AIoT for Aging In Place: From Theory To Practice

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Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from three papers published in the following peer-reviewed conferences and journals, in which I am listed as a co-author.

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- Dr. Jun Lin and Dr. Zhiqi Shen suggested the direction of this research.
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- I co-performed the experiments and analyzed the data with Dr. Yonghui Xu.
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Abstract

The rapidly aging global population necessitates solutions to support the growing preference among seniors to age in place. This thesis presents a novel integration of the Person-Environment (P-E) Fit theory with Artificial Intelligence of Things (AIoT) to guide aging in place (AIP) system design, focusing on personalized, privacy-preserving solutions that allow elderly individuals to live independently while ensuring their safety and well-being. Based on the foundation of the P-E Fit theory, we introduce a comprehensive P-E for AIP model (PE4AIP) that assesses elderly well-being through three primary dimensions: person characteristics, environment characteristics, and person-environment interactions. The model identifies key P-E fit indicators, such as motion, lifestyle regularity, social interactions, and environmental comfort, which are essential for quantifying the 'fit' between seniors and their environments.

To operationalize this model, a PE4AIP-enabled AIP design architecture was developed, guiding the creation of AIP systems with a emphasis on privacy and personalization. Notably, the developed architecture incorporates innovative technologies for real-time monitoring and data processing, including a non-intrusive fall detection system using ambient sensors and edge computing, and a unique notification system using 3D animation to communicate the status of the elderly to caregivers without compromising privacy.

Empirical studies and experiments validate the effectiveness of the proposed model and the architecture. A implementation of the Smart Aging in Place System (SAIPS) demonstrated the practicality and acceptance of the system among elderly participants and their caregivers. The results highlight the system's accuracy in predicting well-being, its unobtrusiveness, and the overall positive reception of the technology.

This research advances gerontechnology by offering a theoretically grounded and empirically validated framework that enhances the independence and quality of

life for the elderly. The breadth and depth of our work stand as a meaningful contribution to the development of intelligent, practical, and effective aging-in-place solutions, with wide-reaching implications for the continually evolving field of assistive technology for older adults.

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Acronyms

ADL	Activities of Daily Living
AIGC	Artificial Intelligence Generated Content
AIoT	Artificial Intelligence of Things
AIP	Aging in Place
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CGA	Comprehensive Geriatric Assessment
EEG	Electroencephalography
EMA	Ecological Model of Aging
GRU	Gated Recurrent Unit
HCI	Human Computer Interaction
HDB	Housing Development Board
ICT	Information and Communication Technologies
IADL	Instrumental Activities of Daily Living
IMU	Inertial Measurement Unit
IoT	Internet of Things
k-NN	k-Nearest Neighbors
LLM	Large Language Models
LSTM	Long Short-Term Memory
ML	Machine Learning
P-E	Person-Environment
P-E Fit	Person-Environment Fit
PE4AIP	Person–Environment Fit Model for Aging in Place
PEO	Person-Environment-Occupation
SAiPS	Smart Aging-in-Place System
SD	Standard Deviation

SEWBI	Socioemotional Well-Being Index
SRMR	Standardized Root Mean Square Residual
SVM	Support Vector Machine
TinyML	Tiny Machine Learning
TWA	Theory of Work Adjustment
VR	Virtual Reality
EMA	Ecological Model of Aging

Chapter 1

Introduction

1.1 Background and Motivation

The world's population is aging rapidly, with the number of individuals aged 60 and above expected to double by 2050, reaching 2.1 billion [1]. Estimates project that the global population aged 65 or more will rise from 12.5% in 2019 to 22% by 2050 [2]. This demographic shift poses various challenges to societies, particularly regarding the provision of adequate healthcare, support services, and suitable living environments for older adults. Aging-in-place (AIP), preferred by most older adults, refers to living at home rather than moving to nursing homes or ageing facilities but comes with increased risks of social isolation, depression, physical frailty, and fall hazards [1, 3].

1.1.1 Demographic Shift and Challenges to Societies

The demographic shift refers to the changes in the age distribution of a population over time, resulting in significant alterations to the population's composition. This phenomenon is driven by factors such as increased life expectancy, declining fertility rates, the aging of the large baby boomer generation, and migration patterns.

- Increased life expectancy: Advances in healthcare, nutrition, and living conditions have led to a significant increase in life expectancy over the past century. As a result, people are living longer, contributing to the growing number of older adults in the population[4].

- Declining fertility rates: Fertility rates have been declining in many countries due to factors such as increased access to family planning, improved education and career opportunities for women, and changing societal norms around family size. This trend results in fewer children being born, which in turn, leads to a higher proportion of older adults in the population[5].

- Aging baby boomer generation: The baby boomer generation, born between 1946 and 1964, constitutes a large cohort that is now entering their senior years. As this generation ages, the proportion of older adults in the population increases, amplifying the demographic shift[6].

- Migration patterns: In some regions, migration patterns can contribute to the demographic shift. Younger individuals might migrate to urban areas or other countries in search of better job opportunities, leaving behind an older population in their place of origin[7].

The rapid aging of the global population presents several challenges to societies across multiple dimensions, including healthcare, social support services, housing, and economic stability. These challenges stem from the unique needs and circumstances of older adults, as well as the overall shift in the age distribution of the population.

- Healthcare systems: Older adults typically require more healthcare services due to the higher prevalence of chronic diseases, functional decline, and age-related health issues. This increased demand can strain healthcare systems, necessitating additional resources, infrastructure, and workforce capacity to meet this growing demand.

- Social support services: The need for social support services, such as caregiving and assistance with daily activities, increases with age. This can lead to a greater demand for both formal and informal caregiving, affecting family structures and caregiving responsibilities.

- Infrastructure and housing: The demographic shift necessitates the adaptation of infrastructure and housing to accommodate the needs of an older population. This includes the development of age-friendly communities, accessible public spaces, and suitable housing options for seniors.
- Intergenerational relationships: The demographic shift can also affect relationships between different generations, as younger individuals may be required to take on increased caregiving responsibilities for their aging family members. This can create tensions and challenges in balancing work, family, and personal life for younger generations.

Addressing the challenges posed by the demographic shift requires proactive planning and a multi-faceted approach. This involves collaboration among government, private sector, and civil society stakeholders, including investing in healthcare and social support systems and creating age-friendly communities and housing options that promote economic stability and intergenerational cooperation. By addressing these challenges, societies can adequately support their aging populations while fostering economic growth and social well-being.

1.1.2 AIP as a Solution

AIP has emerged as a potential solution to address the challenges posed by the rapidly aging global population. AIP is a concept that encourages older adults to remain in their homes and communities for as long as possible, rather than relocating to specialized facilities like nursing homes or assisted living. This approach offers several benefits and can contribute to addressing societal challenges in various ways.

AIP promotes the independence and autonomy of older adults by enabling them to continue living in familiar surroundings and maintain control over their daily lives. This sense of independence can contribute to a higher quality of life and greater well-being, as older adults are empowered to make choices about their care, activities, and social interactions.

Moreover, AIP helps older adults maintain and strengthen their social connections, as they remain in their communities and continue to interact with friends, neighbors, and family members. Strong social connections have been linked to better physical and mental health outcomes, making this an important aspect of AIP.

AIP allows for the provision of customized care and support services tailored to the unique needs of each individual. This can range from home modifications, such as installing grab bars or ramps, to in-home care services, like meal preparation or personal care assistance. By adapting services to meet individual needs, AIP can help older adults maintain their health, safety, and well-being more effectively than a one-size-fits-all institutional setting.

Furthermore, AIP encourages the integration of older adults into their communities, fostering intergenerational relationships and promoting social cohesion. This can lead to more inclusive, age-friendly communities that support the well-being of all residents, regardless of age.

Economically, AIP is generally considered more cost-effective compared to institutional care, as it reduces the need for older adults to move into expensive, resource-intensive facilities. By helping older adults remain in their homes, societies can save on healthcare and long-term care costs, easing the financial burden on both individuals and public systems.

Overall, AIP serves as a versatile solution that not only enhances the lives of older adults but also offers a sustainable approach to managing the demographic shifts facing societies globally. By fostering environments where older adults can thrive independently, AIP mitigates the pressure on healthcare systems and contributes to the creation of resilient, supportive communities. As the global population continues to age, the relevance and necessity of AIP models become increasingly apparent, calling for broader implementation and support from policymakers, urban planners, and community leaders to fully realize its benefits.

1.1.3 Overview of Existing AIP Methods

This section provides an overview of the current methodologies and technologies employed to facilitate AIP, highlighting their objectives and limitations.

Traditional AIP solutions include in-home care services, which consist of professional caregivers who assist the elderly with daily activities, medication management, and health care services. While effective, they are often costly and can be intrusive, which might not be preferred by all seniors. Community and social programs such as senior centers or community gatherings help mitigate loneliness and provide social support. However, their effectiveness heavily depends on the senior's mobility and willingness to participate.

Technology-driven AIP solutions feature emergency response systems, commonly known as personal emergency response systems, which allow seniors to call for help in case of an emergency. While useful in critical situations, they do not contribute to preventing incidents. Telehealth and remote monitoring have seen a significant rise, especially for chronic disease management and routine check-ups. These systems track vital signs and health markers and support health management but often require active engagement from the user and can raise privacy concerns.

Smart home technologies employ sensor-based systems that use various sensors placed around the home to monitor movements, behavior patterns, and potential emergencies like falls. While they provide continuous monitoring without active user engagement, issues of privacy and data security are major concerns. IoT and smart appliances, such as smart thermostats, lighting, and security, indirectly support AIP by reducing the physical strain on seniors.

Machine learning and AI approaches include predictive analytics where AI models predict potential health deteriorations or risks by analyzing behavior changes over time. This proactive approach aims to prevent incidents before they occur. Fall detection systems use advanced AI algorithms, typically with motion sensors or camera feeds, to detect falls in real-time and alert caregivers or emergency services. However, the need for constant monitoring can infringe on privacy.

The existing AIP methods have provided valuable insights and assistance to support the elderly in their desire to live independently. However, these methods also exhibit significant limitations, particularly in personalization, privacy, and user-friendliness.

1.1.4 Summary

AIP has emerged as a promising solution to address the challenges presented by the rapidly aging global population. This approach has the potential to improve the quality of life and independence of older adults by providing support for daily activities and monitoring their well-being. However, despite its promising benefits, several challenges and limitations hinder the widespread adoption and effectiveness of these technologies. Given the constraints of existing methods and the growing need for effective, respectful, and integrative approaches to elderly care, there is a significant demand for innovative solutions. These solutions should not only address the practical aspects of healthcare and daily living but also respect the autonomy, privacy, and personal preferences of the aging population. This recognition leads to the need for a new approach that incorporates personalized design, privacy preservation, and adaptive interaction, which will be discussed in the subsequent sections.

1.2 Problem Statement

People who age in place often face daily challenges such as mobility issues, safety risks, and feelings of loneliness. To address these difficulties, effective Aging-in-Place (AIP) solutions are essential for supporting their independence and well-being at home. The need for innovative AIP technologies and systems is therefore becoming increasingly urgent. These technologies can significantly improve the quality of life and independence of older adults by providing support for daily activities and monitoring their well-being. However, several limitations must be addressed to ensure the widespread adoption and effectiveness of these technologies. In the following, we will discuss four primary concerns associated with AIP technologies, including the lack of theoretical approaches, privacy concerns, reliance on machine learning and data collection, and lack of personalization. By addressing these limitations and challenges, researchers and developers can work towards creating more accessible, user-friendly, and efficient AIP solutions that cater to the needs of older adults.

1.2.1 Limitations of Existing Technologies and Systems for AIP

Current AIP systems face multiple limitations that hinder the widespread adoption and effectiveness of AIP technologies, which have the potential to enhance older adults' quality of life and independence. These limitations include a lack of theoretical foundations, intrusive privacy measures, heavy reliance on machine learning and data collection, absence of personalization, and insufficient consideration of emotional, social, and environmental factors that contribute to older adults' well-being [8]. Furthermore, privacy concerns arise due to invasive monitoring methods often employed in IoT-based AIP solutions [9]. The main challenges in the context of AIP can be summarized as follows:

- Lack of Theoretical Approaches: AIP has become increasingly important due to the growing aging population, yet there is a notable lack of well-established theoretical frameworks guiding research and practice in this area. Most current studies are descriptive and exploratory, lacking the robust theoretical models found in related fields such as technology adoption and gerontechnology.

Barriers to theoretical development include the interdisciplinary nature of AIP research, the complexity of the aging process, diverse needs of older adults, and limited resources[10]. Additionally, the limited incorporation of theoretical frameworks into existing AIP systems is a significant limitation.

To advance this field, researchers should prioritize the development and application of theoretical frameworks, either by adapting existing models from related fields or creating new ones tailored to the unique challenges of AIP. Establishing a proper theoretical framework will enable researchers to pinpoint the exact reasons behind the acceptance or rejection of these systems. A deeper understanding of how individuals interact dynamically with their environments, particularly as they age, is crucial for developing more effective solutions that holistically address older adults' needs. Integrating these theories can help create comprehensive approaches that take into account both the individual's characteristics and their environment[11], ultimately resulting in more tailored and effective AIP systems. Collaboration across disciplines and engagement with stakeholders can further ensure that theoretical models are grounded in real-world experiences and address the needs of older adults[12, 13].

- Privacy Concerns: One of the significant limitations of AIP technologies and systems is the privacy concerns they raise for many older adults [13–16]. Monitoring systems and smart home technologies often involve the collection of personal data, potentially exposing sensitive information to unauthorized access or misuse. This concern may result in some elderly individuals being reluctant to adopt these technologies. Furthermore, the feeling of being under constant surveillance can negatively impact the psychological well-being of older adults, contributing to feelings of intrusion and discomfort.

- Resource and Privacy Challenges in Machine Learning for AIP: Existing AIP systems frequently rely on machine learning approaches, which demand extensive data collection and processing. This dependence leads to the need for significant computational power, storage capacity, and energy consumption. Such requirements, being resource-intensive, often translate to high costs and present practical challenges for deployment in home environments where there may be limitations on power and computing resources. Current machine learning models' extensive consumption of power, computing, and memory renders them less feasible for broad domestic application. Beyond the technical hurdles, the collection of vast amounts of data introduces privacy concerns. Users may be reluctant to divulge personal information to AIP systems, fearing potential risks of data breaches or misuse [17, 18]. To overcome these challenges, a balanced approach must be taken, one that effectively utilizes data while preserving user privacy, optimizes computational and power resources, and tailors algorithms to the specific constraints of home environments. Such a multifaceted strategy can help ensure that AIP systems are accessible, efficient, and pragmatic, meeting the diverse needs and contexts of older adults.

- Lack of Personalization: Many AIP technologies currently available adopt a one-size-fits-all approach, which may not adequately address the unique needs and preferences of individual users. This lack of personalization can hinder the effectiveness and adoption of these technologies, as older adults may perceive them as irrelevant or unhelpful for their specific needs [19]. To enhance the acceptance and usefulness of AIP technologies, it is crucial to develop personalized solutions that consider individual preferences, requirements, and living situations[20].

In order to effectively address the challenges and limitations associated with AIP technologies, it is crucial to develop a multi-faceted approach that considers various factors such as privacy, data utilization, personalization, and adaptability. By fostering interdisciplinary collaboration and engaging with stakeholders, researchers and developers can create innovative solutions that address the unique needs and concerns of older adults. Furthermore, incorporating robust theoretical frameworks can provide valuable insights to guide the design and implementation of these technologies, ultimately leading to more effective and user-friendly AIP systems. As the global population continues to age, it is essential to invest in the development of technologies that not only enhance the quality of life for older adults but also empower them to maintain their independence and well-being in their own homes.

1.2.2 Research Question

The concept of Aging-in-Place (AIP) emphasizes the need for older adults to remain in their familiar surroundings as they age, preserving their independence and enhancing their quality of life. However, the practical realization of AIP faces multifaceted challenges centered around individual needs, environmental adaptability, and privacy concerns. Existing AIP solutions often fall short in addressing these aspects comprehensively. This gap in the current landscape of AIP methods underscores the necessity for a personalized, privacy-aware approach in the design of AIP systems.

Given the limitations of current AIP methods, this research seeks to address the question:

> **"How to guide personalized AIP system design to support the elderly live independently and preserve privacy in their homes?"**

This question is crafted to explore the integration of personalization and privacy in AIP systems, which are critical to the acceptance and effectiveness of such technologies among elderly users.

Personalization in AIP involves tailoring the environment and support systems to meet the unique preferences, habits, and medical requirements of individual seniors. This approach not only enhances comfort and usability but also promotes better health outcomes and increased satisfaction with the living arrangement. A personalized AIP system can dynamically adjust to the changing needs of seniors, thus supporting a longer period of independence and reducing the need for institutional care.

Privacy concerns are a significant barrier to the adoption of technology-based AIP solutions. Seniors are particularly sensitive to their privacy, especially when technologies such as cameras or continuous monitoring are involved. The research question emphasizes the development of AIP systems that uphold the privacy of the elderly by employing non-intrusive technologies and ensuring that data processing complies with privacy regulations and best practices.

The primary aim derived from the research question is to develop a framework that guides the design of AIP systems. This research aims to fill the gap in current AIP practices by providing a detailed blueprint for designing personalized, privacy-preserving AIP systems. The expected contributions include practical guidelines for developers and policymakers, enhanced models for assessing individual-environment fit, and innovative solutions for privacy-preserving monitoring and assistance.

The defined research question is a stepping stone towards developing AIP systems that are not only technologically advanced but also deeply integrated with the personal needs and privacy preferences of the elderly. This approach hopes to redefine the standards of AIP solutions, making them more acceptable and effective for aging populations worldwide.

1.3 Outline of the Thesis

This thesis explores the integration of Artificial Intelligence and the Internet of Things (AIoT) into the concept of Aging in Place (AIP), focusing on enhancing the independence and well-being of the elderly while preserving their privacy. As populations age globally, the need for effective AIP solutions becomes increasingly critical. This work presents a comprehensive examination of this interdisciplinary field, combining theoretical models with practical technological solutions. The outline provided below delineates the structure of this thesis, systematically unfolding the research from foundational theories through to innovative implementations and real-world applications. Each chapter builds upon the last, presenting a cohesive and detailed exploration of the challenges and solutions in creating effective AIP systems.

- **Chapter 1: Introduction** provides the background, motivation, and research questions that guide the research.
- **Chapter 2: Literature Review** discusses relevant literature on AIP, Person-Environment Fit theory, IoT-based monitoring systems, machine learning approaches for health monitoring, and privacy concerns and unobtrusive sensing technologies.
- **Chapter 3: Theoretical Model: The Person-Environment for AIP Model (PE4AIP) and The PE4AIP-Enabled AIP Design Architecture** presents the development of the Person-Environment for Aging in Place Model (PE4AIP) and the PE4AIP-Enabled AIP Design Architecture. It begins with a focus group study aimed at understanding the specific needs, perceptions, and concerns of seniors and their caregivers regarding AIP systems. Insights from this study inform the theoretical model and practical design of a personalized and privacy-preserving AIP system. The chapter outlines the theoretical basis of the PE4AIP model, integrates it into a novel AIP design architecture. A preliminary study introduced to validate the usefulness of the P-E fit indicators in the PE4AIP model. This chapter underscores a comprehensive approach to measure person-environment fit for elderly individuals, paving the way for subsequent chapters that explore the architecture's application in real-world settings.
- **Chapter 4: Privacy Preserving Data Processing: an AIoT-based Fall Detection Approach** presents a novel AIoT-based fall detection approach and system, developed to enhance the effectiveness of AIP designs by addressing fall incidents among the elderly at home. The system utilizes TinyML and unobtrusive infrared array sensors integrated into a lightweight computational framework suitable for devices like Raspberry Pi and MCU platforms. By

employing LSTM neural networks, the system achieves real-time fall detection, ensuring real-time responses to potential falls. The chapter also explores the integration of Privacy Preserving Processing, emphasizing data security and local processing to minimize privacy risks. Experiment on Edge and End devices demonstrated its viability in privacy-sensitive applications and resource-constrained environments.

- **Chapter 5: Data-driven 3D Animation: A Privacy-Preserving Approach to Monitoring Elderly at Home** introduces an approach to monitoring elderly individuals in AIP context using data-driven 3D animation, which prioritizes the privacy and dignity of the elderly. By employing non-intrusive IoT sensors, this method captures environmental and activity data, transforming it into a three-dimensional animation that represents the daily activities of elderly individuals non-invasively. The chapter explores the technical implementation of this novel monitoring system, discusses its alignment with privacy considerations, and evaluates its effectiveness through practical experiments. Special emphasis is placed on the unique "3D Storytelling" feature, which condenses complex daily activities into simple and informative animations, making it easier for caregivers to understand and respond to the needs of the elderly without intrusive surveillance. The results demonstrate how this approach effectively bridges the gap between comprehensive care and respect for personal privacy, offering a promising tool for enhancing elderly care in a respectful and technologically advanced manner.

- **Chapter 6: SAiPS: An AIoT-based Smart Aging-in-Place System** introduces the SAiPS, an AIoT-based solution designed to enhance the independence and well-being of seniors living at home. Addressing limitations in personalization and privacy preservation found in existing AIP solutions, SAiPS leverages the PE4AIP-enabled design architecture to offer a comprehensive system that is both personalized and privacy-preserving. The chapter details the design, implementation, and a field study that evaluates the performance and acceptance of SAiPS among elderly users and their caregivers, focusing on its innovative features like non-intrusive monitoring and data-driven 3D animation for communicating the daily status of the elderly.

Chapter 7: Conclusion and Future Work summarizes the research journey from conceptual foundations to practical implementations. This chapter outlines the theoretical architecture proposed for AIoT-enhanced AIP systems, including a personalized well-being assessment model (PE4AIP), and innovations in privacy-preserving processing and 3D animation notifications. It discusses the validation of the PE4AIP model through various studies and the practical deployment of the Smart Aging-in-Place System (SAIPS), highlighting the research's effectiveness, acceptance, and real-world applicability. Key contributions highlighted include the novel AIP system design architecture, effective fall detection techniques, and an intuitive notification system for caregivers. The chapter concludes with future research directions, focusing on large-scale longitudinal studies and advanced intervention strategies to refine and expand the efficacy and applicability of AIP solutions.

The concluding chapter of this thesis encapsulates the journey from theoretical development to empirical validation and practical application of the AIoT-based Smart Aging-in-Place System (SAIPS). It synthesizes the insights gained, the methodologies employed, and the innovations developed throughout this research. Reflecting on the effectiveness, acceptance, and practical applicability of the proposed systems, this chapter highlights the significant strides made towards personalizing and securing AIP solutions. It not only reaffirms the contributions of this research to the field but also sets the stage for future investigations aimed at enhancing the scalability and precision of AIP technologies. Through proposed longitudinal studies and targeted interventions, the ongoing research will continue to refine the integration of technology in supporting the elderly to live independently and with dignity in their chosen environments.

Chapter 2

Literature Review

This chapter provides an extensive review of the literature relevant to AIP and its associated technologies, theories, and applications. The discussion begins with an overview of AIP, highlighting the importance of independent living and various frameworks for implementing AIP systems. The chapter then explores the technologies employed in AIP solutions, emphasizing their role in promoting a supportive environment for older adults. Subsequently, the Person-Environment Fit Theory is examined, including its various models, applications in gerontology, and relevance to the elderly and technology. Furthermore, the emerging field of TinyML is discussed, focusing on techniques, applications, and its potential role in AIP systems. Finally, the chapter discusses the advantages, challenges, and future directions of incorporating TinyML models into AIP systems, paving the way for a comprehensive understanding of the subject matter and guiding the design and development of AIP solutions for the aging population.

2.1 Aging In Place (AIP)

The term "Aging in Place" is an established concept in the realm of social policy and gerontology, signifying a concerted approach to facilitate older adults' ability to continue residing in their own homes and communities for as long as their health and circumstances permit [21]. This strategy was born out of concerns over the high financial burden of institutional care settings such as residential and nursing facilities. Over time, the rationale for promoting AIP has expanded beyond mere economic considerations, with a considerable body of research substantiating the innate preference of older adults to age in the familiar, comfort-rich environment of their own homes [22].

The global demographic landscape is changing rapidly, characterized by an ever-growing and aging population. This trend is predicted to result in an increased prevalence of chronic diseases and complex health issues [23]. The associated health burden, expected to escalate alongside the aging population, necessitates the development of a comprehensive and diverse healthcare workforce. Such a workforce must be equipped with the requisite skills and competencies for efficient diagnosis, effective management, and empathetic care of patients who present with multifaceted health challenges [24].

AIP is an encompassing philosophy that advocates for seniors' rights to choose where they live, without compromising their quality of life or hindering their access to essential resources needed for daily living [25]. As a multidimensional model, AIP strives to enhance the accessibility and quality of care for older adults while ensuring cost-effectiveness. However, the essence of AIP transcends these pragmatic aspects, venturing into the realm of environmental amelioration. A truly holistic AIP strategy seeks to not only maintain the quality of life and access to resources but also promote continuous improvements in the living environment. This focus on environmental betterment allows the model to cater to the evolving needs and preferences of seniors, thus fostering an atmosphere conducive to dignified and comfortable aging.

2.1.1 Promoting Independent Living Among Older Adults

Despite shifting health requirements or changing life circumstances such as familial relocation, marital dissolution, or widowhood, the preference among seniors to age in place remains remarkably robust [25]. Predominantly, seniors favor remaining at home, within a familiar environment, over spending their later years in care facilities.

Evolving living conditions notwithstanding, seniors who maintain good health and possess adequate financial resources are most likely to enjoy the benefits of independent living. The allure of independent living lies in the preservation of privacy, autonomy, and control, especially for those in advanced years [25]. Concurrently, the deinstitutionalization movement, aimed at transitioning seniors from long-term care facilities back into community settings, has led to the expansion of effective community-based services [22]. These services, which range from adult day programs to in-home care and personal care assistance, often mirror those provided by care facilities, thereby extending the duration of independent living for older individuals.

The role of technology as an enabler of independent living for seniors is gaining significant recognition. Technological innovations, including telehealth, remote monitoring, and intelligent home systems, support AIP by ensuring improved safety, security, and access to healthcare services within the home environment [26]. Furthermore, these technologies play a crucial role in mitigating social isolation, allowing seniors to maintain connections with friends, family, and healthcare providers through digital communication tools.

The concept of age-friendly communities provides an additional layer of support for independent living. These communities are designed with accessible transportation, appropriate housing options, and readily available community-based services, all contributing to the enhanced well-being and quality of life for seniors [27]. They also promote social integration and foster intergenerational interaction, thereby reducing feelings of loneliness and isolation among seniors.

In conclusion, facilitating independent living among older adults necessitates a comprehensive approach that incorporates a variety of elements, including housing, healthcare, technology, community design, and policy development. By adopting a collaborative stance and prioritizing the needs and preferences of seniors, societies can cultivate environments that not only allow seniors to live independently but also enable them to maintain their quality of life for as long as feasible.

2.1.2 Maslow's Hierarchy of Needs

Maslow's Hierarchy of Needs is a psychological theory proposed by Abraham Maslow in 1943, which postulates that individuals are motivated by a hierarchy of needs. From bottom to top, these needs are categorized as physiological, safety, love and belonging, esteem, and self-actualization[28]. Though the theory has faced criticism over the years, it remains a cornerstone in understanding human motivation and has been widely applied in areas such as business, education, and psychology.

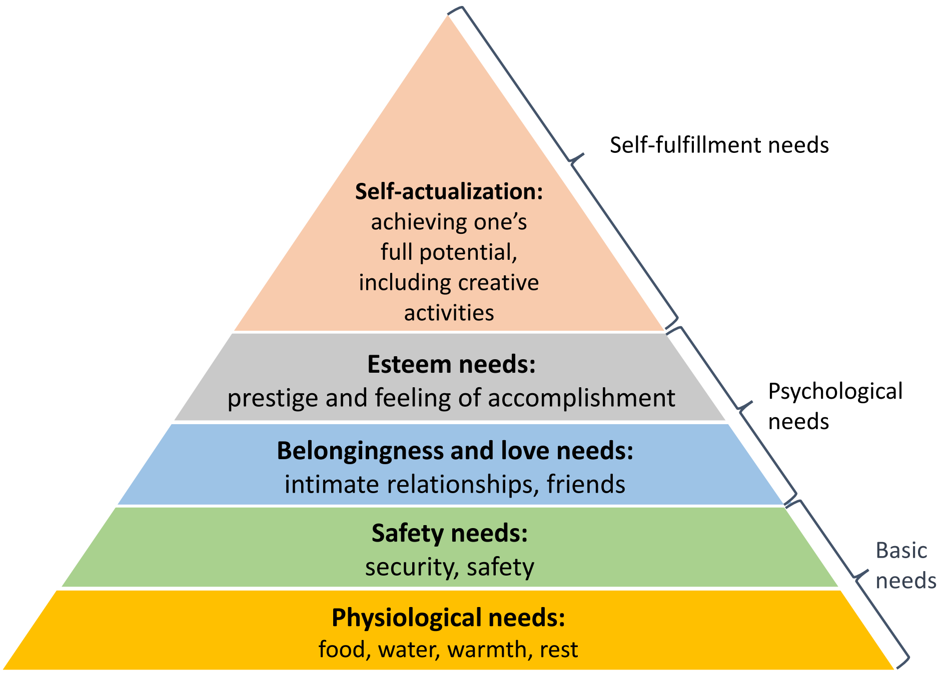

FIGURE 2.1: Maslow's Hierarchy of Needs

Applying this framework to guide AIP for older adults can help ensure that the full spectrum of their needs is considered and addressed.

- Physiological Needs: These are basic needs for human survival, including food, water, sleep, and warmth. In the context of AIP, this could involve ensuring that older adults have easy access to nutritious meals, a comfortable living environment, and appropriate healthcare services to manage any chronic conditions.

- Safety Needs: Once physiological needs are satisfied, the next level includes security and safety. For older adults, this can involve measures to make the home environment safe and secure. This could include installing grab bars in the bathroom, ensuring good lighting to prevent falls, implementing emergency alert systems, and possibly using security systems to ensure their physical safety.
- Love and Belonging Needs: As social creatures, humans have a need to feel a sense of belonging and acceptance. AIP should include opportunities for social interaction and companionship. This could be facilitated through community programs, family visits, or technology solutions like video calls.
- Esteem Needs: These involve the need for self-esteem and respect from others. Empowering older adults to maintain their independence as much as possible can fulfill this need. For instance, assistive technologies can enable them to perform daily tasks independently, contributing to a sense of accomplishment and self-worth.
- Self-Actualization Needs: This represents the need to achieve one's full potential. For older adults, this could involve opportunities for learning, creativity, and personal growth. Providing access to hobbies, classes, or volunteering opportunities can help older adults continue to grow and find fulfillment.

It's important to note that all these needs are interconnected. For example, if an older adult doesn't feel safe (safety needs), they might isolate themselves and thus not fulfill their social needs (love and belonging). Therefore, a comprehensive approach to AIP should consider all levels of Maslow's hierarchy.

While Maslow's Hierarchy of Needs provides a valuable framework for understanding human motivation and behavior, it also has several limitations[29, 30], particularly when applied to the context of AIP for older adults:

- Individual Differences: Maslow's theory assumes a similar pattern of needs for all individuals, which may not necessarily be the case. Older adults, like all individuals, have unique needs, preferences, and priorities that may not align neatly with Maslow's hierarchy. For example, some older adults may prioritize self-actualization needs such as lifelong learning and personal growth over basic physiological needs.

- Cultural Context: The hierarchy of needs may not be universally applicable across different cultures. Some cultures may prioritize community and social bonds (love and belonging) over individual achievement (esteem), for example.

- Fluidity of Needs: The hierarchy suggests that lower-level needs must be satisfied before moving to higher-level needs. However, in reality, people may strive for different needs simultaneously. For instance, an older adult may seek esteem and a sense of belonging (social needs) while still struggling with health issues (physiological needs).

- Lack of Empirical Support: While Maslow's theory is widely referenced, it lacks robust empirical support. Some research suggests that needs don't necessarily follow a hierarchical order, and the satisfaction of certain needs may not lead to predictable outcomes as the theory suggests.

- Overlooking Negative Experiences: Maslow's Hierarchy of Needs focuses on fulfilling positive needs but doesn't adequately consider negative experiences that are common in old age, such as loss, grief, and declining health. These experiences can significantly impact an older adult's needs and their ability to age in place.

- Neglect of External Factors: The theory is centered on individual needs and motivation but doesn't sufficiently account for external factors. In the context of AIP, these factors might include the availability of community resources, accessibility of services, and societal attitudes towards aging.

Despite these limitations, Maslow's Hierarchy of Needs still provides a useful starting point for considering a holistic approach to AIP, as long as these limitations are kept in mind.

2.1.3 Theoretical Frameworks for AIP

Supporting older adults who aspire to live independently and lead a fulfilling life, despite physical or cognitive limitations, has become an increasingly critical issue. A fundamental starting point for understanding the daily life of older adults can be found in the traditional assessment of daily functioning. For an individual to live independently, the capacity to perform basic daily activities (ADLs), such as bathing, eating, and using the toilet, is essential. Additionally, independent living demands the ability to conduct instrumental activities of daily living (IADLs), which may include managing medications, maintaining a household, and preparing healthy meals [31]. Active older adults may require a more expanded skillset, including adaptability to a changing environment, embracing new challenges, and acquiring new skills - these advanced behaviors are often referred to as "enhanced activities of daily living" (EADLs) [22]. Therefore, it's pivotal to ensure older adults AIP are capable of executing basic ADLs, while also providing assistance with IADLs and EADLs as necessary.

To more effectively address the requirements of seniors AIP, several theoretical frameworks have been presented in academic literature. Among these, the Comprehensive Geriatric Assessment (CGA) [32] represents a multidisciplinary diagnostic and treatment process, evaluating an older adult's medical, psychosocial, and functional capabilities to formulate a coordinated plan for treatment and follow-up. Encompassing physical health, mental health, cognitive function, social support, and environmental factors, the CGA provides a comprehensive approach supporting the AIP process.

Another noteworthy framework, the Ecological Model of Aging (EMA) [11], recognizes the intricate interaction between seniors and their physical and social environments. EMA underscores the importance of understanding the individual's capabilities, environmental demands, and the adaptive processes occurring between them over time. Such a model can guide the design and implementation of interventions and services that promote AIP, considering various contextual factors influencing a senior's ability to maintain independence and quality of life.

The Person-Environment-Occupation (PEO) model [33], is yet another valuable framework for comprehending and promoting AIP. It focuses on the interplay between an individual, their environment, and daily activities or occupations. By examining these interactions, the PEO model can assist in identifying factors that either support or inhibit the ability of older adults to carry out desired activities and successfully age in place.

By integrating these frameworks' principles into AIP initiatives, interventions and services can be tailored to the unique needs and circumstances of older adults. For instance, interventions aimed at modifying the environment can draw insights from the EMA and PEO models, highlighting the environment's role in aiding or obstructing senior's functioning and well-being. Similarly, the CGA can direct the creation of comprehensive, interdisciplinary approaches to evaluate and address the diverse needs of seniors AIP, encompassing medical, functional, and psychosocial realms.

These frameworks underscore the significance of a person-centered approach to AIP initiatives. This approach values the unique strengths, preferences, and objectives of older adults, while acknowledging the specific challenges their environments present. Such person-centered strategies can bolster seniors' autonomy, dignity, and sense of control, all critical for successful AIP [34].

In summary, adopting comprehensive frameworks for AIP can guide the creation and application of effective interventions and services that support older adults in maintaining independence, well-being, and quality of life. By considering the intricate relationship between individual factors, environmental demands, and daily activities, these frameworks can contribute to a more inclusive and supportive environment for our aging population.

2.1.4 Utilizing Technology for AIP

The role of technology in AIP is pivotal in enabling seniors to reside in their own homes within their communities for as long as possible, thereby avoiding institutional care. This section presents a review of contemporary technologies that mitigate numerous operational challenges impeding the effective execution of sustainable AIP infrastructures [35]. This is made possible through emerging technologies in robotics, smart sensors, and artificial intelligence. When designing technological interventions, it is crucial to account for both the care recipient and caregiver within the care service model.

The objective of AIP is to construct a secure environment that addresses the functional, physical, medical, emotional, and social needs of the elderly. Such provisions aid older adults in leading a fulfilling life based on their preferences. Information and communication technologies (ICT) have made substantial contributions to this, as demonstrated by ubiquitous intelligent sensor networks that are dynamically responsive to various environmental, physiological, and emotional factors. The idea of a "Smart Home" fundamentally embodies the integration of these elements within a domestic living setting.

The apparent objective of a smart home within the AIP context is to enable older citizens to age with autonomy, safety, dignity, and an acceptable quality of life. This environment perpetually, yet discreetly, monitors the individual's health and well-being, and provides necessary assistance for managing the home and personal mobility. The fundamental constituents of a smart home environment include sensors, communication systems, actuators, and user interfaces. Server-based computer software applications oversee and facilitate the coordination of sensors, systems, and applications.

For technology employed in AIP to be user-friendly and acceptable, it must encapsulate at least three attributes from the user's perspective [36, 37]: unobtrusiveness, familiarity, and autonomy. The system should monitor the health and well-being of older adults subtly, without constantly drawing their attention. Familiarity with their surroundings is especially critical for older adults AIP with cognitive impairments. Any unfamiliar elements within the home environment could provoke confusion and anxiety in individuals with mild cognitive impairment (MCI) or early-stage dementia. In terms of autonomy, older individuals should retain control over the system, with the ability to override it when necessary [38].

Moreover, synergistic efforts among stakeholders, such as technology firms, healthcare providers, community organizations, and government agencies, are vital to establish a supportive ecosystem for AIP technologies. Such collaborations can catalyze funding for research and development, as well as define guidelines and standards for technology design, accessibility, and interoperability [39]. Public awareness campaigns and educational initiatives can additionally enhance understanding and acceptance of AIP technologies among older adults and their caregivers.

In summary, the deployment of technology for AIP holds immense promise for enhancing the quality of life for seniors, allowing them to remain within their homes and communities as they age. However, to unlock this potential fully, it is essential to confront existing hurdles to adoption and implementation, ensuring that these technologies are designed and developed with the preferences and needs of older adults at the forefront. Through collaboration, user-centered design, and consistent evaluation, technology for AIP can foster a more supportive and inclusive environment for our aging population.

2.2 well-being Assessment in Context of AIP

Well-being assessment is essential in designing smart home systems for AIP, as it provides the necessary insights into the occupants' health, safety, and comfort needs. These systems integrate a broad spectrum of assessment methods to create environments that are responsive and supportive. Traditional psychological scales, smartphone applications monitoring physical activity and social interactions, and advanced domotic sensors all play a role in gathering comprehensive well-being data. This variety of approaches, including the introduction of composite indices, is crucial in tailoring smart home environments to promote health, well-being, and independence for the elderly, ensuring they receive appropriate support in their living spaces.

2.2.1 General Well-being Assessment Methodes

To better understand the scope and effectiveness of these methodologies, we delve into several key approaches that have been adopted for assessing well-being across various populations.

Psychological Well-being Measurement Scales: Psychological well-being is traditionally assessed through various scales measuring different aspects of an individual's mental state. A notable approach reviews nine measures of psychological well-being, comparing their psychometric properties and origins. These scales, developed from different conceptual definitions of well-being, underscore the ongoing debate and complexity in accurately measuring this construct [40].

BeWell Smartphone Application: The BeWell smartphone application offers a modern approach to well-being assessment, monitoring user behavior related to sleep, physical activity, and social interactions. Utilizing sensor data and user feedback, BeWell promotes healthier behavior patterns. Its successor, BeWell+, enhances the original by introducing community adaptive well-being feedback and well-being adaptive energy allocation, significantly impacting users' health choices positively [41].

Adapted Physical Activity Programs: Research into Adapted Physical Activity (APA) training programs for the elderly indicates significant psychological benefits and improvements in emotional well-being. Tailored to enhance the mental well-being of older adults, these programs highlight the importance of physical activity in maintaining psychological health in later life [42].

Domotic Sensors and Machine Learning: A novel approach utilizes a network of domotic sensors combined with machine learning algorithms to monitor the well-being of the elderly in home environments. Leveraging daily activity patterns and personal feedback, this method assesses the physical and mental state of older users, showcasing the potential of technology in personal health monitoring [43].

The Socioemotional Well-Being Index (SEWBI): The SEWBI provides a composite measure of subjective well-being, designed for the sociological analysis of life quality and social quality. Combining social indicators with the sociology of emotions, SEWBI offers a multidimensional and hierarchical alternative to traditional scales of happiness and satisfaction [44].

Informatics Applications: Informatics applications support the assessment and visualization of older adults' wellness through diverse technologies integration. Offering a comprehensive view of cognitive performance, physiological and gait variables, and psychometrics related to social and spiritual components of wellness, these applications highlight the role of informatics in enhancing the understanding of aging and well-being [45].

2.2.2 Well-being Assessment for Older Adults

The assessment of well-being in older adults presents unique challenges and opportunities. As the global population ages, understanding and promoting the well-being of the elderly has become increasingly important. Traditional measures, while valuable, may not fully capture the complexities of well-being in later life. The emergence of technology-based assessments, such as domotic sensors and smartphone applications, offers new avenues for real-time, non-intrusive monitoring of health and activity patterns. These methods can provide insights into the physical, psychological, and social aspects of elder well-being, emphasizing the multidimensional nature of health in older age.

Moreover, the adaptation of physical activity programs for the elderly underscores the critical role of tailored interventions in promoting mental and emotional well-being among older populations. The psychological benefits derived from these programs highlight the interconnectedness of physical and mental health, suggesting that comprehensive well-being assessment should encompass a range of factors, including physical activity, social interactions, and emotional health.

Traditional psychological scales assess psychological well-being through various metrics. Although they offer valuable insights, they may not capture all dimensions relevant to older adults, such as daily functional abilities and environmental interactions. Modern approaches like the BeWell smartphone application and the use of domotic sensors integrate technology to monitor physical activity, sleep patterns, and social interactions in real-time. These methods provide a continuous stream of data but may still lack contextual sensitivity to the personal and environmental factors that significantly impact an elderly person's life. Adapted physical activity programs underscore the link between physical health and psychological well-being, showing significant benefits for emotional states in older adults. However, their focus is often limited to physical activity without considering the broader environmental context. Composite indices tools like the SEWBI attempt to blend various dimensions of well-being, including emotional and social aspects. While they offer a more holistic view, the challenge remains in personalizing these indices to reflect individual-environment interactions more accurately.

The assessment of elder well-being requires a multifaceted approach that incorporates traditional scales, innovative technologies, and holistic measures. By embracing the complexity of well-being in older adults, researchers, practitioners, and policy-makers can better address the diverse needs of this growing population, ultimately contributing to a more inclusive and supportive society for individuals at all stages of life.

The Person-Environment Fit (P-E Fit) theory[46] proposes that well-being is significantly influenced by the compatibility between an individual's characteristics and their environmental context. This theory could be an effective approach for well-being assessment in older adults, aligning with the need for AIP systems to be deeply personalized and responsive to the changing needs of the elderly. By integrating P-E Fit theory into the assessment of well-being, it is possible to develop more targeted interventions that enhance the quality of life and independence of older adults.

The detailed application and benefits of the P-E Fit theory will be elaborated in the following section. This discussion will explore how integrating this theory into AIP systems can address the limitations of current well-being assessment methods, leading to innovative solutions that are both effective and respectful of the elderly's desire for independence and privacy.

2.3 Theory of Person-Environment Fit

The phrase "birds of a feather flock together" is often used when discussing the concept of fit. This proverb-indicating that people with similar interests, personalities, values, and so on, are likely to be attracted to the same environments—has extensively influenced the literature on fit and is a common thread in many foundational theories of Person-Environment (P-E) fit [47]. The P-E fit theory, centered on the alignment or compatibility between an individual and their environment, has been the subject of extensive research for several decades [46–50]. The theory is often associated with Lewin's "ecological equation," proposed in 1936 [51]. His theory posits that behavior (B) is a function of the individual (P) and their surrounding environment (E), formulated as $B = f(P, E)$. Consequently, both the individual and the environment must be taken into account when studying scientific psychology.

The P-E fit theory has found applications across diverse contexts, including organizational settings, educational environments, and healthcare [46, 48]. Particularly, P-E fit has been associated with factors such as job satisfaction, work performance, and psychological well-being [52, 53]. Researchers have established various models and methodologies to evaluate and understand the P-E fit, such as the need-press model, the supplemental model, the complementary model, and the congruence model.

These models offer a structure for investigating the interaction between individuals and their environment, and for understanding how this relationship can be optimized to yield better outcomes for both parties [54]. For instance, in the context of AIP, the P-E fit theory can aid in identifying methods to develop living environments that meet the needs, preferences, and abilities of older adults. This approach helps in promoting independence and improving the quality of life of older individuals as they age [11, 49].

2.3.1 Need-Press Model

Murray proposed the need-press model, based on the premise that a person's behavior results from the interaction between the individual and the environment [55]. In this model, a person is seen as having particular needs that define the individual's personality, and the environment is described in terms of features that help or hinder the person from meeting his/her needs. Thus, the level of fit is the degree to which a person's needs are met by the environment.

The need-press model consists of two primary components: personal needs and environmental press. Personal needs refer to the individual's psychological and physiological requirements, which motivate their behavior [55]. These needs can be divided into several categories, such as achievement, affiliation, power, and autonomy [56]. Environmental press, on the other hand, refers to the various external factors and influences that affect an individual's ability to satisfy their needs [57]. The press can be either positive (facilitating) or negative (hindering) depending on how well it aligns with the individual's needs.

The need-press model can be applied in various contexts, including work, education, and personal relationships. In the context of work, for instance, the fit between an employee's needs and the job environment can influence job satisfaction, performance, and turnover [58]. Similarly, in educational settings, the congruence between a student's needs and the learning environment can impact academic achievement, motivation, and well-being [59].

To assess the person-environment fit using the need-press model, researchers often employ a variety of assessment tools and techniques. These may include questionnaires, interviews, and observations to measure the individual's needs and the environmental press. By identifying the areas of congruence and incongruence between the person and the environment, practitioners can develop targeted interventions to enhance the person-environment fit and promote positive outcomes for the individual [60].

The need-press model has practical implications for various settings where the person-environment fit is critical to success and well-being. For example, in organizational contexts, human resource professionals can use the need-press model to inform the recruitment, selection, and development processes [61]. By identifying job candidates whose needs align with the environmental press of the organization, companies can improve employee retention, satisfaction, and performance.

In the realm of education, educators can apply the need-press model to design learning environments that cater to the diverse needs of students, enhancing their motivation and engagement in the learning process [62]. This may involve creating tailored learning experiences, offering a variety of instructional methods, and promoting a supportive and inclusive classroom environment.

In healthcare, the need-press model can be utilized to inform patient-centered care, ensuring that healthcare providers understand and address the unique needs of their patients in various environmental contexts [63]. This approach can lead to more effective treatment plans, better patient-provider communication, and improved health outcomes.

In conclusion, the need-press model provides a valuable framework for understanding the complex interplay between individuals and their environments. By examining the congruence between a person's needs and the environmental press, researchers and practitioners can identify opportunities to enhance the person-environment fit, ultimately leading to improved well-being and success in various life domains.

2.3.2 Competence-Press Model

Lawton proposed a competence-press model [57], which assumes that behavior is the function of the competence of a person and the environmental press. Competence is a concept that simply describes what a person possesses, ranging from low to high. It is a representation of the individual's givens, for example, one's physical and mental strength. Press is "a limited aspect of the environment which has a potential demand character". In other words, it triggers one's behavior. Press ranges from low to high and can be positive, neutral, or negative. For example, the presence of a computer in an environment may be considered a positive press as this may potentially trigger the person in the environment to turn it on and use it; the lack of air-conditioners in an environment may be deemed as a negative press as this may cause the environment to be too cold or hot such that one cannot tolerate. Nonetheless, the presence of a computer or the lack of air-conditioners may be neutral to individuals who do not know how to use a computer or in situations when the room temperature is just nice. In this model, the fit is the balance of a person's competence and the environmental press. A person achieves a state of balance when his or her competence is compatible with the environmental press. When the same person is placed in an environment with either higher or lower press, the person may be pushed into a state of imbalance. Negative affect and maladaptive behavior emerge when the degree of imbalance is too great for the person to bear. In such situations, the person and/or the environment must provide ways to offset

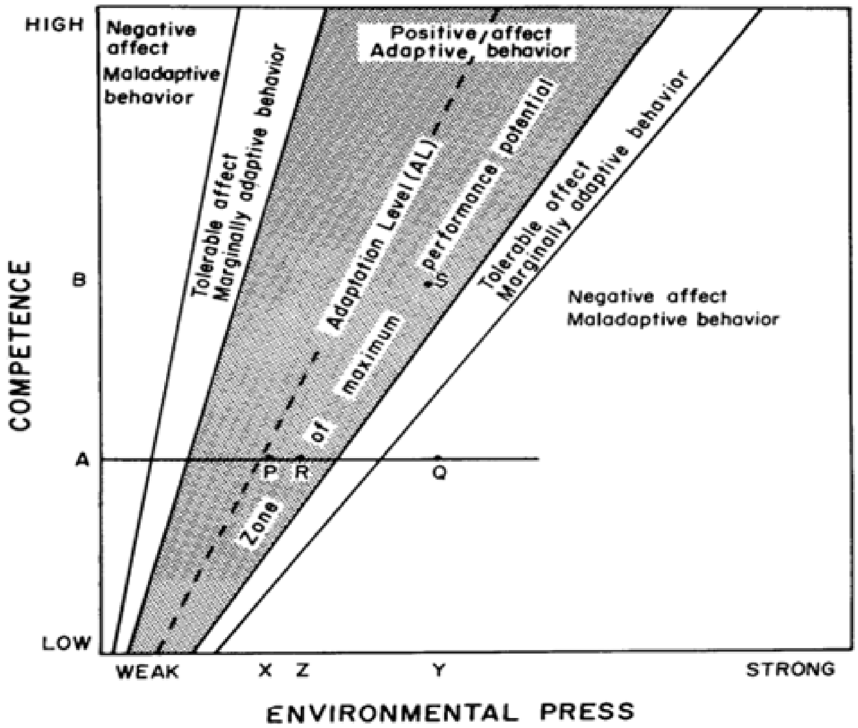

FIGURE 2.2: Competence-Press Model[57].

the excess or shortage of environmental press in order to restore the balance (or fit) between the person and the environment (Figure 2.2). Similarly, within the same environment, people with varying levels of competence may be in different states (balanced, or imbalanced), and thus be affected positively or negatively.

2.3.3 Supplementary and Complementary Fit

Muchinsky and Monahan proposed two types of P-E fit, namely supplementary fit, and complementary fit [64]. Supplementary fit is the fit between an individual and an environment that is made up of a group of people. It is indicated by the parallels between a person's traits, like values and goals, and that of the environment. A person's perception that he or she "fits in" with the environment due to shared qualities is a kind of supplementary fit. Complementary fit, on the other hand, is the congruence between a person's strengths and talents and the environment's related demands. It occurs when a person's features "make whole" the environment or provide what is missing. A person completes an environment with some deficiency with his/her own resources like time and ability is an example of the complementary fit.

2.3.4 Needs-Supplies Fit

The concept of needs-supplies fit, deriving from the complementary fit principle, is frequently employed within job, vocational, or organizational contexts [65–70]. This approach is grounded in Murray's need-press theory [71], as well as the Theory of Work Adjustment (TWA) [72].

The TWA presents a mutual interaction between the individual and the environment, wherein both entities place demands on each other while simultaneously fulfilling the other's needs. This balance or alignment between what both the individual and environment demand and provide is defined as correspondence, or 'fit'.

In the context of the needs-supplies fit model, 'fit' is characterized by how well an environment satisfies the needs of an individual. This assessment of fit involves comparing the resources or opportunities (e.g., financial benefits, job-related responsibilities) provided by an environment to the individual's specific requirements or aspirations (e.g., desired salary, work-related opportunities) [73].

An understanding of the needs-supplies fit is essential, particularly in fields such as gerontology and the design of AIP technologies. Here, the focus is on ensuring that the environment not only meets the physical needs of the older adults but also satisfies their psychological and social needs. This holistic approach is crucial for enhancing their well-being and quality of life. The needs-supplies fit model can offer valuable insights in this regard, aiding in the design of more inclusive and supportive environments for older adults.

Applying the needs-supplies fit model to the context of AIP involves a thoughtful understanding of the varied needs of older adults, which range from physical to emotional, social, and cognitive. The goal is to ensure that the living environment is capable of fulfilling these needs to promote a healthier and more fulfilling lifestyle for older adults. For instance, in terms of physical needs, the environment should be designed with features such as handrails or ramps to support mobility. Emotional and social needs can be met by enabling easy communication with family and friends, perhaps through user-friendly digital devices. Cognitive needs can be addressed by providing engaging activities that stimulate the mind, such as puzzles or reading materials. The living space should also be adaptable to the changing needs of the individual as they age. Thus, the needs-supplies fit model serves as a guiding principle for creating an environment that supports AIP effectively, promoting a high quality of life, independence, and well-being among older adults.

2.3.5 Demands-Abilities Fit

The Demands-Abilities fit, a sub-theory under the broader umbrella of complementary fit, operates on the principle that an individual's abilities should align with the demands or requirements of a specific environment or entity. This model is commonly deployed in various professional contexts such as job recruitment, vocational counseling, and organizational behavior studies [74–77]. In these contexts, the evaluation process involves a comparative analysis of individual characteristics - such as time commitment, knowledge base, skill set, and overall abilities - against the corresponding demands or requirements imposed by the job, vocation, or organization. These demands may encompass expectations related to time investment, requisite knowledge, necessary skills, and other abilities critical for successful engagement [53].

The Demands-Abilities fit model thus serves as a crucial evaluative tool to ensure a harmonious interaction between individuals and their environments. The objective is to ensure that individuals are suitably equipped to meet the demands of their environments, thereby minimizing potential friction, enhancing performance, and promoting overall satisfaction. In the context of employment, for instance, a good fit would imply that an employee has the necessary skills and knowledge to perform their job effectively, thereby leading to higher job satisfaction and productivity. Conversely, a poor fit could result in job dissatisfaction and reduced performance.

Applying the demands-abilities fit model to the concept of AIP necessitates considering the evolving abilities of older adults and ensuring that the demands of their living environment correspond to these abilities. As individuals age, their physical, cognitive, and sensory abilities may change, and the living environment should accommodate these changes rather than impose unrealistic demands. For instance, physical demands of the environment, such as navigating stairs or reaching high shelves, may become challenging as mobility declines. Hence, modifications like installing stairlifts or lowering shelves can help ensure a better fit. Similarly, cognitive demands should be adjusted to match the cognitive abilities of older adults, perhaps by providing clear instructions for using appliances or adopting user-friendly technologies. Furthermore, considering sensory changes like vision or hearing loss and adapting environmental demands accordingly can also promote a better fit. Overall, the demands-abilities fit model highlights the need for a responsive and adaptable environment that aligns with the abilities of older adults, supporting their desire to age in place safely and comfortably.

2.3.6 Measurement of P-E Fit

Understanding the alignment between individuals and their environment, known as Person-Environment (P-E) Fit, is crucial for various domains, including psychology, organizational behavior, and human-computer interaction. To measure the degree of P-E Fit, researchers have employed diverse methods, each offering unique insights into this complex relationship[46, 49, 50, 78, 79].

Subjective Measurement: This method involves collecting data directly from individuals through self-report measures. It often includes the use of questionnaires or interviews where individuals rate their perceived fit with the environment. The questionnaires may inquire about various aspects of the individual's experiences, attitudes, and feelings regarding their compatibility with the specific environmental conditions. By relying on individuals' self-assessments, this method provides insight into how individuals subjectively perceive their alignment with the environment[46].

Objective Measurement: The objective measurement approach focuses on gathering information about individual characteristics and comparing them to the demands of the environment in an unbiased manner. Researchers might utilize standardized tests, skill assessments, or evaluations of qualifications and experience to obtain objective data. The collected data are then compared to the requirements and attributes of the environment to determine the level of alignment. Objective measurement reduces potential biases that could arise from self-reporting and offers a more standardized evaluation of P-E Fit[46].

Subjective and Objective Combination: This method combines both subjective and objective assessments to gain a more comprehensive understanding of P-E Fit. By utilizing self-report measures along with objective data, researchers can cross-validate the information and identify potential discrepancies between individuals' perceptions and objective evaluations. Integrating both approaches helps to validate the overall fit assessment and enhances the robustness of the findings[80].

Matching Index: The matching index is a numerical representation of the degree of alignment between an individual and their environment. It involves quantifying the similarities or congruence between specific attributes of the individual and the corresponding environmental demands. This method often employs statistical techniques to calculate the matching scores, resulting in a quantitative measurement of P-E Fit. The matching index allows researchers to compare multiple individuals and environments efficiently[47].

Discrepancy Measurement: Discrepancy measurement focuses on assessing the gaps or discrepancies between the individual's abilities and the demands of the environment. It does not directly measure the fit but rather identifies areas of mismatch or misalignment. Researchers may quantify these discrepancies through various means, such as calculating the differences between individual attributes and environmental requirements. This method highlights specific areas for potential improvement or intervention to enhance the overall fit[81].

In conclusion, the measurement of Person-Environment (P-E) Fit plays a pivotal role in comprehending how individuals interact with their surroundings and adapt to various environmental conditions. Each of the five methods discussed in this review offers distinct advantages, catering to different research contexts and objectives. Subjective Measurement captures individuals' self-perceptions, providing valuable insights into their subjective experiences and emotional responses to the environment. On the other hand, Objective Measurement ensures a more standardized and unbiased evaluation by examining individual characteristics against environmental demands.

By combining Subjective and Objective assessments, researchers gain a comprehensive understanding of P-E Fit, validating findings and enhancing the overall robustness of the analysis. The use of a Matching Index offers a quantitative representation of the degree of alignment, facilitating comparisons across multiple individuals and environments efficiently. Meanwhile, Discrepancy Measurement pinpoints areas of mismatch, guiding potential interventions to improve the overall fit.

As technology advances, the integration of emerging approaches, such as utilizing Internet of Things (IoT) sensors and machine learning techniques, holds the promise of providing even more nuanced and real-time measurements of P-E Fit. Research endeavors should continue to explore innovative methodologies, enabling a deeper understanding of the dynamic interplay between individuals and their ever-changing environments. Ultimately, a comprehensive understanding of P-E Fit can pave the way for designing tailored interventions to optimize individual well-being, performance, and satisfaction in diverse settings.

2.4 Optimizing AIP: A Person-Environment Fit Approach

The Person-Environment (P-E) fit theory provides a nuanced framework for examining the interactions between individuals and their environments, emphasizing the significance of achieving a harmonious balance, especially in the context of aging. This literature review delves into the application of the P-E fit theory in the realm of AIP technology, organizing the discourse into detailed subsections to cover current research, technological advancements, and practical applications comprehensively.

2.4.1 Foundational Concepts of P-E Fit Theory

The P-E fit theory, rooted in Lawton's competence-press model, articulates that an individual's well-being is optimized when there is a balance between their competencies (personal abilities and attributes) and the environmental demands or 'press' (environmental challenges and supports). This theoretical model underscores the dynamic nature of aging, where declining competencies necessitate adjustments in environmental press to maintain or enhance well-being. Lawton's seminal work posits that environments which are too demanding can overwhelm an individual, whereas environments that are not demanding enough can lead to under-stimulation and decline, highlighting the necessity for a tailored approach to environmental design[57, 82].

2.4.2 Enhancing AIP through Environmental Adaptation

Central to enabling AIP is the concept of environmental adaptation, which involves modifying living spaces to meet the evolving needs of the aging population. Iwarsson and colleagues' Housing Enabler tool represents a pivotal advancement in this domain, providing a systematic method for assessing and addressing the fit between elderly individuals' capabilities and their physical living environments. This approach not only facilitates the identification of potential mismatches but also underscores the critical role of accessible design in promoting independence, safety, and quality of life for older adults. The tool's application in various studies has demonstrated significant improvements in AIP outcomes, such as reduced fall risks and enhanced mobility within the home[83].

2.4.3 Technological Interventions in AIP

Technological interventions represent a frontier in enhancing the P-E fit for aging populations. Innovations in smart home technologies, wearable devices, and telehealth services offer unprecedented opportunities to support the elderly in maintaining independence and managing health conditions. For instance, sensor-based monitoring systems can detect changes in daily activities, potentially alerting caregivers to emerging health issues or risks of falls. Similarly, smart home devices can automate tasks, reduce physical demands, and enhance safety, directly contributing to an improved P-E fit. However, the adoption and efficacy of these technologies are influenced by factors such as usability, affordability, and the digital literacy of the elderly population, presenting a complex interplay of challenges and opportunities for designers and policymakers alike[84, 85].

2.4.4 Health Implications of P-E Fit in Elderly Populations

The application of P-E fit theory in the context of health and well-being among the elderly has yielded insightful findings. Research indicates that a better P-E fit is associated with positive health outcomes, including lower incidence of chronic conditions, reduced risk of mental health issues, and enhanced overall well-being. Environmental adaptations and interventions that improve accessibility, such as the installation of grab bars, improved lighting, and the removal of trip hazards, have been shown to significantly mitigate fall risks and promote physical health.

Moreover, the integration of community-based services and resources can address broader social determinants of health, illustrating the multifaceted nature of P-E fit in supporting elderly well-being[86, 87].

2.4.5 Beyond Physical Health: Social and Psychological Dimensions

Exploring beyond the confines of physical health, the P-E fit theory illuminates the importance of social and psychological dimensions in the aging process. The theory advocates for environments that foster social engagement, emotional well-being, and cognitive stimulation. Research in this domain highlights the benefits of age-friendly communities that offer opportunities for social interaction, engagement in meaningful activities, and access to support services. These environments not only cater to the physical needs of older adults but also support their psychological and emotional well-being, reinforcing the notion that a holistic approach to P-E fit can significantly enhance the quality of life[88, 89].

2.4.6 Challenges and Opportunities for Research on Aging Technology

Despite notable advancements, the application of P-E fit theory in AIP faces several challenges. The reliance on self-reported data and observational studies, while valuable, may not fully capture the dynamic and complex nature of person-environment interactions. Furthermore, the heterogeneity among older adults in terms of health status, preferences, and technological proficiency calls for personalized and adaptive interventions. Research directions are actively exploring the development of real-time monitoring systems, AI-driven personalized support tools, and inclusive design principles that accommodate a wider range of abilities and preferences. These efforts necessitate interdisciplinary collaboration, leveraging insights from gerontology, urban planning, technology design, and public health to forge innovative solutions that enhance the P-E fit for aging populations[90].

In conclusion, the P-E fit theory offers a comprehensive and dynamic framework for understanding and addressing the needs of older adults within their living environments. As society progresses towards more inclusive and supportive environments for the aging population, leveraging the principles of P-E fit in the development and implementation of AIP technologies and interventions will be crucial. The ongoing dialogue between research, practice, and policy must continue to evolve, embracing the complexities of aging and the diverse needs of older adults to foster environments that promote not only longevity but also a high quality of life.

2.5 Tiny Machine Learning (TinyML)

2.5.1 Techniques in TinyML

TinyML is an emerging field in machine learning, aimed at implementing algorithms on low-power, memory-constrained devices such as microcontrollers and IoT devices. It utilizes techniques like model compression, efficient neural architectures, and hardware-aware optimization to enable real-time, privacy-preserving, and energy-efficient on-device intelligence [91–93].

Prominent efficient architectures, including MobileNet, ShuffleNet, and SqueezeNet, reduce model size and computational demands while maintaining accuracy. These architectures employ methods like depth-wise separable convolutions, point-wise group convolutions, channel shuffling, and the Fire module to enhance efficiency [94–96].

TinyML facilitates real-time analysis and decision-making on low-power devices, vital for continuous monitoring and localized decision-making in environmental sensing, healthcare, and industrial IoT [97–99]. In healthcare, TinyML enables wearables to perform fall detection, activity recognition, and vital sign monitoring, significantly improving patient care and device efficiency [100–104].

2.5.2 TinyML in Aging-in-Place (AIP) Systems

In AIP systems, TinyML models are particularly beneficial due to their efficiency and low resource requirements, making them suitable for mobile, edge, and embedded systems [105]. Key applications include:

- **Fall Detection:** Utilizing LSTM and GRU networks to provide timely and accurate fall detection through sensor data analysis [106].
- **Activity Recognition:** Employing compact models like MobileNetV2 to recognize daily activities, aiding routine and health monitoring [94].
- **Health Monitoring:** Enabling continuous monitoring of vital signs to facilitate early detection of health issues [107].

These applications ensure the safety and well-being of older adults, promoting independence through timely interventions.

2.5.3 Advantages, Challenges, and Future Prospects of TinyML

TinyML models are efficient, scalable, and capable of real-time processing, ideal for enhancing the quality of life and independence in AIP systems [94, 105, 106]. Challenges include balancing model complexity with accuracy, limited generalization capabilities, and data collection and annotation issues [108, 109].

The potential of TinyML is amplified when integrated with technologies like IoT and edge computing. This integration can create interconnected networks of sensors and devices for comprehensive, real-time monitoring and support, improving older adults' living environments [106]. Edge computing enhances data privacy and reduces latency by processing data closer to the source, aligning with TinyML principles for efficient local inference.

Future advancements in TinyML will likely involve integration with blockchain for security, explainable AI for transparency, and serverless computing for efficient resource utilization [110, 111]. Continuous improvement in model optimization and transfer learning will address current limitations, enhancing generalization capabilities and performance in diverse AIP scenarios. The merging of TinyML with IoT, edge computing, and other emerging technologies offers promising avenues for creating scalable, comprehensive, and privacy-preserving AIP systems that could significantly improve the quality of life for older adults.

Chapter 3

Theoretical Model: The Person-Environment for AIP Model (PE4AIP) and The PE4AIP-Enabled AIP Design Architecture

The dynamic interplay between individuals and their environments is paramount in the context of AIP, particularly as the global demographic shifts towards a more aged population. This chapter introduces the Person-Environment for Aging in Place Model (PE4AIP) and the PE4AIP-Enabled AIP Design Architecture. Rooted in the P-E Fit theory, the PE4AIP model aims to intricately map and enhance the alignment between seniors' personal needs and their living environments. Through a focus group study, this chapter delves into the prevalent issues, needs, and technological receptiveness among seniors and their caregivers, setting the stage for a nuanced discussion on optimizing AIP systems that are both personalized and privacy-preserving. This foundational exploration serves as a cornerstone for developing a robust AIP application that not only respects but actively supports the independence and dignity of the elderly in their preferred living environment.

3.1 Focus Group Study

A focus group study to explore and evaluate the prevalence of problems in AIP system design.

3.1.1 Experiment Design

The primary objective of this focus group study was to understand the perceptions, needs, and concerns of seniors and their caregivers regarding AIP. This understanding is crucial for designing personalized and privacy-preserving AIP systems.

Participants included six senior individuals over 65 (designated E1 to E6) and six caregivers (designated C1 to C6).

- Six elderly individuals over the age of 65, representing the primary beneficiaries of AIP technologies.
- Six caregivers, either family members or professional caregivers, who regularly interact with the elderly.

Led by our researcher, the group discussions were guided by a structured topic guide to uncover the experiences and ideas of the participants.

The method of focus group was selected for several reasons. Firstly, the senior participants may not be familiar with an Ageing-in-place system. This method facilitates the development of ideas based on group discussions. Subsequently, since the participants have limited experience in a user study, this method helped to encourage a wide variety of different views related to a specific topic. One idea during the discussion may inspire others. Furthermore, a focus group discussion can decrease the concern of the "right or wrong answer," which is quite common in interviews[112].

3.1.2 Experiment Procedure

Participants were initially briefed about AIP systems, their functions, and potential benefits. Following this introduction, they were encouraged to discuss their thoughts on the system's usefulness, data collection preferences, functional improvements, cost concerns, and reasons for potential rejection. The guide questions include:

- Do you feel this system is useful?
- What information would you like or dislike the system to collect?
- What functions do you think can improve the system?
- Would you use this system if it were free?
- Why might you choose not to use this system?

The discussions were extensive and continued until no new ideas emerged, lasting approximately 2 hours. During the discussion, our researcher took notes to record the questions, answers, discussions, and the non-verbal cues. After the meeting, 2 researchers coded the scripts independently to distill the themes from the answers. An 86.5% agreement between coders demonstrated the reliability of the theme generation.

3.1.3 Experiment Results

During the focus-group meeting, the participants showed great interest in the AIP system. The elderly indicated quite some factors they would like the system to monitor, including sleeping, health life patterns, etc. At the same time, the caregivers paid more attention to the information which can help them to assess the well-being of their parents such as the sleeping quality, social activities, diet, etc. Besides these most important factors, some other participants mentioned that they would like to get more information about sudden accidents such as falling, abnormalities, and unhealthy lifestyles.

Some participants showed interest in getting an objective evaluation about their living environment. For instance,

> **E1**: "Can it evaluate how healthy my life is? Can it give me some suggestions to be healthier? ..."
>
> **E2**: "I want the system to assess the design of my platform and give advice to improve it. EDB is providing a voucher to develop our house right now."
>
> **C5**: "It seems like the machine(AIP system) can get some evidence of my dad's bad habits. Watching too much TV, taking coca all day ... Then I can complain to his doctor."

Following the concern of indoor accidents such as falling, the caregivers mentioned another critical expectation to the system; they need to get an alarm or notification from the system. For example,

> **C5:** "My parents always say they are perfect, and they need nothing. If the machine can tell what I can do to improve their life, I will be happy."

Despite the positive feedback, privacy concerns were prevalent among some participants regarding the use of the AIP system,

> **E5**: "I will never install a CCTV system in my house. I do not want to be spied on."
>
> **E3**: "I'm afraid a thief will watch my house video and get where I hide my money."

C1: "My mom will never let me to watch her life. She's shy."

These discussions underscored the delicate balance between the benefits of technological aid and the imperative need to preserve dignity and privacy. The insights gathered will direct future enhancements in system design, ensuring a user-centric approach that respects both the needs and concerns of seniors and their caregivers.

3.1.4 Key Findings

Based on the themes generated from the focus-group meeting scripts, we found several insights for AIP system design. Firstly, all participants expressed the desire to gain an understanding of elderly's well-being continuously. It is necessary to develop a computational model to assess the environment fit and map it to the well-being of the users. Participants expressed specific interests in features that would enhance their independence and quality of life. These features were distilled into six most important key factors:

- **Motion**: Importance of monitoring physical activity to assess mobility and prevent accidents.
- **Regular Lifestyle**: Monitoring daily routines to maintain and promote consistent and healthy habits.
- **Social Interaction**: Assessing social interactions to combat feelings of loneliness and isolation.
- **Indoor Comfort**: Ensuring the living environment is comfortable and conducive to the seniors' health.
- **Sleep**: Monitoring sleep patterns and quality to ensure good health and well-being.
- **Eating**: Observing dietary habits to encourage nutritional intake and healthy eating.

Secondly, it is critical to provide caregivers information about elderly daily activities; thus, it is important for an AIP system to analyze the interaction between the persons and the relevant environment.

Thirdly, all participants expressed concerns about privacy issues. Thus, privacy safety is a key consideration in Ageing-in-place design.

Lastly, from the caregiver's perspective, they want to receive information on the elderly's condition, so an effective and satisfactory Ageing-in-place system should notify caregivers based on the assessment of the care recipients' living environment so they can make changes accordingly.

These findings led to the proposal of the Theoretical Model: The Person-Environment for Aging in Place Model (PE4AIP) and the PE4AIP-Enabled AIP Design Architecture, addressing both the functionalities desired by users and their significant concerns about privacy and usability.

3.2 Unobtrusiveness and Privacy in AIP Context

In light of the discussions in Chapter 1 and Chapter 2, the importance of elderly monitoring systems in healthcare and supportive care technologies is undeniable. Yet, the effectiveness and widespread adoption of such systems are closely tied to their acceptance by the elderly and their caregivers. It is also confirmed by the focus group study in Chapter 3.1, two fundamental concepts that play a pivotal role in this acceptance are Unobtrusiveness and Privacy. These principles are not merely guidelines but form the bedrock of designing and implementing systems that aim to empower the elderly by respecting their independence and dignity. Understanding these concepts is essential not only for designing systems that are both effective and respectful of the users' needs but also for ensuring that these systems are welcomed and trusted by their intended users.

3.2.1 Unobtrusiveness

Unobtrusiveness characterizes the ability of monitoring technologies to collect data and offer insights while causing minimal interference in the daily lives of individuals. It emphasizes the significance of a system that operates discreetly, blending into the environment to avoid disrupting the natural routines and comfort of the monitored individuals. By ensuring that the technology is imperceptible and non-intrusive, the systems aim to support the elderly without altering their standard living conditions or behaviors. This approach directly supports our commitment to privacy protection, demonstrating that it is possible to gather critical information about the elderly's lifestyle and health without compromising their privacy.

- **Objective:** To collect essential data for monitoring and assistance purposes in a way that does not impact the elderly's standard living conditions or routines, thereby supporting our commitment to privacy protection by leveraging non-invasive technology.
- **Implementation:** Through the use of discreet sensors and devices that require no manual intervention and are designed to be as non-invasive as possible, we can effectively monitor health and lifestyle information without invading the user's privacy. This strategy enhances system acceptability and user satisfaction while upholding the respect and protection of users' privacy rights.

3.2.2 Privacy

Privacy within the context of elderly monitoring systems is pivotal, encompassing the safeguarding of sensitive data and the respect for the individual's autonomy over their personal information and space. In this research, 'privacy' is conceptualized as the conscientious avoidance of collecting and transmitting unnecessary personal sensitive data, particularly images and videos, to safeguard the dignity and autonomy of the elderly. This definition extends beyond mere data protection to encompass respect for the personal space and information of the elderly, aligning with ethical monitoring practices.

Ensuring privacy requires the incorporation of stringent data protection strategies, including the use of encryption, data anonymization, and controlled access measures. Although this thesis does not delve into the specifics of encryption methods during data transmission, it is crucial to highlight that our proposed architecture is fully compatible with existing encryption technologies. These can be seamlessly integrated to safeguard data during communication between devices and servers, thereby maintaining privacy throughout data transmission. By designing systems with transparency at their core, we enable users to have a clear understanding of the data collection process, its utilization, and access privileges.

In essence, the principles of unobtrusiveness and privacy are integral to crafting ethical and efficacious monitoring systems for the elderly. These principles are indispensable for the development of technologies that facilitate AIP, ensuring that the support provided does not compromise the well-being or independence of the individuals it aims to assist.

3.3 Development of the PE4AIP Model

This section of the thesis delves into the development of the Person-Environment Fit model for Aging in Place (PE4AIP), providing a comprehensive framework designed to enhance the living conditions of the elderly by aligning their personal needs with environmental characteristics. This model development involves defining the rationale for the model, identifying key P-E fit indicators, and establishing a methodology for their evaluation.

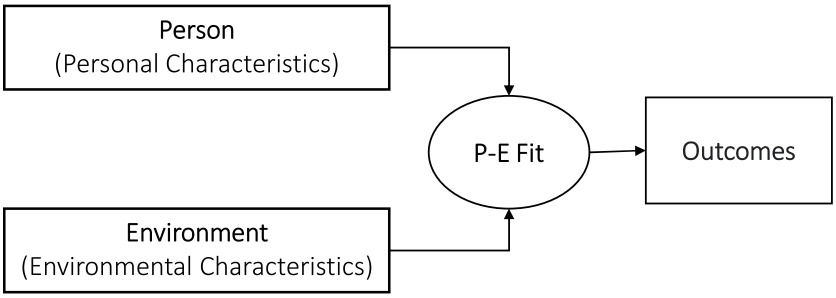

FIGURE 3.1: Person-Environment Theory

3.3.1 Theoretical Basis

The original P-E Fit theory, which is instrumental in various fields of social sciences and organizational studies [46]. This theory emphasizes the interplay between individual characteristics and their surrounding environment and its impact on several outcomes. As shown in Figure 3.1, the P-E fit theory asserts that the 'fit' is a function of person characteristics and environment characteristics. Here, 'person characteristics' encompass an individual's biological and psychological needs, personal values, life goals, and abilities. These characteristics are what make every individual unique, contributing to the diversity of needs and preferences within the aging population. On the other hand, 'environment characteristics' encapsulate both intrinsic and extrinsic rewards, role demands, cultural values, and characteristics of other individuals or groups within the person's social environment [113]. For AIP, the environment refers to both the physical home environment (such as the design of the house, the availability of support facilities) and the broader socio-cultural environment (including social support networks, cultural norms around aging, and available services).

Building on the basic P-E fit theory, some researchers further considered the P-E fit in relation to person-environment interaction [86, 114, 115] (Figure 3.2). This interaction refers to the dynamic exchange processes that occur in the course of daily living activities and lifestyle behaviors, such as bathing, toileting, and sleeping.

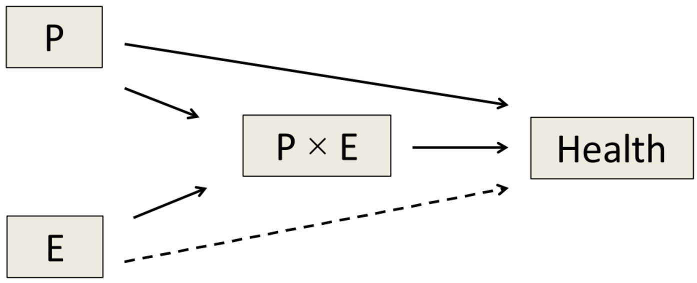

FIGURE 3.2: Person-Environment Interaction [86]

Considering these interactions enhances our understanding of the P-E fit by recognizing that it is not a static concept but one that can evolve and change over time in response to changes in the person's abilities and needs, or changes in the environment. This dynamic view is particularly relevant for AIP, as both the individual's abilities and environmental factors can change significantly over time.

In the following sections, we explore the details of our proposed PE4AIP model, discussing how we have adapted the P-E Fit theory to address the unique challenges and considerations of supporting older adults to live independently and comfortably in their own homes.

3.3.2 Existing Studies on AIP Based on P-E Fit Theory

Originating from environmental psychology, the P-E Fit Theory provides a framework for understanding the reciprocal influence between individuals and their environments. It posits that an individual's well-being and satisfaction are profoundly influenced by the congruence between their personal characteristics and environmental attributes (see Chapter 2.3). This theory has found applications in diverse fields such as organizational behavior, urban planning, and healthcare, facilitating the assessment and enhancement of individual-environment congruence.

In the realm of AIP, studies, summarized in Table 3.1, seek to validate the theory's applicability. They propose that a technologically enriched environment can improve P-E fit [116]. Research by Löfqvist et al. [117], involving health data and observations from Swedish older adults, underscores the vital role of assistive technology in augmenting the P-E fit for this demographic. Similarly, the Housing Enabler tool developed by Iwarsson et al. [83, 118] facilitates a nuanced evaluation of environmental suitability for the elderly, linking functional limitations and environmental barriers to P-E fit outcomes like Activities of Daily Living dependence and general health [119, 120].

Further, research underscores the importance of a holistic approach to evaluating older adults' health, considering the interplay of personal functional abilities and environmental barriers [86, 121]. These studies highlight that not all environmental barriers in homes necessarily lead to accessibility issues or falls, pointing to the importance of understanding older adults' interactions with their environment.

While much of the P-E fit research on aging focuses on physical health aspects, the

Table 3.1: Existing P-E Fit Theory Works in Aging Process

Reference	Characteristics of Person (P)	Characteristics of Environment (E)	Outcomes (O)
Oswald, Frank, et al. 2007	Number of functional limitations, dependence on mobility devices	Potential environmental barriers in the home and the immediate outdoor environment	Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL)
Iwarsson, Susanne, et al. 2009	Number of functional limitations, dependence on mobility devices	Potential environmental barriers in the home and the immediate outdoor environment	Indoor Fall
Slaug, B., et al. 2019	Number of functional limitations, dependence on mobility devices	Potential environmental barriers in the home and the immediate outdoor environment	Self-rated general health
Thomése, F., et al. 2019	Changes in the degree of self-reported functional disability	Changes in the use of informal care and professional home care, number of adjustments in the house, whether the elderly moves to a care setting	Well-being, measured as depressive symptoms

theory encompasses broader attributes, including social and motivational factors [122, 123]. Investigations into age-friendly communities reveal that older adults in rural settings may experience better P-E fit due to access to natural spaces, social connections, and diverse, affordable housing [88, 89].

However, the application of P-E Fit theory in AIP studies is often limited by a narrow focus on certain dimensions [90]. A significant gap in the literature is the lack of a comprehensive definition and measurement criteria for 'Person' and 'Environment' components and their fit. Current methodologies predominantly rely on self-reports, interviews, or observations, which are resource-intensive. Moreover, existing P-E Fit models in AIP contexts overlook the dynamic nature of aging, failing to account for the progressive decline in physical and cognitive abilities of older adults [124]. This necessitates the development of a more dynamic and inclusive P-E fit model that can better capture the evolving nature of individual-environment interactions in AIP settings.

3.3.3 Rationale for the PE4AIP Model

The intricacies of aging necessitate a dynamic model capable of adjusting to the evolving needs of the elderly. Traditional static models of P-E Fit fall short in accurately reflecting the multifaceted and changing nature of AIP. To bridge this gap, the PE4AIP model is introduced, aiming to provide a robust and practical approach to evaluate and monitor the older adults in maintaining their independence, safety, and quality of life by estimate P-E fit level.

The PE4AIP model extends the foundational principles of P-E fit theory, specifically tailored for the aging context. It addresses the shortcomings of traditional P-E fit models, which struggle with quantifying the fit between a person (P) and their environment (E) and dynamically monitoring changes over time. These challenges are particularly acute in aging, where fit dimensions are more complex and require nuanced consideration.

Incorporating Maslow's Hierarchy of Needs, the PE4AIP model adopts a structured perspective on the essential human requirements that influence the concept of fit. Maslow's framework, which arranges human needs from basic physiological necessities to self-actualization, aids in systematically addressing the needs of older adults, thereby enriching the P-E fit analysis within the AIP framework.

Consequently, the PE4AIP model emphasizes continuous evaluation of physical and social fit indicators to assess P-E fit. This approach postulates that these indicators can effectively and dynamically represent the fit between individuals and their environments as they age.

To surpass the constraints of conventional P-E fit evaluations, the PE4AIP model utilizes modern technology and methods, enabling ongoing, dynamic monitoring of fit indicators. This strategy encompasses deploying IoT devices, wearable technology, and ambient sensing to gather real-time data on physical and social activities, health metrics, and environmental conditions. Through these integrations, the PE4AIP model seeks to achieve a more detailed and precise evaluation of P-E fit for older adults, thus enabling timely interventions to enhance their well-being and facilitate AIP.

In essence, the PE4AIP model signifies a significant progression in assessing P-E fit for the aging population. It tackles the challenges related to quantification, measurement, and dynamic monitoring, and incorporates a comprehensive theoretical basis, presenting an innovative method to enhance the well-being of older adults in their preferred living environments.

3.3.4 Model Components

The PE4AIP model, grounded in the P-E Fit Theory, presents a nuanced approach to AIP, delineating three key components designed to achieve an optimal person-environment (P-E) fit, thereby evaluating and enhancing the well-being of older adults. These components are depicted in Figure 3.3, illustrating their synergistic effect on promoting life satisfaction and happiness [46].

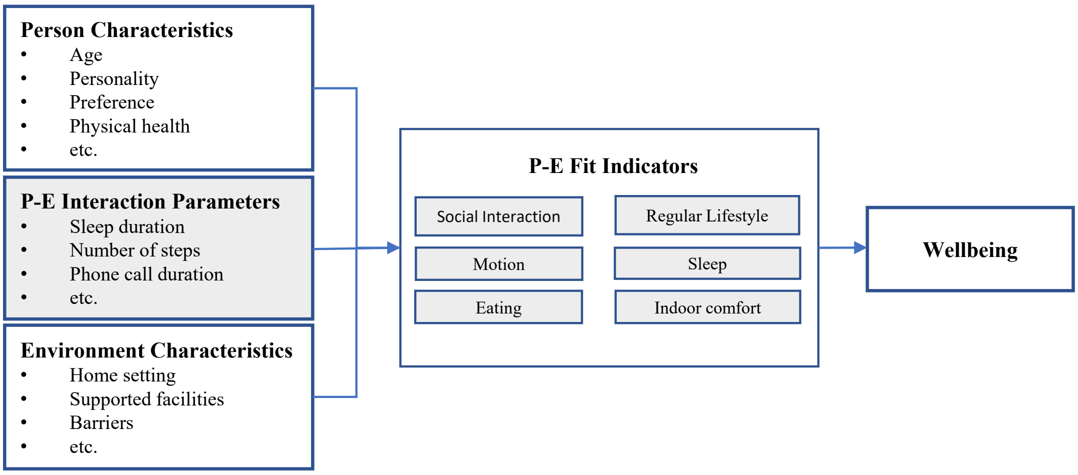

FIGURE 3.3: Person–Environment Fit Model for AIP

This model explicates the interplay between personal characteristics, environmental factors, and their interactions, augmented by additional indicators that precisely reflect the P-E fit. Personal characteristics encompass age, personality, preferences and etc., while environmental factors include home settings, support services, potential barriers and etc. The P-E interaction encapsulates information of elderly activities and behaviors, such as sleep duration and physical activity levels.

We propose P-E fit indicators to monitor the P-E fit level across essential aspects of daily living in older adults, facilitating a comprehensive assessment within the AIP context. These indicators collectively gauge overall well-being. The P-E fit indicators, such as 'Motion,' evaluate the capacity for independent movement, while 'Regular Lifestyle' reflects the regularity of the inhabitants' life patterns. These indicators were identified based on insights from the previous section's focus group study in Section 3.1, emphasizing their relevance and applicability. The detailed attributes of these indicators are enumerated in Tables 3.2, illustrating the alignment between individual capabilities and environmental support.

The feasibility of using these P-E fit indicators to predict the well-being of elderly individuals is substantiated through empirical data gathered during the focus group study and supported by the theoretical underpinnings of the P-E Fit theory. Each indicator provides a quantifiable measure that reflects the interplay between personal and environmental characteristics:

'Motion' and 'Regular Lifestyle' are direct indicators of physical health and daily routine stability, which are critical for maintaining independence and preventing health deterioration.

'Social Interaction' Interactions gauge social well-being, which is vital for mental health and emotional support.

'Indoor Comfort', 'Sleep', and 'Eating' directly impact the physical health and psychological state of the elderly, influencing their overall life satisfaction and well-being.

Predictive modeling techniques such as regression analysis and machine learning can be employed to analyze the relationships between these indicators and overall well-being outcomes. By integrating data from these indicators, the model can effectively predict shifts in well-being, facilitating proactive adjustments to the living environment or personal care plans. This predictive capability is central to the development of responsive AIP systems that adapt to the evolving needs of the elderly, thus optimizing their person-environment fit and enhancing their quality of life.

The P-E Fit indicators are not only grounded in empirical research but also offer a practical method for ongoing assessment and improvement of elder care strategies, making them pivotal to the success of AIP initiatives.

Personal Characteristics

Based on the original P-E fit theory, personal characteristics significantly affect P-E fit. For a more comprehensive assessment of an individual's fit within their environment, the following examples highlight why these personal characteristics are important:

Table 3.2: P-E Fit Indicators

Indicators	Descriptions
Motion	The extent of an individual's ability to move from one position to another and walk independently
Regular Lifestyle	Reflects the regularity of the inhabitants' life patterns
Social Interaction	Assess social interactions
Indoor Comfort	Describes the overall condition of the environment
Sleep	The extent to which a person gets enough sleep
Eating	Evaluating the diet quality

- **Age:** The PE4AIP model considers age as a critical factor influencing an individual's physical capacities, cognitive abilities, and resilience, hence affecting P-E fit. For example, an older adult may require more assistive features in the home, like grab bars or stairlifts, to match their reduced mobility, ensuring a better P-E fit.

- **Personality:** This includes traits and behaviors that define an individual's uniqueness, influencing their interaction with the environment and preferences for activities. For instance, a sociable person might thrive in a community with active social programs, which enhances the P-E fit.

- **Personal Preferences:** Individual likes, dislikes, habits, and routines are considered, as these can significantly impact satisfaction and well-being. For example, a person who enjoys gardening would find a home with a garden more fitting, thereby improving the P-E fit.

- **Health Condition:** The model assesses health status to tailor the environment accordingly. An individual with health conditions requiring frequent medical attention would benefit from proximity to healthcare facilities, improving P-E fit.

These personal characteristics enable the PE4AIP model to provide a more personalized and accurate assessment of an individual's P-E fit.

Environmental Characteristics

To offer a detailed perspective on the environment's role, the PE4AIP model considers the following environmental characteristics:

- **Home Setting:** The physical layout and features of the home environment are crucial for an older adult's functionality. Aspects like lighting, flooring, accessibility, and safety measures are evaluated to determine their contribution to or hindrance in AIP. For example, a well-lit home with non-slip floors and minimal stairs would better suit an elderly person's needs, indicating a good P-E fit.
- **Supported Facilities:** Resources or services within the environment that assist older adults in daily activities, such as home care services, meal delivery, transportation services, and healthcare facilities, are vital. These facilities can significantly enhance the environmental fit for an individual by providing necessary support, reflecting a positive P-E fit.
- **Barriers:** These are obstacles that limit an older adult's functionality or independence within their environment, such as physical barriers, lack of assistive devices, or insufficient services. Identifying and mitigating these barriers improves the fit between the individual and their environment, enhancing P-E fit.

By analyzing these environmental characteristics, the PE4AIP model can provide a more accurate assessment of an older adult's P-E fit.

Person-Environment Interaction

P-E interaction refers to the dynamic interaction between the individual (P, Person) and the environment (E, Environment). This interaction reflects how the match between the individual and their work environment changes over time, affecting the individual's attitudes and performance.

The PE4AIP model builds upon the original P-E fit theory's concept of person-environment interaction by focusing on activity-related information, such as sleep duration or the number of steps taken daily. This information on P-E interactions will help to assess how well an individual's personal characteristics align with their environment and can aid in evaluating the overall P-E fit.

- **Sleep Duration:** Sleep duration is a critical indicator of how well an individual's environment supports their physiological needs. Adequate sleep is essential for cognitive function, emotional well-being, and overall health. A mismatch between the individual's sleep needs and their environment (e.g., noisy or stressful work conditions) can lead to poor sleep quality or duration, impacting their P-E fit. For instance, a work environment that allows flexible scheduling to accommodate sufficient rest would indicate a better P-E fit.
- **Number of Steps:** The number of steps taken daily can reflect the individual's physical activity level and the extent to which their environment facilitates or constrains movement and exercise. An environment that encourages physical activity, such as providing accessible walking paths or fitness facilities, suggests a positive P-E fit. Conversely, an environment that limits movement, such as a sedentary workplace, may indicate a poor P-E fit.
- **Phone Call Duration:** Phone call duration can serve as a proxy for social interaction and communication within the environment. Longer call durations may indicate more substantial social support or engagement at work, reflecting a positive P-E fit. In contrast, shorter call durations could suggest limited social interactions or a mismatch between the individual's social needs and the opportunities provided by the environment, indicating a potential P-E misfit.

By understanding person-environment interaction, along with its associated indicators, we gain a more comprehensive view of how individual characteristics, the environment, and their interplay can impact the P-E fit. This understanding can help to estimate the degree of P-E fit and guide interventions to improve this alignment.

Table 3.3: Rated Usefulness of P-E Fit Indicators (Score range: 1-5, higher is better)

	Motion	Regular Lifestyle	Social Interaction	Indoor Comfort	Sleep	Eating
User 1	4.5	4.3	3.8	4.1	3.9	4.1
User 2	4.2	4.1	4.4	4.5	4.0	4.0
User 3	4.4	4.1	3.5	4.6	3.5	3.7

3.3.5 Preliminary Study on the Usefulness of the P-E Fit Indicators

To verify the usefulness of the P-E Fit indicators, we first conducted a three-month preliminary study with three expert users to evaluate the system's usefulness. The study lasted for three months and was divided into two phases.

In Phase 1 (Duration: 2 months), the three users were required to estimate the scores of the six P-E Fit Indicators based on their own experience. We collected 148 valid data points for each Indicator from the three users. The results from Phase 1 were used to help us refine the normalization factors for computing the Indicators.

In Phase 2 (Duration: 1 month), the six indicators were automatically generated every morning and sent to the users. The expert users were required to rate the usefulness of each indicator daily, using scores from 1 to 5 (with 5 being the most useful). The usefulness ratings for each indicator during Phase 2 are presented in Table 3.3. Overall, the three expert users assigned high usefulness scores to all the indicators. The preliminary study results demonstrated the usefulness of the P-E Fit Indicators in real life.

In summary, the PE4AIP model offers a nuanced view of P-E fit, providing a practical method for the ongoing assessment of elder well-being, which is pivotal to the success of AIP initiatives. This approach enables continuous monitoring and adjustment of the living conditions for the elderly, ensuring that their evolving needs are met and thereby enhancing their overall P-E fit and supporting AIP.

3.4 The PE4AIP-Enabled AIP Design Architecture

This section Introduces the proposed PE4AIP-Enabled AIP Design Architecture. This AIP design architecture incorporates the PE4AIP model to guide the design of AIP systems, emphasizing privacy, personalization, and continuous monitoring to support the elderly in living independently while preserving their privacy.

3.4.1 Architecture Overview

The Architecture, illustrated in Figure 3.4, integrates the PE4AIP model to evaluate key P-E fit indicators, culminating in an assessment of Overall Well-being. It utilizes inputs from Personal Characteristics, Environmental Characteristics, and Person-Environment Interaction parameters to evaluate various P-E fit indicators, as detailed in Figure 3.3. In addition, in using the PE4AIP model to evaluate well-being, the Architecture incorporates two additional components. The Privacy Preserving Processing component processes data at the local point on the device or at the edge, rather than sending it to the cloud, which can significantly reduce privacy risks. Additionally, it processes data with reduced computational power and memory resources. A novel notification approach is proposed; it presents the elderly's living status in 3D animation format to help caregivers understand their conditions without disclosing detailed personal information. This integration facilitates the creation of smart home systems that are not only responsive to the dynamic changes associated with aging but also sensitive to the privacy and personalization needs of the elderly.

3.4.2 Core Components of the Architecture

In using PE4AIP model to evaluate well-being, the Architecture highlights two additional components.

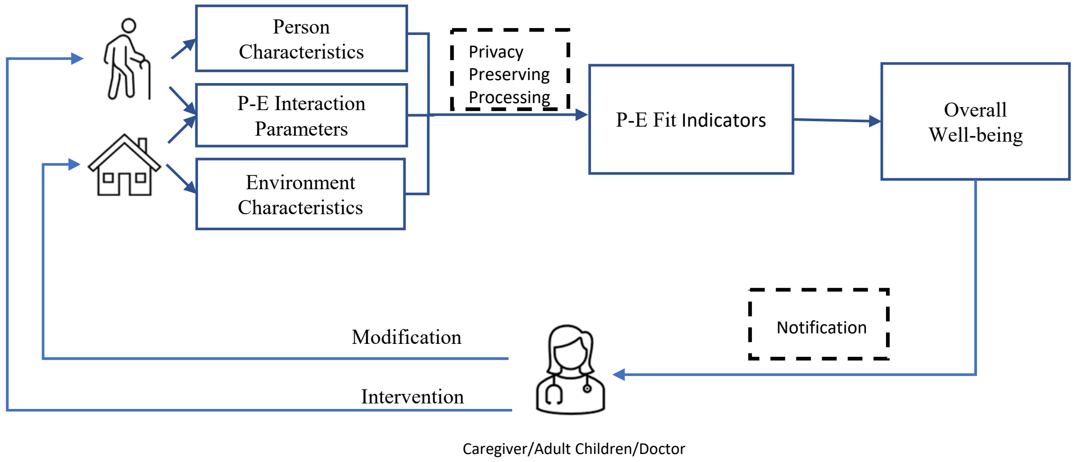

FIGURE 3.4: The PE4AIP-Enabled Design Architecture for AIP

Privacy Preserving Processing

Despite the system's design to minimize disruption in the daily lives of the elderly through non-invasive sensors, we understand that unobtrusiveness alone does not guarantee privacy. To enhance privacy and minimize intrusion, the architecture employs a Privacy Preserving Processing component. This component processes data at the local point on the device or at the edge, rather than sending it to the cloud, significantly reducing privacy risks. It utilizes Tiny Machine Learning (TinyML) technologies, for local data processing, which limits the transmission and sharing of raw data, as these raw data could contain or potentially include information from which a lot of private details can be inferred[125], thereby enhancing privacy protection. Moreover, the use of TinyML can lead to cost savings and increased reliability. Since the data is processed locally on devices, there is less reliance on cloud services, which reduces the costs associated with data storage and management. It also prevents the potential loss of functionality or data during network outages or server maintenance[126].

Overall, TinyML offers a compelling approach for managing and securing data at the edge, leveraging the strengths of edge computing to improve both privacy and operational efficiency.

Novel Notification Approach

The Novel Notification Approach incorporated into the PE4AIP-Enabled AIP Design Architecture represents a significant advancement in how caregivers receive updates and insights about the well-being of elderly individuals. This approach utilizes a 3D animation format to display the living status of the elderly, which serves several key functions in enhancing both the understanding and privacy of caregiving practices.

This innovative system leverages non-intrusive sensors to gather data about the elderly's daily activities and interactions within their living environment. The data collected includes movement patterns, the frequency of room usage, and engagement in various daily activities. Instead of transmitting raw data or detailed personal information, the system processes this data locally and converts it into a generic yet informative 3D animated representation of the elderly's daily life. This animation shows avatars performing activities in a simulated environment that mirrors the actual home layout but does not reveal identifiable details.

The use of 3D animation is particularly beneficial because it provides a clear and intuitive understanding of the elderly's living conditions and routines without compromising their dignity or privacy. Caregivers can see at a glance whether the elderly individual is active, resting, or needs immediate attention based on the activities depicted in the animation. This method avoids the ethical and privacy concerns associated with video surveillance, which can be intrusive and uncomfortable for many individuals.

Furthermore, the notification system is designed to alert caregivers only when necessary, based on predefined thresholds of activity or inactivity that may indicate a need for intervention. For instance, if the system detects an absence of movement over an unusually long period during the day, it can trigger an alert to the caregiver to check in on the elderly person. Conversely, regular activity patterns that reflect a healthy routine will not generate unnecessary alerts, thus avoiding caregiver fatigue and ensuring that attention is given when most needed.

Overall, the Novel Notification Approach in the PE4AIP architecture exemplifies how technology can be used to enhance the caregiving experience by providing essential information in a respectful and privacy-conscious manner. By integrating advanced data processing with 3D visualization, this approach helps bridge the gap between the need for effective monitoring and the imperative to uphold the privacy and dignity of the elderly.

3.4.3 Operational Mechanism

The architecture operates on a continuous feedback loop system, utilizing the PE4AIP model to evaluate well-being based on inputs from personal characteristics, environmental characteristics, and person-environment interactions. These inputs help to evaluate P-E fit indicators, and then based on these indicators, the architecture further assesses the overall well-being of the elderly (see details in Section 3.3).

Initially, all input data are processed locally by the Privacy Preserving Processing component. This component processes data at the local point on the device or at the edge, rather than sending it to the cloud. This approach significantly reduces privacy risks and utilizes reduced computational power and memory resources, which is crucial for maintaining the efficiency and responsiveness of the system.

Subsequently, the architecture employs a novel notification approach that presents the elderly's living status in a 3D animation format. This helps caregivers understand the condition of the elderly without disclosing detailed personal information. This visual representation allows for an intuitive understanding of the elderly's day-to-day activities and overall well-being in a way that respects their privacy and dignity.

If a misfit between the elderly and their living environment is detected, indicating poor well-being, the system alerts caregivers. Caregivers can then modify the living environment or conduct relevant interventions to improve the fit and thereby enhance the elderly's well-being. Conversely, when a good fit is detected, the architecture ensures that the elderly experience satisfaction with their living conditions and can live independently, thus maximizing their quality of life. This approach not only supports the day-to-day management of AIP but also adjusts dynamically to the evolving needs of the elderly, ensuring an optimal living experience.

The PE4AIP-Enabled AIP Design Architecture bridges the gap between theoretical models and practical applications, offering a structured approach to designing AIP systems that support older adults in their desire to age in place safely and with dignity. By focusing on privacy, personalization, and effective monitoring, this architecture promises to enhance the independence and quality of life for the elderly while maintaining robust support from caregivers.

3.5 Empirical Studies with the PE4AIP Model and PE4AIP-Enabled AIP Design Architecture

In AIP design practice, we aim to address issues related to privacy preservation and notification. The following studies evaluate our proposed approaches:

- To implement the architecture in practice, the first study focuses on a critical scenario in AIP: falls at home. In Chapter 4, we introduce a cutting-edge AIoT-based fall detection system that leverages Tiny Machine Learning (TinyML) and infrared sensors. This system enhances safety within AIP settings by providing an effective, privacy-preserving fall detection capability, demonstrating the PE4AIP model's emphasis on using technology to secure the well-being of older adults without compromising their privacy.
- The second study involves the design, implementation, and evaluation of a notification approach that presents living status while preserving privacy. In Chapter 5, we present an innovative 3D animation method as a privacy-conscious solution for monitoring elderly activities. By creating 3D virtual

representations of daily movements, this approach allows respectful remote monitoring by family members and caregivers, exemplifying the PE4AIP model's commitment to balancing technological advances with the need for privacy and dignity.

Following the proposed PE4AIP-enabled architecture, we designed and implemented a personalized AIoT-based Smart Aging-in-Place System (SAIPS). This system integrates the PE4AIP model with local data processing using TinyML and obtrusive sensors, and it notifies caregivers about the elderly's information through 3D animation. We conducted a field study to confirm its effectiveness and acceptance, which will be discussed in Chapter 6.

Through these empirical studies, we aim to validate the theoretical constructs of the PE4AIP Model and the design architecture, while also highlighting their practical significance in creating supportive, adaptable, and respectful environments for AIP. The insights gained from these applications will contribute to the ongoing refinement of strategies and technologies designed to meet the complex needs of the aging population, paving the way for more effective and practical AIP solutions.

3.6 Summary

This chapter has detailed the development of the PE4AIP Model and the PE4AIP-Enabled AIP Design Architecture, offering a comprehensive approach to understanding and enhancing the person-environment fit for elderly individuals. The focus group study provided valuable insights into the needs and concerns of seniors and caregivers, which were crucial in shaping the model and its applications. The practical applications of this model, including its effectiveness and acceptance in real-world settings, will be detailed in the following chapters, the foundational concepts established here underscore our commitment to improving the quality of life for the aging population in a respectful and dignified manner.

Chapter 4

Privacy Preserving Data Processing: an AIoT-based Fall Detection Approach

To implement the proposed PE4AIP-Enabled AIP Design Architecture, this chapter addresses one of the critical scenarios in AIP: falls at home. We have designed and developed an AIoT-based Fall Detection system that employs TinyML and unobtrusive infrared array sensors. By adapting an LSTM neural network model to run on resource-constrained hardware, such as the Raspberry Pi and end-device MCUs, our system provides real-time fall detection at a rate of over 10 frames per second (fps). These results demonstrate the feasibility of the proposed neural network and TinyML model in detecting falls in real-time.

4.1 Emerging Trends in Fall Detection Technology: Leveraging TinyML for AIP

The aging of the global population represents a significant and growing challenge, necessitating rapid advancement in assistive technologies to support the elderly.

These technologies often leverage a variety of sensor-actuator systems, including cameras, light sensors, accelerometers, temperature sensors, gyroscopes, barometers, and infrared sensors, to aid in daily life activities such as health and fitness monitoring, personal biometric signatures, and navigation [127].

Within this technological landscape, fall detection has emerged as an essential component, given that a substantial proportion of elderly individuals are at risk of falling [128, 129]. Swift detection and treatment of falls can have life-saving implications [130].

Traditional technology-based fall detection has evolved to include wearable devices, ambient sensors, and cameras, each with their unique advantages and limitations [127]. This chapter, we introduce a pioneering fall detection system that leverages the power of TinyML, emphasizing privacy preserving data processing. Using unobtusive Grid-Eye infrared array sensors, which provide privacy-preserving, low-resolution thermal data, we apply a lightweight Long Short-Term Memory (LSTM) model. This approach ensures that personal raw data remains local, while still providing accurate fall detection capabilities. The novelty of this work lies in the integration of the model into a tiny, energy-efficient platform: the Raspberry Pi 3 and STM32WB55 MCU.

The remainder of this chapter is structured as follows: We first review existing literature on fall detection systems and privacy-preserving techniques. Next, we evaluate the proposed lightweight LSTM model's performance on the Raspberry Pi 3, then transfer the model to a TinyML model and assess its performance and the memory and RAM requirements on the STM32WB55 MCU. This leads to a conclusion that the proposed neural network and the TinyML model on edge and end devices demonstrated their feasibility in detecting real-time falls with a focus on preserving privacy.

4.2 Fall Detection Technologies: From Wearables to Ambient Sensing

Existing fall detection systems can broadly be classified into three main categories: wearable devices, camera systems, and ambient sensors [127].

Wearable Devices: These are sensors affixed to the human body that capture bodily movements and recognize activities. Primarily, these devices employ accelerometers and gyroscopes [131, 132]. Various parts of the user's body, such as the waist [129], chest [128], and shoes [133], may serve as attachment points for these sensors. However, the requirement to wear these devices continuously poses a significant inconvenience, compounded by instances where users often forget to wear the device.

Camera Systems: These typically utilize RGB cameras [134], with recent studies incorporating devices such as Microsoft Kinect [135, 136]. Commonly installed throughout homes or in public spaces, these systems offer extensive coverage but suffer from drawbacks related to privacy intrusion from video monitoring and system robustness issues.

Ambient Sensors: This category includes fall detection systems that leverage a variety of sensors or devices, such as Doppler radar [137], passive infrared sensors [138–141], pressure sensors [142, 143], sound sensors [144], and Wi-Fi routers [145].

Considerable research effort has been invested into the development of fall detection classification algorithms [130, 146]. Predominantly, two types of methods have been proposed: rule-based techniques that heavily rely on domain knowledge, and machine learning methods that discern fall characteristics from sensor data [147, 148]. Early fall detection research, such as [149–152], employed threshold-based algorithms, triggering a fall alert upon the surpassing of a preset threshold. However, these approaches lack the adaptability and flexibility required for broader applicability.

Concurrently, numerous machine learning-based fall detection classifiers have been developed [153]. Common machine learning approaches like decision trees [154], support vector machines (SVM) [155], k-nearest neighbors (k-NN) [156], and hidden Markov models [157] have been implemented for fall detection, with many relying on manually designed features for classification [141, 158–160].

Several works closely align with our research focus. L. Liu et al. [137] developed a dual Doppler radar system for fall detection, integrating partial decision information from two sensors using three different classifiers—k-NN, SVM, and Bayes—to form a fall/non-fall decision based on Mel-frequency Cepstral Coefficients (MFCC) features. This approach achieved an AUC of 0.88 and 0.97.

Liu et al. [138] proposed a two-layer hidden Markov model to recognize fall events based on the signals of five passive infrared sensors positioned at varying heights on a wall. The sensitivity and specificity of this algorithm were 92.5% and 93.7%, respectively.

Chen et al. [141] utilized 16-by-4 thermopile array sensors for fall detection and elderly tracking. Their system, employing two sensors with a k-NN classifier, achieved 95.25% sensitivity, 90.75% specificity, and 93% accuracy. Sixsmith and Johnson [161] similarly developed a “Smart Inactivity Monitor” using array-based detectors for fall detection.

Lastly, Mashiyama et al. [140] introduced a fall detection system using an infrared array sensor. Their system extracted four manually crafted features from a data sequence captured in a fixed window. The system achieved a 94% accuracy using a k-NN algorithm for classifying falls or non-falls.

4.3 Privacy-Preserving Data Processing Techniques in Fall Detection Systems

In the context of AIP, privacy is crucial, especially for the elderly who are particularly sensitive to it, making the acceptability of monitoring technologies heavily dependent on their data handling practices. By implementing local data processing and using privacy-preserving technologies, fall detection systems can achieve wider acceptance among older adults, enhancing their sense of safety and comfort in their living environments. Following a comparative analysis of various fall detection technologies, it becomes evident that exploring privacy-preserving techniques in data processing is essential. These techniques address privacy concerns among elderly users, who may perceive surveillance in their personal spaces as intrusive.

One aspect of privacy-preserving data processing is the local processing of data on edge or end devices. This approach ensures that raw data do not leave the local environment, thus maintaining privacy. For example, using localized TinyML models on devices can process data directly on the device without needing to transmit sensitive information to a central server. This method not only secures personal data but also reduces latency and dependency on external networks, which is critical for real-time applications like fall detection.

Traditional, privacy-preserving ML models often employ methods such as Federated learning (FL)[162], which has been widely recognized for its potential to preserve privacy by enabling multiple devices to collaboratively train a machine learning model without sharing their raw data[163]. Instead, these devices share model updates with a central server, which then aggregates these updates to improve the global model. This approach limits the exposure of sensitive personal information during the training phase. However, despite the privacy benefits during training, federated learning does face challenges during the inference phase. Typically, raw data might still need to be sent to the server for processing.

Data encryption techniques are often be used to perform computations on encrypted data, providing an additional layer of security. However, users often do not fully trust the security of data encryption technology and are concerned about unauthorized decryption usage. The safest approach is to process data on endpoint devices and only upload essential data, thus avoiding the security risks associated with raw data.

The proposed PE4AIP-Enabled AIP Design Architecture fully supports current encryption technologies. These can be integrated smoothly to protect data during its transmission between devices and servers, ensuring privacy is maintained throughout the process. This thesis does not explore the details of encryption techniques during data transmission.

In conclusion, the integration of privacy-preserving data processing techniques, especially those processing data locally on edge and end devices, is essential in developing non-intrusive, acceptable, and effective fall detection systems for the aging population. This approach not only protects personal privacy but also ensures the systems' efficacy and responsiveness, which are critical for immediate medical response and continuous monitoring without compromising personal dignity or security.

4.4 Fall Detection System

4.4.1 Unobtrusive Infrared Array Sensor

The infrared array sensor is widely used across various fields such as robotics, automotive systems, environmental monitoring, and medical equipment. This sensor type capitalizes on the infrared spectrum to detect and measure the heat emitted by objects in its vicinity, enabling it to capture thermal images without

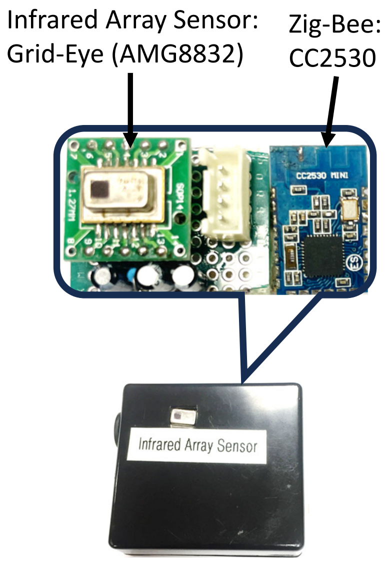

Figure 4.1: The Infrared Array Sensor Module

physical contact. This functionality makes it invaluable in applications where non-invasive or distant measuring is required, such as in night vision systems, occupancy sensing, and even in preventive healthcare diagnostics.

The infrared array sensor Grid-Eye (AMG8832), which outputs an 8-pixel by 8-pixel temperature map within a 60-degree field of view at a maximum rate of 10 frames per second, is used in the fall detection system. The sensor can detect objects at a distance of up to 5m, provided that there is a temperature difference of $\geq 4°C$ between the object in the foreground and the surrounding ambient temperature. We employ a ZigBee CC2530 microprocessor to manage the sensor through an I^2C bus, as depicted in Figure 4.1. The recorded temperature distribution is relayed to another ZigBee CC2530 at a frequency of 10Hz, and a PC or a Raspberry Pi is utilized for subsequent data processing and classification.

The Grid-Eye sensor measures temperatures from -20°C to 100°C with a 3.0°C accuracy, crucial for detecting human motion for fall detection despite noisy data, as depicted in Figure 4.2.

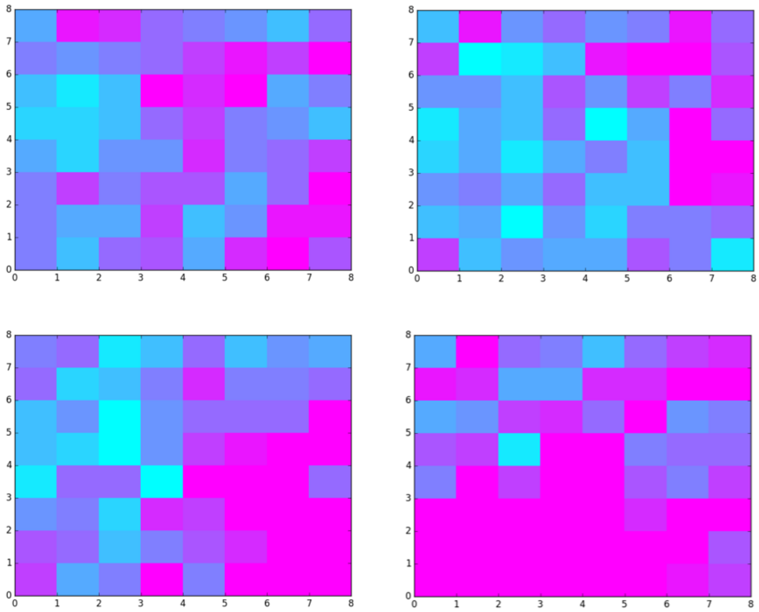

FIGURE 4.2: Depiction of Grid-Eye images. Top left: an empty field of view with no person. Top right: a person positioned on the right-hand side. Bottom left: a person captured in the act of falling from the right-hand side. Bottom right: a person shown lying down in front of the Grid-Eye.

4.4.2 Fall Detection Classifiers

Since thermal image based fall detection depends on correctly identifying the abrupt movement of a human body, the ability to recognize the subtle temperature difference between the human body and the ambience is key to ensuring correct detections. However, data obtained from Grid-Eye sensors is noisy (see Figure 4.2). Therefore, a fall detection system with two main components is developed: (1) data filters for pre-processing and (2) neural networks for classification. As illustrated in Figure 4.3, Data produced by the Grid-Eye is passes through filters before feeding into the neural network. And classifies the data as ‘Fall’ or ‘No Fall’.

Three filters, Median, Gaussian and Wavelet, are experimented with in this work. For neural network classifiers, experiments are conducted with two-layer perceptron networks, long short-term memory (LSTM) networks, and gated recurrent unit (GRU) networks, each with and without attention links.

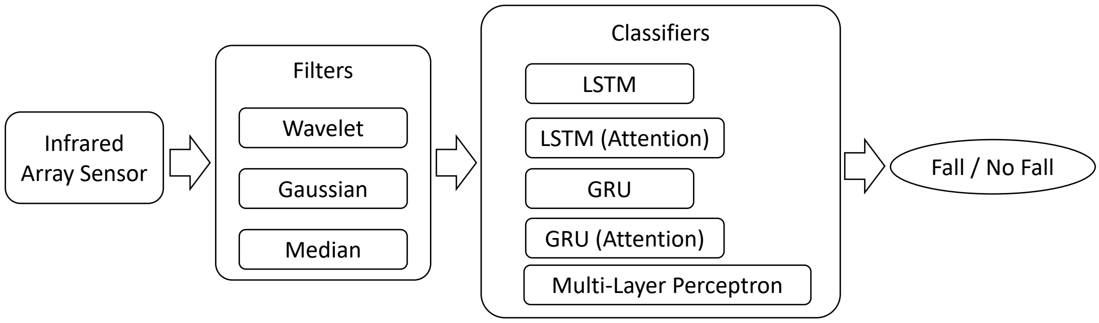

FIGURE 4.3: Architecture of Fall Detection Classification and System.

The system operates by taking thermal readings from the Grid-Eye at each time step t, represented as a 1×64 vector. Within a 2-second window, 20 such vectors are collected at a 10Hz frequency. One of the three filters is then applied to this collected data, with no change in data size, and the filtered data is directed to the neural network classifiers for further processing.

Two-layer perceptron networks are selected. The input layer comprises $64 \times 20 = 1280$ nodes (based on the size of the Grid-Eye output vector and the outer window), connected to a fully hidden layer with 400 nodes and an output layer of 2 nodes (indicating a fall or no fall).

LSTM and GRU networks have been prevalent in recent years and consist of special memory structures such as LSTM cells and GRU units to retain previous information. The structure of these networks both contain 64 nodes in the input layers and a fully connected perceptron layer of 64 nodes leading to a 2-node output layer.

The introduction of an attention mechanism into both LSTM and GRU models in this work is made simple. Conceptually, the attention mechanism provides a means for specifying the relative importance of each frame in a classification window (20-frames in this case).

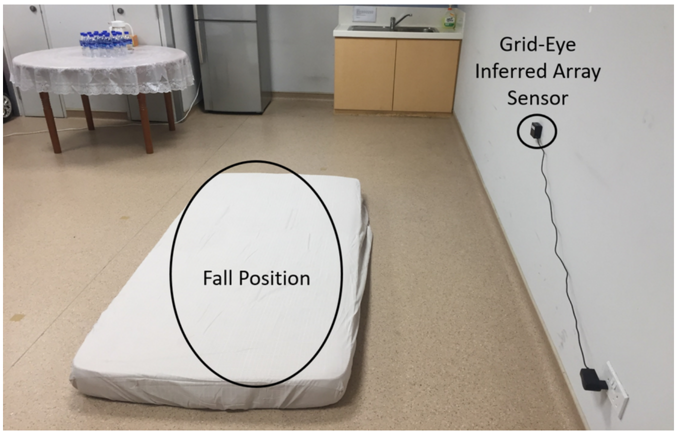

FIGURE 4.4: Illustration of the Testing Environment (Displayed for One Test Configuration).

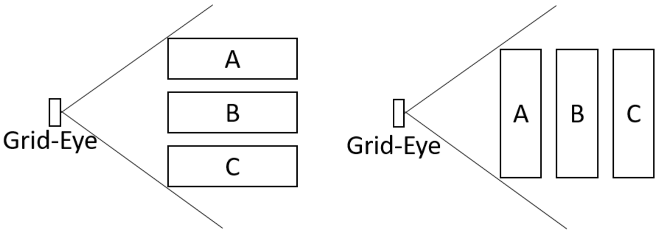

FIGURE 4.5: Depiction of Experimental Configurations. The left side shows the subject falling perpendicularly at positions A, B, and C to the Grid-Eye sensor. The right side depicts falls parallel to the Grid-Eye at the same positions.

4.4.3 Assessment of Performance

The developed system's performance is assessed through a series of fall detection experiments conducted in the laboratory setup (Figure 4.4). Our evaluation dataset comprises 312 falls, organized into two distinct configurations. Figure 4.5 demonstrates these two experiment sets. The first involves the test subject falling perpendicular to the Grid-Eye sensor at three varying positions: A, B, and C. The second set requires the subject to fall parallel to the Grid-Eye sensor at the same positions. Both sets also included negative instances such as random walking, sitting down slowly, jumping, running, and laying down near the sensor. The dataset was compiled over several sessions on different days, with ambient temperatures ranging between 19°C and 23°C.

For the assessment, the dataset was split into a training set with 240 falls and a testing set with 72 falls, with equal falls for each position. Robust fall detection requires excellent precision and recall, minimizing both false positives and negatives. Thus, the F1 scores for every test scenario were compared as detailed below.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}, \tag{4.1}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}, \tag{4.2}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{4.3}$$

Results from the experiments are depicted in Figure 4.6 for falls perpendicular to the sensor and in Figure 4.7 for falls parallel to the sensor. Key observations include:

- Classifiers achieve higher F1 scores when detecting falls parallel to the sensor, suggesting easier classification compared to perpendicular falls.
- Noise-reduction filters enhance performance, with the median filter outperforming others.
- The LSTM based neural network perform the best with median filer among all tested models.
- Attention mechanisms in LSTM and GRU models do not consistently offer performance benefits, indicating equal importance of all frames in fall detection.
- MLP models maintain effectiveness in simpler parallel settings but struggle in the more challenging perpendicular scenarios.

Moreover, we probed various outer window sizes for fall detection utilizing four distinct classifiers. Originally, the outer window spanned 20, signifying that each fall detection unfolds within a 2-second window, corresponding to the Grid-Eye's

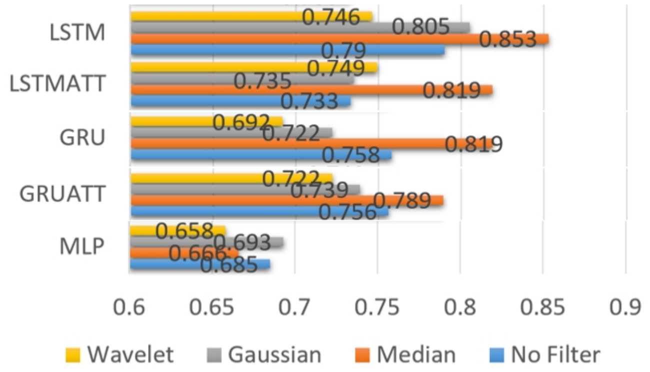

FIGURE 4.6: F-Scores for Tests Where Subject's Fall is Perpendicular to the Sensor.

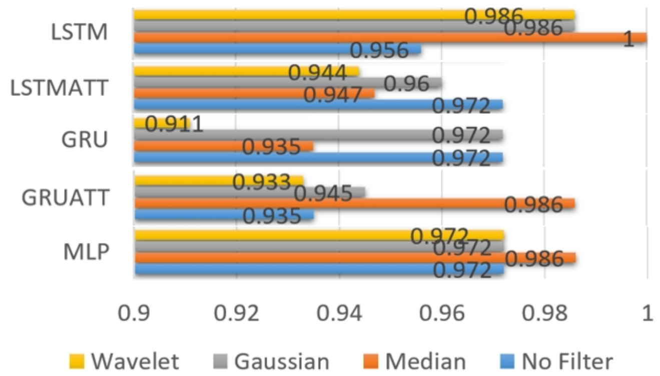

FIGURE 4.7: F-Scores for Tests Where Subject's Fall is Parallel to the Sensor.

	Precision	Recall	F1
GRU-ATT	0.632	0.861	0.729
GRU	0.731	0.833	0.779
LSTM-ATT	0.695	0.888	0.780
LSTM	0.82	0.888	0.853

TABLE 4.1: Performance in Detecting Falls with a 30-frames Detection Window (Perpendicular to the infrared array sensor).

operation at 10Hz. In Tables 4.1 and 4.2, we present the outcomes of fall detection with the outer window extended to 30, observing a considerable reduction in performance across all four classifiers (the Median filter was applied in these trials). We interpret these outcomes thus: since a fall is an abrupt event, enlarging the window dimension fails to enhance detection efficiency.

	Precision	Recall	F1
GRU-ATT	0.7	0.972	0.813
GRU	0.809	0.944	0.871
LSTM-ATT	0.875	0.972	0.921
LSTM	0.947	1	0.972

Table 4.2: Performance in Detecting Falls with a 30-frames Detection Window (Parallel to infrared array sensor).

4.5 Experiment on Edge-device: Raspberry Pi

In conjunction with our primary laboratory environment, an experiment was conducted using the Raspberry Pi 3 as a computation platform specifically targeting fall detection. The experimental configuration comprised the Raspberry Pi 3, integrated with the Grid-Eye sensor through the Zig-Bee wireless module(see Figure 4.1). Building upon the LSTM algorithms outlined in the section 4.4, we adapted and deployed them onto the Raspberry Pi 3, enabling real-time detection of falls.

For a quantitative assessment of the system's real-time capabilities on the Raspberry Pi 3, we examined processing speed. The speed performance, utilizing the trained LSTM machine learning algorithm, remained consistent and exceeded 10 frames per second (fps), facilitating real-time fall detection.

Despite its low-power and resource-constrained nature, the Raspberry Pi 3 met the computational requirements of the light machine learning model. The experiment accentuated the potential for embedding the fall detection system in applications where both energy efficiency and real-time processing are pivotal. It fortifies the argument for the employment of tiny machine-learning algorithms in scenarios necessitating portable and real-time fall detection solutions.

4.6 TinyML Model Experiment on End-device: STM32WB55 MCU

To minimize data transmission and enhance resource efficiency while preserving user privacy, we have tailored fall detection to be optimized for the end-device microcontroller unit (MCU). This MCU is specifically designed for energy-efficient and secure Internet of Things (IoT) applications, incorporating privacy-preserving techniques to ensure sensitive data is processed locally without being exposed externally.

The STM32WB55 MCU is part of the STM32 family, renowned for its robust architecture designed for versatile applications, including those in the Internet of Things (IoT) domain. This microcontroller unit (MCU) combines a dual-core architecture (ARM Cortex-M4 and Cortex-M0+) which facilitates complex application and radio processing. Its integration of Bluetooth Low Energy (BLE) 5.0 and IEEE 802.15.4 wireless standards (supporting protocols like Zigbee or Thread) makes it a prime candidate for advanced IoT applications that require wireless communication capabilities. The MCU's ability to operate in a high-efficiency low-power mode enhances its suitability for wearable and mobile IoT devices where power consumption is critical.

STM32Cube.AI is an extension of the broader STM32Cube software technology aimed at bridging the gap between AI-based software models and the hardware capabilities of STM32 microcontrollers. This tool facilitates the conversion of pre-trained neural networks into optimized C code that can run on STM32 MCUs, thereby enabling the implementation of intelligent functionalities directly on edge devices. The tool supports a wide range of AI frameworks, such as TensorFlow and Keras, allowing developers to easily integrate machine learning models with existing STM32 projects. By leveraging STM32Cube.AI, developers can effectively deploy AI applications on low-cost, low-power devices without needing external computation resources, thus democratizing AI at the edge.

Employing STM32Cube.AI, we have transformed our proposed lightweight LSTM model into a TinyML model that is executable on the MCU. Simulation metrics provided by STM32Cube.AI showcase that the TinyML model retains a high accuracy level, closely replicating the performance of the original LSTM model with minimal root mean square error (RMSE) and mean absolute error (MAE).

The validation results confirm that the fall detection model can be efficiently deployed on the STM32WB55 MCU, utilizing approximately 59% of flash memory and 12% of RAM. The model executes a total of 1 million multiply-accumulate (MACC) operations, managing to achieve an average of 11.2 inferences per second. This deployment demonstrates the practicality of implementing a fall detection neural network on the MCU.

In conclusion, our methodology introduces a privacy-preserving fall detection system that integrates infrared sensors with TinyML. This combination ensures accurate fall detection while safeguarding personal data through localized edge and end-device processing. Notably, the system reduces data exposure and conserves computational resources. With the ability to perform over 10 frames per second on both Raspberry Pi and MCU platforms, our approach is validated to be swift, resource-efficient, and reliable for real-time fall detection.

4.7 Summary

Falls are a significant health risk, especially for the elderly, necessitating prompt and effective detection mechanisms. In this chapter, we have introduced a fall detection system that incorporates an unobtrusive infrared array sensor, which is particularly suited for deployment in privacy-sensitive areas such as washrooms.

The system also integrates a crucial component of Privacy Preserving Processing, which ensures that data is processed locally on devices or at the edge, rather than being transmitted to the cloud. This approach reduces the risk of privacy breaches, as it minimizes the exposure of raw data that could potentially reveal sensitive personal information. Employing TinyML technologies further enhances privacy protection by limiting data transmission and focusing on local processing.

The experimental deployments on both the Raspberry Pi and the STM32WB55 MCU confirmed the viability of using lightweight machine-learning algorithms for real-time fall detection within resource-constrained environments. The systems consistently achieved processing speeds exceeding 10 frames per second (fps), highlighting the feasibility of this approach with lightweight, cost-effective hardware. Despite the limitations of the platforms, they successfully met the computational demands of the TinyML model, showcasing the potential for widespread embedded applications where energy efficiency and real-time processing are paramount.

This chapter reinforces the practical application of the PE4AIP-enabled AIP design architecture in effectively detecting falls, ensuring privacy, and maintaining high processing efficiency in real-world environments.

Chapter 5

Data-driven 3D Animation: A Privacy-Preserving Approach to Monitoring Elderly at Home

This chapter introduces an approach to monitoring elderly individuals in AIP context using data-driven 3D animation, which prioritizes the privacy and dignity of the elderly. By employing non-intrusive IoT sensors, this method captures environmental and activity data, transforming it into a three-dimensional animation that represents the daily activities of elderly individuals non-invasively. The chapter explores the technical implementation of this novel monitoring system, discusses its alignment with privacy considerations, and evaluates its effectiveness through practical experiments. Special emphasis is placed on the unique "3D Animation" feature, which condenses complex daily activities into simple and informative animations, making it easier for caregivers to understand and respond to the needs of the elderly without intrusive surveillance. The results demonstrate how this approach effectively bridges the gap between comprehensive care and respect for personal privacy, offering a promising tool for enhancing elderly care in a respectful and technologically advanced manner.

5.1 Enhancing AIP with 3D Animation Monitoring

As the global population ages, many seniors desire to age in place, that is, remain independent in their own homes for as long as feasible. This growing trend towards solitary living is compounded by increasing youth mobility. The growing global elderly population and the increasing need for AIP solutions have driven the development of innovative monitoring methodologies. A viable solution lies in the combination of Internet of Things (IoT) technologies and ambient intelligence, which together create a conducive environment for AIP [164].

These smart home systems usually monitor residents' activities, health data, environmental safety, medication compliance, and social interactions with a twofold aim: ensuring the health and safety of elderly individuals, especially those with chronic diseases or disabilities, and providing caregivers with convenient access to crucial information and services[165, 166].

The adoption of these technologies and the effectiveness of long-term monitoring pose challenges[164]. Many AIP systems utilize video camera monitoring, which seniors often avoid due to privacy and dignity concerns[167]. To address these issues, we propose a novel approach using unobtrusive sensors to record interactions with everyday objects. This data-driven 3D animation approach maintains the privacy of the elderly and increases system acceptability[168–171].

Our solution circumvents traditional smart home limitations by providing a data-driven visualization approch, enabling caregivers to observe a virtual representation of the elderly's activities in real-time. This innovative approach employs a 3D avatar to replicate the elderly individual's movements and activities within a virtual 3D home, providing a real-time, privacy-respecting view of their daily routine.

Focused on preserving seniors' privacy and dignity, our 3D animation approach adheres to AIP principles, replacing continuous surveillance with a more acceptable alternative. It introduces "3D Animation," a mechanism that condenses the day's activities into a brief animation, enabling caregivers to quickly grasp the elderly's daily life and adjust the playback speed as needed.

By merging the benefits of non-intrusive sensors and animation, this approach respects privacy, facilitates interpretation, and supports effective aging-in-place. Our objective is to enable seniors to age at home comfortably while enhancing the caregiving process, thus ensuring their dignity, safety, and well-being[165, 166]. This chapter explores the design of the methodology, its potential benefits, its role in upholding the dignity and privacy of older adults, and its effectiveness in delivering remote monitoring capabilities. It also discusses initial performance evaluations and future developments.

5.2 Data-Driven 3D Animation Approach

The data-driven 3D animation approach is designed for monitoring the elderly within their home environments. This method leverages advancements in AIoT technologies and 3D animation to provide a non-intrusive solution for notification and monitoring. As depicted in Figure 5.1, this approach encompasses several key stages: Data Collection and Processing, Activity Segmentation and Selection, 3D Animation Generation, and 3D Animation Summarization and Replay. These stages form the workflow of the method and are instrumental in achieving the overarching goal of dignified and effective monitoring of the elderly. The subsequent subsections detail the design and functionality of each stage.

5.2.1 Data Collection and Processing

The Avatar-Based 3D Animation Monitoring approach begins with a thoughtful combination of non-intrusive sensor technology for data collection. The process integrates data gathering and processing into a seamless module, designed to facilitate the flow of information, laying the groundwork for subsequent stages such

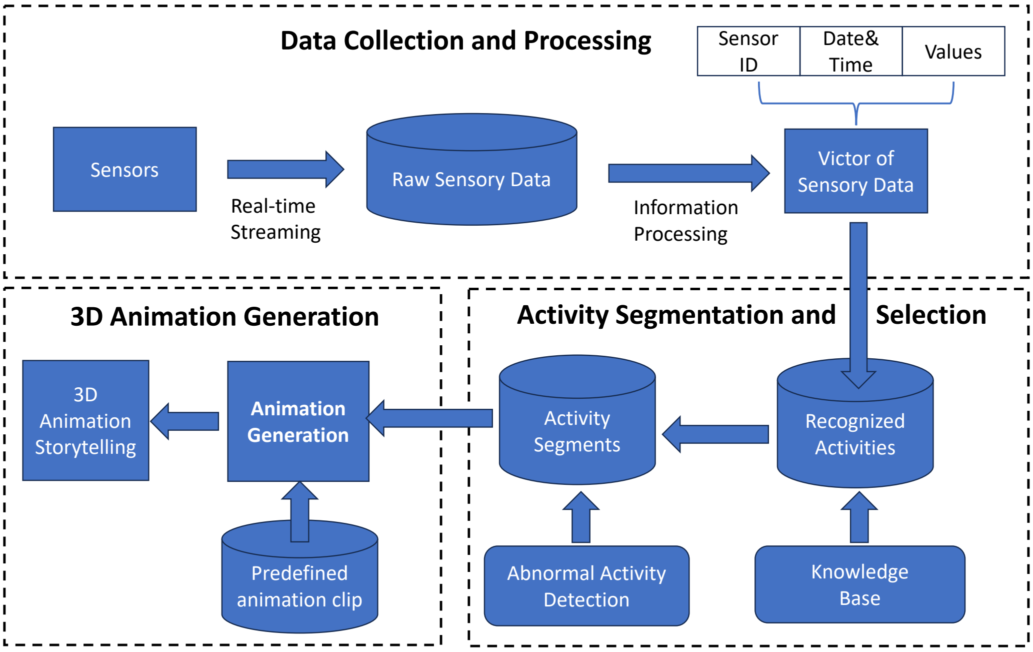

FIGURE 5.1: Overview of the Data-driven 3D Animation Approach

as 3D animation generation and summarization. The fusion of data collection and processing into one module showcases the efficiency of our approach, bridging the real-world activities of the elderly to the digital domain where they can be visualized and analyzed.

5.2.2 Activity Segmentation and Selection

This stage of the approach concentrates on converting the raw sensor data into actionable insights by breaking down the collected data into discrete units that represent unique activities. Through the processes of segmentation and selection, high-level activity descriptors derived from the data processing stage are employed to segment the processed data into distinct units. This effectively translates sensor data into meaningful insights regarding the elderly's daily routines. The selection phase utilizes an evaluative approach to determine which activities should be included in the final 3D animation summary, taking into account factors such as duration, frequency, and occurrence timing. Crucially, this module prioritizes customization and relevance, facilitating personalization based on caregivers' specific preferences, thereby ensuring the resulting 3D animation summary closely aligns with individual needs and concerns, enhancing its relevance and utility.

Knowledge-based methods are employed to recognize activities. These methods leverage historical data and expert insights to establish a comprehensive database encompassing a wide array of both normal and abnormal activities frequently performed by the elderly. By comparing incoming sensor data against this knowledge base, the system is better equipped to identify the specific nature of each activity, including its significance and potential implications for the elderly individual's health and well-being.

For example, the knowledge base may include detailed profiles of activities such as cooking, sleeping, and exercising, alongside variations that could signify distress or health issues, like prolonged inactivity or erratic movement patterns. When the system identifies data that matches or closely resembles an activity pattern from the knowledge base, it categorizes the activity accordingly. This approach not only enhances the precision of activity recognition but also enriches the 3D animation generation with contextually relevant animations that accurately depict the elderly's daily routines.

Abnormal Activity Detection is designed to pinpoint activities that diverge from the elderly individual's typical behavior patterns, highlighting potential health or safety concerns. This mechanism continuously monitors sensor data for anomalies, swiftly flagging activities that deviate from the norm, such as an unusually long period of inactivity that might suggest a fall or sudden illness, or erratic movement patterns indicating possible confusion or distress.

Additionally, this detection capability augments the 3D animation visualization by emphasizing critical events that demand immediate attention, thereby offering a more comprehensive overview of the elderly's well-being. Through this sophisticated approach, the system not only captures the elderly's daily routines in 3D animation but also serves as a vigilant monitor, poised to alert caregivers when abnormal activities are detected, maintaining a balanced focus on both routine monitoring and emergency response.

The Activity Segmentation and Selection Module acts as an essential intermediary, enhancing the comprehensiveness and specificity of the final 3D animation summary. It refines the output from the data processing stage into a focused subset of data that is optimally suited for visualization and interpretation.

5.2.3 3D Animation Generation

The approach then advances to the 3D Animation Generation stage, where selected activities are paired with predefined animation clips. This design ensures a comprehensive yet concise visual representation of the elderly's daily routines. Through a balanced methodology, this stage creates a visualization that serves the caregivers' needs while respecting the privacy of the elderly individual.

Formally, this process can be represented by a mapping function, denoted as f, that pairs each selected activity a_i with a corresponding animation clip c_j, such that $f(a_i) = c_j$. The assembly of the clips into a final 3D animation summary, S, is guided by the chronological order of the selected activities, respecting the temporal sequence T derived from the initial dataset:

$$S = f(C, T) = \langle f(c_1, t_1), f(c_2, t_2), \ldots, f(c_n, t_n) \rangle$$

In this expression, n denotes the total number of selected activities, and $f(c_i, t_i)$ is the function that assigns each animation clip c_i to its correct temporal position t_i in the summary.

By means of this approach, the 3D Animation Generation Module creates an insightful and time-efficient visualization of the monitored individual's daily life. The resulting animation summary serves as an intuitive and privacy-preserving tool for effective remote monitoring.

5.2.4 3D Animation Summarization and Replay

The 3D animation summarization and replay function provides a dynamic and personalized approach for caregivers to review a summary of 3D animations. It enables the quick understanding of an elderly individual's overall life status by presenting a highly condensed version of the animation, facilitating rapid comprehension without sacrificing detailed insights.

The function employs the following methods to distill the animation into a succinct summary:

- Extended periods of inactivity, such as sleeping or sitting, are excluded from the replay. These intervals are communicated to the viewer via scripts like "after X hours of sleeping/sitting...," where 'X' denotes the length of the inactivity.
- Activities of longer duration, such as cooking, ambulating, watching TV, reading, eating, etc., are encapsulated in summary form. Scripted like "X hours later..." are incorporated to indicate the elapsed time of these prolonged activities.
- The display of activities is tailored based on their significance. Setting a higher playback rate suggests a preference for a broad overview, prompting the removal of trivial and less significant activities to further condense the animation. In contrast, a lower playback rate maintained for users who wish to delve into more detail will preserve a greater number of activities within the animation.
- The playback speed is modulated to align with the user's input, ensuring the animation meets their review expectations.

By integrating these four methods, users can view and comprehend 24 hours of 3D animation in approximately 5-10 minutes at a standard playback rate. This approach significantly enhances the efficiency of the review process for caregivers.

5.3 Experimental and Results

To evaluate the effectiveness of the Avatar-Based 3D Animation Monitoring System, we conducted an experiment to assess understanding, privacy protection, intuitiveness, and accuracy in representing daily life of the proposed approach.

We developed a 3D virtual animation system that serves as both a real-time visualization tool and an essential part of our survey experiment. This interface, which is built on the Unity 3D engine, allows users to engage with the visualization of the elderly's daily activities, facilitating an assessment of the effectiveness of our monitoring methodology.

5.3.1 The Data-driven 3D Animation Interface

The elderly's activities are visually represented in real-time by mapping them onto a virtual avatar within a 3D environment that replicates the layout of the elderly's home(see Figure 5.2) . The avatar can be customized to reflect the physical appearance of the elderly for a more personalized and realistic representation.

FIGURE 5.2: The 3D Environment Replicates Resident's Living Environment

FIGURE 5.3: The Panels of Data-driven 3D Animation System

- The 3D virtual house environment panel (main panel): Displays a 3D model of the entire home.
- The message board panel: Presents status updates or warning messages about the home environment (e.g., "Resident forgot to close the fridge door").
- The statistics readings panel: Visualizes environmental data such as temperature, humidity, and noise levels inside the home.
- The date and time panel: Indicates the current date and time.
- The activity zoom-in and replay panel: Enables the close examination or replay of a particular activity.
- The warnings and annotations panel: Highlights possible mental and physical states of the resident at different times, based on analytic results derived from our machine learning algorithms.

The movements and actions of the 3D avatar are controlled by the data received from the sensors (see Figure 5.4). The 3D animations representing different actions are triggered when a new activity is recognized by the online activity recognition model. When no activity is detected, the 3D avatar remains in its previous state.

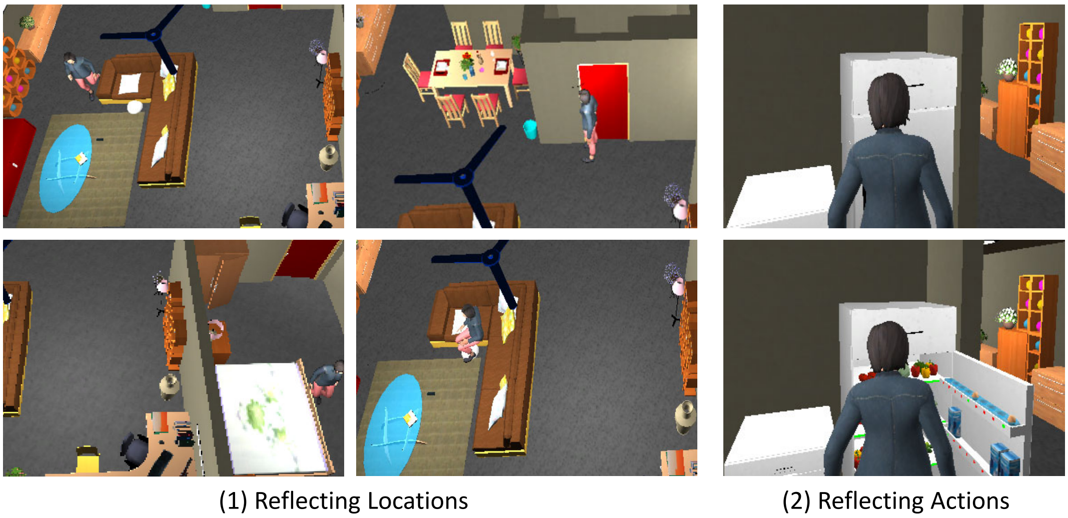

Figure 5.4: Information Reflected in the 3D Animation Notification System

The system also incorporates a unique replay function (Figure 5.5), further enhancing the caregiver's ability to monitor and understand the elderly's activity patterns and lifestyle.

Figure 5.5: The Replay Function

By implementing this 3D virtual animation interface, we were able to conduct a survey experiment.

5.3.2 Experimental Setup

The experimental setup was designed to closely mimic the living conditions of an elderly individual's home. The test environment was installed with various non-intrusive IoT sensors that were placed to capture activities. These sensors were integrated into common household items and areas such as refrigerators, washing machines, and dining areas to ensure they remained unobtrusive.

Participant Recruitment and Briefing

A total of 30 participants were recruited for this experiment, comprising both family caregivers and professional caregivers to provide a diverse range of perspectives on the usability and effectiveness of the system. Prior to the commencement of the experiment, participants were given a thorough briefing about the purpose of the system and detailed instructions on how to use the replay function. This was to ensure that all participants had a clear understanding of the system's capabilities and the nature of the data being presented.

Activity Simulation

To simulate typical daily activities, a research staff performed various actions that are common in the daily routine of an elderly person. These activities included opening the refrigerator, doing laundry, dining, and other typical household tasks. Each activity was chosen to represent different aspects of daily life that might require monitoring for safety or well-being purposes.

Real-Time 3D Animation Representation and Replay Function

As these activities were performed, the data collected by the sensors was processed and converted into real-time 3D animations. These animations were designed to accurately reflect the movements and interactions of the elderly individual within the home. The real-time visualization enabled participants to observe how the system tracks and displays activity, providing a dynamic and interactive way to monitor an individual's daily routine.

Following the real-time demonstration, participants were shown a short summary of the day's activities, generated by the system's Replay Function. This feature compiles the events of the day into a condensed format, allowing caregivers to quickly review the elderly individual's daily activities at a glance. The Replay

Function is particularly useful for caregivers who cannot monitor their loved ones continuously but still want to ensure their well-being and safety.

Questionnaire and Data Collection

The questionnaire was designed to evaluate the effectiveness of different monitoring approaches—Activity Log, Camera-based monitoring, and 3D Animation—in terms of Understanding, Privacy, Intuitiveness, and Accuracy. Participants were asked to rate their level of agreement with the following statements using a 5-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree.

Q1: I found the Activity Log easy to understand.

Q2: I found the Camera-based monitoring easy to understand.

Q3: I found the 3D Animation approach easy to understand.

Q4: I feel the Activity Log respects the privacy of the elderly.

Q5: I feel the Camera-based monitoring respects the privacy of the elderly.

Q6: I feel the 3D Animation approach respects the privacy of the elderly.

Q7: I found the Activity Log intuitive to use.

Q8: I found the Camera-based monitoring intuitive to use.

Q9: I found the 3D Animation approach intuitive to use.

Q10: I believe the Activity Log accurately represents the daily activities of the elderly.

Q11: I believe the Camera-based monitoring accurately represents the daily activities of the elderly.

Q12: I believe the 3D Animation approach accurately represents the daily activities of the elderly.

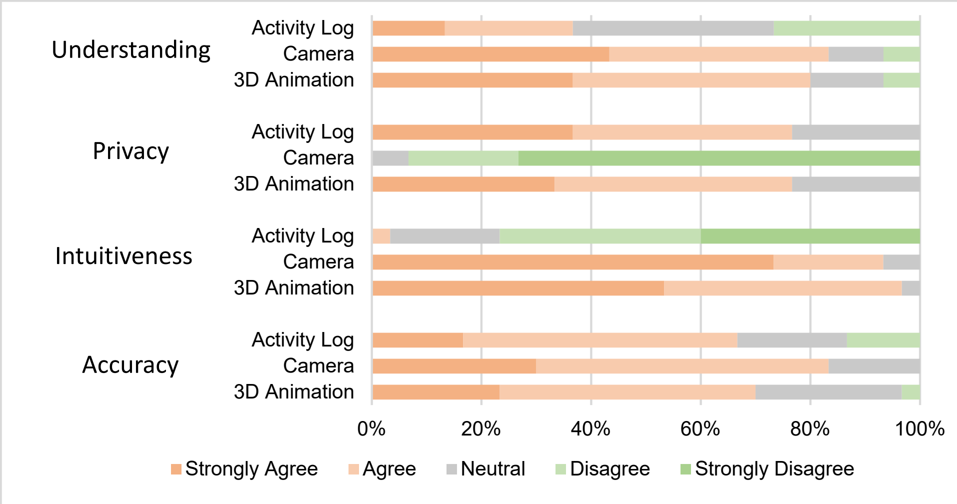

FIGURE 5.6: Ratings on the Effectiveness of Different Monitoring Approaches in Terms of Understanding, Privacy, Intuitiveness, and Accuracy

Participants were provided with the questionnaire after being introduced to each monitoring approach and observing both the real-time animations and the replay summaries, participants were asked to complete a questionnaire. Responses were collected anonymously and analyzed to determine the overall effectiveness and acceptability of each system. The results were then visualized in a bar chart to facilitate a comparative analysis across all approaches.

5.3.3 Results and Analysis

The collected survey data provided valuable insights into the effectiveness of the system. As illustrated in Figure 5.6, the majority of participants expressed a preference for the 3D Animation approach over traditional Camera Surveillance and Activity Logs across all evaluated aspects

Understanding

The feedback on understanding indicates a high level of agreement among participants that the 3D Animation is an effective method for comprehending the daily activities of the elderly. A significant majority expressed either agreement or strong agreement in this regard, outperforming the traditional activity log approaches.

This suggests that the 3D animation bridges the gap between complex data and caregiver comprehension.

Privacy

Privacy protection is a critical concern in monitoring systems, and the results reveal a stark preference for the 3D Animation approach. Participants felt that it better safeguarded the privacy of the elderly compared to camera surveillance, with a considerable proportion of participants indicating their agreement. This result supports the system's aim to deliver information while maintaining the dignity and privacy of the elderly.

Intuitiveness

In terms of intuitiveness, the 3D Animation system was found to be more user-friendly than the Activity Log method. A clear majority of the participants agreed or strongly agreed that the 3D Animation system was easy to understand and use. This is indicative of the system's potential for integration into the caregivers' routines.

Accuracy

As for the accuracy of representing daily life, the 3D Animation was rated highly, with most participants acknowledging its precision in depicting elderly daily lives. It surpassed the camera method, which, despite being accurate, faces privacy challenges and the activity log method, which may lack detail.

Overall, the survey results demonstrate a positive reception to the 3D Animation approach. It effectively assists caregivers in understanding the living status of the elderly, striking an optimal balance between detail and privacy. The system's design facilitates a high degree of comprehension, adopts privacy-respecting principles, and provides an intuitive user experience while accurately portraying the dynamics of daily activities.

In conclusion, the Avatar-Based 3D Animation Monitoring System stands out as a promising tool in the realm of AIP technologies. Its ability to convey critical information about the elderly's day-to-day activities in a privacy-conscious and user-friendly manner holds implications for enhancing the caregiving process while respecting the privacy of the elderly. The positive feedback culminates in a endorsement of the system's potential for widespread adoption in real-world caregiving scenarios.

5.4 Summary and Conclusion

The data-driven 3D animation approach presented in this chapter marks a advancement in the field of AIP technologies. By integrating IoT sensor data with 3D animation, we have developed a system that provides real-time and summarized insights into the daily activities of the elderly without compromising their privacy. The effectiveness of this approach was validated through extensive testing in a real-home setting, with participants affirming its capability to preserve privacy while providing clear, intuitive insights into the elder's daily routines. The positive feedback from participants indicates that the proposed Approach effectively helps caregivers understand the elderly's living status without compromising detailed personal information. This chapter has demonstrated that through thoughtful application of innovative technologies, we can improve the quality of life for our aging population while adhering to ethical standards of privacy and respect.

Chapter 6

SAiPS: A AIoT-based Smart Aging-in-Place System

The rapid aging of the global population presents significant challenges, particularly in enabling seniors to continue living independently at home. Aging-in-Place (AIP) solutions aim to support this independence while addressing key concerns such as safety, mobility, and social interaction. This chapter introduces the Smart Aging-in-Place System (SAiPS), a novel AIoT-based solution designed to overcome existing limitations. Developed using the developed PE4AIP-enabled AIP design architecture, SAiPS integrates advanced technologies to provide a personalized, privacy-preserving, and effective AIP system. This chapter details the system's design, implementation, and the field study conducted to evaluate its performance and acceptance among elderly users and their caregivers.

6.1 Innovations in AIP Solutions

Rather than spending their later years in an unfamiliar institutionalized environment, most senior citizens prefer to age in place, which means they want to remain in their own homes independently for as long as possible. However, older adults may require supervision and assistance in the home environment as they age. Therefore, smart home systems have been proposed to provide AIP solutions [172–175]. Additionally, the market offers various commercialized products such as Rest-Assured [176], which integrates wireless monitoring and two-way video chat with trained caregivers, providing home-based healthcare facilities that include motion monitoring and emergency buttons. According to [14], technology can be used to enable aging-in-place in two general ways: (1) monitoring and sensing, and (2) explicit communication and interaction. The first aspect focuses on developing smart sensing devices for accurate physical activity detection while the second one cares about the social and emotional well-being of older adults. Various studies [177–180] have been done to tackle the two key technical challenges, and we will review the related works of these two aspects.

To enable monitoring and sensing, cameras [177, 178] are popularly adopted in many smart home solutions. However, cameras are always deemed to be a bad choice for aging-in-place systems due to their intrusion into personal privacy[179, 180], unless the person suffers from certain severe life-threatening chronic diseases that require intensive and continuous monitoring [181]. To mitigate privacy issues of camera-based monitoring, various unobtrusive sensing technologies are proposed [182, 183]. For example, wearable devices are now commonly adopted to capture the bio-parameters of the older adult, which are then used to interpret the well-being of the older adults [184]. However, wearable devices may sometimes cause discomfort to the older adults and the regular charging makes them inconvenient to use [13]. However, wearable devices may cause discomfort to the older adults and regular charging makes them inconvenient to use. Moreover, it is easy for the older adult to forget to put on the device, making data collection unreliable[179]. Therefore, in this work, we adopt low-cost sensors (e.g., infrared and light sensors) that are attachable to furniture or walls to unobtrusively collect users' behavioral trajectory at home, which incurs minimum privacy intrusion or discomfort.

Explicit communication and interaction are crucial challenges in designing AIP smart homes. Social communication is particularly vital in maintaining good cognitive health for older adults, especially those living alone. Supporting a healthy and long-term social relationship is of utmost importance [185]. For instance, Mynatt et al.[186] proposed a digital family portrait that provides qualitative visualizations of a family member's daily life to promote the social well-being of older adults. Morris [187] suggested a social network system that utilizes a "solar" graph indicator to visualize an individual's social relationships and encourage social interaction among family members. Wallbaum et al. [188] developed the StoryBox to bridge the technological gap between grandparents and grandchildren. However, many older adults may not be familiar with or comfortable using technology, even the well-educated ones [189]. Vines et al. [15] deployed a telecare system that enables caregivers to remotely monitor older adults' activities at home via a web protocol. However, the activity logs are too detailed and cumbersome for users to understand, and it requires the users to first make sense of the data and then identify abnormal patterns that are truly of interest to the users [190]. In comparison, the SAiPS provides more compact summarized analytic results through P-E fit indicators and more human-interpretable data-driven 3D animation and storytelling.

6.2 System Design

The SAiPS has been designed and implemented based on the developed PE4AIP-enabled design architecture. The system is structured into three primary layers: 1) an AIoT hardware layer for data acquisition in the home environment, 2) a server layer for data processing, and 3) user interfaces that allow different stakeholders to access and interact with the processed data.

- **AIoT Hardware Layer:** Comprises a variety of unobtrusive AIoT sensors and edge devices placed within the home environment to gather data. The data are processed locally on end devices and edge devices, facilitating the continuous monitoring of behavioral and social signals while respecting the privacy of older adults.

- **Server Layer:** Processes the information gathered by the hardware layer, computes P-E fit indicators, estimates well-being, and generates 3D animations. These functionalities are crucial for assessing the well-being of older adults effectively.

- **User Interface Layer:** Displays the P-E fit indicators, well-being assessments, and 3D animations to users—older adults, family members, and caregivers. This layer enhances interaction and supports informed decision-making based on the processed data.

Adhering to the PE4AIP-Enabled AIP design architecture, the Smart AIP System integrates these components to offer a comprehensive, technology-driven AIP solution. This system is aimed at enhancing the quality of life and satisfaction of older adults in their preferred living environments.

6.2.1 P-E Fit Indicators and Living Well Indices

Integrating the PE4AIP model, the SAiPS system initially evaluates the proposed six P-E fit indicators. Subsequently, it assesses the overall well-being of the elderly based on these indicators. To accurately fit the model for estimating these six P-E fit indicators and overall well-being, it is essential to label the ground truth values accurately. To enhance comprehension among ordinary users and enable real elderly users to more easily grasp the significance of these indicators in practical settings, we have translated the P-E fit indicators into six Living Well indices. These indices are scored on a scale from 0 to 10, where a higher score indicates better outcomes. The correspondence between the indicators and the indices is as follows:

- **Motion Index:** Represents the Motion indicator.

- **Regular Lifestyle Index:** Corresponds to the Regular Lifestyle indicator.

- **Social Index:** Maps to the Social Interaction indicator.

- **Environment Index:** Reflects the Indoor Comfort indicator.
- **Sleep Index:** Denotes the Sleep indicator.
- **Cooking Index:** Previous studies [191, 192] have shown that the frequency of eating home-cooked meals is positively correlated with diet quality and health. In this SAiPS, we use the Cooking Index to represent the Eating indicator, which evaluates the diet quality.

This approach not only facilitates the elderly users in labeling the ground truth for the six P-E fit indicators and overall well-being but also makes the indicators more tangible and understandable in everyday contexts. This practical application is vital for enhancing the user-friendliness and effectiveness of the SAiPS system in real-world AIP scenarios.

To comprehensively understand how SAiPS quantifies six Living Well indices and overall well-being, this section provides a detailed example of the computational methods that underpin the effective operation of the system. We begin by introducing the primary mechanisms for sensing and data collection used in SAiPS. In order to how the indicator can be calculated, we first introduce a serious terms. Let $AM_i(t)$ denote whether a motion sensor (id $= i$) is activated during the time window T from t to $t + t_d$; the ids of motion sensors in the living room, bedroom, kitchen, and toilet are *0*, *1*, *2*, and *3*, respectively. $AM_i(t)$ is set as 1 if the motion sensor (id $= i$) is triggered during t to $t + t_d$, otherwise, $AM_i(t)$ is set as 0.

Regarding the selection of the time window T, its determination encompassing both the duration and segmentation of the day into discrete intervals for sensor activation monitoring is pivotal for precisely capturing an individual's motion patterns. The choice must strike a balance between granularity, which refers to the capability to detect detailed movements, and practicality, encompassing the computational and data storage demands posed by very short time windows. Ideally, T should be selected based on empirical evidence reflecting the typical movement patterns of older adults. This ensures the time window is short enough to capture pertinent activities without being so brief as to produce excessive data noise.

A shorter time window enhances the granularity of movement tracking but can result in a larger volume of data and increased noise. Conversely, a longer time window can simplify data processing and reduce noise but risks overlooking brief yet significant activities. The optimal time window must accurately mirror the activity patterns of the inhabitants while also being manageable in terms of data handling. In this work, after careful consideration of these aspects, the time window T has been set to one minute. This duration was selected to efficiently document significant activities, offering a balanced approach to managing data volume and analytical complexity.

Let $AM(t)$ denote whether any motion sensor is activated during the time window from t to $t + t_d$. $AM(t)$ is set as 1 if any motion sensor (id = 0, 1, 2, or 3) is triggered during t to $t + t_d$, otherwise, $AM(t)$ is set as 0. It is calculated as:

$$AM(t) = \min(AM_0(t) + AM_1(t) + AM_2(t) + AM_3(t), 1). \tag{6.1}$$

We describe each index subsequently.

Motion Index: This index describes the overall activeness of the older adult at home during a given day. Older adults may trigger different sensors located in various areas while they are moving around at home. As such, motion level is inferred from the sensor triggering patterns. For a given day, the Motion Index is defined as:

$$I_{Mo} = \min(w_0 \sum_{t=0}^{T-1} AM(t), 10.0), \tag{6.2}$$

where T is the amount of the measured time window (t_d) of a whole day, and w_0 is a normalization factor according to experience.

The Motion Index provides a quantitative measure of the inhabitant's daily activity level. By monitoring motion levels, caregivers can identify potential issues that may require attention, such as a decline in mobility or increased sedentary behaviour.

Regular Lifestyle Index: Maintaining a regular activity schedule has both physical and mental benefits. This index describes the regularity of the inhabitant's activity patterns. For example, if the inhabitant gets up one hour later than usual on a particular day, the different sensor triggering patterns for that day would be noticeable. The Regular Lifestyle Index is defined as:

$$I_{Rl} = \min(w_1 \sum_{d=1}^{D} \sum_{i=0}^{T-1} |AM(i) - AM(d,i)|, 10.0), \tag{6.3}$$

where w_1 is the normalization factor according to experience, D is the number of days are considered, and $AM(d,t)$ denotes $AM(t)$ obtained in the past d days.

The Regular Lifestyle Index provides a quantitative measure of the inhabitant's activity regularity. By tracking activity patterns, caregivers can identify deviations from the inhabitant's regular routine and take appropriate measures to ensure they maintain a healthy lifestyle.

Social Index: This index describes the amount of indoor social interactions the inhabitant has in a particular day. Essentially, if two or more sensors are triggered at the same time and more frequently than normal, it can be inferred that there are visitors in the house, indicating a form of social interaction. The duration of such patterns indicates the interaction's intensity and is taken into consideration when calculating the index. The *Social Index* is defined as:

$$I_{So} = \min(w_2 \sum_{i=1}^{N} W_s(i), 10.0), \tag{6.4}$$

where N is the total number of multiple motion sensors triggered events, and $W(i)$ denotes the duration of the i-th event. w_2 is a normalization factor according to experience.

The Social Index provides a quantitative measure of the inhabitant's social interactions within their home, which can provide insight into their overall well-being and quality of life. By monitoring social interactions, caregivers can gain a better understanding of the inhabitant's social support network and identify potential issues that may need attention. The Social Index could be further refined to incorporate additional factors.

Environment Index: Environmental factors, such as noise, temperature, and humidity, have a significant impact on people's quality of life. This index describes the overall condition of the environment, taking into account these factors. In general, people feel comfortable with a temperature between 20 to 25 degrees Celsius and a relative humidity level between 30% to 70%. Deviations from these conditions can cause discomfort. Similarly, noise levels can also have a significant impact on comfort, with levels exceeding 60 dB often causing discomfort. The Environment Index is defined as:

$$I_{En} = \min(w_T \cdot q_T + w_H \cdot q_H + w_N \cdot q_N, 10.0), \tag{6.5}$$

where w_T, w_H, and w_N are weights assigned to temperature, humidity, and noise, respectively. q_T, q_H, and q_N represent the differences between the detected temperature, humidity, and noise levels, and the comfortable levels of each factor.

The Environment Index provides a quantitative measure of the inhabitant's comfort level in their environment. It could be further refined to incorporate additional environmental factors that may impact comfort, such as lighting and air quality.

Sleep Index: This index describes the inhabitant's sleep quality. In this work, the Sleep Index is designed to describe the amount of time spent in bed, and a value close to zero indicates abnormal sleeping patterns. It is assumed that most older adults go to bed after 8 PM at night and get up before 8 AM the next morning. During this sleeping period, a lack of sensor triggers indicates that the user is likely sleeping. During the sleeping period, if the user is not staying in the bedroom, which means abnormal sleep is detected, then set Sleep Index, $I_{Sl} = 0$. Otherwise, we deduce the Sleep Index as,

$$I_{Sl} = \min(w_3 \sum_{t=t_0}^{T_s} |AM(t) - 1|, 10.0), \tag{6.6}$$

where w_3 is a normalization factor which is set according to experience, t_0 is the time of 8 PM, and T_s is the number of time windows from 8 PM at night to 8 AM the next morning.

The Sleep Index provides a quantitative measure of the inhabitant's sleep quality and can help caregivers to monitor any changes in sleeping patterns that may indicate underlying health issues. The use of motion sensors to deduce the Sleep Index is a non-invasive and convenient way to monitor sleep quality, without requiring the user to wear any additional devices. In future work, the Sleep Index could be further refined.

Cooking Index: This index calculates whether the older adult has spent enough time to prepare his/her meals. The proposed Cooking Index is defined as:

$$I_{Co} = \min\left(w_4 \sum_{t=0}^{T-1} AM_2(t), 10.0\right), \tag{6.7}$$

where T is the amount of the measured time window of a whole day, and w_4 is a normalization factor which is set according to experience.

The Cooking Index 6.7 provides a quantitative measure of the older adult's cooking habits, which can help caregivers monitor their overall health and well-being. By tracking the amount of time spent preparing meals, the Cooking Index can also provide insight into whether the older adult is receiving proper nutrition. The Cooking Index could be further refined to incorporate additional factors that may affect meal preparation, such as the types of foods being cooked and the frequency of cooking.

Well-being:

As illustrated in Figure 3.3, the values of all indicators, described earlier, are used to calculate the overall well-being score using the following formulation:

$$S_{well-being} = Norm(w_{Mo}I_{Mo} + w_{Rl}I_{RI} + w_{So}I_{So} + w_{En}I_{En} + w_{Sl}I_{Sl} + w_{Co}I_{Co}), \quad (6.8)$$

where, $S_{well-being}$ represents the overall well-being score. The scores for the indicators I_{Mo}, I_{RI}, I_{So}, I_{En}, I_{Sl}, and I_{Co} correspond to 'Motion', 'Regular Lifestyle', 'Social Interaction', 'Indoor Comfort', 'Sleep', and 'Eating', respectively. The weights w_{Mo}, w_{Rl}, w_{So}, w_{En}, w_{Sl}, and w_{Co} represent the importance assigned to each indicator. The function $Norm$ normalizes the well-being score to a range of 0-10, ensuring uniformity across evaluations.

In conclusion, the suite of Living Well indices and corresponding computational models described here plays a crucial role in the effective functioning of the SAiPS. By providing a detailed, real-time analysis of the conditions within the elderly's living environment, these indices and well-being allow caregivers and family members to maintain a continuous and general understanding of the elderly's daily life. This ongoing monitoring is essential not only for ensuring immediate interventions when necessary but also for making long-term adjustments to enhance the quality of life and well-being of older adults.

6.2.2 Data-driven 3D Animation and Storytelling

The SAiPS system implements the 3D Animation notification approach as detailed in Chapter 5. This approach utilizes non-intrusive AIoT sensors to collect data from the home environment, which is then used to animate a 3D avatar within a digitally replicated home setting. The avatar's activities, modeled after the real-time movements of the elderly resident, are rendered in 3D to provide caregivers with a visual understanding of the elderly's daily routine without compromising privacy.

In addition, the system employs a template-based storytelling module. Each Living Well index is categorized into five levels, with several templates predefined for each level to describe the respective index status. To generate a short narrative, a template is randomly selected from each index category based on its current level. Here are some examples of the generated stories:

Sample Story 1: *The living environment was good at mother's place. Mother was engaged in a moderate amount of activities. Nobody dropped in for a visit at her place. Mother did not spend a lot of time in the kitchen. Mother had a refreshing sleep last night.*

Sample Story 2: *The noise level, temperature, and humidity feel great at mother's place. Mother was very energetic. Mother may have hosted some guests at home. Mother spent a lot of time in the kitchen. Mother had medium quality sleep last night.*

6.2.3 User Interfaces

The Living Well indices, 3D animation and short stories can be accessed by the older adults and their caregivers anytime through a web interface (Figure 6.1) and the 3D animation system interface (Figure 5.3). They may also view the historical stories and Living Well indices and through this website. An SMS related to an older adult's daily information will be automatically generated and sent to his/her caregivers every day.

6.3 Field Study

To evaluate our proposed the proposed PE4AIP model, PE4AIP-enabled AIP design architecture in real life situation, we conducted a field study with senior participants living alone and their family caregivers. Our primary aim was to assess the accuracy of the Person-Environment Fit indicators and well-being developed within the SAiPS system, and their effectiveness in aiding caregivers to understand

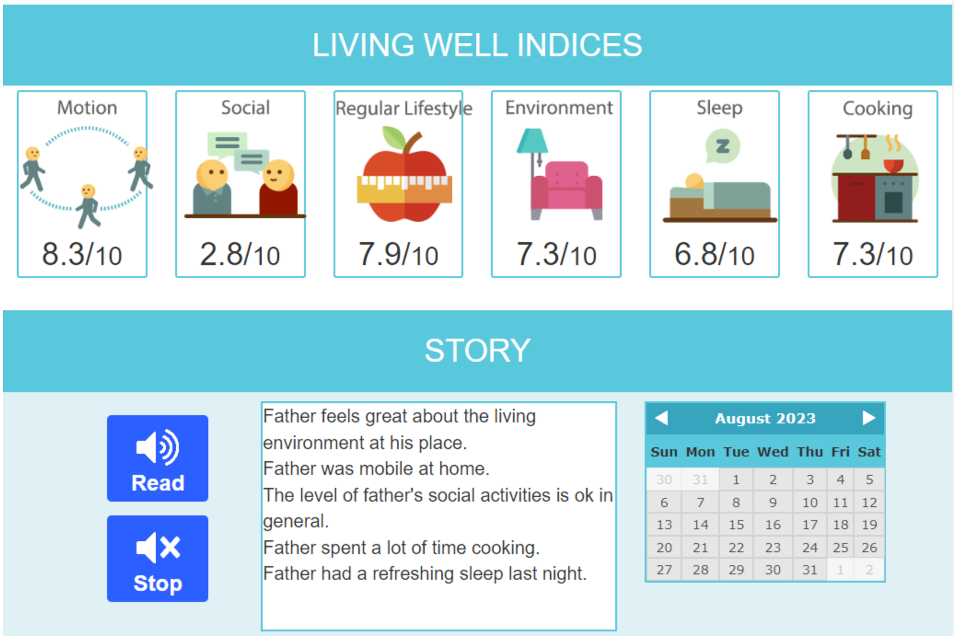

Figure 6.1: Web Interface

the elderly's living status. We also aimed to evaluate the overall acceptance and unobtrusiveness of the designed AIP system, SAiPS.

6.3.1 Experimental Setup

The SAiPS was meticulously designed and implemented to reflect the proposed PE4AIP model and the PE4AIP-enabled AIP design architecture, focusing on privacy preservation, personalization, and continuous monitoring. We recruited 10 elderly participants over the age of 70, living independently in Singapore, along with their caregivers. Over an eight-week period, semi-structured interviews were conducted, and daily logs were maintained to gather comprehensive data on participants' experiences with the system.

To assess the functionality and acceptance of SAiPS, we deployed sensor units in the living environments of the elderly participants. These sensors were part of the SAiPS infrastructure, collecting data used to generate non-intrusive notifications and reports on the seniors' well-being. This data-driven approach also supported a novel notification system that presented daily activity summaries via 3D animations to caregivers, ensuring privacy and minimizing intrusiveness.

We recruited ten elderly participants (7 Female, 3 Male) in Singapore who lived alone and were in stable health. Each senior participant nominated one caregiver, typically an adult child, to participate in the study as a pair. Consent was obtained from all participants before the SAiPS system was installed in their homes.

The field study was conducted over an eight-week period. At the onset, we installed the SAiPS in each participant's home, ensuring minimal disruption to their living space. Each installation involved sensor units placed in key areas like the living room, bedroom, kitchen, and toilet (Figure 6.2). The system did not require any active maintenance from the participants.

Initial interviews (I_1^P and I_1^C) were conducted at the time of system deployment to gather baseline data on the participants' profiles, technology acceptance, and daily lives. These interviews also explored the caregivers' interaction patterns and their acceptance of technological products.

After eight weeks of system usage, follow-up interviews (I_2^P and I_2^C) were conducted to assess:

- The overall experience of using the system.
- Opinions on the privacy aspects of the system.
- The effectiveness of the 3D animation notifications in enhancing caregiver understanding.
- The system's impact on the daily lives and well-being of the participants.
- Suggestions for system improvements and potential extensions.

This revised section ensures that the field study details are consistent with the experimental objectives and findings presented in the notes from the PhD oral defense. It also clarifies the relationship between the system's features and the

FIGURE 6.2: Sensor units deployed in real home environment: (a) in living room, (b) in bedroom, (c) in kitchen, and (d) in toilet.

study's goals, focusing on evaluating the PE4AIP model's effectiveness and the system's impact on privacy and caregiver understanding.

6.3.2 Results of the Field Study

In this subsection, we present the results of our study investigating the effectiveness of the SAiPS system. The evaluation was structured around four primary measurements: the accuracy of P-E Fit indicators and well-being assessment, the effectiveness in aiding caregivers' understanding of the elderly's living status, the overall acceptance of the SAiPS among users, and the system's unobtrusiveness in the daily lives of the participants.

Accuracy of P-E Fit Indicators and Well-being in PE4AIP

The efficacy of the PE4AIP model is evaluated based on the precision of its predictive indicators and the well-being assessments it generates. These elements are crucial in accurately reflecting the live status of the elderly within their own living environments. To determine the model's accuracy, we measure the average distance of the predicted indicators and overall well-being from the ground truth. A lower distance value indicates a higher accuracy and a closer approximation to the actual observed data. The formula employed for this assessment is the absolute difference: $|\hat{y}_{\text{predicted}} - \bar{y}|$.

Table 6.1 presents the average distances of the predicted indicators and well-being relative to the logs maintained by senior participants. The indicators cover a range

TABLE 6.1: Average Distance Between Predicted Indicators and Well-being to Logs by Senior Participants

	Motion	Regular Lifestyle	Social Interaction	Indoor Comfort	Sleep	Eating	Well-being
Average Distance	0.86	0.94	1.32	0.76	1.09	1.39	1.13

of daily life aspects essential for AIP solutions: Motion, Regular Lifestyle, Social Interaction, Indoor Comfort, Sleep, Eating, along with the aggregate measure of well-being. These distances provide quantitative evidence of the model's predictive accuracy.

The findings from Table 6.1 confirm that the proposed PE4AIP model exhibits a reliable degree of accuracy across all indicators. The Motion and Indoor Comfort indicators, in particular, showcase a closer alignment with the ground truth, while the Eating indicator suggests an area for further refinement. This underpins the efficacy of the model, enabling caregivers and stakeholders to make informed decisions to enhance the living conditions and thereby, the well-being of the elderly.

The results demonstrate the model's positive predictive capability, suggesting that the PE4AIP model has potential in real-world applications for AIP. Each indicator has been formulated to capture distinct yet interrelated dimensions of an elder's life, reflecting upon their P-E fit within their personal living space.

The Effectiveness of Understanding of Elderly's Living Status

Previous research [186, 187, 193] has highlighted that enhancing caregiver awareness often necessitates increased effort from users or the disclosure of extensive personal activity details. In contrast, our proposed approach leverages unobtrusive AIoT technologies combined with six P-E fit indicators, 3D animations, and short text-based narratives to provide caregivers with a succinct yet comprehensive view of their elderly relatives' well-being, effectively balancing the need for information with privacy concerns. The utility of this approach is particularly evident in the interactions between caregivers and the elderly, as demonstrated by the experiences of participants and their caregivers.

For instance, the C2 of P2 noted significant benefits from the system, stating, *"Yes, it's very helpful in helping me know my mother's condition better. There were a few days when my mother's Social Index was lower than before. I was quite worried about her, so I went to visit her and talked with her. After that, I found that the Social Index went back to normal. I was quite relieved."* P2 also remarked on the unexpected awareness of their social activities by their son, which led to a meaningful conversation that improved their mood, *"Yes. My son visited me one day and asked me why I didn't go out for a few days as usual. I didn't expect he knew about this because the system told him. After talking with him, I felt much better..."*

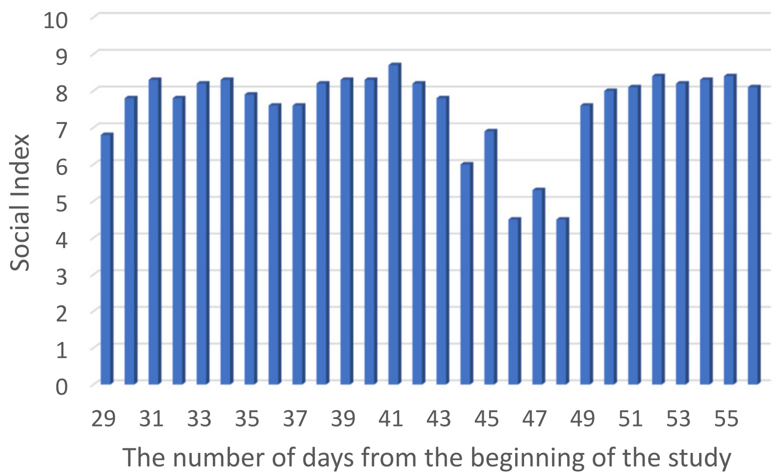

FIGURE 6.3: Social Index of Participant 2 from the 29th to the 55th day of the study.

The data aligns with the qualitative feedback received from interviews. As depicted in Figure 6.3, a noticeable dip in Social Index was quickly identified and addressed through caregiver intervention, which not only demonstrates the system's accuracy but also its practical utility in facilitating timely and effective caregiver responses.

Further analysis during our interviews revealed a consensus among caregivers on the daily presentation of information, which they found crucial for continuous monitoring, especially during periods when direct interaction was limited. For example, the caregiver of P4 expressed, *"Yes, it's definitely helpful as things may change every day. During the period when I was busy with work and had less time to visit my father, the information helped me know that my father was in good condition and made me feel less worried."*

The system's impact extends beyond just monitoring, fostering increased interaction and dialogue about daily life. Caregivers reported using the system's outputs as conversation starters, which not only enhanced the quality of interactions but also provided deeper insights into the elderly's daily life and challenges. For instance, a caregiver mentioned, *"...I can also communicate with her regarding the indices provided. For example, one day when I saw the sleep index is 2.9 (usually the value is around 5 to 6 for his mother), I asked her what was going on with her sleep the previous night. She would talk to me about the details, and I would learn more about her."*

The system not only meets the information needs of caregivers but also enriches the interactions between caregivers and the elderly, thereby significantly enhancing the understanding of the elderly's living status while maintaining a respectful and protective stance towards their privacy. Overall, all caregiver participants gave positive feedbacks the information provided is help to get to know their parent. Thus, we conclude The proposed notification approach is helpful to understand the elderly's living status.

Acceptance of the SAiPS System

The Technology Acceptance Model (TAM) [194, 195] is a widely-used model for understanding user adoption of new technologies. It posits that when users are presented with a new technology, a number of factors influence their decisions about how and when they will use it. The main constructs of TAM are perceived ease of use and perceived usefulness, which are crucial in determining users' attitudes towards technology and their eventual adoption behavior.

Perceived Ease of Use refers to the degree to which a person believes that using a particular system would be free of effort [194]. Perceived usefulness, on the other hand, is the degree to which a person believes that using a system would enhance their job performance or bring value to their lives [194, 196]. By assessing these two factors, we can evaluate the acceptance of our proposed system among the senior participants and their caregivers [195, 197].

We evaluated the perceived Ease-of-Use of our system for the following two major components: sensor units and the interface. In terms of sensor units deployed at the senior participants' homes, all the senior participants expressed that they barely felt the existence of the system during their daily life. For example, P2 said, "*These sensor units totally do not affect my daily life*". In terms of the web interface (see figure 6.1), the majority of the participants, including seniors and caregivers, favored it for its clarity and ease of interpretation. For instance, P1 stated, "*I can browse your website via my mobile phone and laptop easily. Interface is good as it is quite easy to understand.*"

Three styles of result notification, i.e., Living Well indices, 3D animation and story, allow the caregivers to select the one fit them better. Regarding the question: "Which one do you prefer to use between Living Well indices 3D animation or story?" C1 said, "*I like the short story as it is easier to help me understanding my mother.*" C2 expressed, "*I prefer indices, it is very concise for me to understanding my mother, just have a look, can save my time. The story is also good and can help understand the index at beginning.*" C3 expressed that he likes indices because he was busy every day, and he could check the indices quickly to know his mother's condition. C8 said, "*I appreciate the 3D animation that not only tracks my father's real-time status but also provides a concise summary, which is extremely helpful for staying updated on his condition during my busy periods.*" Overall, all the participants agreed that the system was quite easy to use.

The Perceived Usefulness of the system was generally positive among participants, as they found the indices and stories valuable for understanding and

Table 6.2: Rated Usefulness of the P-E fit indicators (Score range: 1-5).

	Motion	Regular Lifestyle	Social Interaction	Indoor Comfort	Sleep	Eating	Well-being
Average	4.5	4.6	3.8	4.7	4.5	4.4	4.6

supporting the older adults, felt the system was helpful in reducing worry, and expressed purchase intentions, emphasizing the system's importance in providing essential information about older adults' daily lives.

In the second interview (I_2^P and I_2^C), all caregivers agreed that the indices, well-being, 3D animation and stories were valuable for them to understand their parents, and all the senior participants agreed that the system was useful for both themselves and their children. When asked, "Do you feel the system is helpful? And in what ways?" C2 provided the following statement: "Yes, it is useful for me. The system not only lets me know about my mother's sleeping, cooking, movement, etc., but also..." P3 believes her son will worry less about her with our system, and P4 shares a similar opinion, saying, "I think the system is helpful for my son. I like the system as it can help caregivers know some information about the older adults."

During the interviews (I_2^P and I_2^C), all participants were asked to rate the usefulness of each predicted indicators and the well-being with scores from 1 to 5. The results are shown in Table 6.2. Generally, participants agreed that the six indices and the well-being were important for understanding the older adults' daily status, reflecting the system's usefulness.

Unobtrusiveness

Privacy is an important factor to be considered when designing home-based AIP service systems. This study, we want to find out to what extent is unobtrusive sensing accepted among senior users and the caregivers.

During the first interview (I_1^P and I_1^C), we asked the senior participants and their caregivers' for their opinions about camera-based home monitoring systems. As expected, all the senior participants held quite negative views towards such systems.

They all explicitly stated that they would not like to install cameras in their homes because they feel it would invade their privacy and compromise their dignity. The caregivers also expressed hesitance to use cameras for monitoring their senior parents. C3 remarked, "*I like to install a camera in my mother's place that I can see whether she is in a normal status from my smart-phone at any time I want, but my mother completely disagrees.*" C2 pointed out the limitation of using camera, stating, "*Camera can only be installed in the living room for the older adult who has serious diseases*"

After the participants used our system for more than a month, we conducted a second interview to gather feedback on privacy-related aspects of our system. All participants strongly agreed that the system is unobtrusive and minimally invasive to seniors' privacy. They all responded "Yes" to the question "Do you think the system preserves enough privacy?" and "Never" when asked to describe a time when our product disturbed them in some aspects of life. Unobtrusive sensing is non-intrusive, as confirmed by P1, "*All sensors are just there, no noise, no luminescence, I have never been disturbed by them. I don't feel uncomfortable about them at any time... It is OK that the system provides my daughter with information related to sleeping, cooking, etc.*" P4 said, "*There are no privacy issues for me. It would be better if the provided information could be customized according to the requirements of different older adults to avoid privacy issues. I guess some people may not like to disclose whether they have guests at home.*"

In summary, all participants agreed that the system is unobtrusive and minimally invasive, ensuring there is little invasion to the elderly's privacy. This unanimous agreement highlights the system's effective design in integrating seamlessly into daily life without compromising the dignity or comfort of senior users, effectively meeting the key objectives of the system design.

6.3.3 Discussion and Limitations

This study has provided significant insights into the effectiveness of the SAiPS system, particularly in the application of the PE4AIP model to enhance Aging in Place (AIP). However, several aspects warrant further discussion, and some limitations must be acknowledged to contextualize our findings.

Discussion

The results underscore the practical applicability and accuracy of the PE4AIP model in a real-world setting, demonstrating its potential to significantly improve elderly care by accurately predicting P-E fit indicators and well-being. This predictive accuracy is crucial for caregivers to intervene proactively, ensuring that the elderly maintain an optimal quality of life in their familiar environments.

Furthermore, the study revealed the system's effectiveness in aiding caregivers' understanding of the elderly's living status through unobtrusive monitoring. This is particularly important in reducing the emotional and physical burden on caregivers, as they can obtain critical information without constant physical oversight, which in turn can reduce stress and improve the relationship between caregivers and elderly family members.

The overall acceptance of the SAiPS system, as evidenced by high scores in perceived ease of use and usefulness, suggests that both elderly users and their caregivers see the value in integrating this technology into daily life. This acceptance is critical for the long-term success of any AIP solution.

Limitations

Despite these positive outcomes, the study has limitations that must be addressed in future research. First, the sample size and demographic diversity are limited, which may affect the generalizability of the findings. Participants were primarily from specific social and cultural backgrounds, and extending the study to a more diverse population could help validate the model across different settings.

Second, while the accuracy of P-E Fit indicators is promising, the variability in some indicators, such as Eating and Social Interaction, suggests that these areas may require further refinement. These indicators are crucial for a holistic assessment of well-being, and their lower accuracy could impact the system's overall effectiveness.

Third, the reliance on technology acceptance and the subjective assessment of unobtrusiveness could be seen as a limitation. Participants' perceptions might be influenced by their familiarity with technology or their personal attitudes towards privacy, which could introduce bias in the reported levels of acceptance and perceived invasiveness.

Finally, the technical aspects of the system, including the stability of sensor data transmission and the robustness of the backend algorithms, were not the focus of this study. Future studies should consider these elements to ensure the system's reliability and to address any technical challenges that could affect user experience.

6.4 Conclusions

The SAiPS represents a advancement in the field of AIP technology. Throughout the evaluation study, SAiPS demonstrated its ability to accurately reflect the well-being of elderly participants through innovative P-E Fit indicators. The system was highly effective in enhancing caregivers' understanding of the elderly's living conditions without compromising privacy, thanks to its unique 3D animation notification approach. Feedback from both elderly participants and their caregivers confirmed the system's usefulness, ease of use, and non-intrusive nature. These findings affirm the potential of SAiPS to provide a supportive, adaptive, and respectful environment for seniors wishing to maintain their independence at home. As we continue to refine and expand upon this technology, the insights gained from this study will guide further improvements, ensuring that SAiPS remains at the forefront of AIP solutions.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

By conducting a literature review and a focus group study, we identified challenges that our research seeks to address, delineated as the Research Question. In response, we proposed a theoretical architecture for AIP system design. This model incorporates a personalized well-being assessment model based on P-E Fit theory, termed the PE4AIP model, alongside Privacy Preserving Processing to process raw data on edge and end devices using AIoT technologies ensuring privacy. Furthermore, the architecture integrates a novel Data-Driven 3D Animation approach to notify caregivers while safeguarding privacy. We conducted a preliminary study involving three expert users over a period of three months, validated the usefulness of the P-E fie indicators proposed in the PE4AIP Model. An experimental study was also executed, demonstrating the feasibility in detecting real-time falls of the proposed TinyML algorithm on edge and end devices.

Further, a survey study with thirty participants explored the usability of the Data-Driven 3D Animation approach for notifications and monitoring elderly individuals at home. Lastly, a field study involving ten senior households assessed the real-world effectiveness, acceptance and practicality of our proposed SAiPS system, an implementation of the proposed design architecture. This research methodology showcases a logical progression from theoretical foundations through various testing phases, culminating in a practical Aging-in-Place application.

7.2 Summary of Contributions

This thesis presents contributions to the field of AIP enabled by advancements in AIoT technologies. The core contributions are summarized as follows:

1. **PE4AIP-Enabled AIP Design Architecture:** A novel AIP system design architecture, guided by the P-E Fit theory, has been proposed and validated through the Smart Aging in Place System (SAiPS). This architecture integrates privacy, personalization, and continuous monitoring, providing a robust framework for the design of systems that support the elderly in living independently and securely in their homes.

2. **Personalized PE4AIP Well-being Assessment Model:** The development of the PE4AIP model represents a paradigm shift in assessing the well-being of the elderly. This model captures the dynamic interactions between person characteristics, environmental characteristics, and person-environment interactions, offering a comprehensive and personalized approach to evaluating elderly well-being.

3. **Privacy-Preserving Fall Detection:** The thesis introduces a privacy-preserving fall detection technique using infrared sensors and TinyML technologies. Implemented on AIoT devices, this approach ensures that data processing occurs on the device, substantially enhancing privacy and enabling real-time and accurate fall detection.

4. **3D Animation Notification Approach:** A novel notification system that uses data-driven 3D animations to present the daily activities of the elderly has been developed. This approach addresses the privacy concerns associated

with conventional monitoring techniques and provides caregivers with intuitive and non-intrusive insights into the elderly's living conditions.

These contributions collectively enhance the capability of AIP systems to support the elderly in maintaining their independence while addressing critical aspects such as privacy, personalization, and caregiver communication. The implications of this research extend to improving the quality of life for the elderly and potentially reducing the need for traditional care facilities.

7.3 Future Work

The research presented in this thesis lays a robust foundation for advancing AIP solutions. While the outcomes have proven effective, several areas of future research have been identified to further refine and expand upon the current findings.

7.3.1 Large-Scale Longitudinal Studies

To validate the scalability and generalizability of the PE4AIP model and associated AIP systems, it is crucial to conduct longitudinal studies involving a broader demographic. The Large-scale longitudinal studies is centered on broadening the participant base to include diverse and broad ethnic groups. The aim is to incorporate a vast array of households from different ethnic backgrounds to ensure that the findings are not skewed by cultural biases. Since cultural factors greatly influence aging experiences, capturing a range of ethnic perspectives is essential for a holistic understanding. The expected outcome is a set of data that offers a comprehensive and insightful look into the lives of the elderly across cultures, leading to AIP solutions that are universally applicable and culturally sensitive.

Additionally, the study plans to extend its duration, recognizing that the conditions and needs of the elderly evolve over time. A longer study period will allow researchers to observe how the PE4AIP model adapts to these changes and to validate the long-term applicability of the P-E fit indicators. The long-term data collected will be invaluable in understanding the sustained impact of AIP systems on elderly care and will contribute to the longevity of the benefits provided by the system.

7.3.2 Advanced Intervention Strategies

The future direction of advanced intervention strategies aims to delve deeper into the principles of interventions and modifications guided by the Person-Environment Fit (P-E Fit) theory. The goal is to address current gaps in providing actionable guidance for caregivers on how to implement interventions or modifications when the fit between the elderly and their environment is less than ideal.

Research will focus on the development of sophisticated, automated systems that can analyze P-E Fit indicators in real time and propose customized interventions. By pinpointing specific areas where the person-environment fit is lacking, the system could suggest tailored environmental adjustments or intervention activities. For instance, if an elderly individual's motion levels are low, the system could recommend modifications to the home layout to encourage more movement or propose specific exercises tailored to the individual's abilities and health status.

Furthermore, this line of research aims to empower caregivers with the knowledge and tools to conduct these interventions effectively. Instead of a one-size-fits-all approach, the approch would consider the unique needs and preferences of each individual, leading to more personalized and effective care. The interventions could range from simple changes like adjusting the lighting and furniture placement to more significant modifications, such as installing assistive technologies or restructuring daily routines to enhance engagement and well-being.

Ultimately, the research into P-E Fit guided interventions and modifications will not only provide immediate benefits for the elderly and their caregivers but will also contribute to the broader understanding of how tailored environmental adjustments can improve quality of life for the aging population. This proactive and responsive approach to AIP has the potential to revolutionize elderly care by ensuring that living spaces and routines continuously evolve to meet the changing needs of individuals as they age.

By addressing these areas of future work, the research community can significantly advance the state of AIP systems, ensuring that they are more effective, personalized, and capable of supporting the elderly in maintaining a high quality of life independently.

List of Author's Awards, Patents, and Publications

Awards

- **Most Entertaining Video**, "Explainable and Persuasive AI for Successful TKR Rehabilitation," *IJCAI 18 Video Competition.*

Patents

- Weiming Li, **Huiguo Zhang**, Jun Lin, Yonghui Xu, Liang Zhang, and Chunyan Miao, "A method and device for adaptive leg kicking status recognition based on a nine-axis sensor," *China Patent ZL202011106339.1, May 24, 2022.*

Journal Articles

- Yonghui Xu, Shengjie Sun, **Huiguo Zhang**, Chang'an Yi, Yuan Miao, Dong Yang, Xiaonan Meng, Yi Hu, Ke Wang, Huaqing Min, Hengjie Song, and Chuanyan Miao, "Time-Aware Graph Embedding: A Temporal Smoothness and Task-Oriented Approach," in *ACM Trans. Knowl. Discov. Data 16, 3, Article 56 (June 2022), 23 pages, 2022.*

Conference Proceedings

- **Huiguo Zhang**, Yonghui Xu, Jun Lin, Weiming Li, and Zhiqi Shen, "A Serious Mobile Game for Neurodegenerative Diseases Rehabilitation and Risk Estimation," in *5th International Conference on Crowd Science and Engineering (ICCSE '21). Association for Computing Machinery, New York, NY, USA, 103–107.*

- Benny Tan, **Huiguo Zhang**, Chunyan Miao, and Siyuan Liu, "Exploring the use of Virtual Reality for Evaluating Activities of Daily Living: A Usability Study," in *5th International Conference on Crowd Science and Engineering (ICCSE '21). Association for Computing Machinery, New York, NY, USA, 119–123.*

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