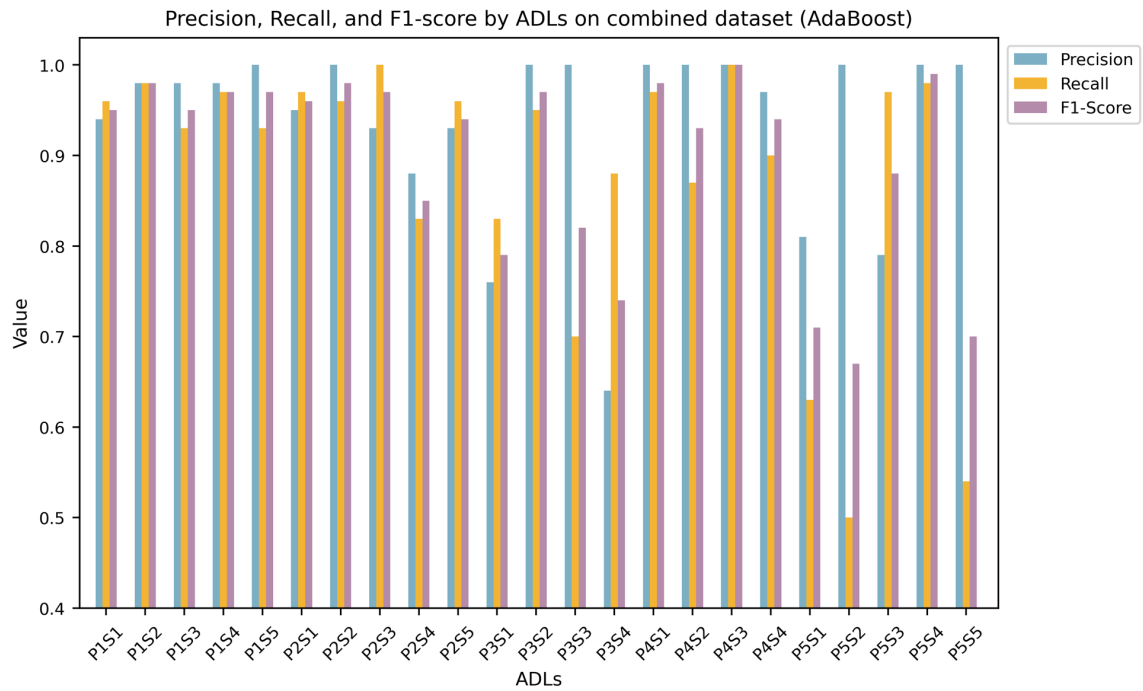


Figure 33. Best performed model's (Adaboost) performance by scenarios on combined data.

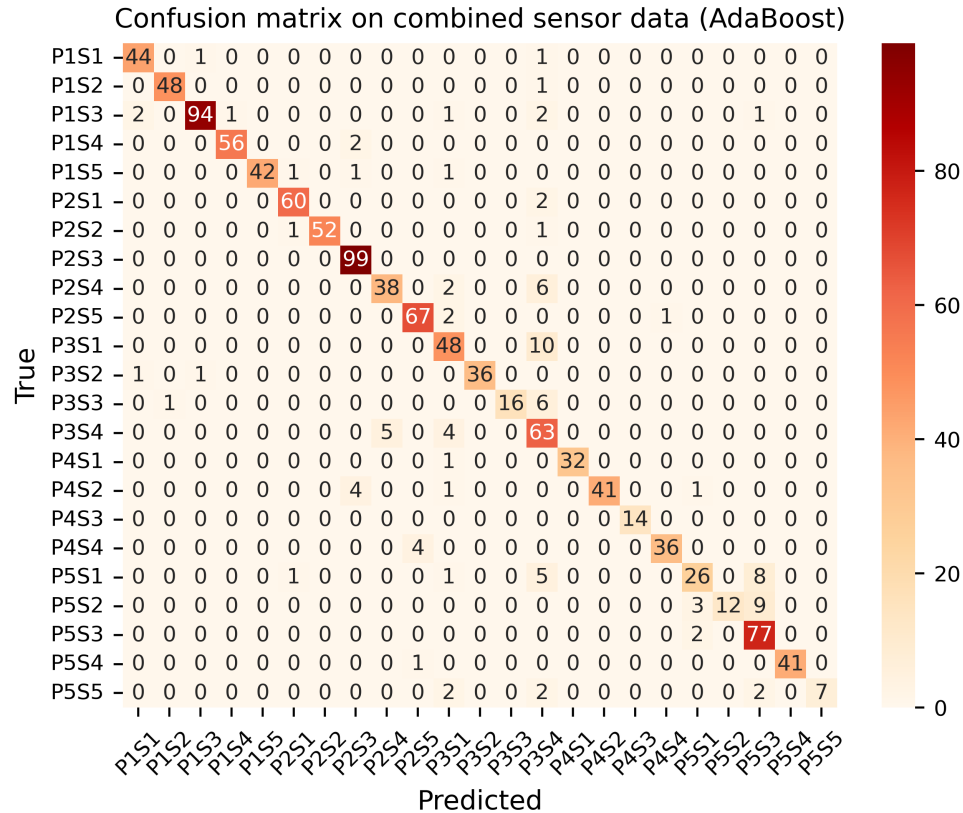


Figure 34. Best performed model's (Adaboost) confusion matrix on hybrid data

7.2.5.6 Activity recognition for single room

To investigate the performance of activity recognition within individual rooms, and to address the potential bias arising from location information inherent in smart home sensors, we organized the dataset based on room-specific data, controlling the spatial information. This means that data corresponding to activities occurring in the same room were aggregated into distinct sub-datasets. Within each sub-dataset, the Adaboost model was employed to classify activities associated with that particular room. Activities that spanned multiple rooms were included in each relevant sub-dataset to maintain the integrity of the analysis. Detailed information about the activity distribution in each room and the corresponding number of data instances can be found in Table 19.

Table 19. ADLs with spatial overlap

Room	Activities	Number of data instances
Living room	P1S1, P2S1, P2S2, P3S1, P3S3, P3S4, P4S1, P5S5	1804
Kitchen	P1S2, P1S4, P2S3, P3S3, P4S2, P5S1, P5S2, P5S3, P5S5	2163
Dining room	P1S2, P2S2, P3S3, P4S2, P5S5	932
Bedroom	P1S3, P1S5, P2S4, P3S1, P3S4, P4S3, P5S5	1749
Bathroom	P1S1, P1S3, P1S5, P2S5, P3S2, P4S4, P5S4, P5S5	1976

Table 6 presents the distribution of data instances across rooms, showing variations in activity occurrence. The Kitchen recorded the highest number of activities with 2163 instances, whereas the Dining room experienced the fewest, with only 932 instances. Certain activities, such as the P5S5 scenario, occurred in multiple rooms, resulting in their presence across all sub-datasets. The performance of the Adaboost model in recognizing activities within each individual room is detailed in Table 20.

Table 20. Adaboost performance on classifying ADLs in single room

	ACC	Precision	Recall	F1-score
Living room	0.965	0.966	0.965	0.965
Kitchen	0.958	0.960	0.958	0.958
Dining room	0.985	0.986	0.985	0.985
Bedroom	0.982	0.982	0.982	0.982
Bathroom	0.975	0.977	0.975	0.976

The results demonstrated the model's robust ability to classify activities within single room contexts, obtaining high accuracy and precision consistently across all rooms with minimal location bias. Notably, slightly better performance was achieved on the sub-datasets for activities in the Bedroom and Dining room, with accuracy, precision, recall, and F1-score all exceeding 0.980. This indicates that activities in these spaces have distinct and recognizable sensor patterns, which the RF model can capture effectively. Even in rooms with comparatively lower performance metrics, such as the Kitchen and Living room, the

model maintained an accuracy and F1-score above 0.950. These findings across various rooms suggest that sensors' spatial information alone does not excessively influence the positive results. The classification performance for scenarios in each room, as detailed in the confusion matrix, is depicted in Figure 35. One notable observation was in the Kitchen, where the scenario P5S2 could still easily be misclassified as P5S3 or P5S1. Furthermore, comprehensive metrics (precision, recall, F1-score) for each scenario within each room are available in Appendix D.

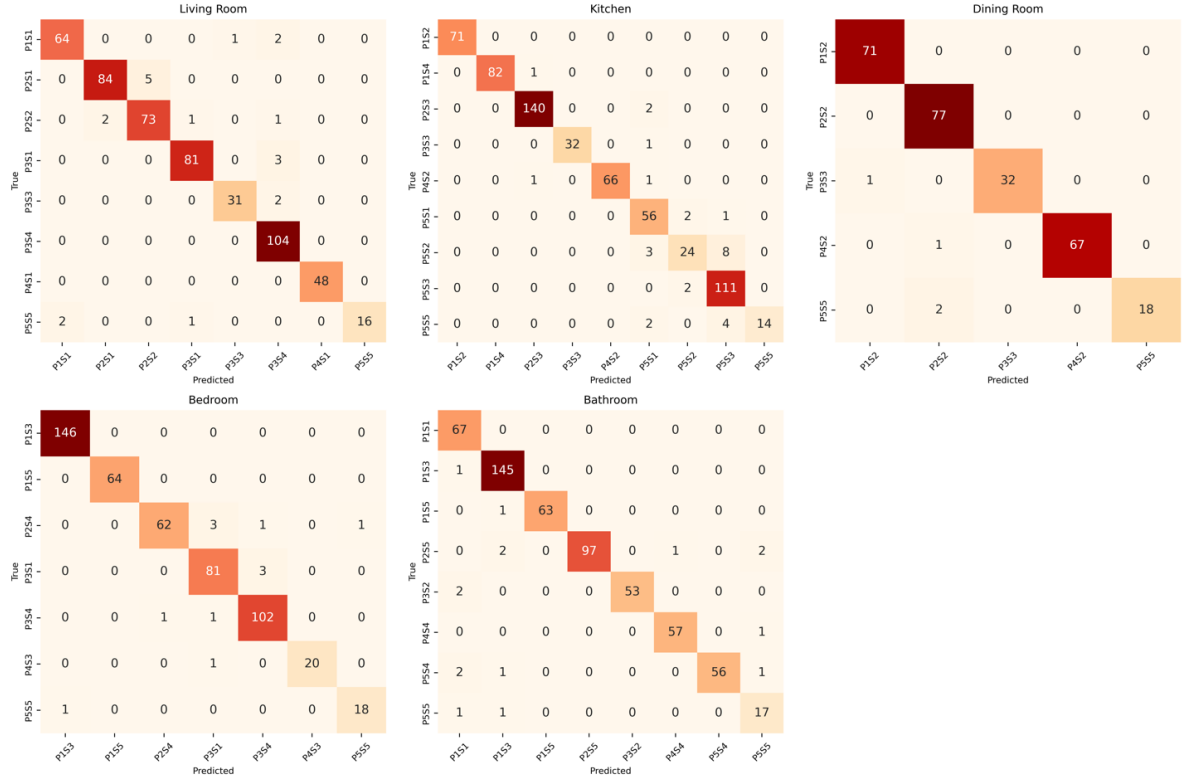


Figure 35. Confusion matrix for activity recognition with spatial overlap in each room.

7.2.5.7 Feature importance for classification

To discern which features significantly contribute to human activity recognition, we employed SHapley Additive exPlanations (SHAP) to assess feature importance. We identified the top 20 features using SHAP, and the results are illustrated in Figure 36.

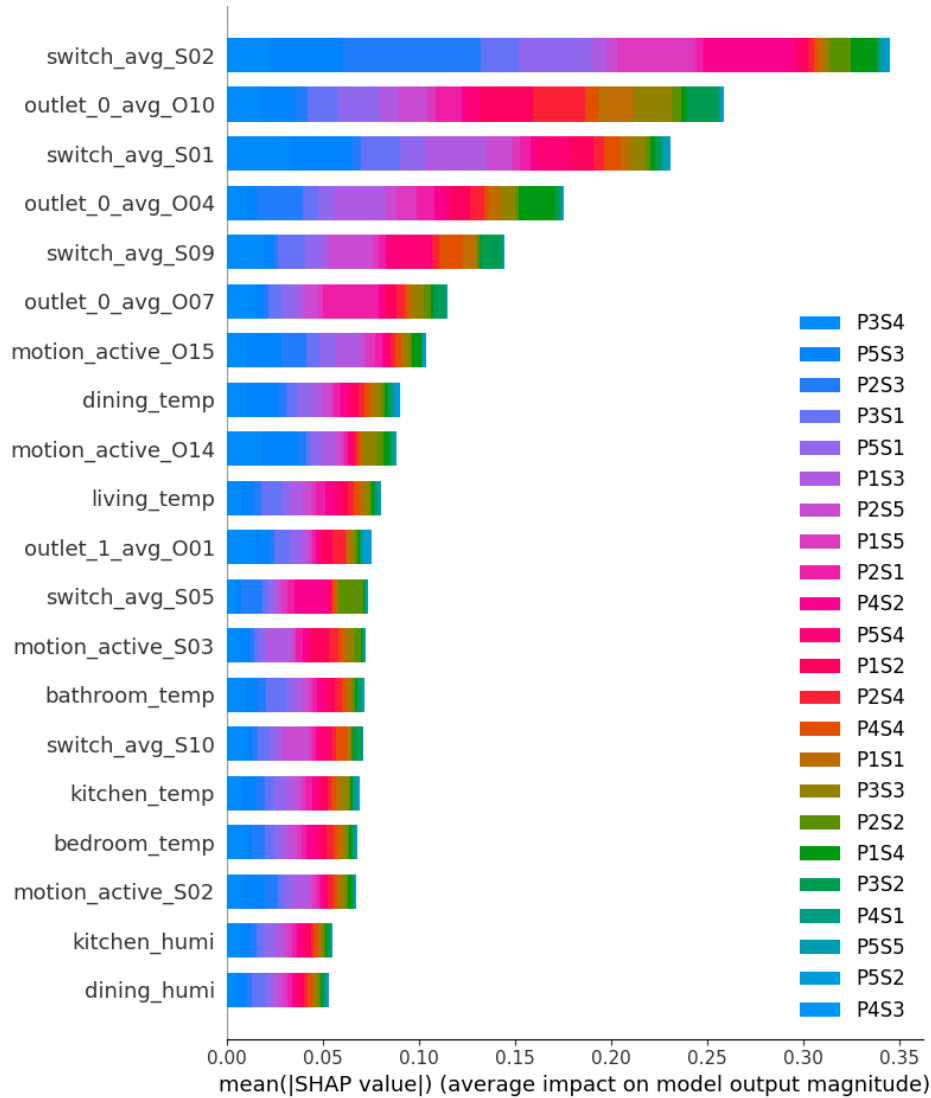


Figure 36. SHAP results for feature importance

The analysis highlighted a clear hierarchy of climatic, electrical, and motion sensor-based factors influencing the predictive model. As is shown in Figure 36, ‘switch_avg_S02’ was identified as the most influential feature, reflecting the power consumption of switch 02. This switch is situated in a central location where many activities occur (Figure 1), suggesting a strong correlation between interactions with this particular switch and various activities. Other features related to switch power consumption (‘switch_avg_S01’, ‘switch_avg_S09’, ‘switch_avg_S05’, and ‘switch_avg_S10’) also ranked within the top 20 important features, each distinctly positioned in different rooms (switch 01 located at entrance, switch 09 is outside of bathroom, switch 05 is between dining room and living room, and switch 10 is in the bathroom), which underscores the interaction with these sensors to their substantial impact on model predictions.

In addition to switch-related features, those related to outlet usage—‘outlet_0_avg_O10’, ‘outlet_0_avg_O04’, and ‘outlet_0_avg_O07’—were also highly significant, ranking 2nd, 4th, and 6th respectively. This prominence is understandable given that in our study, we did not engage participants with actual kitchen appliances, resulting in less frequent activation

of kitchen outlet sensors. However, in some scenarios, participants used a vacuum cleaner to tidy the room, which was primarily connected to these three outlets. However, activities happened in the kitchen still can be well captured because of the motion sensors that placed in the kitchen, as reflected by the importance of ‘motion_active_O15’, ‘motion_active_O14’, ‘motion_active_S03’, and ‘motion_active_S02’ shown in Figure 36. The analysis further implies that sensors with higher interaction rates during activities contribute more significantly to prediction accuracy.

Moreover, the role of environmental conditions was underscored by the ranking of temperature and humidity features—such as ‘dining_temp’, ‘living_temp’, ‘bathroom_temp’, ‘kitchen_temp’, ‘bedroom_temp’, ‘kitchen_humi’, and ‘dining_humi’—as top influencers. This suggests that even in controlled environments, the ambient microclimate, including temperature and humidity, plays a pivotal role in human activity recognition. However, features pertaining to air quality were notably absent, indicating their relatively weak impact on prediction.

7.2.6 Discussion

The discussion section will discuss the results from the results section, in order to validate the proposed hypotheses and answer the proposed research questions.

7.2.6.1 Research question 1

To answer research question 1, we employed machine learning models on three distinct datasets: ambient-only, wearable-only, and the combined dataset. We initially hypothesized that machine learning models could achieve competitive recognition results using either wearable sensors or ambient sensors. Breaking down to different scenarios situations, at posture-focused scenarios, relaying on wearable sensors may achieve better results than ambient sensors. We further assumed that combining these two sensor types would improve performance. However, our findings challenge these hypotheses, revealing that ambient sensors significantly outperform wearable sensors overall.

Performance on ambient data

Ambient sensor data proved highly effective in recognizing a broad spectrum of ADLs. Machine learning models, particularly the AdaBoost model, achieved high accuracy rates (up to 0.964) when analyzing ambient data alone. This demonstrates the strength of ambient sensors in capturing diverse activity patterns, consistent with prior findings [280] that highlighted the sufficiency of ambient data for ADLs monitoring in smart home environments.

Examining specific phases and scenarios, ambient sensors performed particularly well in activities characterized by distinct environmental or contextual interactions. For instance, in P4S1 (cleaning rooms), ambient sensors perform good due to the noticeable environmental changes associated with the activity. These included the use of switches, the operation of the vacuum cleaner, and associated power consumption, all of which created clear and detectable patterns for ambient sensors. Similarly, in P1S1 (arriving home), the sequential transitions, such as unlocking the door, turning on lights, and interacting with

objects like the remote and teacup, generated strong contextual cues. These distinct spatial and temporal patterns allowed ambient sensors to effectively distinguish this activity from others.

Despite their strengths, ambient sensors show limitations in recognizing more complex instrumental ADLs that involve multitasking or similar sequential activities. For example, activities such as P5S1 (arriving home and organizing groceries) and P5S2 (cleaning the kitchen) share overlapping sensor triggers, such as light switches and appliance usage, which can lead to misclassification. This underscores the challenges ambient sensors face in distinguishing between activities with similar environmental cues.

Performance on wearable data

Wearable sensors demonstrated significantly lower performance compared to ambient sensors across all activities. The best-performing model (RF) achieved an accuracy of only 0.367 on wearable-only data. However, in certain scenarios where involves much body posture change, wearable sensors performed relatively better than other scenarios where not. These cases may highlight specific conditions where wearable sensors align well with activity recognition.

For example, in P1S3 (sleep preparation and sleep), wearable sensors effectively captured sequential physical movements, such as brushing teeth, walking, and transitioning from standing to lying down. These body-centric actions generated distinct motion patterns that were recognizable by accelerometers and gyroscopes. Similarly, in P2S3 (meal preparation), dynamic movements such as bending, reaching, and cutting produced consistent and identifiable data streams. Actions like deliberately dropping and retrieving a pepper further introduced unique movement signatures that enhanced recognition accuracy. Finally, in P3S2 (shower preparation and showering), repetitive full-body motions, such as mimicking washing and drying off, created clear patterns detectable by wearable sensors. While these scenarios achieved better results than others for wearable sensors, their performance was still significantly lower compared to ambient sensors.

To improve wearable sensor performance, enhancements in feature extraction techniques are essential to better capture activity characteristics. For example, incorporating features that reflect the velocity, acceleration patterns, and periodicity of body movements could better differentiate between similar activities. Leveraging time-series analysis to capture temporal dependencies and transitions between movements would allow for more accurate modeling of activity sequences. Additionally, combining features like motion intensity and variability across different axes could provide a more comprehensive representation of the physical activities, potentially improving classification performance.

Performance on combined data

Contrary to the assumption that combining wearable and ambient data would improve ADLs recognition, our study observed a decrease in performance across all models, compared with ambient data when analyzing the combined dataset. This finding is

particularly notable as it challenges the widespread belief in the benefits of data enrichment through sensor fusion. For instance, the AdaBoost model's accuracy slightly decreased from 0.964 (ambient only) to 0.909 (combined), highlighting potential complexities and redundancies arising from merging different data sources. This aligns with the study from Nweke et al. [281], which highlighted the complexities of data fusion, particularly the difficulties in managing increased dimensionality and ensuring data coherence from heterogeneous sources, suggesting that the integration of different data sources requires careful optimization to realize potential benefits.

Overall, our findings challenge the hypotheses we proposed before. Our analysis reveals that ambient sensors significantly outperform wearable sensors in all scenarios. In addition, the integration of wearable and ambient data introduced additional complexity and redundancy, leading to decreased accuracy in most cases.

7.2.6.2 Research question 2

To answer research question 2, we organized the ambient sensor data corresponding to activities that occurred in the same room into separate sub-datasets. Within these subsets, we applied Adaboost models to evaluate the performance for activity recognition.

Our results reveal that ambient sensors are capable of effectively distinguishing between various activities in the same area, maintaining high accuracy (over 0.95) across different scenarios. This outcome challenges the preconceived limitations associated with spatial overlap [282], suggesting that ambient sensors may capture distinct environmental changes or patterns specific to different activities, despite their occurrence in the same spatial area.

The implications of these findings are significant. Specifically, we can refine the design of AAL systems to be more sensitive and less intrusive. For instance, in a smart home environment designed to support independent living, the use of ambient sensors that accurately identify activities despite spatial overlap means that fewer sensors are needed, as traditionally, ensuring recognition of same spatial activities coverage in a smart home might involve deploying a dense network of sensors. This minimalistic approach not only addresses privacy concerns but also avoids cluttering living spaces, making technology an invisible aide rather than an intrusive presence. For seniors and individuals with disabilities, this means their living environments can remain familiar and comfortable, while still being equipped with the necessary technology to monitor their safety and well-being.

Moreover, the ability to accurately recognize activities in spatially constrained environments allows for more personalized and precise interventions. For example, if an ambient sensor system can differentiate between cooking and eating in a kitchen-dining area, it can provide timely reminders or assistance specifically tailored to those activities, such as medication reminders immediately after meals or alerts to turn off the stove after cooking. This specificity enhances the autonomy and safety of individuals, enabling them to confidently perform daily tasks with the knowledge that their environment is equipped to support them discreetly and efficiently.

7.2.6.3 Research question 3

To address the third research question, we utilized SHAP to analyze the importance of features related to ambient sensors. The SHAP analysis results highlights the importance of indoor climatic, electrical, and motion sensor-based factors in the accurate recognition of activities within smart living environments. This is supported by the study from Naccarelli et al. [274], who demonstrated the potential of machine learning to optimize sensor configurations for ADL measurement in smart living environments, focusing on data characteristics over spatial information.

The implications of these findings are profound, particularly concerning sensor selection and configuration in practical applications within smart homes and assisted living environments. It becomes evident that the choice of sensors in smart environments should be informed by their demonstrated impact on activity recognition accuracy. Climatic sensors, for example, which monitor conditions such as temperature, humidity, can provide essential clues about occupant behavior. For instance, a significant change in temperature or humidity might indicate cooking or showering activities. Similarly, electrical sensors, which track energy consumption patterns, offer insights into the usage of appliances, potentially signaling activities like laundry or entertainment. Motion sensors, detecting movement within the environment, play a pivotal role in identifying the presence and location of occupants, thereby facilitating the recognition of physical activities ranging from simple movements to complex routines.

The strategic selection and combination of these sensors based on their utility in capturing meaningful activity data can greatly improve the accuracy and reliability of activity recognition systems. For instance, integrating motion sensors with climatic sensors can help distinguish between activities that have similar motion patterns but different climatic impacts, such as cooking (which may increase temperature and humidity) versus exercising (which might not have the same climatic effect). This level of detail in activity recognition is crucial for creating adaptive and responsive smart environments that can cater to the specific needs and preferences of their occupants.

Moreover, results from evaluating the importance of different sensor-based factors highlights the potential for optimizing sensor networks, not only to reduce redundancy and cost but also to prioritize privacy and unobtrusiveness. By focusing on these sensors that provide the most significant contributions to activity recognition, in real-world applications, designers can minimize the number of sensors required, thereby addressing concerns about privacy and the expense impact of technology within living spaces.

7.2.7 Limitation, indication, and future work

Limitations

A key limitation of this study is the reliance on younger participants to emulate the behaviors and conditions of older adults. While this approach was necessitated by the constraints of the COVID-19 pandemic, it introduces several potential biases and does not

fully capture the complex dynamics of aging. Younger individuals may not accurately replicate the physical and cognitive changes that occur with aging, such as decreased mobility or slowed reaction times, which can impact the authenticity of the data collected. Additionally, this simulation could potentially lead to psychological and physical strain on the participants, as they adjust to unnatural activity levels and patterns. These factors could influence the study's outcomes, introducing variability that would not be present with an actual older adult population.

The limited sample size constrains our ability to fully capture the diversity of population, including variations in physical abilities, health conditions, demographic characteristics, and behavioral interactions with the environment and sensors. This limitation reduces the representativeness of the dataset and could hinder the development of machine learning models capable of generalizing effectively to a broader population, as smaller or less diverse datasets have been shown to impact model performance and generalizability adversely [347]. As is highlighted by Vabalas et al. [348], small sample sizes often produce biases in the validation process, leading to overfitting and inflated performance metrics. In the context of this study, these issues may influence the robustness of the models when applied to scenarios outside the controlled environment of the study.

Furthermore, the controlled environment in which the study was conducted limits the generalizability of our findings. The activities, environment, and duration of the tasks were predefined and carefully structured, which does not fully reflect the complexity, unpredictability, or variability of real-world scenarios. For example, the specific duration of each activity was shorter than typical daily tasks performed by older adults, limiting accurate predictions and interpretations of activity patterns for sustained cognitive and physical engagement. Furthermore, the structured nature of the experiment, with specific environmental conditions and task durations, may not fully replicate the dynamic and unstructured nature of real-life activities that older adults encounter daily. This could result in a reduced ability to generalize the results to more variable and complex real-world settings. Nevertheless, we should emphasize that the controlled environment allowed us to establish a proof of concept, and the findings from this study should be interpreted as a foundational step to future work.

Indications

Despite the limitations, this study serves as an initial exploration in the development of ADL recognition models using AAL technology. Our objective was to assess the effectiveness of AAL technology for ADL recognition using various machine learning models in a controlled setting, providing valuable insights that will inform subsequent studies. The controlled environment allowed for systematic evaluation of different models, ultimately establishing a foundation upon which future research can build.

We envision that the findings from this pilot study will guide future investigations into more dynamic, real-world environments. By iterating on this research in uncontrolled conditions and employing advanced methods such as transfer learning, we aim to achieve

a greater level of robustness and adaptability in ADL recognition. This study, therefore, functions as a critical step towards achieving effective real-world implementations, while also identifying potential directions for further exploration.

Future work

Future work will aim to address these limitations by conducting experiments with actual older populations to validate our findings in more dynamic real-world settings. This will allow us to better capture the variability, unpredictability, and complexity of everyday activities. Additionally, we plan to extend the duration of activities to more closely mirror the typical daily chores of older adults, thereby enhancing the realistic validity of our research. Furthermore, we plan to increase the sample size and include a broader diversity of participants, considering various physical abilities and health conditions, thereby improving the representativeness of dataset, which ensures the robustness and generalizability of our approach. We also intend to explore more optimized data characteristics and sensor configurations to enhance the accuracy and reliability of activity recognition using AAL technology. Specifically, we will investigate varying data granularity to determine the optimal resolution needed for detecting daily activities effectively. In addition, we will examine sensor location and density to determine how these factors influence recognition performance, balancing effectiveness with resource utilization. By identifying these optimal configurations, we aim to achieve robust ADL recognition that is effective in diverse real-world environments.

In addition, for the future study in real-world, we plan to re-train the models using data collected from real-world activities to address any biases introduced by the controlled setting. We also plan to explore advanced modeling techniques such as transfer learning to adapt models trained and promising results in controlled environments to real-world settings.

7.2.8 Conclusion

This study has advanced the understanding of activity recognition for individuals using AAL technology. By employing machine learning algorithms to analyze and compare the efficacy of AAL sensors against wearable sensors, assessing activities within spatially overlapping environments and identifying key sensor features, we have highlighted the potential of contactless AAL sensors in enhancing recognition accuracy. The findings demonstrate the feasibility of contactless activity recognition and underscore the importance of selecting appropriate sensors and features. This contributes to the development of smarter, more responsive environments for older individuals' independent living. Such advancements in monitoring and assistance technologies could lead to reduced healthcare costs, lower rates of hospital readmissions, and improved long-term health outcomes.

7.3 Discussion

The findings from this chapter demonstrate the feasibility and effectiveness of using AAL technology for contactless recognition of ADLs among older adults. The high accuracy

achieved by the machine learning models underscores the potential of AAL systems to support independent living and enhance the quality of life for aging populations. However, it is important to note that this proof-of-concept study was conducted with younger adults in a controlled environment, which presents limitations when considering the applicability of these results to real-world settings for the elderly.

The use of a controlled setting and a younger participant group, while effective for initial testing, introduces challenges related to generalizability. The controlled nature of the environment means that participants followed strict instructions when performing ADLs, which may not reflect the complexity and variability of real-world activities in the homes of older adults. Furthermore, the physiological and behavioral differences between younger and older individuals can significantly affect the performance of ADL recognition models when applied to the elderly. These factors highlight the need for further studies that directly address the challenges posed by applying these models to older adults in less controlled, real-life environments.

Future work will focus on adapting the models developed in this chapter to better accommodate older adults and real-world conditions. This adaptation is crucial for ensuring that AAL systems are truly effective in supporting independent living for the elderly, especially in the unpredictable and diverse environments typical of their daily lives.

Chapter 8 – Activity of Daily Living Recognition for Older Adults

– A Domain Adaptation Method

Kang Wang, Ashish Saragadam, Jasleen Kaur, Shi Cao, Moojan Ghafurian, Zahid A. Butt, Plinio P. Morita. (submitted). "A Hybrid Transfer Learning Framework for Activity Recognition in Older Adults using Ambient Assisted Living Technology, " Engineering Applications of Artificial Intelligence.

8.1 Foreword

Building on the results of the previous chapter, which demonstrated the feasibility of using AAL technology for contactless recognition of ADLs, this chapter addresses the challenges of adapting these models to older adults in real-world settings.

To bridge this gap, this chapter explores a hybrid transfer learning framework aimed at enhancing the generalizability of ADLs recognition models across different populations and settings. Given the challenges of data scarcity and the difficulties associated with collecting labeled data from older adults, a transfer learning approach is leveraged to adapt the well-performing models from controlled experiments with young participants to scenarios involving older adults in less structured environments. This approach is expected to mitigate the limitations of data scarcity and enhance the robustness of the ADL recognition models in diverse, real-world contexts. By aligning the feature distributions between datasets from younger and older populations, the hybrid transfer learning framework aims to improve model performance despite the scarcity of labeled data from older adults.

Furthermore, this chapter seeks to address the discrepancy between controlled experimental conditions and the more dynamic, real-world environments in which older adults reside. The proposed hybrid transfer learning framework not only aims to adapt the models to a different age group but also to increase their resilience to environmental variability. This adaptability is essential for ensuring that AAL systems can provide meaningful support in the day-to-day lives of older adults, thereby promoting independence and enhancing quality of life.

The work presented in this chapter aims to ensure that the benefits of AAL technology can be effectively extended to the elderly, thereby supporting their independence and well-being in everyday living environments. By adapting models to better accommodate the unique challenges associated with aging populations and unstructured settings, this chapter contributes to the broader goal of creating scalable and effective AAL solutions that can facilitate healthy aging and improve quality of life.

8.2 A Hybrid Transfer Learning Framework for Activity Recognition in Older Adults using Ambient Assisted Living Technology

8.2.1 Overview

Background

Recognizing activities of daily living is essential for developing intelligent monitoring systems for older adults. A key challenge is the scarcity of labelled data from older adults in real-world scenarios, which adds difficulty to developing robust activity recognition models for them. This study aims to investigate a hybrid transfer learning framework to bridge the gap in activity recognition from young populations in controlled settings, where labeled data is abundant, and recognition performance is high, to older adults in real-world-like settings using Ambient Assisted Living technology.

Methods

The study was conducted in an Ambient Assisted Living environment with two trials forming distinct datasets: 40 young adults in a controlled setting and 26 older adults in a semi-controlled setting. The hybrid transfer learning framework integrates Correlation Alignment and Conditional Domain Adversarial Network to align features while incorporating a small amount of labelled target data. Experiments evaluated the framework's effectiveness against naïve transfer learning and other domain adaptation methods.

Results

The hybrid transfer learning approach significantly improved older adults' activity recognition performance, with the hybrid method achieving an accuracy of 0.576 (compared to a random guess baseline of 0.062) and an F1-score of 0.538. This outperformed standalone methods such as Domain Adaptation Network (accuracy: 0.479) and Conditional Domain Adversarial Network (accuracy: 0.502). Naïve transfer learning showed poor performance, with accuracies and F1-scores under 0.1 across all models. Incorporating few labeled target domain data into the learning can further enhance performance, with a maximum increase of 0.344 in accuracy.

Conclusion

The proposed hybrid framework provides a practical solution for improving activity recognition performance to older adults. By leveraging transfer learning techniques and limited labeled target data, this study highlights the potential of Ambient Assisted Living technology to support older adults' independence and health monitoring, offering innovative solutions for public health challenges.

Keywords: Ambient Assisted Living, Transfer Learning, Domain Adaptation, Human Activity Recognition, Aging Population, Machine Learning

8.2.2 Background

The aging population represents a significant and growing global trend, posing both challenges and opportunities for healthcare systems worldwide [1]. According to the United Nations, the number of individuals aged 65 and older is projected to more than double, reaching approximately 1.5 billion by 2050 [306]. This demographic shift is driven by

declining birth rates and increasing life expectancy, which together result in an increasing proportion of older individuals within the global population. As this trend continues, it places immense pressure on healthcare systems to provide adequate care and support for older adults. The demand for healthcare services that can support aging in place—allowing individuals to live independently in their own homes for as long as possible—is greater than ever [307]. This trend necessitates an increased emphasis on in-home healthcare services that can provide continuous monitoring, timely interventions, and support, all while fostering independence and reducing the burden on traditional healthcare facilities [308].

In particular, the ability to monitor Activities of Daily Living (ADLs) is critical for maintaining the quality of life for older individuals, especially those managing chronic health conditions such as cardiovascular disease, diabetes, or mobility limitations [37]. Monitoring ADLs provides essential insights into an individual's health status and functional ability, enabling early detection of potential health problems, timely medical interventions, and personalized care planning [309]. Human Activity Recognition (HAR) plays a crucial role in enabling such monitoring, as it facilitates the identification of normal behavior patterns and the detection of deviations that may indicate potential health issues, such as falls, reduced mobility, or changes in routine that could signal cognitive decline [286]. HAR systems, therefore, have the potential to significantly enhance the quality of life for older adults by providing continuous, unobtrusive monitoring and enabling timely interventions when necessary [310].

Ambient Assisted Living (AAL) technology has emerged as a promising solution to address the growing in-home healthcare needs of the older adults, providing a viable alternative to traditional wearable sensors [24]. AAL systems utilize a range of non-intrusive ambient sensors, such as motion detectors, pressure sensors, door sensors, and smart appliances, to monitor individuals' activities without requiring them to wear any devices [283]. This approach offers several advantages over wearable technologies, which can be uncomfortable, intrusive, and prone to non-compliance, particularly among older adults. Wearable devices often require regular maintenance, such as charging or calibration, and may be forgotten or removed by the user, leading to gaps in monitoring data [311]. In contrast, AAL systems are seamlessly integrated into the living environment, providing continuous, reliable monitoring without requiring active participation from the individual [312].

When integrated with artificial intelligence (AI), AAL systems can effectively interpret sensor data to recognize activities and detect health anomalies [313], thereby offering a comprehensive monitoring solution that supports aging in place. AI algorithms enable the extraction of meaningful information from raw sensor data, identifying patterns and detecting deviations that may be indicative of health concerns [314]. This integration allows for proactive healthcare interventions, such as alerting caregivers to a potential fall or a decline in activity levels that may suggest worsening health [204]. Compared to traditional monitoring methods, AAL systems coupled with AI can provide a more holistic view of an

individual's health, capturing a wide range of activities and behaviors that can be used to assess both physical and cognitive well-being [283]. By leveraging AI, AAL systems can offer personalized insights and adaptive support, ultimately enhancing the independence and safety of older adults.

Despite the potential benefits of AAL technology, a significant challenge in developing accurate HAR models for older adults is the scarcity of relevant data [283]. Collecting data from older populations is often constrained by privacy concerns, ethical considerations, and practical challenges related to recruiting participants [315]. Older adults may be reluctant to participate in data collection studies due to concerns about privacy, data security, or the intrusiveness of monitoring technologies [316]. Additionally, physical or cognitive impairments may limit their ability to participate in long-term data collection efforts, resulting in smaller and less diverse datasets [317]. In contrast, data collection from younger populations is more feasible, resulting in an abundance of datasets from young, healthy individuals who are more likely to participate in controlled experimental settings [283].

However, models trained exclusively on young adults' data may not generalize well to older adults due to physiological and behavioral differences between the two populations. For instance, some older adults may exhibit slower movement, reduced range of motion, and different activity patterns compared to younger individuals [318]. These differences can significantly impact the performance of HAR models, as algorithms trained on young adults may fail to accurately recognize activities or detect anomalies in older adults [318]. This discrepancy poses a substantial barrier to the effective deployment of AAL systems for older adults, as the lack of representative data limits the accuracy and reliability of activity recognition models [318]. Addressing this challenge requires innovative approaches to improve model generalizability and ensure that HAR systems can effectively serve older populations.

Another challenge pertains to the environment in which the data is collected. Data collected under highly controlled conditions, with specific instructions for performing activities in a structured manner, is often easier to obtain and can be used to train accurate models [319]. However, these controlled environments fail to capture the variability and unpredictability inherent in real-world settings, such as those typical of older adults' homes [319]. In real-world environments, activities are performed in a less structured and more dynamic context, influenced by a variety of factors such as physical limitations, environmental obstacles, and individual preferences [320]. Consequently, a significant challenge is how to apply models trained on controlled data to semi-controlled or uncontrolled environments, which are more reflective of daily living conditions [321]. Bridging this gap is crucial for developing HAR models that are not only accurate but also robust and adaptable to the complexities of real-world applications.

Transfer learning has increasingly been utilized in human activity recognition to overcome these data limitations [322]. Transfer learning is a machine learning technique that involves

transferring knowledge from a source domain with abundant data to a target domain with limited data, thereby improving model performance in the target domain [322]. By employing transfer learning, models trained on data-rich domains—such as young adults in controlled environments—can be adapted to perform well in data-scarce domains, such as older adults who live alone in real-world environments [323].

The use of transfer learning in HAR is particularly advantageous when dealing with heterogeneous data sources and limited labeled data from the target population [324]. By leveraging the similarities between activities performed by young and older adults, transfer learning can effectively adapt models to recognize activities in older adults without requiring extensive new data collection. This not only addresses the challenge of data scarcity but also enables the rapid development and deployment of HAR models that are capable of serving diverse populations. Transfer learning has the potential to enhance the scalability and inclusivity of AAL systems, ensuring that they can provide reliable monitoring and support for individuals across different age groups and living conditions [325].

The aim of this research is to develop a robust approach to human activity recognition for older adults by leveraging transfer learning techniques, to address the challenges of data scarcity and environmental variability. Specifically, this study seeks to investigate whether models trained on young adult data can be adapted using transfer learning method to provide more accurate activity recognition for older adults in less controlled, real-world environments. By doing so, this research aims to enhance the applicability and reliability of AAL systems, ultimately contributing to the advancement of in-home healthcare for the aging population. The outcomes of this research have the potential to improve the quality of life for older adults by enabling continuous, unobtrusive monitoring, early detection of health issues, and timely interventions, thereby supporting independent living and reducing the burden on healthcare systems.

8.2.3 Related works

The development of HAR systems has been an area of significant research interest, particularly in the context of healthcare applications for older adults. Traditional HAR systems have predominantly relied on wearable sensors to monitor ADLs. Bao and Intille pioneered the use of multiple accelerometers worn on different parts of the body, demonstrating their effectiveness in recognizing activities like walking, sitting, and running with high accuracy in controlled environments [326]. Similarly, Ravi et al. combined signal processing methods and machine learning classifiers such as decision trees and k-nearest neighbors to analyze sensor data, offering a foundational approach to HAR [327].

While wearable sensors provide accurate and granular data, they come with limitations, particularly for older adults. Issues such as discomfort, the need for compliance, and the risk of devices being forgotten or removed pose significant challenges [328]. These challenges have prompted researchers to explore alternative methods like environmental sensing, which avoids the burden of direct interaction with devices.

AAL systems have emerged as an effective alternative to wearable sensors for ADLs recognition, particularly for older adults. Unlike wearable devices, AAL systems rely on environmental sensors, such as motion detectors, pressure sensors, and smart home appliances, to unobtrusively monitor activities. For example, Chen et al. presented a survey to examine the potential of AAL systems in ADLs recognition, highlighting their ability to provide continuous and non-intrusive monitoring in real-world environments [329]. Similarly, Rashidi and Mihailidis reviewed AAL technologies, emphasizing their advantages in reducing user burden and improving data reliability for older adults [204]. These systems also integrate seamlessly with machine learning models to enhance activity recognition performance, as shown by Yuan et al., who utilized multi-model sensor fusion in AAL environments to achieve high accuracy in ADLs detection [330].

The integration of machine learning and deep learning into HAR has been transformative, enabling automated feature extraction and classification. Anguita et al. employed Support Vector Machine classifiers, demonstrating their ability to classify activities, such as walking, sitting, and laying down, using accelerometer and gyroscope data with high accuracy in structured settings [331]. Their work highlighted the advantages of traditional machine learning methods in reducing computational complexity while maintaining high performance. With the rise of deep learning, researchers have moved towards neural network architectures capable of handling more complex patterns in data. Ordóñez and Roggen introduced DeepConvLSTM, a hybrid convolutional and recurrent neural network architecture designed to capture both spatial and temporal dependencies in activity data [332]. Their method outperformed traditional machine learning classifiers, particularly in datasets with diverse activities. Similarly, Hammerla et al. conducted a comparative analysis of deep learning models, emphasizing the potential of recurrent architectures for time-series HAR data [333]. However, despite these advancements, domain generalization remains a significant challenge, as models trained on one dataset often struggle to adapt to new sensor placements, user populations, or environmental settings.

Transfer learning has emerged as a key technique for addressing domain shift and data scarcity in HAR. Pan and Yang provided a comprehensive survey, categorizing transfer learning methods into instance-based, feature-based, and parameter-based techniques [334]. These methods are particularly relevant for HAR, where labeled data from diverse populations and real-world is often limited. An et al. employed transfer learning to reveal common features that can be transferred across users and adapted models to target domain, demonstrating its effectiveness in cross-domain generalization with reduced computation time [335].

Adversarial learning methods have further advanced transfer learning in HAR. For instance, Tzeng et al. proposed Adversarial Discriminative Domain Adaptation, which aligns feature spaces between source and target domains using adversarial networks [336]. In HAR, such approaches can be employed to bridge the gap between controlled and real-world datasets or between younger and older populations. Other domain adaptation techniques, such as

Domain-Adversarial Neural Networks by Ganin et al. [337], leverage gradient reversal layers to align source and target feature distributions, achieving robust cross-domain performance.

Alternative approaches like Maximum Mean Discrepancy [338] have also been applied in HAR to minimize the statistical distance between source and target domains [339]. By leveraging the inherent similarities between activities performed by young and older adults, these methods can reduce the need for extensive labeled data from older populations. This has shown promise in addressing the challenges of HAR for aging populations.

8.2.4 Current challenges

One of the primary challenges in HAR for older adults is the scarcity of representative labeled data [283]. Data collection from older populations is often constrained by ethical concerns, privacy issues, and logistical difficulties, making it challenging to obtain large and diverse labeled datasets. Consequently, datasets from older adults tend to be smaller and less diverse, which limits the ability of machine learning models to generalize effectively. In contrast, data collection from younger populations is more feasible, but models trained solely on this data struggle to generalize effectively to older adults due to physiological and behavioral differences. These differences include variations in movement patterns, speed, and range of activities, which can lead to decreased accuracy and reliability of HAR models when applied to older populations.

Another significant challenge is the discrepancy between controlled data collection environments and real-world settings [340]. Data collected in controlled environments is easier to obtain and can be used to train accurate models, but these models often fail to capture the complexity and variability inherent in real-world situations. Real-world environments, particularly in older adults' homes, are less structured and subject to numerous influencing factors, such as environmental obstacles, personal preferences, and physical limitations. Consequently, models trained in controlled settings may not perform well in semi-controlled or uncontrolled environments.

8.2.5 Contribution of study

Key contributions of this study:

- 1) This study addresses the scarcity of representative labeled data from older adults by leveraging a hybrid transfer learning framework to adapt models trained on younger populations. By aligning feature distributions between younger and older adults' data, the research enhances the generalizability of human activity recognition models, making them applicable to older populations without the need for extensive data collection.
- 2) The study contributes by developing methodologies that improve the robustness and adaptability of HAR models trained in controlled environments to perform effectively in real-world, less structured conditions. This approach can help models remain accurate and reliable when deployed in the dynamic, real-world environments typical of older adults' homes, thereby supporting real-life applications of AAL technology.

8.2.6 Research questions

- 1) How effectively can AAL sensor data be used to recognize human activities in different populations and control settings?
- 2) How to create a hybrid transferring learning framework that can be utilized to improve the generalizability of human activity recognition models trained on younger adults' data to effectively recognize activities in older adults?

8.2.7 Method

This section outlines the methods used in the study, including the materials used, ADLs scripts, conducted study experiment, and the proposed approach framework.

8.2.7.1 Materials

The materials utilized in the study include a variety of AAL devices, and an AAL environment.

8.2.7.1.1 AAL devices

In this study, a smart home environment was designed using advanced sensor technologies from Swidget Corporation. Unlike traditional smart home systems that depend on a central hub, which may quickly become outdated, this approach replaced existing electrical outlets and switches with intelligent versions that incorporate smart hub functionality. These outlets and switches were enhanced with interchangeable sensor inserts (e.g., temperature sensor, humidity sensor) to add various smart features as needed.

The smart home environment featured Swidget's intelligent outlets and switches, along with three types of sensor inserts to monitor indoor conditions. Specifically, the sensors included air quality sensors, temperature and humidity sensors, and motion sensors. These sensors collected data at a 30-second frequency, providing continuous monitoring of the environment. Their detailed features are shown in Table 21.

Table 21. AAL sensor information

Device type	Parameter measured	Value range / unit	Data type
Smart outlet	Activity state	0 = Off, 1 = On	Binary
	Energy usage	Measured in watts (W)	Numeric
Smart switch	Activity state	0 = Off, 1 = On	Binary
	Energy usage	Watts (W)	Numeric
Air quality sensor	Air quality index (AQI)	0 - 500	Numeric
	eCO ₂	400 - 6000 ppm	Numeric
	Air pressure	300 - 1100 hPa	Numeric
	bVOCs	0 - 1000 ppb	Numeric
Temperature & Humidity sensor	Room temperature	-10 °C - 40 °C	Numeric
	Relative humidity	0 - 100%	Numeric
Motion detector	Movement detection	Up to 3 meters, 120° angle	Binary

The selection of these sensors was informed by a scoping review by Wang et al. [283], which identified key sensor types most effective for AAL systems in recognizing ADLs. The review highlighted that occupancy, environmental, and power sensors are the most suitable for activity recognition in smart home environments. The chosen sensors ensured a comprehensive, well-balanced monitoring solution for tracking environmental parameters, movement, and device usage, enabling robust data collection for activity analysis.

8.2.7.1.2 AAL environment

To create a realistic AAL environment, an actual apartment within the Research Institute for Aging in Waterloo was adapted as a smart home setting, as illustrated in Figure 37. The unit included essential living spaces such as a bedroom, bathroom, living room, and kitchen, all furnished to reflect the daily needs of its occupants.

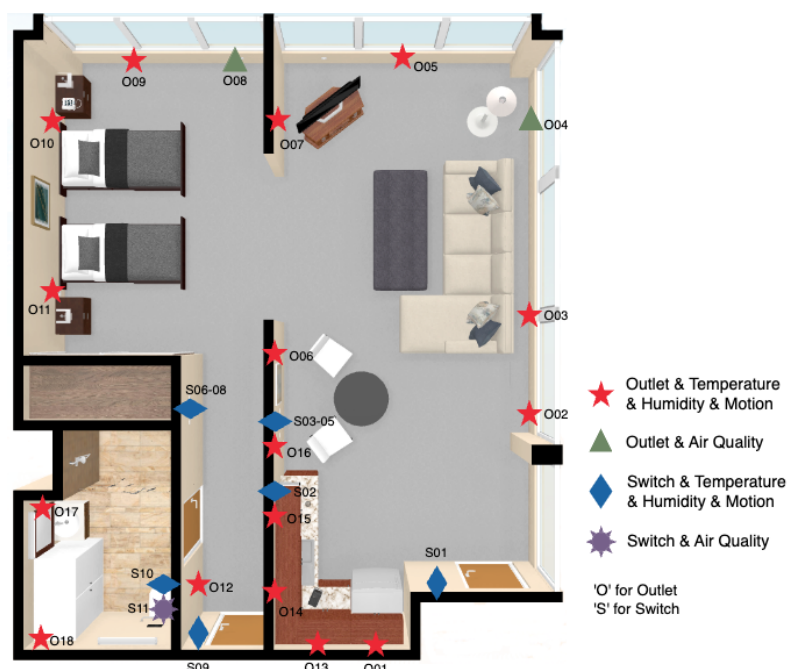


Figure 37. AAL environment

The smart home setup was constructed using the devices described in above section. Specifically, Swidget's intelligent outlets and switches, along with the appropriate sensor inserts, were deployed throughout the apartment to maximize data collection from routine activities. Standard switches and outlets were replaced with smart versions to create a versatile infrastructure capable of supporting various sensor inserts. The placement of selection of these sensors was informed by the unique characteristics of each space and the typical activities performed there.

For example, the kitchen was equipped with a higher concentration of temperature and humidity sensors to monitor fluctuations induced by cooking activities. Air quality sensors were installed in the living room and bathroom to capture changes related to occupancy and exposure to moisture or chemical emissions. Motion sensors were attached to each smart

outlet and switch throughout the apartment to ensure comprehensive detection of activities across different areas. This deployment strategy enabled a robust network of sensors to effectively capture environmental and activity data, resulting in a highly functional AAL environment.

The final sensor deployment consisted of 17 smart outlets, 6 smart switches, 23 motion sensors, 23 temperature and humidity sensors, and 2 air quality sensors, providing extensive coverage of all living spaces. This configuration ensured a thorough and well-distributed monitoring solution that could support detailed analysis of ADLs within a smart home context.

8.2.7.2 ADLs scripts for two settings

The ability of older adults to perform ADLs is a crucial indicator of their autonomy and overall functional capacity. In line with the methodology described in [248], the development of ADL scripts focused on five key categories: initial familiarization activities, posture adaptation tasks, movement coordination activities, basic ADLs (BADLs), and instrumental ADLs (IADLs). These scripts aimed to comprehensively capture the spectrum of activities typically performed in a home environment, allowing for a realistic simulation of daily routines. Each category of ADLs was carefully designed to test distinct physical and cognitive skills, thereby offering a well-rounded representation of daily functional requirements. For each category, four to five scenarios were developed to represent the associated ADLs.

Specifically, phase 1 was designed to introduce participants to simple tasks and help them become comfortable with the experimental environment. Phase 2 focused on activities involving posture changes and body positioning, emphasizing participants' ability to adjust their posture to carry out various tasks effectively. Phase 3 introduced activities requiring greater movement throughout the home, concentrating on the coordination of movement with daily activities, thus enhancing mobility and reach. Phase 4 centered on essential BADLs, such as cleaning and meal preparation, which are fundamental for independent living. Finally, phase 5 included IADLs, which involve more complex activities necessary for independent functioning but do not necessarily fall under basic self-care.

As the objective of the study is to investigate whether the outcomes from the controlled setting could be generalized to a semi-controlled setting, we created two associated sets of ADL scripts. These scripts followed the same five phases described above, ensuring that the activities remained consistent across the two experimental conditions, allowing for a direct comparison of participant performance and system efficacy between the controlled and semi-controlled ADLs settings. Detailed descriptions of the controlled and semi-controlled settings are as follows:

Controlled ADLs setting

The controlled setting meant that participants performed ADLs under detailed instructions provided by the researcher. These instructions included specific actions to be performed,

the sequence of those actions, and the duration for which each action should be carried out. This highly controlled setting allowed for consistency and minimized variability, providing a stable baseline for understanding how participants interacted with the AAL technology. The detailed ADLs instructions can be found in Appendix E.

Semi-controlled ADLs setting

In this setting, participants still received instructions, but the level of detail was significantly reduced compared to the first trial. Instead of receiving step-by-step guidance, participants were given a general scenario and tasks at beginning, allowing them the freedom to decide the interaction with the environment, additional actions, and the duration of each action within that scenario. This semi-controlled approach introduced moderate variability, simulating a more realistic and flexible environment. The detailed ADLs instructions can be found in Appendix E.

This dual ADLs setting approach allowed us to assess the adaptability of the AAL system across different conditions, particularly when transitioning from a controlled to a semi-controlled setting. The semi-controlled environment was especially useful for evaluating the system's effectiveness for older adults, who may experience age-related challenges in mobility or cognitive function, as it more accurately reflected the variability of real-world living environments.

8.2.7.3 Study

The entire study was conducted in two distinct trials, each involving a different group of participants and designed under varying conditions. Each trial was characterized by specific participant demographics and experimental environments to comprehensively assess human activity recognition in AAL settings.

- The first study trial was conducted with young adult participants in the controlled setting to establish a baseline dataset.
- The second study trial involved older adults in the semi-controlled environment to better represent the target population and capture real-world conditions while maintaining sufficient structure for reliable data collection.

HYAC: healthy younger adults in controlled setting

HOASC: healthy older adults in semi-controlled setting

8.2.7.3.1 Participants

The first study trial's cohort were recruited by engaging students from the University of Waterloo, utilizing both campus-wide flyer distribution and the university's internal participant pool. A preliminary screening using a detailed questionnaire was conducted to assess participants' ability to independently perform ADLs, based on predetermined inclusion and exclusion criteria. The inclusion criteria required participants to be capable of performing ADLs without assistance, have no health conditions affecting mobility, and be willing to comply with study procedures. They also needed to understand and follow the instructions provided. Individuals unable to comply with study protocols were excluded.

Following the screening process, the cohort was formed, comprising 40 participants (17 men and 23 women), aged between 18 and 39 years, with an average age of 24 years old.

For the second study trial, participants were recruited from the Waterloo Research in Aging Participant Pool. Recruitment involved sending emails and providing a pre-screening questionnaire to determine eligibility, focusing primarily on participants' independence in performing ADLs. This trial included 26 older adult participants, consisting of 6 men and 20 women, aged between 65 and 86 years, with an average age of 76 years old.

To ensure participants' privacy, all personal data were de-identified. The entire study was conducted under ethical approval ORE #43843, obtained from the University of Waterloo's Research Ethics Office.

8.2.7.3.2 Study procedure and data collection

Prior to the start of the experiment, participants provided written informed consent and completed a demographic questionnaire. They were subsequently introduced to the smart home environment, becoming familiar with its sensor-equipped appliances, various living spaces, and furniture. This familiarization phase ensured that participants were comfortable with the setup before beginning the experimental procedures.

Throughout the experiment, participants' activities were continuously monitored via cameras from an observation room, and instructions for each activity were provided through a mobile phone. All two participant groups followed the same study procedure and data collection process, differing only in the level of control applied. Observers provided different levels of instruction based on whether the ADLs setting was controlled or semi-controlled. The sequence of activities was predetermined and aligned with the phases and scenarios described earlier. Participants were encouraged to proceed independently, with additional guidance provided only upon request. A brief one-minute break was allotted between each scenario to reset the sensors and prepare for the next activity. An observer recorded the start and end times for each activity on a log sheet, facilitating data annotation and labeling during subsequent analysis. Each session was conducted individually. In the controlled setting, each scenario lasted approximately five minutes, with the entire experimental session taking around two hours. In the semi-controlled setting, no specific time requirement was imposed, allowing the duration of each activity to vary based on participants' preferences and natural pace.

Ambient sensor data was collected using the UbiEco cloud-based big data pipeline [279]. Raw sensor data was gathered through the manufacturer's Application Programming Interface (API) and reformatted for secure storage in a MySQL database on the Azure cloud platform.

8.2.7.3.3 Data cleaning and pre-processing

To ensure the reliability of the ambient sensor dataset prior to analysis, a thorough cleaning and pre-processing phase was undertaken. The sensors deployed for data collection

functioned solely as raw data acquisition tools, without any capabilities for data standardization or processing. Raw data was retrieved directly from the manufacturer's API and processed locally using dedicated servers.

The dataset included numerical readings such as temperature and humidity, as well as binary indicators for occupancy states. To integrate data from various sources, all measurements were standardized in terms of units and formats. For example, temperature readings from different sensors were converted to a uniform scale (i.e. degrees Celsius). Additionally, timestamps were synchronized across all sensors to ensure temporal alignment, enabling consistent data granularity across the dataset.

Outlier detection and removal were applied to numerical data using z-score analysis, which identified and excluded extreme values that could affect subsequent analyses. This ensured that the dataset reflected typical environmental conditions. Binary data was applied with contextual and logical validations to identify anomalies. For instance, rapid changes in occupancy states were flagged as unrealistic during contextual checks, while logical inconsistencies, such as conflicting sensor readings for the same event, were identified and addressed.

Missing data were handled differently depending on the data type. For numerical attributes, missing values were imputed with the mean of the corresponding variable within the scenario to preserve continuity. For binary indicators, missing values were replaced with the mode to maintain the integrity of categorical data.

To address redundancy, particularly in rooms equipped with multiple temperature and humidity sensors, correlations between sensor outputs were analyzed. When high correlations were observed, readings from these sensors were averaged to create a single representative value per parameter for each room. This step reduced data redundancy while retaining the essential environmental information, enhancing interpretability and simplifying subsequent analyses.

8.2.7.4 A hybrid transferring learning framework

This section introduces the theories of models used in the proposed hybrid transferring learning framework and its structure.

8.2.7.4.1 Theories

Correlation alignment (CORAL)

CORAL [341] is a feature-based method for domain adaptation in transfer learning, designed to align the distribution of feature representations between a source and a target domain. This alignment is achieved by minimizing the discrepancy between their covariance matrices, which helps reduce domain shift and improves the transferability of a model trained in one domain to another. CORAL specifically adjusts the second-order statistics of the source and target features by applying a whitening and re-coloring transformation. This process encourages the source features to match the statistical properties of the target features, facilitating more robust performance across domains.

The core principle of CORAL involves minimizing the difference between the covariance matrices of the source (H_s) and target (H_t) domain features. The objective function for CORAL is given by:

$$\mathcal{L}_{CORAL} = \frac{1}{4d^2} \|Cov(H_s) - Cov(H_t)\|_F^2$$

Here d represents the feature dimensionality, and $\|\cdot\|_F$ denotes the Frobenius norm. The function $Cov(X)$ stands for the covariance matrix of the feature matrix X , calculated as:

$$Cov(X) = X^T C_n X$$

where $C_n = I_n - (1_n 1_n^T) / n$ is the centering matrix, I_n is the identity matrix of order n , and 1_n is n -dimensional vector of ones. This centering process ensures that the covariance matrices accurately capture the structure of the data in each domain.

By minimizing $\mathcal{L}_{CORAL}$, CORAL effectively aligns the feature distributions between the source and target domains, enhancing the model's generalization capabilities across different domains. This technique is especially beneficial when incorporated into deep neural networks [344], as it enables the alignment of intermediate feature representations, thereby reducing the discrepancy between domains.

Conditional domain adversarial networks (CDAN)

CDAN is an advanced approach to domain adaptation that builds upon adversarial learning by conditioning domain alignment on class-specific information [323]. Traditional adversarial domain adaptation methods focus on aligning global feature distributions across the source and target domains, which can overlook the structure within each class. CDAN addresses this limitation by aligning the conditional distributions, ensuring that features within each class in the source domain align closely with those in the target domain, thereby preserving class-specific discriminative characteristics across domains.

The key mechanism behind CDAN involves using a conditional domain discriminator that receives features conditioned on their class labels. This discriminator is trained to differentiate between source and target features within each class, encouraging the model to produce domain-invariant representations that retain class separability. The CDAN objective function is formulated as a combination of an adversarial loss and a classification loss:

$$\mathcal{L}_{CDAN} = \mathcal{L}_{adv} + \lambda \mathcal{L}_{cls}$$

where λ is a hyperparameter controlling the trade-off between the adversarial loss $\mathcal{L}_{adv}$ and the classification loss $\mathcal{L}_{cls}$.

The adversarial loss $\mathcal{L}_{adv}$ is designed to align feature distributions in a class-conditioned manner. The domain discriminator, denoted by D , takes as input the features extracted by the feature extractor $f(x)$ along with the predicted class probability $p(y = k|x)$. The adversarial loss is defined as:

$$\mathcal{L}_{adv} = - \mathbb{E}_{\mathbf{x} \sim \mathcal{X}} \sum_{k=1}^K p(y = k|\mathbf{x}) \log D(f(\mathbf{x}), y = k)$$

where $D(f(\mathbf{x}), y = k)$ represents the probability that the feature $f(\mathbf{x})$ belongs to the source domain given the class label $y = k$. $p(y = k|\mathbf{x})$ is the predicted probability of class k for input $\mathbf{x}$, computed by a classifier over the feature representations.

This adversarial term encourages the discriminator D to fail in distinguishing between source and target domains for each class, thereby aligning the conditional distributions $p(y = k|\mathbf{x})$ across the domains.

The classification loss $\mathcal{L}_{cls}$ is a standard supervised loss applied to the labeled source data to ensure that the learned features retain their predictive power. For a source domain sample $\mathbf{x}_s$ with true label y_s , the classification loss is typically defined as the cross-entropy loss:

$$\mathcal{L}_{cls} = - \mathbb{E}_{(\mathbf{x}_s, y_s) \sim \mathcal{X}_s} \sum_{k=1}^K 1[y_s = k] \log p(y = k|\mathbf{x}_s)$$

where $1[y_s = k]$ is an indicator function that equals 1 if the true label y_s is k , and $p(y = k|\mathbf{x}_s)$ is the predicted probability of class k for the source sample $\mathbf{x}_s$.

The overall objective of $\mathcal{L}_{CDAN}$, seeks to minimize the classification loss for source domain samples while maximizing the conditional alignment of source and target features.

8.2.7.4.2 Hybrid transfer learning framework

We propose a hybrid transfer learning framework that integrates CORAL with CDAN to enhance domain adaptation in this human activity recognition task. As illustrated in Figure 38, the framework consists of three main components: the modified class-wise CORAL module, a shared feature extractor, and a conditional domain adversarial alignment module.

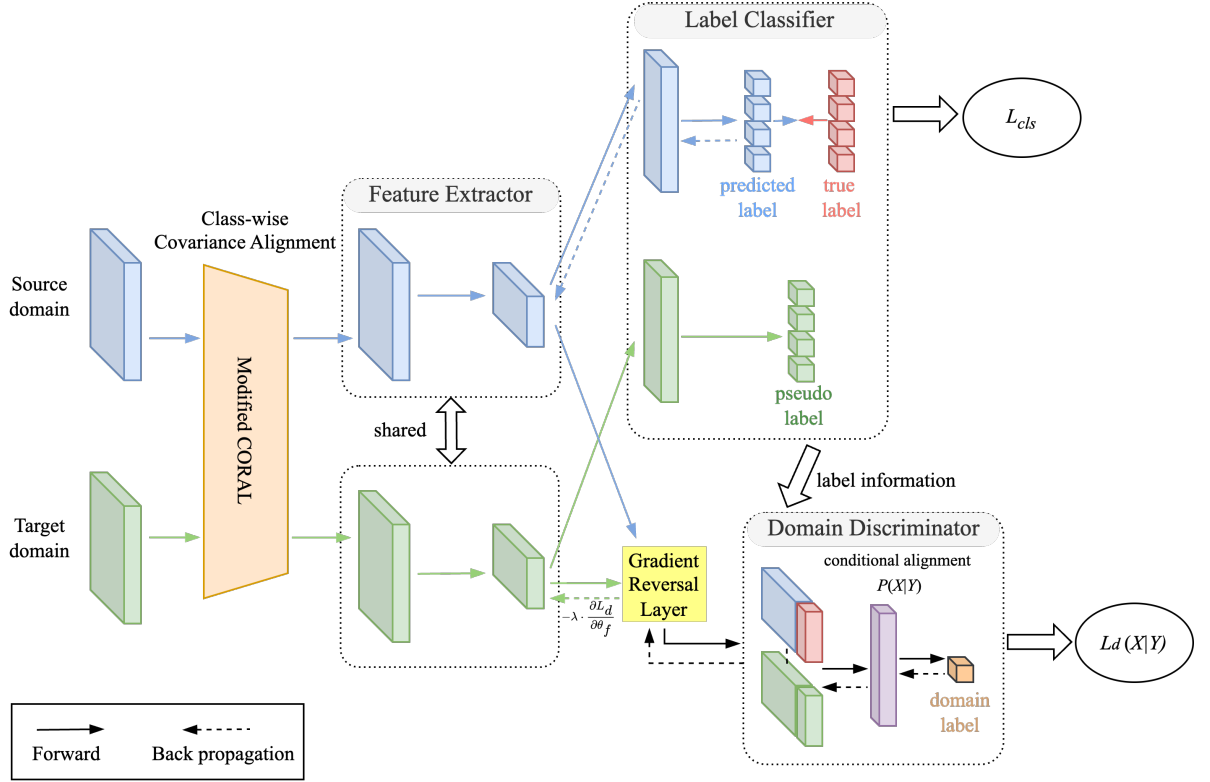


Figure 38. Hybrid transfer learning framework

The process begins with the modified CORAL module, which performs class-wise covariance alignment between the source and target domains. This ensures that the feature distributions for each class are aligned, minimizing inter-class interference and allowing for more precise adaptation. The aligned features are then passed to the shared feature extractor, which maps the data into a common feature space. These features are subsequently utilized by two branches: a label classifier and a domain discriminator. The label classifier predicts activity labels for the source domain and generates pseudo-labels for the target domain. These pseudo-labels enable conditional alignment, as they approximate the target domain's class distribution. Concurrently, the domain discriminator is used to align the feature representations from both domains. To achieve this, a Gradient Reversal Layer is introduced between the feature extractor and the domain discriminator. This adversarial training process ensures that the feature extractor learns to generate domain-invariant features that make it difficult for the discriminator to distinguish between the source and target domains. This approach ensures that if the classifier achieves good performance in the source domain, it can also achieve comparable performance in the target domain by leveraging the shared, domain-invariant feature representations.

8.2.7.5 Data summary

Following data cleaning and the exclusion of noisy data, two primary datasets corresponding to each trial were prepared for this study. We use HYAC and HOASC to represent each dataset, respectively. HYAC dataset is with 7532 instances and the HOASC dataset is with 4772 instances. Both datasets include 125 features (Table 22), which associated with sensor and environmental information.

Table 22. AAL features table

Features	Description
<i>Outlet_0_on_01-18</i>	18 features Binary data reflecting the on/off states of the upper ports as captured by outlet sensors designated as O01 to O18.
<i>Outlet_1_on_01-18</i>	18 features Binary data reflecting the on/off states of the lower ports as captured by outlet sensors designated as O01 to O18.
<i>Outlet_0_avg_01-18</i>	18 features Continuous data reflecting the energy usage of the upper ports as captured by outlet sensors designated as O01 to O18.
<i>Outlet_1_avg_01-18</i>	18 features Continuous data reflecting the energy usage of the lower ports as captured by outlet sensors designated as O01 to O18.
<i>switch_avg_S01-S11</i>	11 features Continuous reflecting the energy usage of switch sensors designated as S01 to S11.
<i>living_temp</i>	10 features Measurement of temperature and humidity across five rooms.
<i>living_humi</i>	
<i>kitchen_temp</i>	
<i>kitchen_humi</i>	
<i>dining_temp</i>	
<i>dining_humi</i>	
<i>bedroom_temp</i>	
<i>bedroom_humi</i>	
<i>bathroom_temp</i>	
<i>bathroom_humi</i>	
<i>motion_01-23</i>	23 features Binary data reflecting the occupancy states from 23 passive infrared sensors.
<i>aq_co2_O04</i>	9 features Measurement of air quality related parameters from 3 environmental sensors.
<i>aq_iaq_O04</i>	
<i>aq_tvoc_O04</i>	
<i>aq_co2_O09</i>	
<i>aq_iaq_O09</i>	
<i>aq_tvoc_O09</i>	
<i>aq_co2_S11</i>	
<i>aq_iaq_S11</i>	
<i>aq_tvoc_S11</i>	

<i>Activity Label</i>	Label category that associated with each daily living activity, such as P1S1.
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Figure 39 shows the label distribution for each dataset. The labels are associated with activity scenarios.

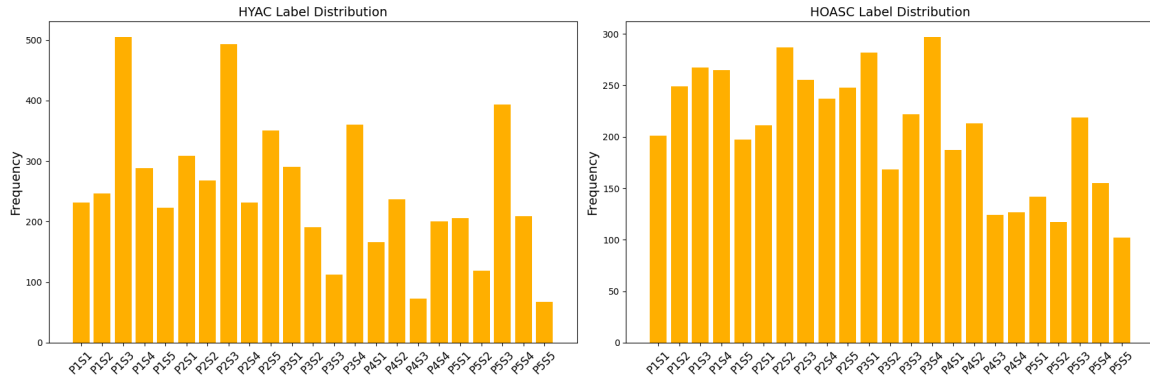


Figure 39. Data label distribution

Figure 40 presents the t-SNE visualizations for each dataset. Different colors represent different activity labels. Both visualizations show overlaps among labels, with the HOASC dataset exhibiting more severe overlap, indicating the challenges of distinguishing activities and generalizing models from source to target.

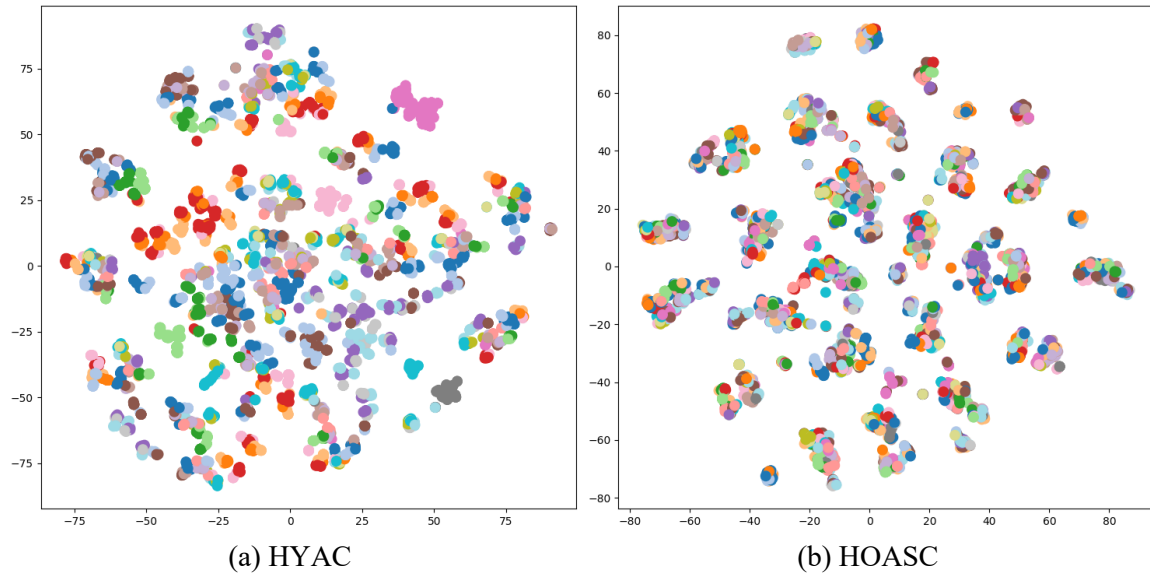


Figure 40. t-SNE visualization on two datasets

8.2.8 Results

This section presents the machine learning models, evaluation metrics, computational setup used in analytics, and the results obtained from the analysis.

8.2.8.1 Models & Evaluation Metrics

During the data analysis stage, apart from transfer learning models, we also utilized five commonly employed machine learning algorithms: K-Nearest Neighbours (KNN), Decision Trees (DT), Random Forest (RF), Adaptive Boosting (AdaBoost), and Gaussian Naive Bayes (GNB).

To thoroughly assess the performance of these machine learning models, we adopted four key metrics: Accuracy (ACC), Precision, Recall, and F1-Score. These metrics offer a comprehensive evaluation of the model's strengths and weaknesses. The definitions of the metrics are given below:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1-score} = 2 \times ((\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}))$$

where TP, FP, FN, and TN represent True Positive, False Positive, False Negative, and True Negative, respectively. In the results, we use weighted F1 score.

8.2.8.2 Computational setup

The evaluation was performed on a Linux server running Ubuntu version 22.04.3, with 16GB of RAM to ensure stable and efficient data handling. The software environment consisted of Python version 3.10.12, along with essential libraries, including Pandas v1.3.5, Matplotlib v3.5.1, and Numpy v1.21.5, among others. For machine learning and deep learning, Scikit-learn version 1.3.2 and PyTorch v2.5.1 were used as the main framework.

8.2.8.3 Separate performance on individual datasets

The following results in Table 23 are based on separate training and testing on each dataset (8:2 training and test ratio) with 5-folder cross validation. It shows considerable differences in model performance across different population groups and environmental conditions.

Table 23. Model performance when separate training and test (no transfer learning)

		ACC	Precision	Recall	F1-score
HYAC	KNN	0.937	0.940	0.937	0.936
	DT	0.863	0.861	0.863	0.860
	GNB	0.546	0.627	0.546	0.516
	RF	0.953	0.951	0.953	0.950
	AdaBoost	0.964	0.966	0.964	0.964
HOASC	KNN	0.476	0.472	0.476	0.470
	DT	0.505	0.506	0.505	0.504
	GNB	0.192	0.159	0.192	0.133
	RF	0.596	0.596	0.596	0.588
	AdaBoost	0.661	0.672	0.661	0.653

The performance of the machine learning models on the HYAC dataset is notably high across all evaluation metrics, with the highest ACC achieved by AdaBoost (0.964) and RF (0.953). These results indicate that the controlled environment of the HYAC dataset enables the models to achieve high accuracy, precision, recall, and F1-score, suggesting that activity recognition is more straightforward in such settings. Specifically, AdaBoost outperformed other models, achieving consistent performance across all metrics, with an F1-score of 0.964. This high performance highlights the benefit of the controlled nature of

the dataset, where activity patterns are easier to identify. Similarly, RF achieved competitive results, with high accuracy and F1-score, reflecting the advantages provided by the controlled setting of the HYAC dataset. The KNN classifier also achieved good results, with an accuracy of 0.937, though it lagged slightly behind the ensemble methods, again benefiting from the controlled dataset environment. The DT classifier showed moderate performance (ACC of 0.863), while GNB was the weakest model (ACC of 0.546), indicating that even in controlled settings, simpler models may struggle to capture the complexity of activity data.

In contrast, the performance of all models on the HOASC dataset is significantly lower. Even the best-performing model, AdaBoost, achieved only an accuracy of 0.661 and an F1-score of 0.653. The Random Forest classifier also struggled, achieving an accuracy of 0.596, which is considerably lower compared to its performance on the HYAC dataset. The KNN and DT models performed poorly, with accuracies of 0.476 and 0.505, respectively, indicating that these models struggle to handle the variability and increased complexity present in the HOASC dataset. The GNB classifier, with an accuracy of only 0.192, was unable to provide reliable activity classification, which is unsurprising given its limitations in handling complex, overlapping feature distributions typical of semi-controlled environments.

These results highlight the challenge of recognizing activities in older adults under semi-controlled conditions, where increased variability and complexity of activities make classification more difficult. The HOASC dataset's semi-controlled nature introduces greater unpredictability compared to the controlled HYAC dataset, which likely contributes to the lower performance. Furthermore, in real-world applications where labeled data is even harder to obtain, training effective models solely on such limited datasets becomes significantly more difficult.

8.2.8.4 Transfer learning

In transfer learning, an unsupervised learning approach is typically employed, where a source domain dataset with labels is used to transfer knowledge to a target domain dataset without labels. In this study, the HYAC dataset is used as the source domain, while the HOASC dataset serves as the target domain. It is important to note that in this experiment, we reuse the same training and test sets from the previous analysis for consistency, with a modification: the HYAC dataset, originally split in an 8:2 ratio for training and testing, now uses its test portion as the validation set. The HOASC dataset retains its original 8:2 split for training and testing. During the training phase, we use unlabeled training HOASC data to assist the transfer, while the labels are employed only during the testing phase to evaluate model performance.

8.2.8.4.1 Naïve transfer

Naïve transfer refers to a simple approach where we train a model on the source dataset and then directly apply it to the target dataset without any domain adaptation or specific transfer

learning techniques. In this analysis, we trained and validated the model on the HYAC dataset and then applied it to the HOASC test dataset. The results are shown in Figure 41.

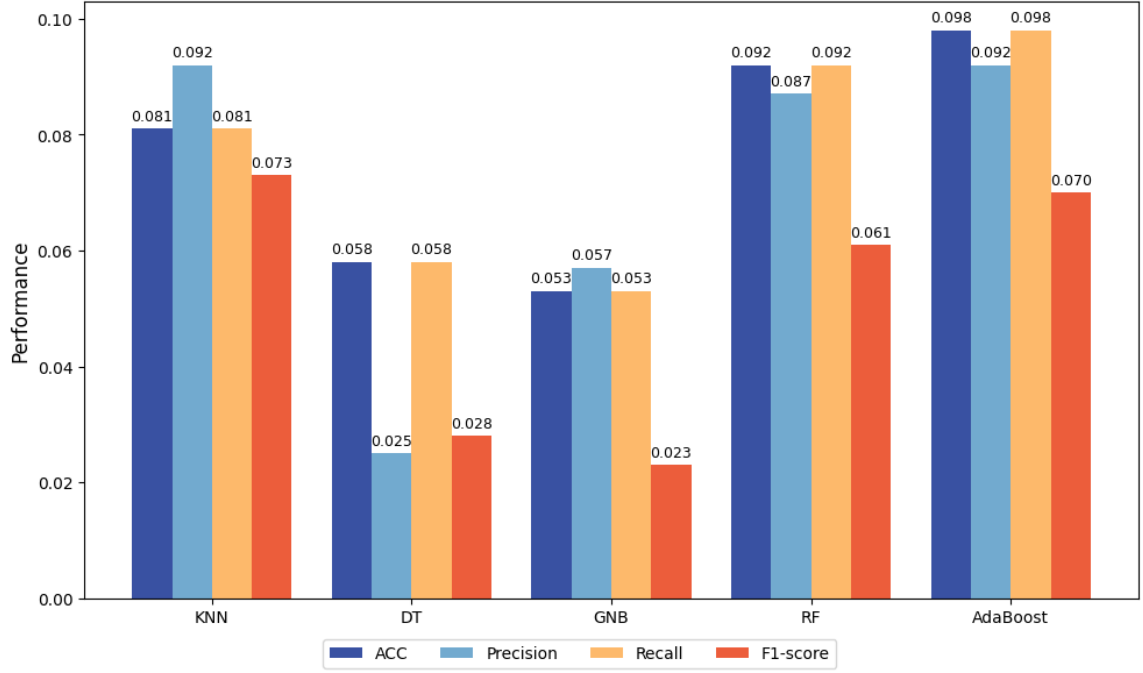


Figure 41. Naïve transfer performance using five models

The results of the naïve transfer approach demonstrate very poor performance across all models, with accuracy, precision, recall, and F1-score all under 0.1, comparing to a random guess baseline of 0.062. Specifically, AdaBoost achieved an accuracy of 0.098, followed closely by RF (0.092), indicating that direct transfer from the controlled HYAC dataset to the semi-controlled HOASC dataset leads to a significant decline in performance. KNN showed an accuracy of 0.081, while DT and GNB performed even worse, with accuracies of 0.058 and 0.053, respectively.

The precision, recall, and F1-score metrics also reflect the poor transferability of the models. For AdaBoost, the F1-score was only 0.070, with similar metrics for RF (0.061) and KNN (0.073). DT and GNB showed the lowest F1-scores, at 0.028 and 0.023, respectively. These results clearly highlight that the models trained on the controlled HYAC dataset are unable to effectively generalize to the HOASC dataset, which exhibits higher variability and complexity.

The decline in performance across all models highlights the difficulty of directly applying activity recognition models trained on controlled datasets to semi-controlled settings, particularly when dealing with a population that exhibits different movement characteristics, such as slower and less consistent motions.

8.2.8.4.2 Hybrid transfer learning

In this section, we extended the exploration of transfer learning by employing a hybrid approach that combines CORAL with CDAN. The aim is to address the limitations

observed with naïve transfer by leveraging advanced domain adaptation techniques to align the feature distributions between the source and target domains more effectively.

We conducted a comparative analysis of the hybrid approach (CORAL + CDAN) against four other transfer learning methods: CORAL, Reverse Transfer Network (RTN), Domain Adaptation Network (DAN), and CDAN alone. For CORAL, we aligned the feature distribution from the target domain (HOASC) to the source domain (HYAC) and then applied the previous five machine learning models as classifier. For the other methods (RTN, DAN, CDAN, and the hybrid approach), the network structure inherently includes a classifier, and we used that classifier directly to evaluate performance. Specifically, the hybrid approach first applied CORAL to align the features between domains, followed by CDAN for further adaptation and classification. The results are shown in Table 24.

Table 24. Comparison of using different transfer learning methods

		ACC	Precision	Recall	F1-score
CORAL	KNN	0.176	0.234	0.176	0.165
	DT	0.095	0.128	0.095	0.066
	GNB	0.344	0.446	0.344	0.322
	RF	0.154	0.161	0.154	0.126
	AdaBoost	0.139	0.192	0.139	0.105
RTN		0.053	0.018	0.053	0.011
DAN		0.479	0.472	0.471	0.448
CDAN		0.502	0.497	0.502	0.472
CORAL+CDAN		0.576	0.572	0.576	0.538

The results reveal notable improvements of the hybrid transfer learning approach compared to the other methods, although the overall performance metrics still fall under 0.6. The hybrid approach achieved an accuracy of 0.576, with an F1-score of 0.538. This represents a significant improvement over the individual methods, such as CORAL and CDAN alone, where CDAN achieved an accuracy of 0.502, and CORAL showed varying performance depending on the classifier used. Among the classifiers used with CORAL, GNB exhibited the highest accuracy (0.344), while KNN, DT, RF, and AdaBoost performed poorly, with accuracies ranging from 0.095 to 0.176. The better performance of GNB can be attributed to its reliance on estimating Gaussian probability distributions, which benefits from CORAL's alignment of feature covariances between the source and target domains. In contrast, classifiers like KNN, DT, RF, and AdaBoost, which depend more on raw feature relationships or decision rules, may be less sensitive to this covariance alignment, contributing to their lower accuracies. The hybrid approach outperformed the standalone CORAL, RTN, DAN, and CDAN methods. Specifically, RTN, with an accuracy of only 0.053, showed minimal ability to adapt the source-trained model to the target domain. DAN performed slightly better, with an accuracy of 0.479, while CDAN achieved a moderate accuracy of 0.502.

The precision, recall, and F1-score metrics for the hybrid method also highlight its advantage over other methods. For the hybrid approach, precision and recall were both 0.572, compared to 0.497 and 0.502 for CDAN, and 0.472 and 0.471 for DAN, respectively. The F1-score for the hybrid method (0.538) is also the highest among all the tested approaches, indicating better overall balance between precision and recall. Notably, GNB, when used with CORAL, achieved the highest accuracy among the classifiers (0.344), but the F1-score remained low (0.322), suggesting that the predictive capability was not well balanced between false positives and false negatives.

The visual representation of the source and target data using t-SNE is presented in Figure 42, with Figure 42(a) showing the distribution before adaptation and Figure 42(b) showing the distribution after applying the hybrid approach. Before adaptation, there is a clear boundary between the source and target data, indicating minimal overlap. After applying the hybrid transfer learning approach, the data becomes clustered, with significant overlap or approaching position between the source and target domains, indicating improved alignment and adaptation performance. In Figure 43, which is annotated by data labels, Figure 43(a) shows that all data points from target and source domain are mixed and hard to distinguish by labels. However, Figure 43(b) shows that after adaptation, target data points overlap or are positioned closer to the source data with the same label, indicating successful grouping and improved class separability.

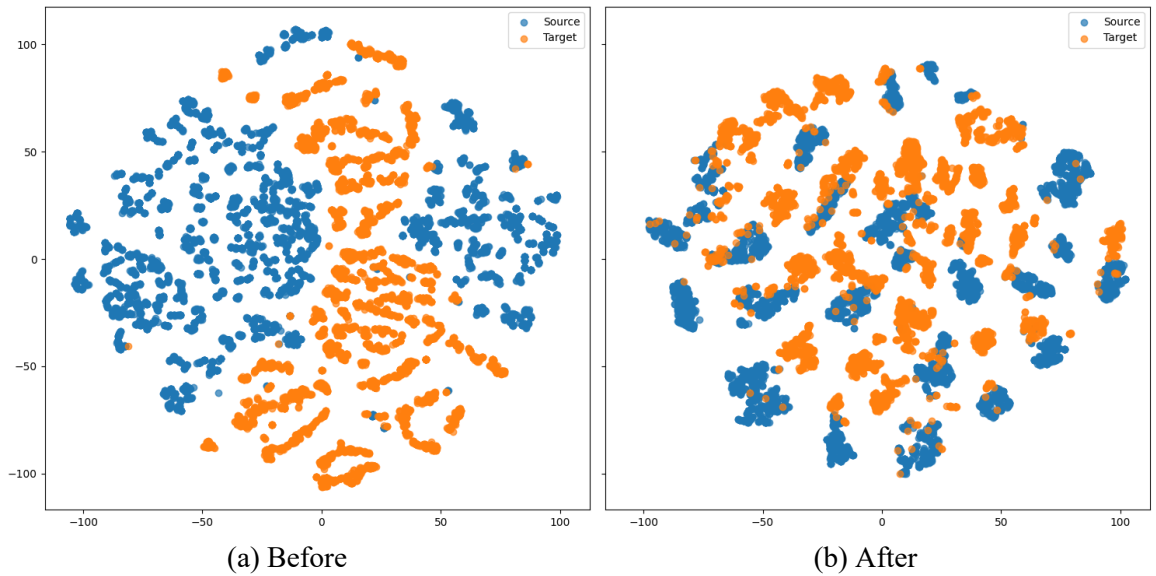


Figure 42. t-SNE visualization on source and target domain before and after transfer

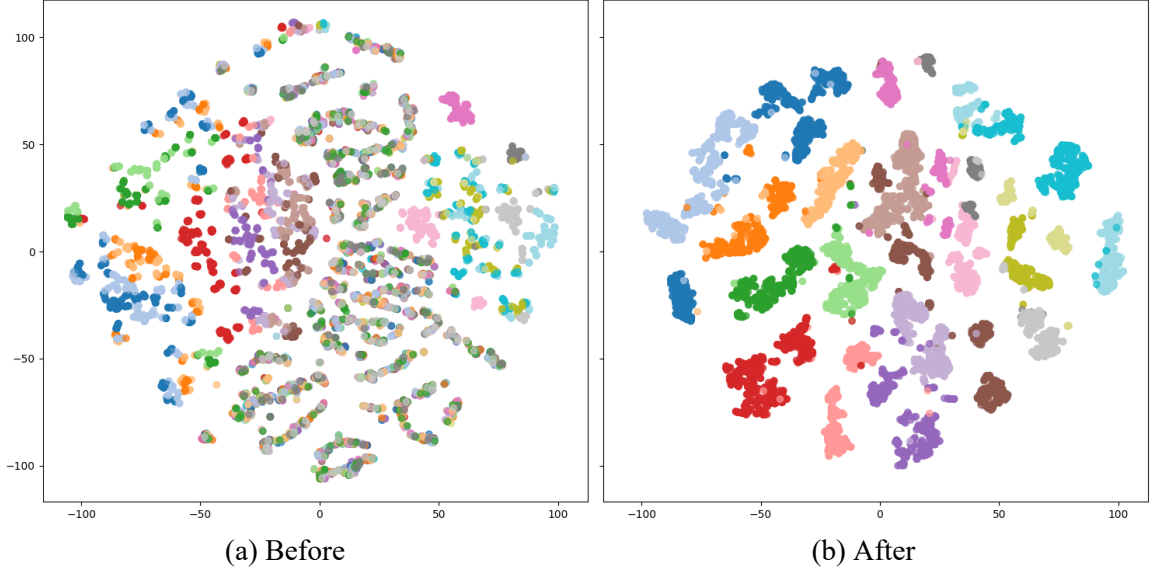


Figure 43. t-SNE visualization by labels before and after transfer

8.2.8.4.3 Mixing HOASC data analysis

Increasing training set size

In order to further improve performance, we explored an approach that involved mixing target domain data (HOASC) with source domain (HYAC) data during the training phase. The goal was to determine whether incorporating different proportions of target domain data into training could enhance the model's ability to generalize to the target environment. The hybrid transfer learning approach demonstrated the potential of domain adaptation, and thus we leveraged the feature extractor layer trained in the hybrid network to extract features from both source and target domain. After that, we trained classifiers by mixing varying percentages of target domain training data (ranging from 0% to 50% in increments of 10%, and the number of target domain samples added is calculated by percentage with number of source domain data) with source domain data, using the five machine learning models: KNN, DT, GNB, RF, and AdaBoost. This strategy will increase the training set size when mixing different portion of target domain data. The target domain test data was then used as the test set to evaluate model performance. The results are shown in Figure 44. The detailed values of these results can be found in Appendix F.

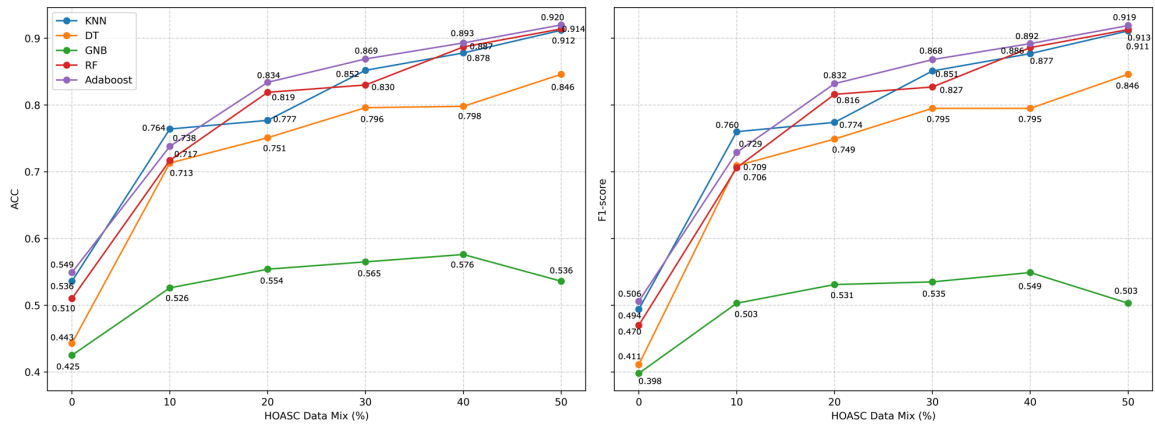


Figure 44. Model performance with mixing different ratio of target domain data (after transfer learning and with increasing training set size)

The accuracy and F1-score trends depicted in the results clearly demonstrate an overall improvement in performance as more target domain data was incorporated into the training process. The most notable improvement was observed in the AdaBoost classifier, where accuracy increased from 0.549 with no target domain data to 0.920 when the amount of HOASC data added was equal to 50% of the total number of HYAC. Similarly, Random Forest showed a substantial increase in accuracy, from 0.510 to 0.914, as the proportion of HOASC data in the training set grew. These results indicate that blending the source and target domain data during training can significantly enhance the models' capability to handle the variability inherent in the HOASC dataset.

For other models such as KNN and DT, the trend was also positive, although not as significant compared to AdaBoost and RF. KNN achieved an accuracy of 0.912 at the highest mixing level, while DT improved from 0.443 to 0.846 as the proportion of HOASC data increased. The gains in both accuracy and F1-score highlight the value of including even small amounts of target domain data in the training process to enhance performance. In contrast, GNB exhibited a different trend; while initial increases were observed with small percentages of target data, performance plateaued and then slightly decreased at higher percentages, with accuracy dropping from 0.576 at 40% mixing to 0.536 at 50%.

The F1-score data closely mirrors the accuracy trends. AdaBoost demonstrated the highest F1-score, increasing from 0.506 with no HOASC data to 0.919 with 50% HOASC data, indicating a well-balanced performance between precision and recall as more target domain data was included. Random Forest followed a similar pattern, with its F1-score rising from 0.470 to 0.913. KNN and DT also experienced improvements, reaching F1-scores of 0.911 and 0.846, respectively, at the highest mixing levels. GNB, however, showed an inconsistent pattern, with the F1-score peaking at 0.549 at 40% mixing before declining slightly.

Fixed training set size

In the previous analysis, we augmented the source domain (HYAC) by adding increasing proportions of target domain data (HOASC), resulting in a growing training set size as the target ratio rose from 0% to 50%. This approach raised the possibility that the observed improvements in model performance were primarily due to the increased volume of training data rather than the incorporation of target-specific information. To investigate this hypothesis, we conducted a complementary analysis where the total training set size was held constant across all models and ratios. Specifically, for each increment of target domain data added (e.g., 10%, 20%, 30%), we randomly removed an equivalent number of samples from the source domain, maintaining a fixed training set size. The following Figure 45 is showing the results. The detailed values of these results can be found in Appendix G.

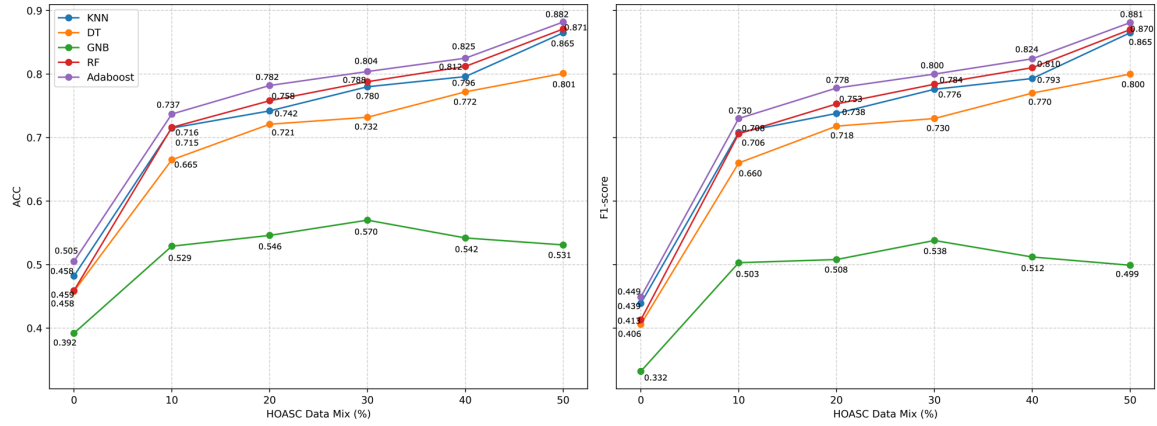


Figure 45. Model performance with mixing different ratio of target domain data (after transfer learning and with fixed training set size)

The accuracy and F1-scores for five classifiers are illustrated in Figure 45, reflecting their performance on the HOASC test set as the mixed target data ratio increased from 0% to 50%. In this fixed-size setup, all models exhibit a consistent upward trend in performance with higher target data proportions, mirroring the pattern observed in the increasing-size condition. For instance, KNN's accuracy rises from 0.482 at 0% to 0.865 at 50%, while RF improves from 0.459 to 0.871, and Adaboost advances from 0.505 to 0.882. Similarly, F1-scores follow suit, with DT climbing from 0.406 to 0.800 and GNB from 0.332 to 0.499.

To evaluate the contribution of training set size to performance improvements, we compared the fixed-size results with those from the increasing-size condition. Across all models and target data ratios, the fixed-size setup consistently exhibits slightly lower performance. For example, at a 50% target ratio, KNN achieves an accuracy of 0.865 in the fixed-size condition, compared to 0.912 in the increasing-size condition, despite the latter incorporating 50% more training data. Similarly, RF achieves an accuracy of 0.871 in the fixed-size setup, compared to 0.914 in the increasing-size setup, while Adaboost records 0.882 relative to 0.920. Even GNB, which exhibits the smallest disparity, drops only marginally from 0.536 to 0.531 at the 50% ratio. This modest performance gap indicates that the additional data volume in the increasing-size setup contributes only minimally to the observed enhancements. These findings suggest that the primary factor driving performance gains is the increasing proportion of target domain data, rather than the overall expansion of the training set size.

These results suggest that after domain adaptation with the hybrid framework, incorporating target domain data into the training process can significantly improve model performance, particularly for ensemble methods such as AdaBoost and Random Forest. This experiment provides a practical strategy: mixing even a small percentage of target domain data with source domain data can yield notable performance gains, which is especially useful in scenarios where labeled data is scarce, but improved model performance is desired.

8.2.9 Discussion

The discussion section discusses and addresses the two primary research questions posed in this study, based on the findings from the results.

8.2.9.1 AAL effectiveness for HAR in different populations and settings

The results of this study demonstrate that AAL sensor data can be highly effective in recognizing human activities when used in controlled environments with homogeneous populations, such as younger adults. The strong performance of models on the HYAC dataset confirms the effectiveness of AAL sensor data in ideal, well-structured settings, where activities are consistent and predictable. These findings align with those of Damaševičius et al. [352], who reported high classification accuracy using data from controlled AAL environments with younger participants. They use the method of random projections benefited from the structured nature of the environment and the consistency in activity execution.

However, the decline in performance observed with the HOASC dataset underscores the challenges associated with generalizing models to more diverse and less structured environments. The significant drop in accuracy, precision, recall, and F1-scores when applying naïve transfer from the HYAC dataset to the HOASC dataset highlights the limitations of models trained solely on younger adults under controlled conditions. These finds are consistent with the study by Stojchevska et al. [353], who noted that models trained on data from controlled lab conditions showed reduced effectiveness in real-world scenarios for HAR. The differences in movement characteristics, such as slower, less consistent motions, and the more dynamic nature of older adults' activities in semi-controlled environments, make direct transfer ineffective. This finding indicates that while AAL sensors are capable of capturing activity data, the model's ability to generalize depends heavily on the similarity between the source and target domains.

Incorporating a portion of the target domain data into the training process led to substantial improvements in model performance. The results from mixing target domain data with the source domain demonstrate that even small amounts of context-specific data can significantly enhance generalizability. This suggests that the heterogeneity of populations and environments needs to be accounted for during the training phase. In real-world applications, such as those involving older adults in home environments, the inclusion of even a limited amount of labeled data from the target domain can make a significant difference in the accuracy and reliability of HAR systems. These observations align with findings by Kfari and Lüdtke [354] who showed that integrating labeled and unlabeled target domain data to adapt HAR models to new users reduced cross-subject variability and improved accuracy. Thus, the shared observations emphasize that while AAL sensor data is valuable, it must be complemented by domain-specific data to achieve effective generalization across different populations and environments.

8.2.9.2 Transfer learning for generalizability

The second research question aimed to develop a hybrid transfer learning framework that could improve the generalizability of HAR models trained on younger adults' data to

effectively recognize activities in older adults. While previous studies, such as Damaševičius et al. [352], have focused on younger populations, this study provides new insights into older adults by employing a hybrid transfer learning approach. The results from employing the hybrid transfer learning approach by combining CORAL with CDAN illustrate the potential of advanced transfer learning techniques in addressing the challenges associated with domain adaptation.

The hybrid framework significantly outperformed other methods, such as naïve transfer, CORAL, and CDAN alone. This improvement suggests that a multi-step approach that first aligns feature distributions and then applies adversarial learning is more effective in reducing the domain shift between younger and older populations. Similar results have been observed in other domains, such as in Chen et al. [355], where the combination of feature alignment methods and adversarial learning effectively mitigated domain discrepancies. The use of CORAL to align the source and target feature distributions helped to mitigate the discrepancies between the datasets, while CDAN further refined this alignment through adversarial training. This two-step process effectively reduced the differences in activity patterns and movement characteristics between younger and older adults, allowing for better model adaptation.

In addition to the hybrid model architecture, the incorporation of labeled target domain data into the training process also played a crucial role in improving model performance. By mixing varying percentages of target data with the source domain data, significant gains in accuracy and F1-score were observed, particularly for ensemble models like AdaBoost and Random Forest. The inclusion of even small amounts of labeled target data provided the model with valuable information about the target domain's characteristics, thereby enhancing its ability to generalize [354]. This hybrid approach, combining both advanced model architectures and data blending strategies, underscores the importance of leveraging multiple dimensions of transfer learning to improve generalizability.

The findings indicate that hybrid transfer learning can be a practical solution for enhancing the robustness of HAR models, particularly in the context of aging populations. The t-SNE visualizations further support these conclusions, showing that the hybrid approach led to a more uniform overlap between source and target domains. This indicates that the adaptation process was successful in bringing the feature spaces of the two populations closer together, which is crucial for accurate activity recognition.

8.2.9.3 Implications for public health

The findings of this study have significant implications for public health, particularly in supporting aging populations through in-home healthcare solutions. These findings align closely with needs of international and national public health initiatives that prioritize aging in place and the development of age-friendly environments. For instance, the WHO launched programs for age-friendly cities and communities [349], which emphasize the creation of home environments that support the independent living of older adults. Similarly, Public Health Agency of Canada conducted projects to create “age-friendly”

community [350] to help older adults age actively. By facilitating independent living through AAL technologies and HAR, this research supports the broader goal of enabling older adults to live independently and maintain their well-being.

AAL techniques integrated with HAR provide continuous, unobtrusive monitoring of older adults, which is particularly critical for detecting behavioral changes indicative of potential health issues. Such early detection aligns with public health objectives of preventive care and timely intervention to improve health outcomes and reduce healthcare burdens. The emphasis on preventive care aligns with priorities identified by National Research Council Canada's Aging in Place: Technology and Innovation program [351], which highlights the importance of leveraging assistive technologies to enhance preventive care and reduce caregivers' burden.

The proposed hybrid transfer learning framework addresses the challenge of adapting HAR models trained on younger adults to older populations, thereby enabling more effective monitoring for aging individuals. By adapting these models, AAL systems can better meet the specific needs of older adults, ensuring reliable monitoring even in semi-controlled or uncontrolled environments. This approach reduces the need for extensive labeled datasets, which are often difficult to obtain in public health contexts, and allows for more practical, adaptive healthcare solutions.

Ultimately, the ability to generalize HAR models to diverse populations enhances the potential for AAL systems to support aging in place. By providing accurate, real-time monitoring, these systems can help prevent serious health events, reduce the need for institutional care, and contribute to a higher quality of life for older adults. The integration of adaptive, intelligent monitoring solutions is a critical step toward addressing the evolving needs of an aging society.

8.2.9.4 Limitation and future work

A key limitation of this study is the reliance on some labeled target domain data to achieve efficient performance, which can be challenging to obtain from older adults due to privacy and logistical concerns. The approach is not entirely independent of labeled data from target domain. Moreover, observer bias may have influenced the participants, as they were aware of being watched during the experiment. This awareness could have led them to be more cautious in their actions, resulting in behavioral patterns that differ from their usual habits. Additionally, the variability in activity patterns between younger and older adults makes domain adaptation challenging, affecting model generalizability.

Future work should explore more efficient transfer learning methods to reduce the need for labeled target data and develop advanced domain adaptation techniques that better capture inter-population variability. Expanding the evaluation to diverse datasets and settings would further enhance the robustness and applicability of the proposed framework, particularly in real-world environments with fully uncontrolled conditions. In addition, determining the optimal amount of target domain data to be mixed for improving

performance remains further investigation. Future research should explore adaptive selection strategies to balance model performance and data availability, ensuring efficient utilization of limited labeled target data.

8.2.10 Conclusion

This study introduced a hybrid transfer learning framework to improve the generalizability of HAR models trained on younger adults to older adults. By integrating CORAL with CDAN, the proposed approach significantly enhanced model performance with an average increase of 0.5 in accuracy compared to naïve transfer methods. Incorporating small amounts (no more than 50%) of target domain data further improved adaptability, achieving a maximum increase of 0.344 (59.7%) in accuracy, providing a practical strategy for applications with limited labeled data. These findings highlight the potential of transfer learning to create more effective AAL systems for diverse populations.

8.3 Discussion

The findings from this chapter demonstrate the potential of a hybrid transfer learning framework to enhance the generalizability of HAR models across diverse populations. By integrating CORAL with CDAN, the proposed approach effectively addressed the challenges of adapting models trained on younger adults in controlled environments to older adults in less structured, real-world settings.

A key contribution of this study lies in addressing the scarcity of labeled data from older adults, a common limitation in aging research. By leveraging a hybrid transfer learning framework, the study demonstrates how models trained on data from younger adults can be effectively adapted to older populations, reducing the need for extensive label annotation efforts. The integration of small amounts of labeled target domain data further enhances model adaptability, presenting a practical strategy to overcome label scarcity while maintaining model accuracy and reliability.

The methodology developed in this study also contribute to the robustness and adaptability of HAR models trained in controlled environments, ensuring their effectiveness in less structured, real-world conditions. This capability is essential for real-life applications of AAL technology, as it ensures that models can perform reliably when deployed in the dynamic and unpredictable environments characteristic of older adults' living spaces. By achieving this, the study bridges the gap between controlled research settings and real-world implementation.

The next chapter will synthesize the findings from this thesis (chapter 4 to 8), discussing their implications for aging research and public health. It will also outline future directions, ensuring that this work lays a foundation for advancing AAL technologies in supporting healthy aging.

Chapter 9 – Discussion and Conclusions

This thesis explored the potential of integrating AI with AAL technology to support healthy aging through a series of studies focused on data ecosystem development, physiological monitoring, and human activity recognition. The findings presented in this work contribute to the fields of (a) public health surveillance using AAL technology and (b) ADLs recognition for older adults. This chapter highlights the contributions, discusses the limitations, and identifies future research directions arising from this research.

9.1 Contributions to public health surveillance using AAL technology

One of the foundational contributions of this thesis is a scoping review (chapter 4) that mapped the integration of AI within commercially available AAL technologies to support older adults aging in place. The review revealed significant trends, including the increasing adoption of ambient sensors for real-time monitoring and the application of machine learning algorithms to enhance data interpretation and decision-making. However, it also identified critical gaps, such as the lack of centralized data management systems and limited adoption of cloud technologies, which hinder the scalability and practicality of existing AAL solutions. These insights provided a crucial starting point for the research program, guiding the subsequent development of more integrated and effective AAL frameworks.

Building on the insights from the scoping review, this thesis developed a cloud-native data ecosystem (chapter 5) designed to address these identified gaps. The ecosystem was specifically tailored to integrate data from commercially available sensors, enabling real-time collection, storage, and analysis of health and environmental parameters. This infrastructure represents a significant advancement in AAL research, offering a scalable and accessible solution for continuous health monitoring. Unlike traditional methods that rely on isolated sensor networks, the cloud-native approach allows for seamless integration of heterogeneous data sources, improving the system's ability to provide comprehensive and actionable insights.

The application of this data ecosystem was demonstrated through a heart rate prediction study (chapter 6), where contactless ambient sensors collected data in a smart home environment. Machine learning models, including Support Vector Machines and Random Forests, were applied to predict heart rates, achieving high accuracy and validating the ecosystem's capability to support advanced analytical techniques. This study addressed a previously unexamined area—using AAL technologies for physiological monitoring—highlighting the ecosystem's versatility in supporting diverse healthcare applications. By enabling non-intrusive monitoring, this approach reduces the burden on older adults and their caregivers while ensuring consistent and reliable data collection.

The implications of this contribution extend beyond individual studies. The data ecosystem lays a robust foundation for scalable public health surveillance systems, enabling continuous and context-aware monitoring of older adults. Its design leverages commercially available technologies, ensuring accessibility and cost-effectiveness, which

are critical for real-world implementation. Moreover, by addressing the technical challenges of integrating diverse sensor data and providing a centralized platform for analysis, this ecosystem serves as a template for future AAL systems aimed at enhancing public health outcomes for aging populations.

9.2 Contributions to ADLs recognition for old adults

ADL recognition emerged as a focal point of this thesis, reflecting its importance for assessing the functional status of older adults. This capability is particularly critical for older adults, as it directly impacts their ability to live independently and maintain a good quality of life. Monitoring ADLs provides key insights into potential health issues, enabling early interventions that can prevent significant declines in mobility, cognitive function, or overall well-being. The studies presented demonstrated the feasibility and effectiveness of using contactless AAL sensors to recognize ADLs with high accuracy. This research offers significant advancements in the ability of AAL systems to support independent living by enabling timely detection of changes in activity patterns, which can signal health issues or functional decline.

The study in chapter 7 focused on young adults in a controlled environment as a proof-of-concept for using contactless AAL sensors in ADL recognition. This study validated the capability of machine learning models, such as AdaBoost, Random Forest, and K-Nearest Neighbors, to achieve high accuracy in classifying daily activities. The findings demonstrated that ambient sensors, particularly when paired with advanced machine learning models, significantly outperformed wearable sensors, showcasing the potential of contactless technologies in activity recognition. This study laid the groundwork for adapting these systems to older adults, the primary target population for AAL solutions.

Building on this foundation, the study in chapter 8 addressed the challenges of applying ADL recognition models to older adults in semi-controlled environments. The transition to older adults presented unique challenges, such as variability in activity execution and reduced control over environmental factors. These conditions reflect the realities of real-world settings, making this phase of the research a critical step toward practical application. To address these challenges, a hybrid transfer learning framework was developed, integrating CDAN and CORAL. This approach effectively aligned feature distributions between datasets collected from young and older adults, enhancing model generalizability and performance.

The results demonstrated that the hybrid transfer learning framework significantly improved activity recognition accuracy for older adults, even in less controlled settings. By leveraging small amounts of labeled data from the target domain, the framework provided a practical solution to the data scarcity issue commonly faced in aging populations. This methodological advancement underscores the importance of domain adaptation techniques in extending the applicability of AI-driven AAL systems to diverse user groups.

This contribution has profound implications for public health. Accurate ADLs recognition systems tailored to older adults can enable large-scale monitoring programs that proactively identify health risks and functional declines within the aging population. By facilitating early interventions and personalized care strategies, these systems not only enhance individual well-being but also reduce the burden on healthcare infrastructures. Furthermore, the methodologies developed in this research pave the way for integrating AI-driven AAL technologies into public health initiatives, ensuring broader societal benefits and promoting independent living among older adults.

9.3 Global deployment considerations for the AAL ecosystem

Expanding an AAL platform for global use may introduce a number of practical and regulatory challenges. One of the key issues is data privacy and protection, as countries and regions have different legal frameworks governing personal data. For example, the European Union enforces strict guidelines under the General Data Protection Regulation (GDPR), while other regions may follow less restrictive or differently structured laws. Ensuring compliance requires local data handling practices, including clear data consent mechanisms, anonymization procedures, and in some cases, local data residency.

Data storage and transmission also present complications, especially in settings where cloud infrastructure is subject to local jurisdiction. Decisions must be made regarding where data is stored (e.g., country of origin or centralized storage), how it is transmitted (e.g., encrypted channels), and who has access. Regulatory alignment is another layer of complexity, especially in healthcare environments where devices and services must often be approved by national health authorities (e.g., FDA in the U.S., CE marking in Europe). Each deployment may require separate certifications, adding time and cost to scaling efforts.

On the technical side, device compatibility and integration are critical, as smart home and sensor technologies may vary by market. Differences in wireless communication standards (e.g., Zigbee, Z-Wave, Wi-Fi, LoRa), power supply voltages, and interoperability protocols can affect how smoothly devices work together across regions. For instance, Zigbee may be better suited for small apartments with low power needs, while LoRa may be preferred in larger homes with sparse device placement. Therefore, the AAL platform should be flexible enough to support different communication protocols and allow configuration based on the structure and layout of each home environment.

Together, these challenges require careful planning and adaptation of both the technical infrastructure and governance model when transitioning from localized use to global implementation in the future.

9.4 Limitations and future work

In this section, key limitations of the research program are discussed in detail, along with suggestions to address or mitigate them in future studies.

9.4.1 Generalizability

One of the primary limitations of this thesis lies in the generalizability of the findings to a broader population of older adults. While the studies focused on advancing ADLs recognition for older adults, the participant pool was predominantly composed of healthier individuals who could adhere to structured experimental protocols in semi-controlled environments. This limited representation restricts the applicability of the findings to the diverse realities of the aging population.

Older adults are a highly heterogeneous group, encompassing a wide range of physical, cognitive, and demographic characteristics. For instance, older adults with mobility impairments, chronic illnesses, or cognitive decline may exhibit distinct patterns of movement and activity that differ significantly from those of healthier peers. These differences could affect the performance and reliability of the developed models. Additionally, variations in socioeconomic status, cultural practices, and living conditions further complicate the generalizability of AAL technologies. Older adults from underrepresented or marginalized communities might face barriers to technology adoption, such as limited access to smart devices or reduced digital literacy, thereby limiting the effectiveness of the proposed solutions.

Another critical generalizability limitation is the restricted variety of activities performed in this thesis's studies, which does not fully reflect the extensive variability of real-world activities among older adults. The types of activities analyzed were predefined and largely structured, focusing on specific ADLs to ensure consistency and model accuracy. However, in real-world scenarios, older adults often engage in a broader and more diverse range of activities, many of which may be spontaneous or unstructured. For example, an older adult might combine tasks, such as cooking while conversing with family members, or perform activities at irregular intervals depending on personal preferences or environmental factors. This variability presents a challenge for models trained on a limited set of structured activities, as they may fail to generalize effectively to the full spectrum of real-world behaviors.

9.4.2 Limited testing in real-world uncontrolled environments

A second major limitation of this thesis is the limited testing and validation of the proposed methodologies in fully real-world uncontrolled environments. While semi-controlled settings provided an essential foundation for ensuring experimental rigor and consistency, they lack the dynamic and unpredictable characteristics of everyday living conditions for older adults. This gap restricts the ability to fully evaluate the robustness and practicality of the developed models in unstructured scenarios where these technologies are ultimately intended to be deployed.

Real-world environments are inherently dynamic and variable, characterized by factors such as diverse household configurations, fluctuating lighting and noise levels, and unanticipated interactions with visitors or pets. For instance, the presence of overlapping or multitasking activities—such as answering a phone call while preparing a meal—

generates data patterns that are significantly more complex than those encountered in structured experiments. Such scenarios can introduce noise and ambiguity into sensor data, challenging the robustness of models trained under controlled conditions.

Unstructured and overlapping activities present another layer of complexity. Unlike controlled experiments where tasks are performed in a predefined order, real-life scenarios often involve multitasking or interruptions. For instance, an older adult might pause a meal preparation to answer a doorbell or simultaneously engage in a conversation while tidying up. Such overlapping activities generate data patterns that are noisier and more intricate than those encountered in structured settings, challenging the models' ability to accurately classify behaviors.

Additionally, the controlled or semi-controlled settings in this thesis do not account for the day-to-day variability in individual routines and behaviors. Real-world conditions may include spontaneous deviations from typical activity patterns due to health fluctuations, emotional states, or unexpected household events. This variability underscores the importance of testing models in authentic environments where such factors can be observed and accounted for. Unlike issues of generalizability, which focus on diverse demographic and health conditions, this limitation pertains to the ecological validity of deploying AAL systems in dynamic and unpredictable living contexts.

Another critical factor is the absence of long-term validation in real-world environments. Factors such as device maintenance, wear-and-tear, and variations in user compliance over extended periods remain unaddressed in this research. For example, sensor accuracy might degrade over time, or older adults may intermittently deviate from recommended usage patterns, affecting data quality. Understanding these practical challenges is crucial for ensuring that AAL systems are both reliable and user-friendly in everyday applications.

9.4.3 Future work

The limitations identified in this thesis pave the way for several avenues of future research, emphasizing the need to enhance the applicability and reliability of AAL systems for diverse and dynamic real-world scenarios.

Future studies should aim to address the challenges of generalizability by expanding participant recruitment to include a more diverse range of older adults. This would involve recruiting individuals with varying physical and cognitive conditions, as well as those from different socio-economic and cultural backgrounds. Such an approach would ensure that the developed models are representative of the full spectrum of the aging population. Moreover, data collection should extend beyond predefined and structured activities to encompass a broader range of spontaneous and unstructured behaviors, capturing the complexity and variability of real-world scenarios.

Real-world testing and validation must become an important point in future research efforts. Deploying AAL systems in authentic residential settings over extended periods will provide

critical insights into their robustness and practicality. Long-term studies would enable researchers to evaluate the impact of factors such as device maintenance, user compliance, and environmental variability on system performance. Adaptive learning mechanisms, capable of updating and refining models based on real-time data, should also be explored to enhance the systems' ability to respond to dynamic conditions.

To further improve the scalability and inclusivity of AAL technologies, advanced transfer learning and domain adaptation techniques should be developed. These methods could align feature distributions across diverse datasets, enabling models trained on one subgroup (e.g., healthier individuals) to perform effectively on another (e.g., older adults with chronic illnesses or mobility impairments). This would reduce the reliance on extensive labeled data from underrepresented groups, addressing both scalability and generalizability concerns.

By addressing these directions, the field of AAL technology can advance toward creating solutions that are inclusive, adaptable, and capable of meeting the diverse needs of older adults in dynamic environments.

9.5 Conclusion

This thesis explores the transformative role of AAL technologies combined with AI in addressing the challenges associated with healthy aging. By introducing novel infrastructure and models, the research sets a foundation for advancing the agetech space and fostering innovations in healthcare monitoring and support systems for older adults.

The development of a cloud-native data ecosystem in this thesis not only enables seamless integration and real-time processing of commercial AAL sensor data but also establishes a scalable platform for future research in smart living environments. This infrastructure provides support for advancements such as the contactless prediction of physiological indicators, highlighting the feasibility of non-invasive monitoring solutions. Moreover, the introduction of machine learning and deep learning-based activity recognition models demonstrates how AAL technologies can improve the precision and reliability of detecting ADLs across diverse demographic and environmental conditions.

The impact of this work extends beyond technical contributions. By promoting non-intrusive, privacy-preserving solutions, this thesis directly supports older adults' independence, enabling them to live safely and autonomously in their homes. The models and systems developed here strengthen healthcare providers with actionable insights, improving their capacity to deliver timely, individualized interventions. This advancement represents a critical step in creating more resilient health systems capable of supporting independent living for aging populations.

Ultimately, this research demonstrates the potential of AI-driven AAL technologies to transform aging in place into a practical reality, bridging the gap between innovation and real-world application. By addressing technical, social, and healthcare challenges, this

work contributes to a future where equitable and accessible technologies improve the quality of life for older adults and reduce the burden on healthcare systems.

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Appendices

Appendix A. Detailed search strings for each electronic database

Databases

Pubmed

#1: smart home[tiab] OR smarthome[tiab] OR ambient intelligence[tiab] OR active assisted living[tiab] OR ambient assist*[tiab] OR assist* environment[tiab] OR IoT[tiab] OR internet of things[tiab] OR internet of things[mesh] OR self-help devices[mesh]
#2: elder*[tiab] OR older people[tiab] OR senior*[tiab] OR aging[tiab] OR older adult*[tiab] OR geriatric[tiab] OR aged[mesh]
#3: artificial intelligence[tiab] OR machine learning[tiab] OR deep learning[tiab] OR neural network*[tiab] OR artificial intelligence[mesh]
#4: real-world[tiab] OR home[tiab] OR house[tiab]
#5: #1 AND #2 AND #3 AND #4

CINAHL

#1: TI ("smart home" OR smarthome OR "ambient intelligence" OR "active assisted living" OR "ambient assist*" OR "assist* environment" OR IoT OR "internet of things")
#2: TI (elder* OR "older people" OR senior* OR aging OR "older adult*" OR geriatric)
#3: TI ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*")
#4: TI (real-world OR home OR house)
#5: #1 AND #2 AND #3 AND #4

#1: AB ("smart home" OR smarthome OR "ambient intelligence" OR "active assisted living" OR "ambient assist*" OR "assist* environment" OR IoT OR "internet of things")
#2: AB (elder* OR "older people" OR senior* OR aging OR "older adult*" OR geriatric)
#3: AB ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*")
#4: AB (real-world OR home OR house)
#5: #1 AND #2 AND #3 AND #4

Scopus

(TITLE-ABS-KEY ("smart home" OR smarthome OR "ambient intelligence" OR "active assisted living" OR "ambient assist*" OR "assist* environment" OR IoT OR "internet of things")
AND
TITLE-ABS-KEY (elder* OR "older people" OR senior* OR aging OR "older adult*" OR geriatric)
AND

TITLE-ABS-KEY (“artificial intelligence” OR “machine learning” OR “deep learning”
OR “neural network*”)

AND

TITLE-ABS-KEY (real-world OR home OR house))

IEEE Xplore

("Publication Title": "smart home" OR "Publication Title": smarthome OR "Publication
Title": "ambient intelligence" OR "Publication Title": "active assisted living" OR
"Publication Title": "ambient assist*" OR "Publication Title": "assist* environment" OR
"Publication Title": IoT OR "Publication Title": "internet of things")

AND

("Publication Title": elder* OR "Publication Title": "older people" OR "Publication
Title": senior* OR "Publication Title": aging OR "Publication Title": "older adult*" OR
"Publication Title": geriatric)

AND

("Publication Title": "artificial intelligence" OR "Publication Title": "machine learning"
OR "Publication Title": "deep learning" OR "Publication Title": "neural network*")

AND

("Publication Title": real-world OR "Publication Title": home OR "Publication Title":
house)

("Abstract": "smart home" OR "Abstract": smarthome OR "Abstract": "ambient
intelligence" OR "Abstract": "active assisted living" OR "Abstract": "ambient assist*" OR
"Abstract": "assist* environment" OR "Abstract": IoT OR "Abstract": "internet of
things")

AND

("Abstract": elder* OR "Abstract": "older people" OR "Abstract": senior* OR "Abstract":
aging OR "Abstract": "older adult*" OR "Abstract": geriatric)

AND

("Abstract": "artificial intelligence" OR "Abstract": "machine learning" OR "Abstract":
"deep learning" OR "Abstract": "neural network*")

AND

("Abstract": real-world OR "Abstract": home OR "Abstract": house)

("Author Keywords": "smart home" OR "Author Keywords": smarthome OR "Author
Keywords": "ambient intelligence" OR "Author Keywords": "active assisted living" OR
"Author Keywords": "ambient assist*" OR "Author Keywords": "assist* environment"
OR "Author Keywords": IoT OR "Author Keywords": "internet of things")

AND

("Author Keywords": elder* OR "Author Keywords": "older people" OR "Author
Keywords": senior* OR "Author Keywords": aging OR "Author Keywords": "older
adult*" OR "Author Keywords": geriatric)

AND

("Author Keywords": "artificial intelligence" OR "Author Keywords": "machine learning" OR "Author Keywords": "deep learning" OR "Author Keywords": "neural network*")
AND
("Author Keywords": real-world OR "Author Keywords": home OR "Author Keywords": house)

ACM Digital Library

[[Title: "smart home"] OR [Title: smarthome] OR [Title: "ambient intelligence"] OR [Title: "active assisted living"] OR [Title: "ambient assist*"] OR [Title: "assist* environment"] OR [Title: IoT] OR [Title: "internet of things"]]

AND

[[Title: elder*] OR [Title: "older people"] OR [Title: senior*] OR [Title: aging] OR [Title: "older adult*"] OR [Title: geriatric]]

AND

[[Title: "artificial intelligence"] OR [Title: "machine learning"] OR [Title: "deep learning"] OR [Title: "neural network*"]]

AND

[[Title: real-world] OR [Title: home] OR [Title: house]]

[[Abstract: "smart home"] OR [Abstract: smarthome] OR [Abstract: "ambient intelligence"] OR [Abstract: "active assisted living"] OR [Abstract: "ambient assist*"] OR [Abstract: "assist* environment"] OR [Abstract: IoT] OR [Abstract: "internet of things"]]

AND

[[Abstract: elder*] OR [Abstract: "older people"] OR [Abstract: senior*] OR [Abstract: aging] OR [Abstract: "older adult*"] OR [Abstract: geriatric]]

AND

[[Abstract: "artificial intelligence"] OR [Abstract: "machine learning"] OR [Abstract: "deep learning"] OR [Abstract: "neural network*"]]

AND

[[Abstract: real-world] OR [Abstract: home] OR [Abstract: house]]

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AND

[[Keywords: elder*] OR [Keywords: "older people"] OR [Keywords: senior*] OR [Keywords: aging] OR [Keywords: "older adult*"] OR [Keywords: geriatric]]

AND

[[Keywords: "artificial intelligence"] OR [Keywords: "machine learning"] OR [Keywords: "deep learning"] OR [Keywords: "neural network*"]]

AND

[[Keywords: real-world] OR [Keywords: home] OR [Keywords: house]]

Web of Science

"smart home" OR smarthome OR "ambient intelligence" OR "active assisted living" OR "ambient assist*" OR "assist* environment" OR IoT OR "internet of things" (Title)

AND

elder* OR "older people" OR senior* OR aging OR "older adult*" OR geriatric (Title)

AND

"artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" (Title)

AND

real-world OR home OR house (Title)

"smart home" OR smarthome OR "ambient intelligence" OR "active assisted living" OR "ambient assist*" OR "assist* environment" OR IoT OR "internet of things" (Abstract)

AND

elder* OR "older people" OR senior* OR aging OR "older adult*" OR geriatric

(Abstract)

AND

"artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" (Abstract)

AND

real-world OR home OR house (Abstract)

"smart home" OR smarthome OR "ambient intelligence" OR "active assisted living" OR "ambient assist*" OR "assist* environment" OR IoT OR "internet of things" (Author

Keywords)

AND

elder* OR "older people" OR senior* OR aging OR "older adult*" OR geriatric (Author

Keywords)

AND

"artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" (Author Keywords)

AND

real-world OR home OR house (Author Keywords)

Appendix B. Features table

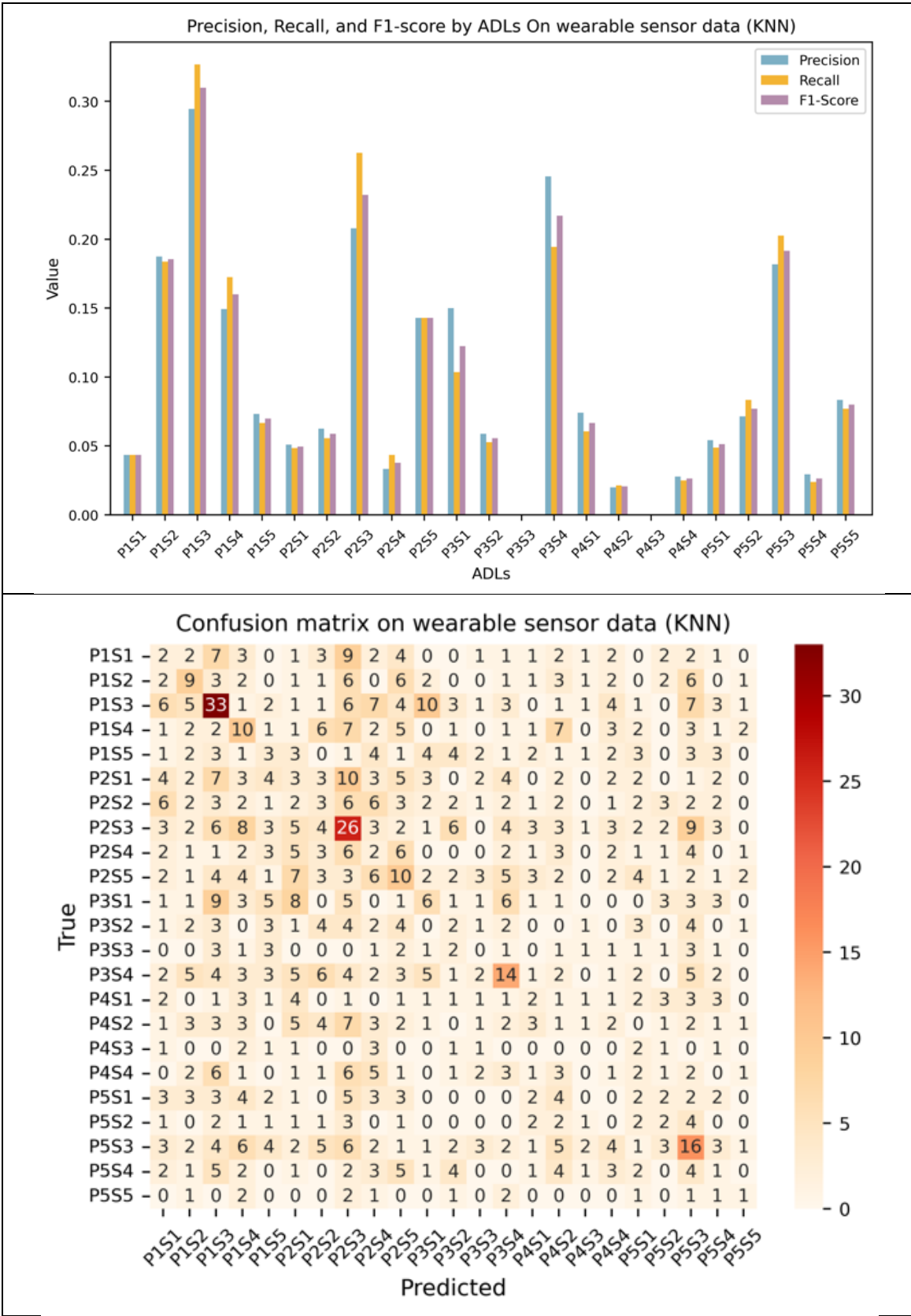
Feature name	Description
outlet_0_on_O01-O18	18 features Binary data reflecting the on/off states of the upper ports as captured by outlet sensors designated as O01 to O18.
outlet_1_on_O01-O18	18 features Binary data reflecting the on/off states of the lower ports as captured by outlet sensors designated as O01 to O18.
outlet_0_avg_O01-O18	18 features Continuous data reflecting the energy usage of the upper ports as captured by outlet sensors designated as O01 to O18.
outlet_1_avg_O01-O18	18 features Continuous data reflecting the energy usage of the lower ports as captured by outlet sensors designated as O01 to O18.
switch_avg_S01-S11	11 features Continuous reflecting the energy usage of switch sensors designated as S01 to S11.
living_temp	10 features Measurement of temperature and humidity across five rooms.
living_humi	
kitchen_temp	
kitchen_humi	
dining_temp	
dining_humi	
bedroom_temp	
bedroom_humi	
bathroom_temp	
bathroom_humi	
motion_01-23	23 features Binary data reflecting the occupancy states from 23 passive infrared sensors.
aq_co2_O04	9 features Measurement of air quality related parameters from 3 environmental sensors.
aq_iaq_O04	
aq_tvoc_O04	
aq_co2_O09	
aq_iaq_O09	
aq_tvoc_O09	
aq_co2_S11	
aq_iaq_S11	
aq_tvoc_S11	
door_contact_01-12	12 features

	Binary data reflecting the door open/close states from 12 door contact sensors.
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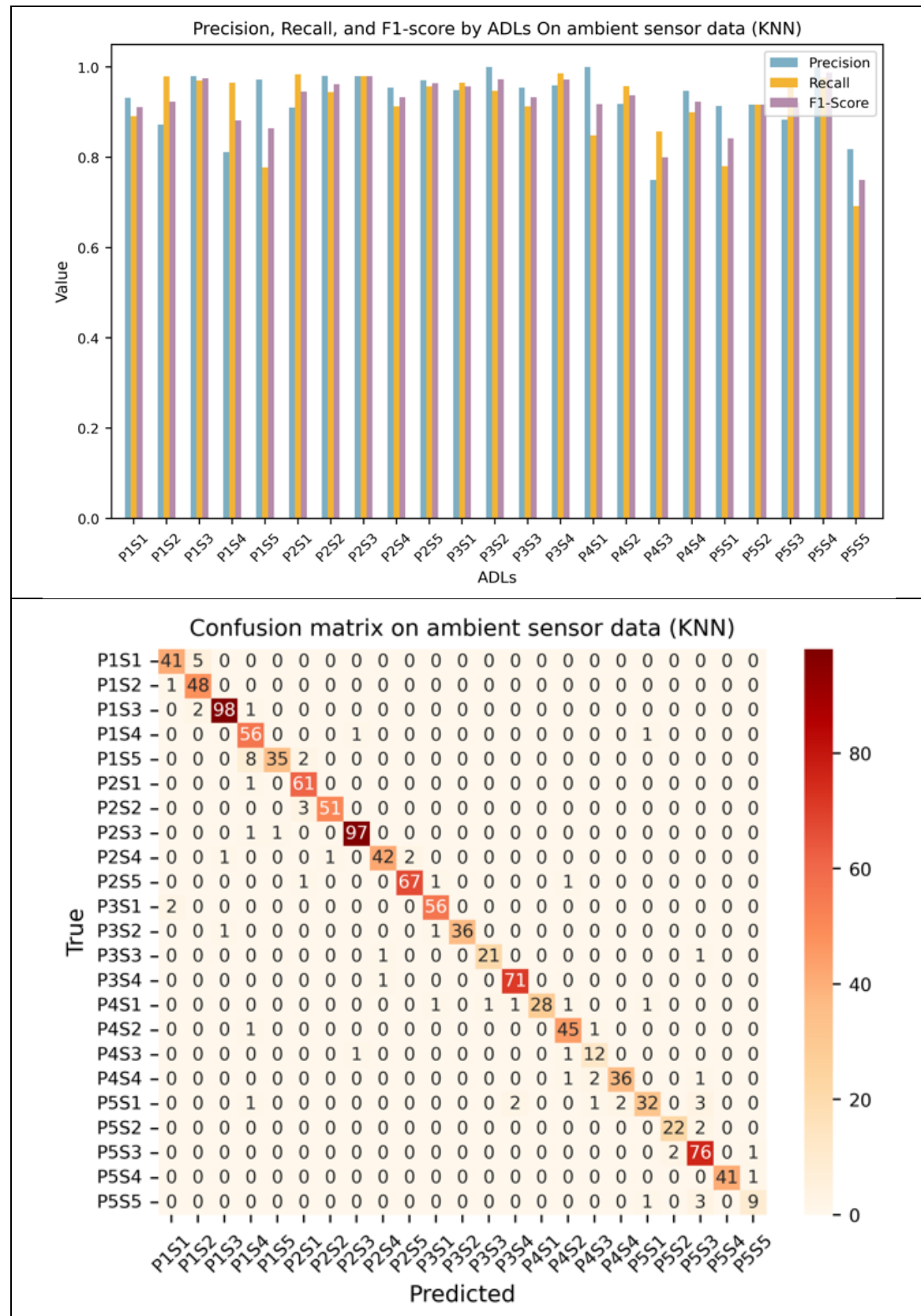
Appendix C. All models performance across all scenarios

KNN

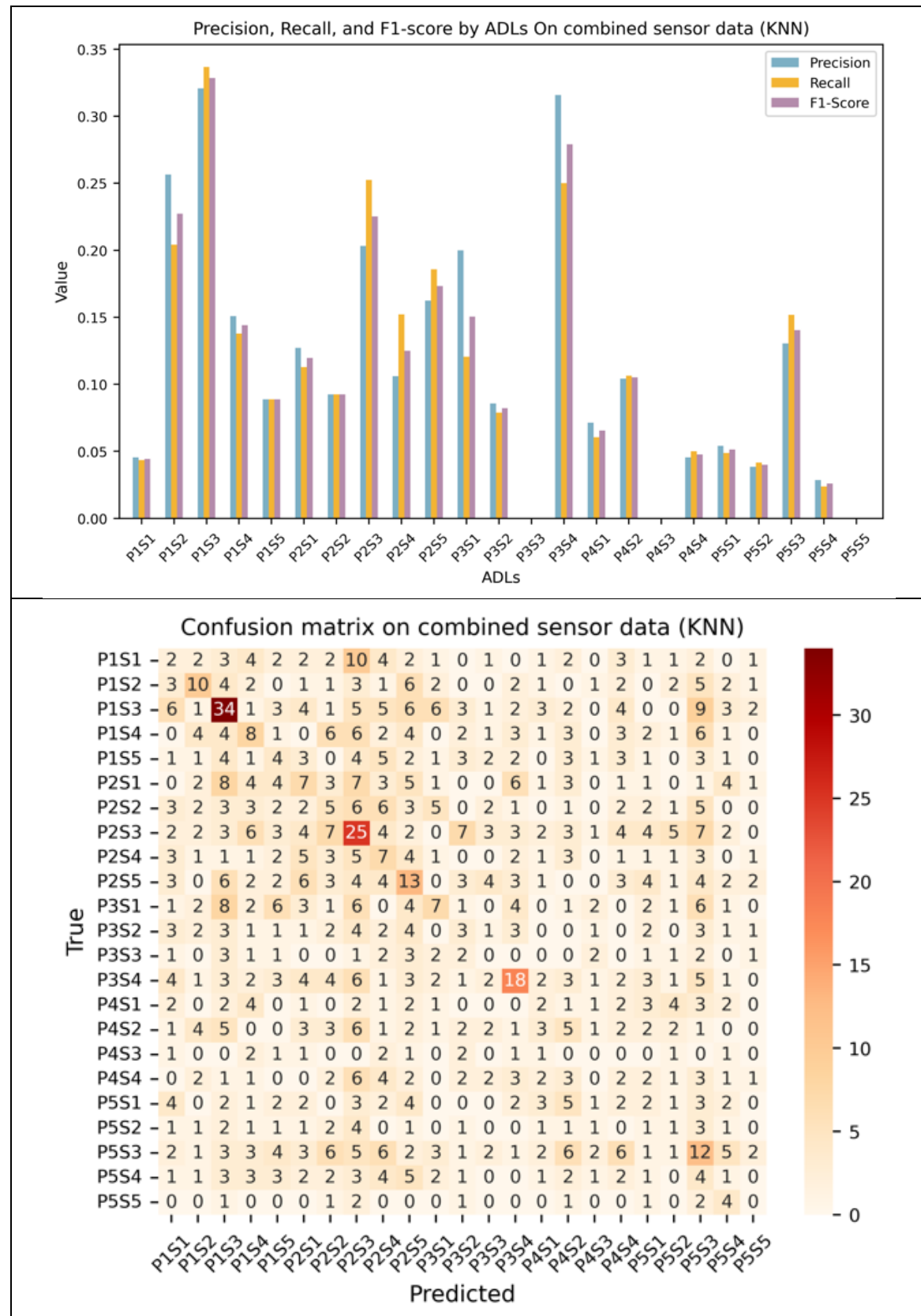
Performance on wearable sensor data



Performance on ambient sensor data

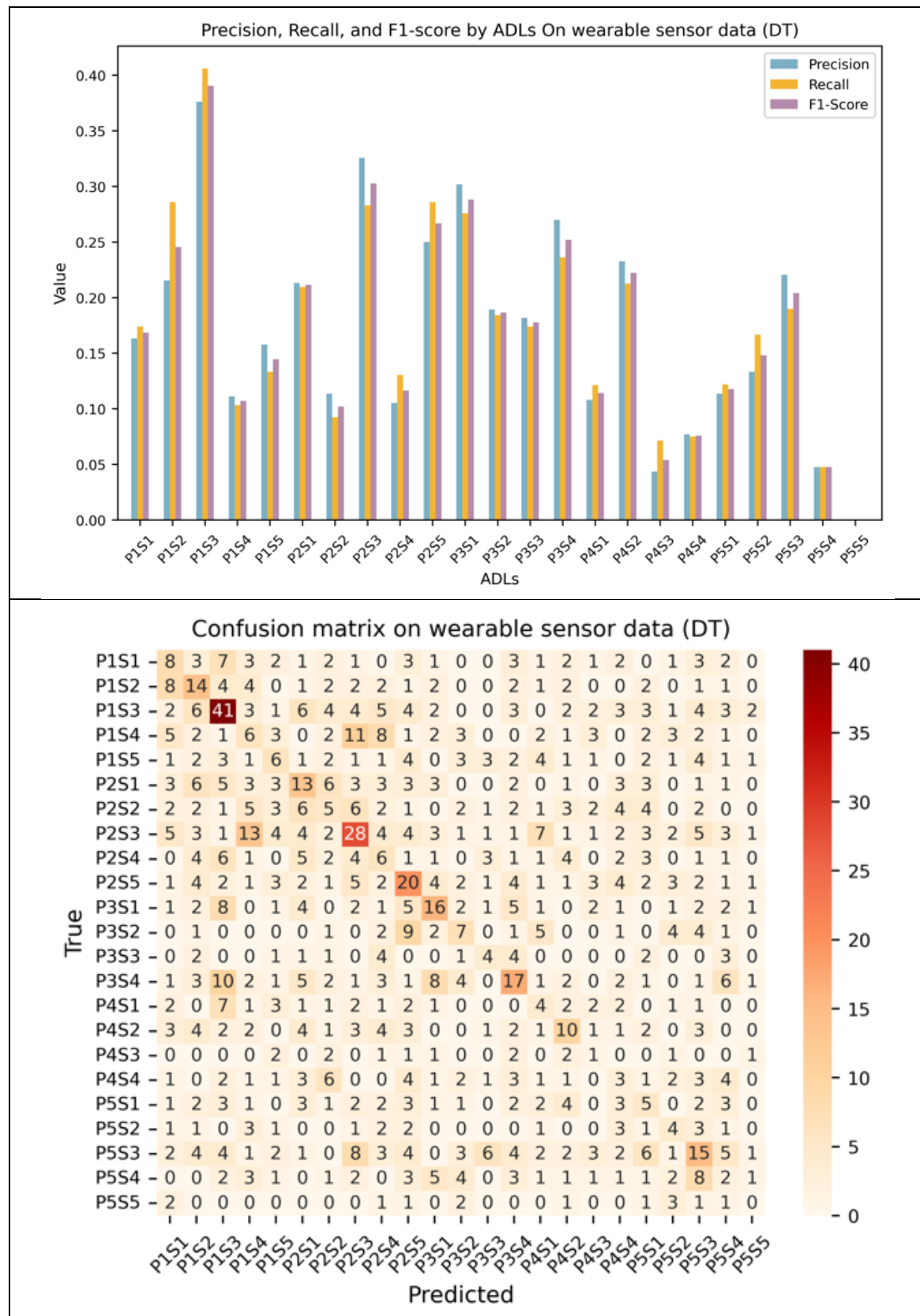


Performance on combined sensor data

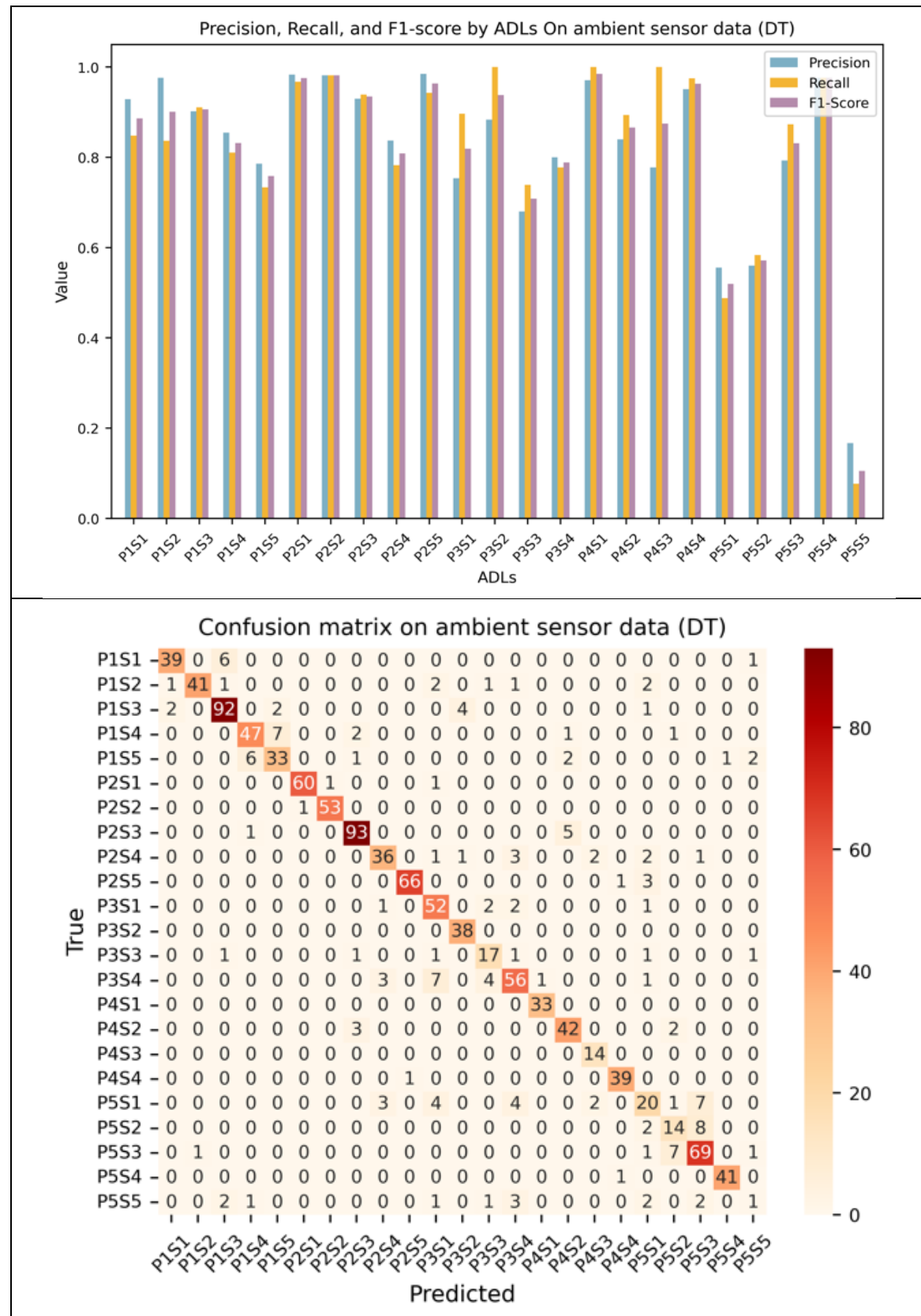


DT

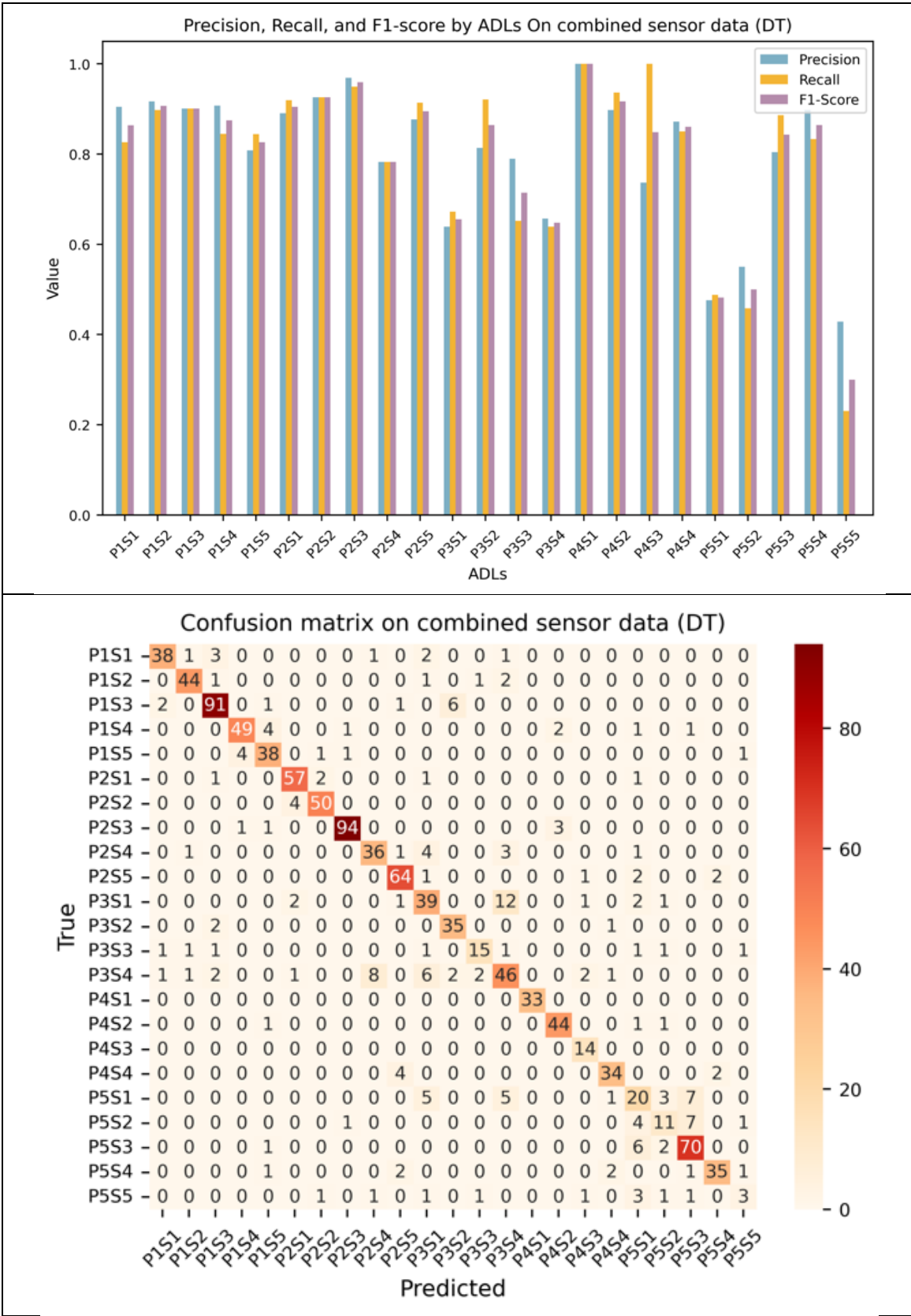
Performance on wearable sensor data



Performance on ambient sensor data

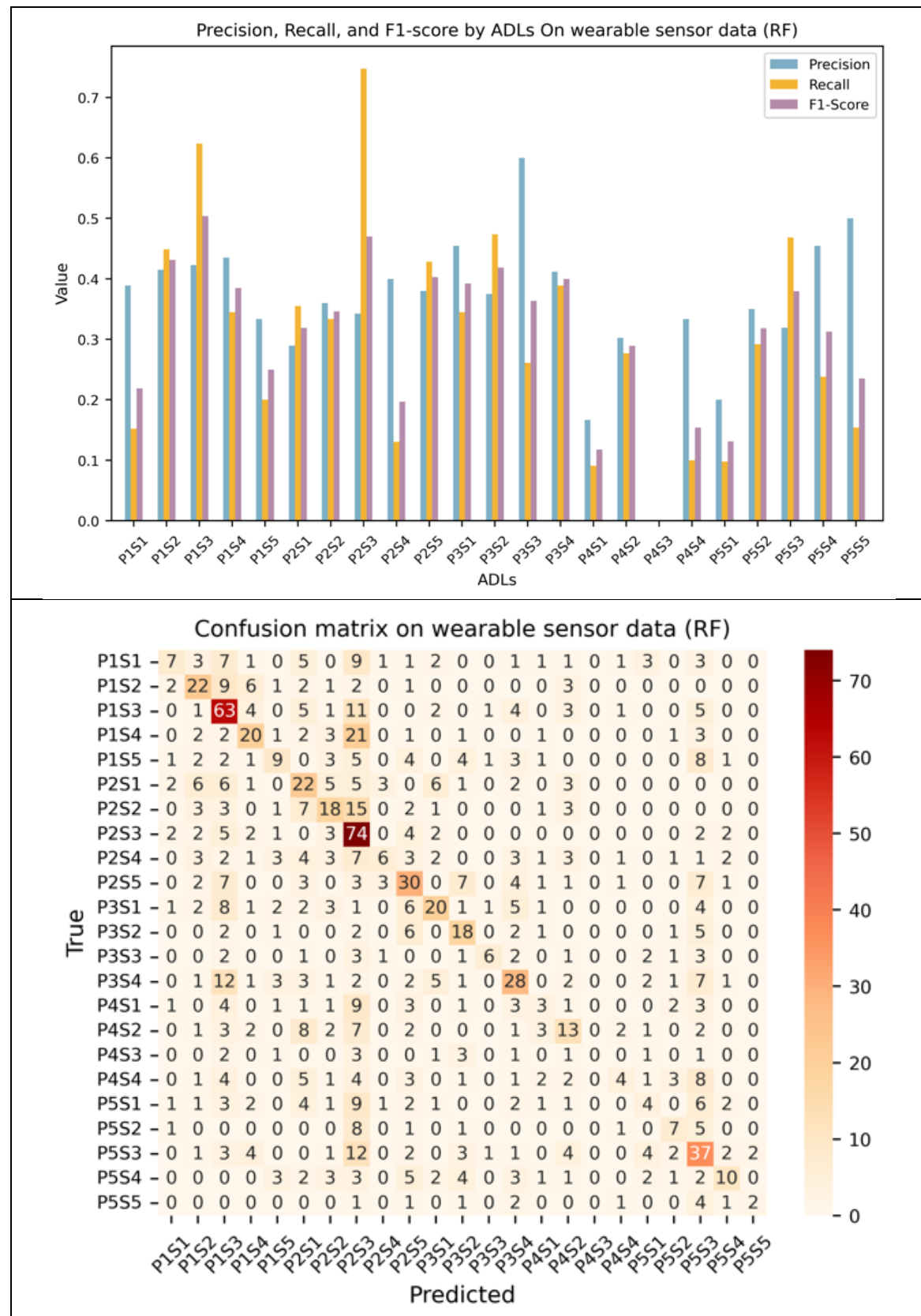


Performance on combined sensor data

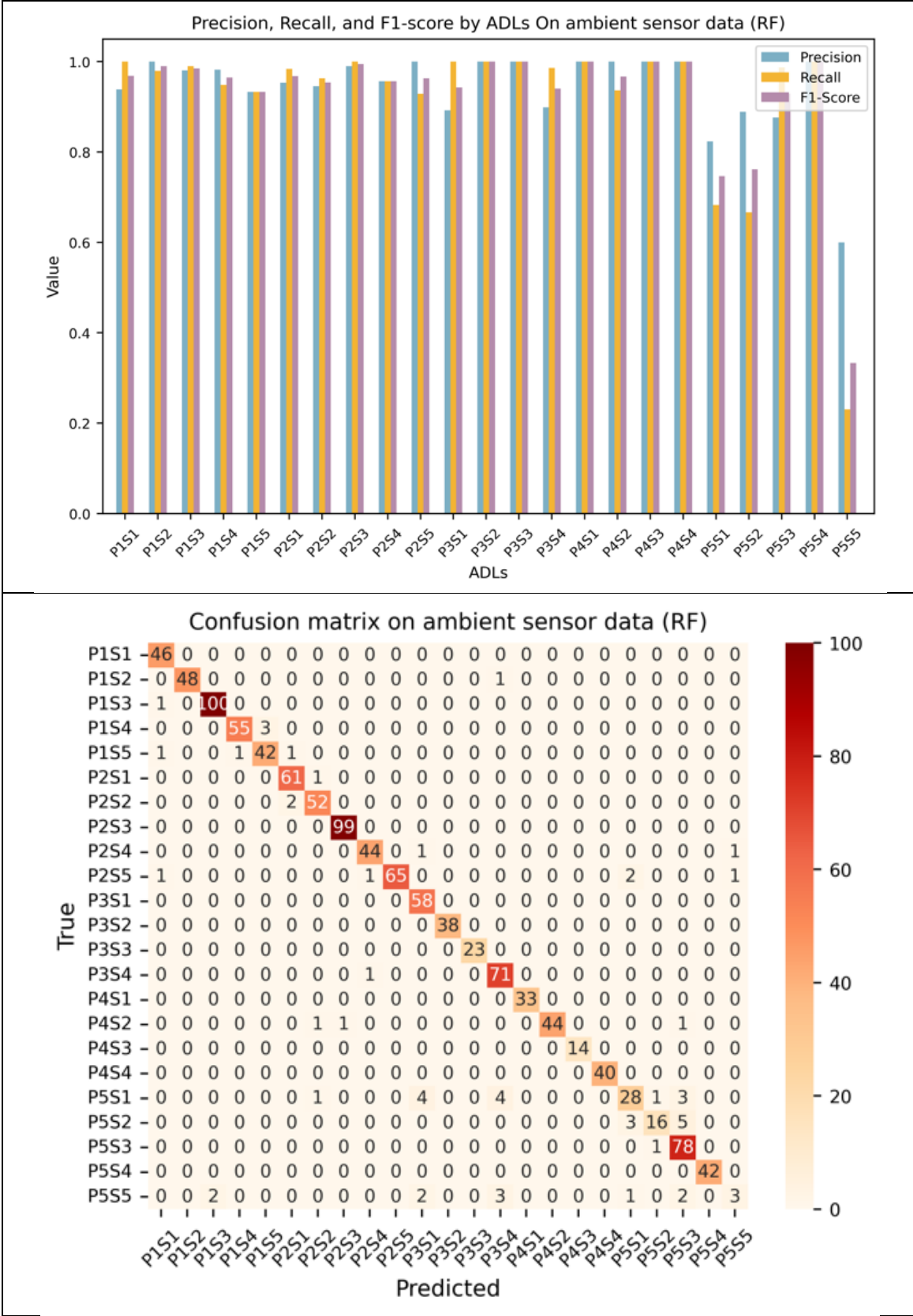


RF

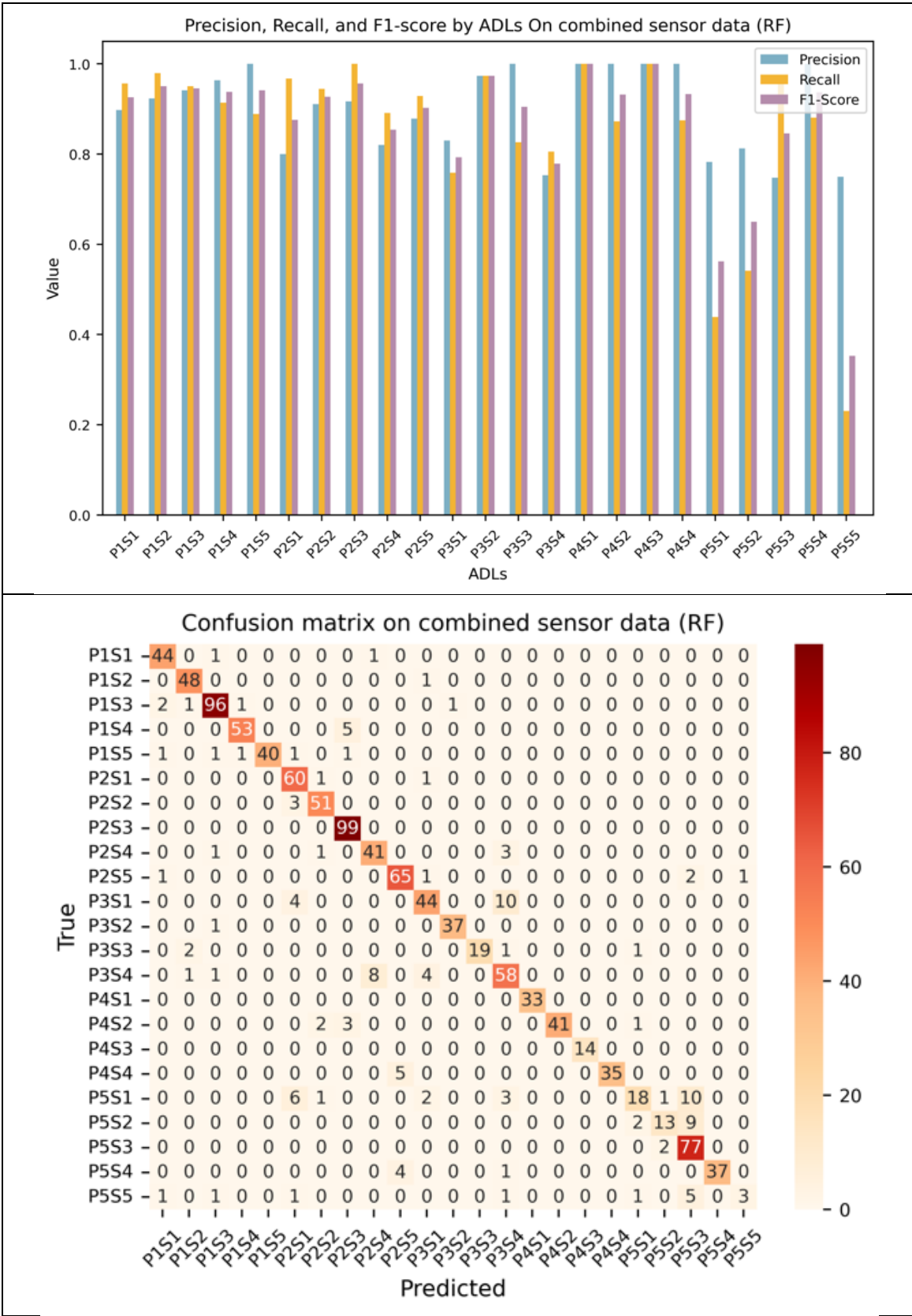
Performance on wearable sensor data



Performance on ambient sensor data

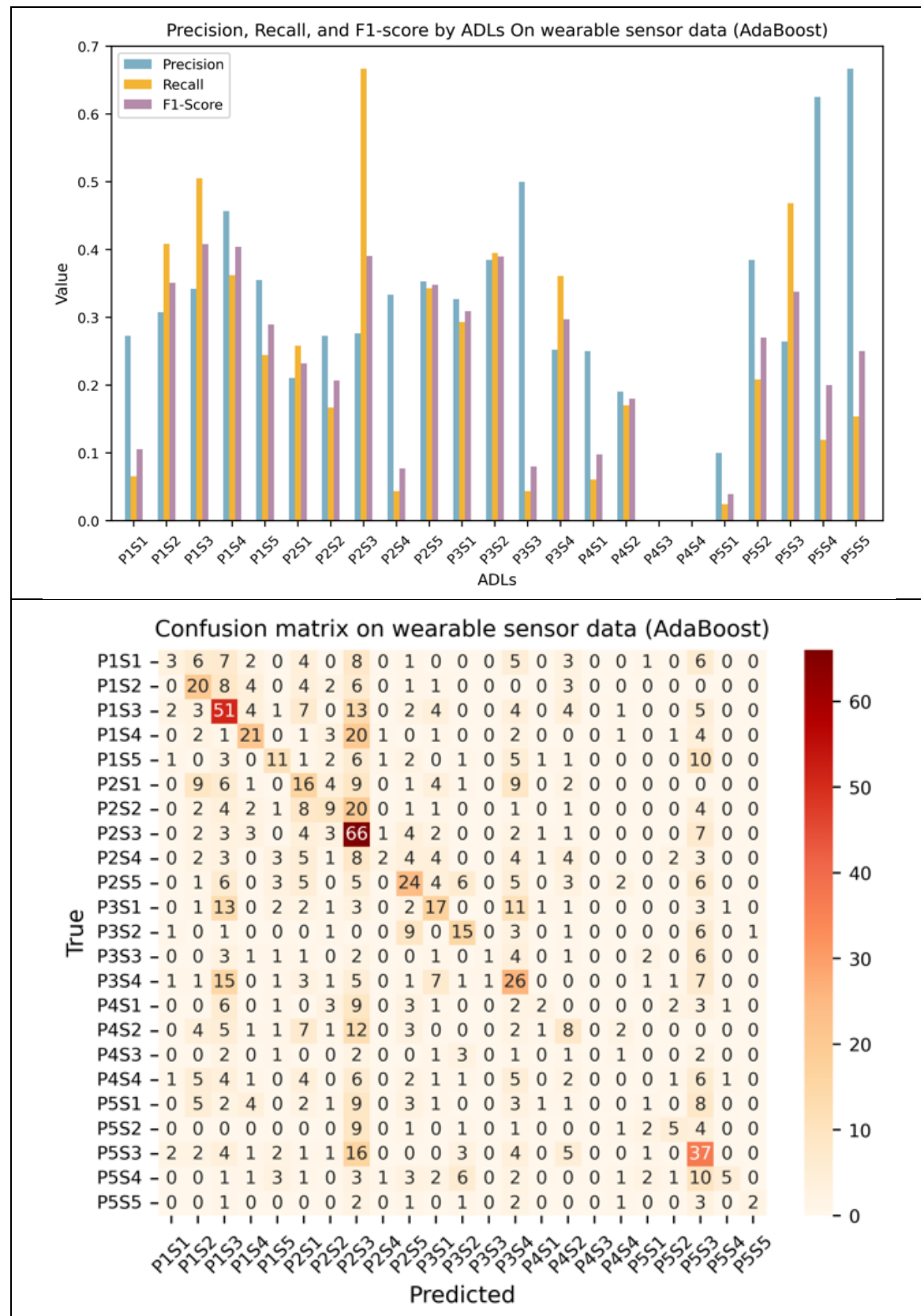


Performance on combined sensor data

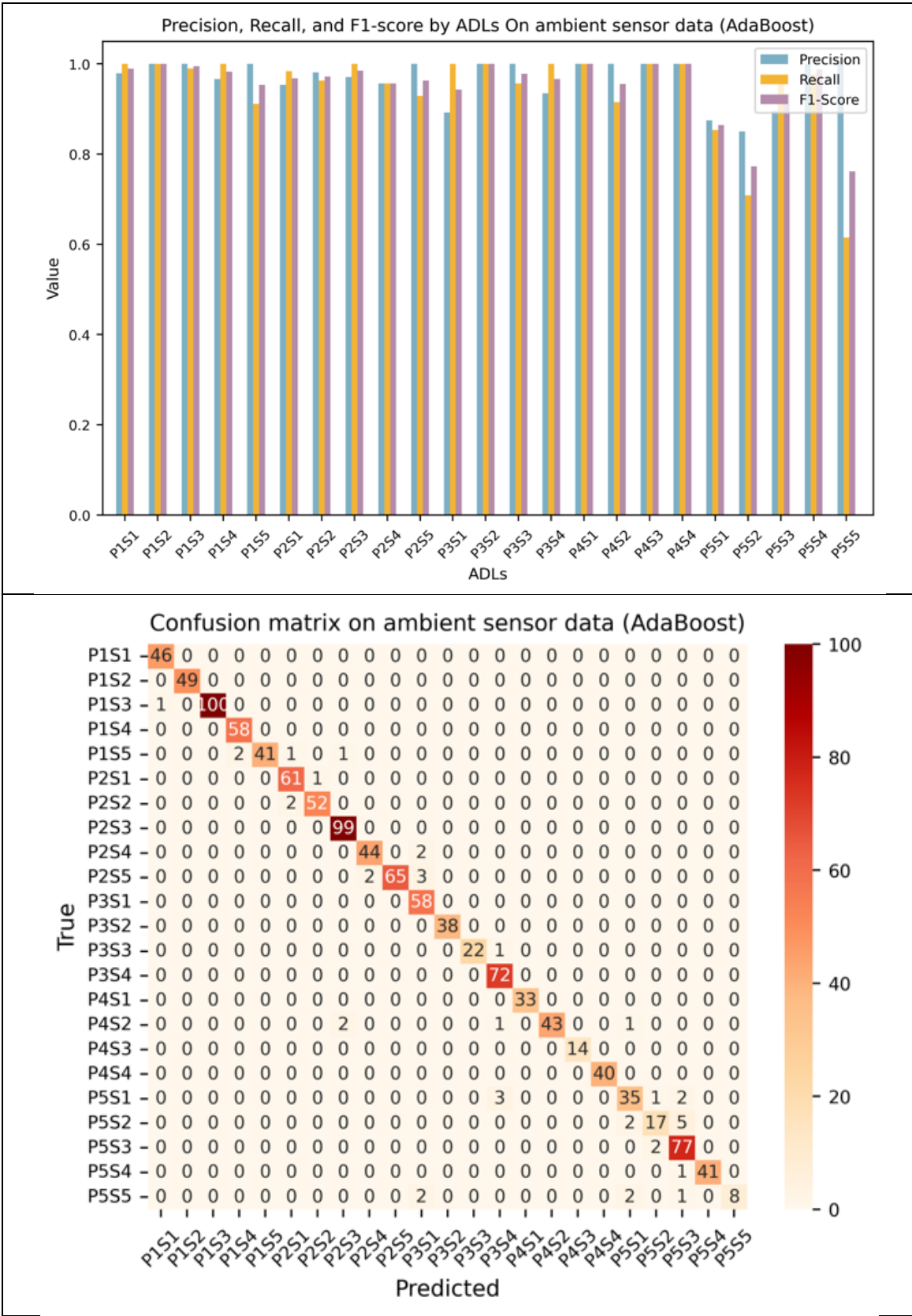


Adaboost

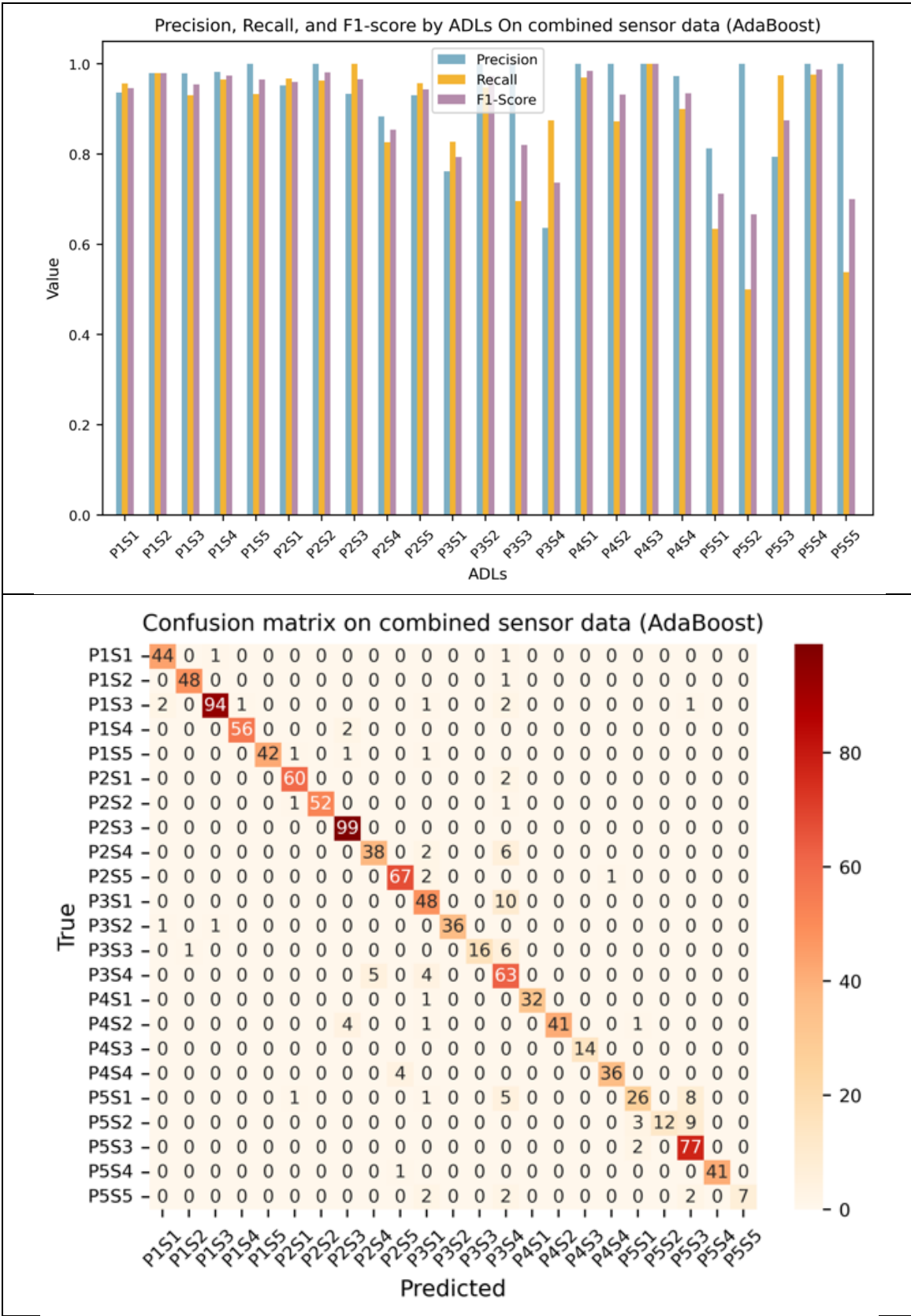
Performance on wearable sensor data



Performance on ambient sensor data

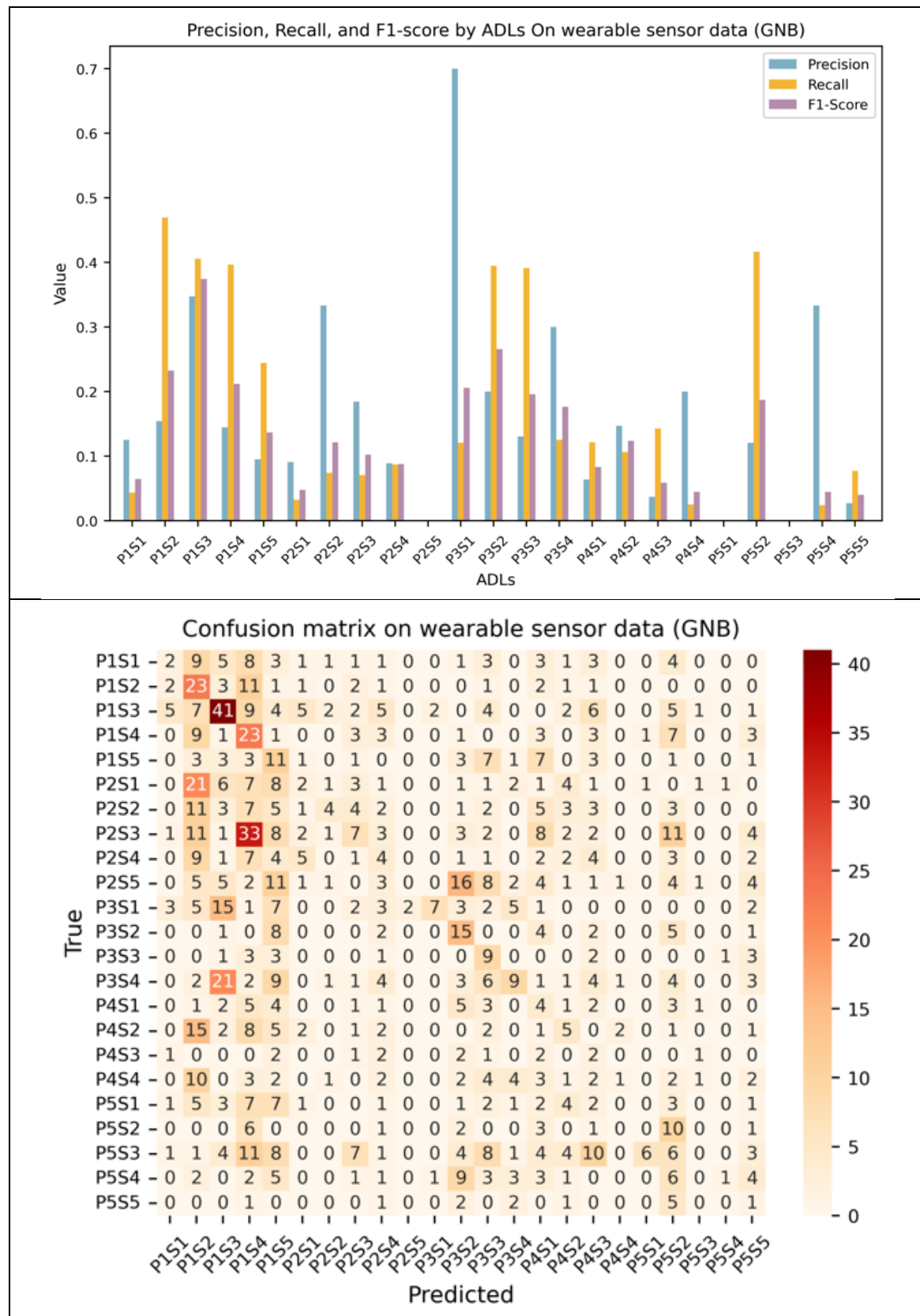


Performance on combined sensor data

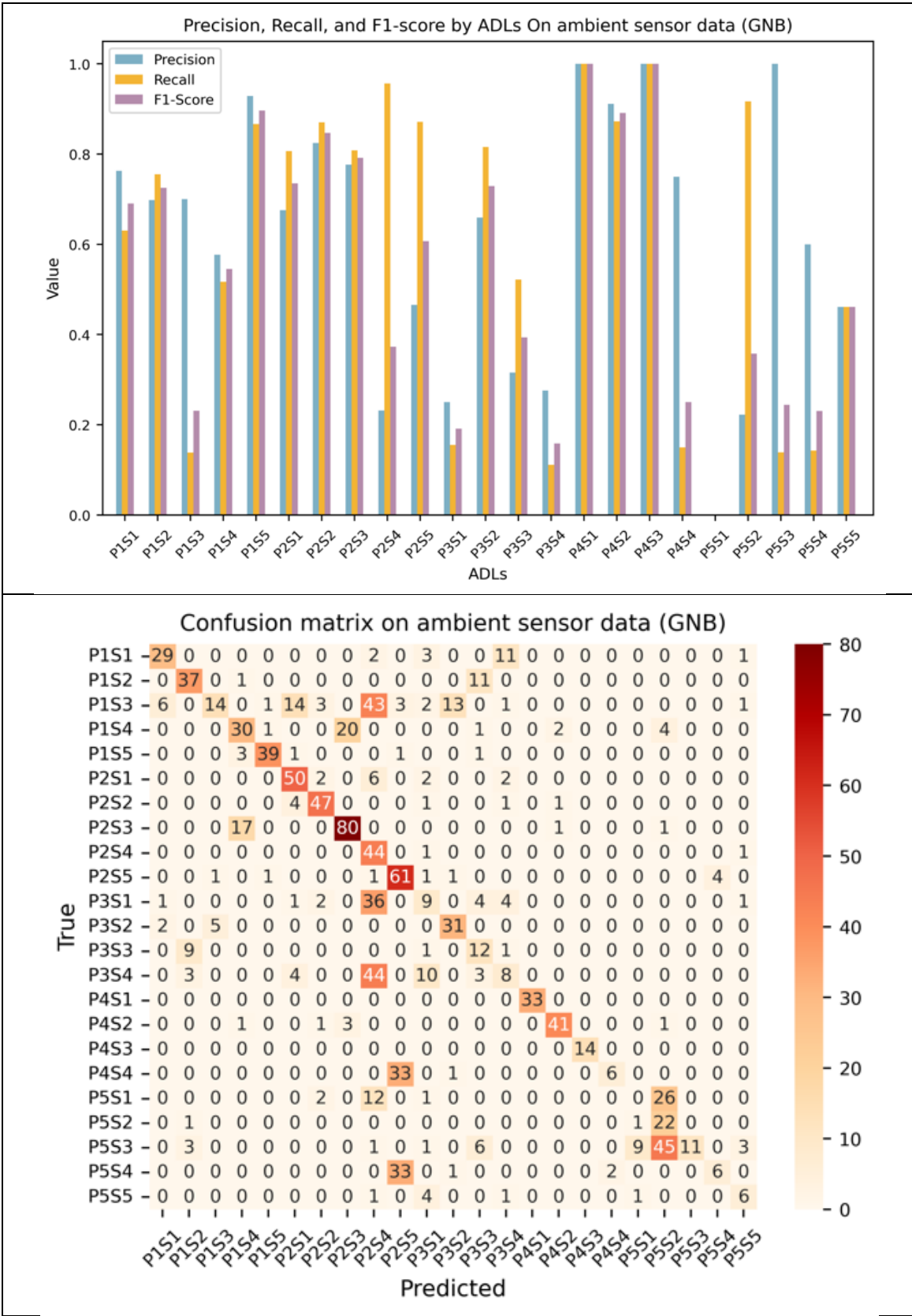


GNB

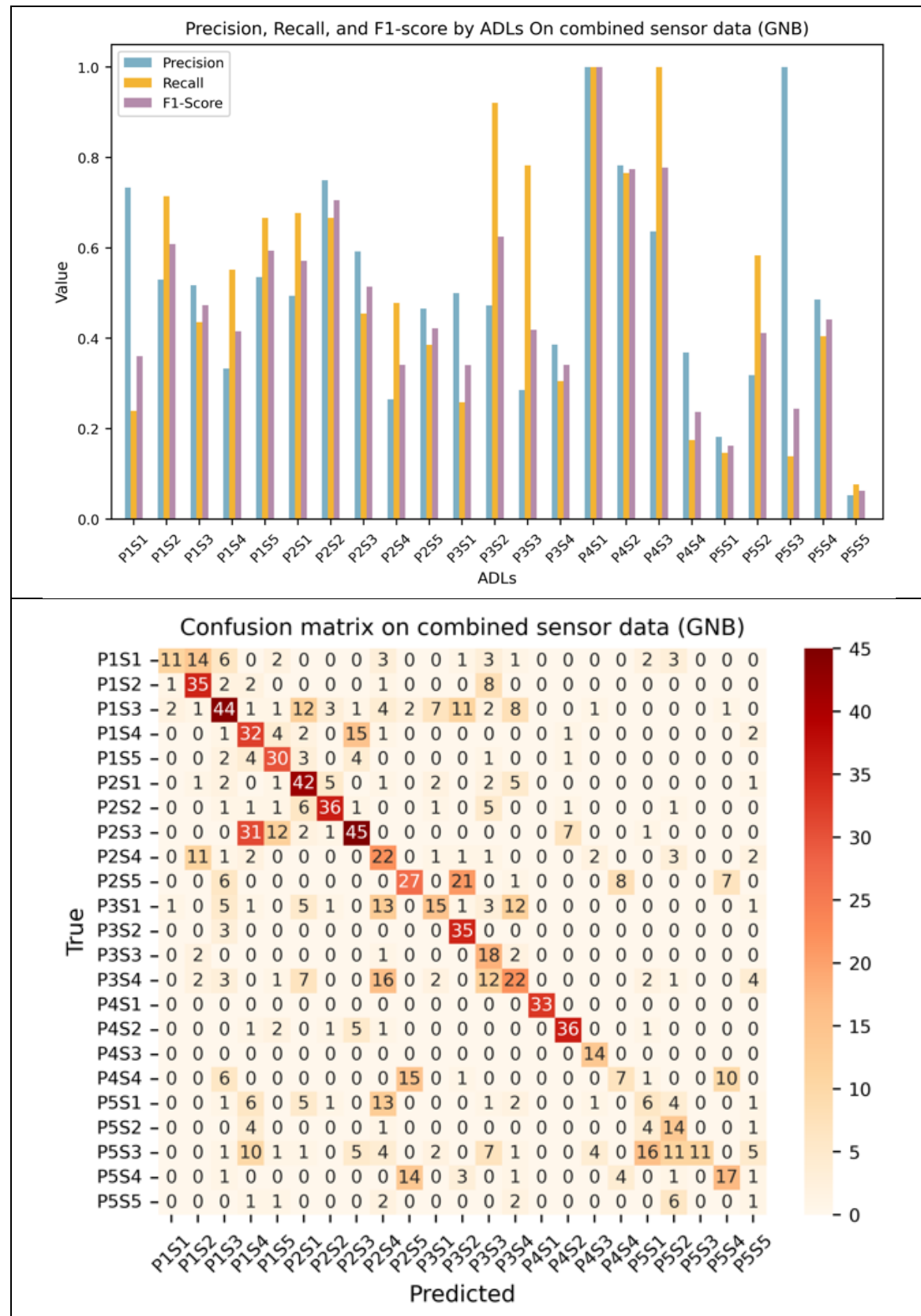
Performance on wearable sensor data



Performance on ambient sensor data



Performance on combined sensor data



Appendix D. Spatial overlap analysis for activities in same room

Living room

	Precision	Recall	F1-score
P1S1	1.00	0.96	0.98
P2S1	0.98	0.96	0.97
P2S2	0.95	0.96	0.95
P3S1	0.96	0.95	0.96
P3S3	0.97	0.94	0.95
P3S4	0.93	1.00	0.96
P4S1	1.00	1.00	1.00
P5S5	1.00	0.89	0.94

Kitchen

	Precision	Recall	F1-score
P1S2	1.00	1.00	1.00
P1S4	1.00	0.99	0.99
P2S3	0.98	0.99	0.98
P3S3	1.00	0.97	0.98
P4S2	1.00	0.96	0.98
P5S1	0.89	0.95	0.92
P5S2	0.87	0.74	0.80
P5S3	0.90	0.98	0.94
P5S5	1.00	0.75	0.86

Dining room

	Precision	Recall	F1-score
P1S2	0.99	1.00	0.99
P2S2	0.96	1.00	0.98
P3S3	1.00	0.97	0.98
P4S2	1.00	0.99	0.99
P5S5	1.00	0.90	0.95

Bedroom

	Precision	Recall	F1-score
P1S3	0.99	1.00	1.00
P1S5	1.00	1.00	1.00
P2S4	0.98	0.94	0.96
P3S1	0.97	0.99	0.98
P3S4	0.98	0.98	0.98
P4S3	1.00	0.95	0.98
P5S5	0.90	0.95	0.92

Bathroom

	Precision	Recall	F1-score
P1S1	0.92	1.00	0.96
P1S3	0.97	0.99	0.98
P1S5	1.00	1.00	1.00
P2S5	1.00	0.97	0.99
P3S2	1.00	0.96	0.98
P4S4	1.00	0.98	0.99
P5S4	1.00	0.93	0.97
P5S5	0.81	0.89	0.85

Appendix E. ADLs scripts used in controlled setting and semi-controlled setting

Categories	Name of Scenarios	Controlled setting	Semi-controlled setting
Phase 1 - foundational familiarization	Scenario 1 - “Arriving home”	Participant opens the door from outside using their key, locks the door from inside, and turns on switch 01 to illuminate the space. They proceed to the bathroom, turn on switch 10, and wash their hands with soap for 30 seconds before rinsing. After turning off the faucet and drying hands, they turn off the light (switch 10) and exit, closing the door behind them. They head back to the living room, turn on the living room lamp, retrieve the remote from drawer 4, and turn on the TV. After placing the remote back into drawer 4 and closing it, they pick a teacup and a glass. Sitting on the couch, they mimic drinking for 1 minute before placing the teacup on the glass table. They then wait seated on the couch for 1 minute as a transition.	The participant arrives home and enters the bathroom to wash hands. After washing, the participant sits on the couch in the living room and sips tea while watching TV.
	Scenario 2 - “Eating dinner”	Participant retrieves a bowl of food from the middle shelf of the fridge, opens the microwave, and places the bowl of food inside. They set the microwave for 30 seconds and wait. Once the microwave finishes, they close it, retrieve a fork/spoon from drawer 2, and walk towards the dining room. They pull the chair from the dining table closer to the couch, sit, and mimic	The participant warms up a bowl of food and mimics the act of eating. Afterward, the participant cleans up the area used for the meal.

		eating for 2 minutes. Afterwards, they stand up, push the chair back, and return the bowl into the fridge. The transition involves sitting on another chair for 1 minute.	
	Scenario 3 - "Sleep preparation and sleep"	Participant enters the bathroom, turns on switch 9, which is outside the bathroom. They then turn on switch 10, closing the door behind themselves. They pick up a toothbrush, apply toothpaste, and mimic brushing teeth for 1 minute before rinsing and washing the toothbrush. They then wash their face for 30 seconds, dry it with a paper towel, and step onto the weighing scale before stepping off and turning off switches 9 and 10. They enter the bedroom, walk towards the bed, turn off the bedroom lamp, and lie on the bed in a simulated sleep position for 5 minutes. The transition allows them to use their phone if they wish, for 1 extra minute before sleep.	The participant brushes teeth, washes the face, and checks body weight. After completing these tasks, the participant goes to sleep.
	Scenario 4 - "Cooking"	Participant enters the kitchen and turns on switch 02. They retrieve a vegetable (potato) from the fridge's first shelf, open the faucet to wash the vegetable, then close the faucet. They dry the vegetable with a paper towel, dispose of the towel in garbage bin in Cabinet 10, and then get a knife from drawer 2. They cut the vegetable on a cutting	The participant collects and prepares vegetables for cooking. Dishes are gathered for cutting, and the vegetables are chopped and transferred to a bowl. Salt and pepper are added to the vegetables. Finally, the participant washes

		board from drawer 3 for 30 seconds, place the slices on a pan, and season them with salt and pepper from cabinet 3. After cooking (2 minutes), they wash the knife, board, and other utensils in the sink and dry them, putting everything back into their respective drawers and cabinets. They remain where they are for a 1-minute transition.	and puts away the dishes and stores the prepared food.
	Scenario 5 - "Going out"	Participant enters the bedroom, opens the closet, and mimics the process of getting dressed by sequentially putting on a shirt, pants, belt, and jacket. They close the closet, enter the bathroom, turn on the light switch 10, and mimic styling hair for 30 seconds, followed by applying makeup/moisturizer/sunscreen for 1 minute. Exiting the bathroom, they close the door behind them, enter the living room, retrieve the remote from drawer 4, and turn off the TV. They also turn off the living room lamp and switch 02, place the remote back into drawer 4, and transition by standing by the door for 1 minute.	The participant mimics getting dressed, performs the morning bathroom routine, and then leaves the living room to outside.
Phase 2 - posture adaptation	Scenario 1 - "Reading on the sofa"	Participant picks up a magazine from the glass table and sits on the sofa in the living room to read for 3 minutes. They change postures while sitting; at 45 seconds, they lean on the sofa arm, at 1 minute 30 seconds	The participant reads a magazine, ensuring to change positions occasionally. Afterward, the participant lies down to relax.

		lean forward on knees, and at 2 minutes lean backwards. After reading, they put the magazine back on the glass table, adjust to lay down on the sofa, shifting around for 1 minute, changing sides, sit up, and place feet onto and off the ottoman for 30 seconds. Transition includes sitting on the couch for an additional minute.	
	Scenario 2 - “Completing a puzzle”	Participant retrieves a puzzle from cabinet 14, which is designated as the TV rack, and ensures the cabinet door is securely closed afterward. They then proceed into the dining room, where they illuminate the space by activating switch 05. A dining room chair, positioned closest to the couch, is pulled out to be used. The participant takes a moment to sit still on the chair for one minute, possibly to prepare mentally for the task ahead. The puzzle-solving process begins shortly thereafter, with the participant adjusting their posture at various intervals: leaning forward at the 45-second mark and leaning backward at 1 minute and 15 seconds, all the while making adjustments to their legs for added comfort. This routine is maintained for a total of 2 minutes. During this period, a puzzle piece is accidentally dropped but promptly retrieved by the participant. Upon completion of the	The participant retrieves a puzzle and moves to the dining room. The puzzle is solved by the participant, and afterward, everything is organized and returned to its original place.

		puzzle activity, the pieces are methodically returned to their box. The participant stands, tucks the chair back into its original position, and turns off switch 05, reverting the dining room to its initial state. The puzzle box is then placed back into cabinet 14. The activity concludes with the participant transitioning to the living area, where they take a moment to sit on the couch for one minute, marking the end of the sequence.	
	Scenario 3 - “Meal preparation”	Participant enters the kitchen and turns on switches 01 and 02. They collect ingredients for a meal (pepper, mushroom) from the fridge and gather utensils: a bowl from cabinet 4, a knife from drawer 2, and a cutting board from drawer 3. They cut vegetables for 2 minutes, changing postures once 1 minute has passed, asking a participant to drop a piece of pepper on the ground, and pick it up and place in the garbage (cabinet 10). Vegetables are placed in a bowl, and any remnants back into the fridge. They get a pan from cabinet 8, spatula from drawer 1, and cook the ingredients on a pretend stove, shifting weight between feet for 1 minute while cooking. The cooked vegetables are transferred into a bowl, and dirty dishes are placed into the sink. The participant dries dishes, puts	The participant prepares some ingredients for a meal in the kitchen and cleans up once the preparation is complete. Vegetables are then cooked, and the food is stored appropriately. Finally, the participant cleans and puts away the dishes.

		away clean dishes, cutting board, and utensils back into their respective places. Transition includes staying by the door for 1 minute.	
	Scenario 4 - “Reading in the bedroom”	Participant enters the bedroom, retrieves a magazine from drawer 5, turns on the bedside lamp, and sits down on the bed. They place a pillow against the wall for support to sit up on the bed and read the book for 2 minutes, adjusting positions while seated for comfort. Then they lie down on the bed to read, marking positions (45 seconds mark lay on your back, at 1:30 minutes on the stomach). After reading, they put the magazine back into drawer 5, unplug the phone from the charger, and turn off the bedside lamp. Transition includes standing up in the bedroom for 1 minute.	The participant charges the phone, reads a magazine, and then organizes everything back to its original state.
	Scenario 5 - “Bathroom job”	Participant enters the bathroom, turns on switches 9 and 10, closes the bathroom door, lifts the toilet lid, sits on the toilet for 2 minutes, and flushes. They step into the shower area, mimic showering actions for 2 minutes like washing arms, legs or shaving. After stepping out, they mimic drying the body with a towel for 30 seconds. They turn off switch 10, exit the bathroom, close the door behind them, and turn off switch 9. Transition includes waiting in the hallway for 1 minute.	The participant mimics using the toilet in the bathroom, followed by mimicking showering and drying off. Finally, the participant leaves the bathroom.

Phase 3 - movement integration	Scenario 1 - "Waking up & morning exercise"	Participant starts lying on the bed and changes postures while lying on the bed before sitting on the bed side. They turn on the bedroom lamp, walk out of the bedroom, walk to the living room, and turn on the TV using the remote from drawer 4, which they return after use. The participant then jogs around the living room for 1 minute. The transition includes sitting on the couch for 1 minute.	The participant goes to sleep and later wakes up. After waking up, the participant moves to the living room to watch TV and perform some exercises.
	Scenario 2 - "Taking a shower"	Participant walks towards the bathroom, turns on switch 09, enters, and closes the door behind them. They turn on the bathroom light with switch 10 and step into the shower area, mimicking the act of turning on the faucet while facing the faucet, turning back to the faucet, and mimicking washing arms and legs for 2 minutes. They turn off the faucet, get out of the shower with a towel, dry off, turn off the bathroom lights with switches 09 and 10, exit the bathroom, and close the door. Transition involves waiting in the hallway for 1 minute.	The participant mimics showering in the bathroom, dries off, and then exits the bathroom.
	Scenario 3 - "Tidying"	Participant walks to the living room, retrieves a crumpled paper from the TV rack, turns on switch 01 in the kitchen, and throws the paper into the trash in cabinet 10. They obtain a broom beside a table, sweep in front of the cabinet area for 1 minute, return the broom beside the table, and turn off switch 01. They walk	The participant cleans the living room, followed by cleaning the kitchen. Afterward, the participant relaxes in the dining room.

		back to the dining room and pull the chair (the one closest to the couch) back into position. Transition includes sitting on the chair for 1 minute.	
	Scenario 4 - “Going to sleep”	Participant sits on the sofa for 1 minute, stands from their sitting position, walks around the living room for 1 minute, grabs the remote from drawer 4, turns off the TV, returns the remote, and turns off the living room lamp. They walk to the bedroom, walk to the bed side, turn off the bedroom lamp, close the blinds, sit on the bed, lie on the bed, and change positions on the bed for 3 minutes. Transition involves staying still in bed for 1 more minute.	The participant relaxes on the sofa, watches TV, and walks around in the living room. After completing these activities, the participant goes to the bedroom to sleep.
Phase 4 - BADLs	Scenario 1 - “Cleaning rooms”	Participant enters the living room, turns on switches 03 and 04, removes pillows from couch and vacuum (beside the TV) into outlet and on. They vacuum the sofa and floor for 1 minute, turn off the vacuum, unplug, and organize the pillows onto the couch. Switches 03 and 04 are then turned off. The transition involves sitting on the couch for 1 minute.	The participant cleans the living room and vacuum the sofa.
	Scenario 2 - “Meal-time”	Participant enters the kitchen and turns on switches 02 and 01, gets a plate of food in the fridge (continues from phase 1) and places the bowl from the cabinet 4 and plate on the counter. They grab a spoon from drawer 2 and transfer the food from the plate to the	The participant transfers food from a bowl in the fridge to a plate to simulate eating leftovers. The participant mimics eating the food and then puts everything away.

		bowl using the spoon, then take the bowl of food and spoon and place it on the dining table. They turn on switch 05, pull out the chair closest to the couch, sit, and mimic eating for 2 minutes, get up from chair and tuck it in. The spoon and plate are placed into the garbage (or empty into the garbage) and the bowl back into the fridge. Switches 01, 02, and 05 are turned off. The transition is to stay where you are for 1 minute.	
	Scenario 3 - “Changing footwear”	Participant enters the bedroom, turns on the light 06, walks over to drawer 7 and pretends to grab a new pair of socks, removes shoes from feet, sits on the bed, and removes socks on feet. They then change into a new pair of socks, put shoes back onto feet, and turn off switches 06 and 07. Transition includes staying in the bedroom for 1 minute.	The participant changes socks.
	Scenario 4 - “Bathroom visit”	Participant walks towards the bathroom, turns on switch 9, enters the bathroom, and turns on switch 10, closes the door behind. They lift the toilet lid, sit on the toilet for 2 minutes, stand up from the toilet and flush. Walking to the sink, they turn on the faucet, wash hands for 30 seconds, turn off the faucet and dry hands using paper towel, dispose of the paper towel when done. They then turn off switch 10 and leave the bathroom, closing	The participant mimics using the toilet, washes hands, and then exits the bathroom.

		the door behind, and turn off switch 9. Transition involves waiting in the hallway for 1 minute.	
Phase 5 - IADLs	Scenario 1 - “Arriving home and organizing groceries”	Participant stands outside the apartment for 1 minute with a grocery bag in hand, then enters, closes the door behind them, and turns on switch 01. They walk to the kitchen, place the grocery bag on the kitchen floor, and unload groceries, placing them into the fridge, cupboard, or cabinets for 2 minutes. Once done, grocery bags are placed in cabinet 09. Transition includes waiting in front of the fridge for 1 minute.	The participant brings groceries into the apartment, organize the groceries.
	Scenario 2 - “Cleaning kitchen”	Participant washes dishes until they are clean, returns bowl and spoon to cabinet 4 and drawer 2 respectively. They sweep the kitchen floor for 1 minute, put broom back into place, get the vacuum cleaner, and vacuum for 1 minute, then put the vacuum cleaner back. They get a mop, mop the kitchen for 1 minute, and return the mop to its place. The participant then grabs a kitchen cloth, wipes down the counter area for 1 minute, and sits on the chair closest to the kitchen for the transition time of 1 minute.	The participant washes the dishes and puts them away. Next, the participant sweeps the kitchen floor, vacuums, and mops the kitchen. Finally, the counter area is wiped down.
	Scenario 3 - “Emptying garbage”	Participant opens cabinet 10, picks up the garbage bag, closes the door, and leaves the bag outside. They then replace the garbage bag with a new one, close the cabinet door, and wash hands using	The participant throws out the garbage, replaces the garbage bag, and cleans up afterward.

		soap. After drying hands with paper towel, they dispose of the towel in the garbage bin in cabinet 10. Transition includes waiting in the kitchen for 1 minute.	
	Scenario 4 - “Morning routine”	Participant walks towards the bathroom, turns on switch 09, enters the bathroom, turns on switch 10, closes the door behind them, and puts toothpaste onto toothbrush. They brush teeth for 1 minute, rinse brush, wash face for 30 seconds, turn off faucet, and dry hands and face with paper towel before disposing of it. They comb hair/apply makeup for 1 minute, step onto the weighing scale, then off again. The participant turns off switches 10 and 09 and waits in the hallway for 1 minute as a transition.	The participant mimics brushing teeth, washes the face, styles the hair, and then checks their weight.
	Scenario 5 - “Wrap up things for going out”	Participant turns on bedroom lamp, ensures all items needed are gathered, and walks around the house as if collecting things. They turn off all switches that are on, turn off the lamps if they are on, and leave the apartment, closing the door behind them.	The participants wrap up and leaves the apartment.

Appendix F. Model performance with mixing different ratio of target domain data (increasing training set size)

Whole HYAC and no HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.536	0.597	0.536	0.494
DT	0.443	0.480	0.443	0.411
GNB	0.425	0.521	0.425	0.398
RF	0.510	0.565	0.510	0.470
AdaBoost	0.549	0.594	0.549	0.506

Mixing 10% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.764	0.766	0.764	0.760
DT	0.713	0.712	0.713	0.709
GNB	0.526	0.544	0.526	0.503
RF	0.717	0.738	0.717	0.706
AdaBoost	0.738	0.757	0.738	0.729

Mixing 20% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.777	0.777	0.777	0.774
DT	0.751	0.759	0.751	0.749
GNB	0.554	0.565	0.554	0.531
RF	0.819	0.820	0.819	0.816
AdaBoost	0.834	0.837	0.834	0.832

Mixing 30% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.852	0.854	0.852	0.851
DT	0.796	0.798	0.796	0.795
GNB	0.565	0.574	0.565	0.535
RF	0.830	0.832	0.830	0.827
AdaBoost	0.869	0.871	0.869	0.868

Mixing 40% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.878	0.880	0.878	0.877
DT	0.798	0.800	0.798	0.795
GNB	0.576	0.597	0.576	0.549
RF	0.887	0.887	0.887	0.886
AdaBoost	0.893	0.894	0.893	0.892

Mixing 50% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.912	0.912	0.912	0.911
DT	0.846	0.848	0.846	0.846
GNB	0.536	0.557	0.536	0.503
RF	0.914	0.915	0.914	0.913
AdaBoost	0.920	0.920	0.920	0.919

Appendix G. Model performance with mixing different ratio of target domain data (fixed training set size)

Whole HYAC and no HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.482	0.492	0.482	0.439
DT	0.458	0.514	0.458	0.406
GNB	0.392	0.435	0.392	0.332
RF	0.459	0.500	0.459	0.413
AdaBoost	0.505	0.499	0.505	0.449

Mixing 10% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.715	0.714	0.715	0.708
DT	0.665	0.666	0.665	0.660
GNB	0.529	0.520	0.529	0.503
RF	0.716	0.718	0.716	0.706
AdaBoost	0.737	0.746	0.737	0.730

Mixing 20% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.742	0.743	0.742	0.738
DT	0.721	0.727	0.721	0.718
GNB	0.546	0.515	0.546	0.508
RF	0.758	0.760	0.758	0.753
AdaBoost	0.782	0.787	0.782	0.778

Mixing 30% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.780	0.783	0.780	0.776
DT	0.732	0.736	0.732	0.730
GNB	0.570	0.563	0.570	0.538
RF	0.788	0.790	0.788	0.784
AdaBoost	0.804	0.808	0.804	0.800

Mixing 40% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.796	0.799	0.796	0.793
DT	0.772	0.777	0.772	0.770
GNB	0.542	0.548	0.542	0.512
RF	0.812	0.815	0.812	0.810
AdaBoost	0.825	0.830	0.825	0.824

Mixing 50% HOASC in training

	ACC	Precision	Recall	F1-score
KNN	0.865	0.870	0.865	0.865
DT	0.801	0.804	0.801	0.800
GNB	0.531	0.539	0.531	0.499
RF	0.871	0.875	0.871	0.870
AdaBoost	0.882	0.886	0.882	0.881