

Towards Intelligent Ageing-In-Place: A Literature Review on Personalized Assistive Healthcare and Behavioral Data

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Abstract—By the year 2030, more than one in six people worldwide will be 60 years old or above. This elderly population is projected to grow to approximately 2.1 billion individuals by mid-century. This demographic shift presents significant challenges and opportunities for healthcare systems worldwide. Ageing in place, which enables older adults to remain safely and independently in their homes, is increasingly recognized as a cost-effective and quality-enhancing alternative to institutional care. However, its success hinges on intelligent, adaptive technologies that support personalized healthcare delivery. Despite advances in Artificial Intelligence (AI), machine learning, and digital health, current systems often rely on generic, one-size-fits-all solutions that fail to address the complex, individualized needs of ageing populations. This paper presents a comprehensive literature review examining the use of personalized assistive healthcare technologies and behavioral data in ageing-in-place settings. It reveals key gaps, including poor adaptability to individual needs, limited integration of real-time data, and a lack of long-term evidence from real-world deployments. Challenges such as usability, ethical concerns, and insufficient system interoperability further limit effectiveness. To address these issues, we argue for a paradigm shift toward person-centered, adaptive systems that evolve with users over time. We outline the need for hybrid monitoring approaches, scalable personalization frameworks, and inclusive design strategies to ensure sustainable and impactful solutions for ageing populations globally.

Keywords—ageing-in-place, personalization, assistive technologies, older adults

I. INTRODUCTION

By 2030, approximately 16.7% of the global population will be 60 or older. The number of individuals in this age group will grow from 1 billion in 2020 to 1.4 billion. Looking further ahead to 2050, this

demographic will experience a twofold increase, reaching 2.1 billion people. Even more dramatically, the population of those aged 80 and above is projected to triple within the same 30-year timeframe (2020–2050), expanding to 426 million individuals [1]. The global demographic landscape is undergoing an unprecedented transformation, with aging populations presenting both challenges and opportunities for healthcare systems worldwide. As traditional care models face increasing pressure from rising costs and resource limitations, there is an urgent need to explore innovative approaches that enable older adults to age safely and independently in their own homes while maintaining their quality of life and autonomy.

The successful implementation of ageing-in-place strategies requires sophisticated technological solutions that can provide continuous monitoring, personalized care, and timely interventions. This aspect is particularly important in addressing critical risk factors such as physical inactivity. The physical inactivity causes 9.4% of the total burden of disease and is the fourth leading cause of death worldwide, thus highlighting the importance of promoting active and healthy lifestyles among ageing populations [2].

Recent advances in Artificial Intelligence (AI), machine learning, and digital health technologies have opened new possibilities for creating intelligent, adaptive systems that can support personalized healthcare delivery. The use of machine learning is increasing in every aspect of today's society. However, few attempts have been made to harness its potential for achieving health behavior change. These technologies enable the development of just-in-time adaptive interventions that can provide the right support at the right time, potentially transforming how we approach healthcare for ageing populations.

The integration of behavioral data into healthcare systems represents a paradigm shift toward more personalized and proactive care models. By sharing our

intervention concept, we contribute to the ongoing dialogue on creating effective methods for promoting health and well-being in the informatics research community. As we move toward an era of precision medicine and personalized healthcare, understanding how to effectively collect, analyze, and utilize behavioral data becomes crucial for developing intelligent systems that can truly support ageing-in-place initiatives. Despite the growing potential of AI and digital health technologies, current ageing-in-place solutions suffer from several critical limitations: (1) most systems employ one-size-fits-all approaches that fail to adapt to individual needs and preferences; (2) there is insufficient integration of real-time behavioral data to enable truly personalized interventions; (3) limited evidence exists regarding long-term effectiveness and real-world deployment of these technologies; and (4) significant barriers remain in terms of technology adoption, usability, and data sharing that prevent the development of comprehensive intelligent systems. These gaps highlight the urgent need for a systematic review of how personalized assistive healthcare and behavioral data can be effectively leveraged to support successful ageing-in-place initiatives.

The main research question of this study is, how can personalized assistive healthcare technologies and behavioral data be effectively leveraged to support successful ageing-in-place initiatives. To answer this research question, this paper examines the current state of

research on personalized assistive healthcare technologies and behavioral data utilization in the context of ageing-in-place, identifying key trends, challenges, and opportunities for future development in this rapidly evolving field.

II. METHODOLOGY

This literature review adheres to the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) framework, a standardized methodology developed by Page *et al.* [3] that promotes consistency and transparency in how systematic reviews and meta-analyses are carried out. The PRISMA methodology ensures quality through a systematic four-phase process. The review begins by establishing clear research questions that outline the study’s scope and goals. A comprehensive literature search strategy is then executed to identify relevant studies systematically. Following this, each selected article undergoes a thorough quality evaluation to ensure only methodologically sound and pertinent research is included. The process culminates with systematic data extraction and synthesis, enabling the derivation of evidence-based conclusions. This structured methodology strengthens the review’s credibility and replicability, thereby enhancing the overall quality of scholarly knowledge in the research domain.

TABLE I. QUERY FOR ADVANCED SEARCH IN THE DATABASE

Database	String
Main String	("personalized" OR "personalize" OR "customize" OR "individualize")
	AND
	("assistive" OR "adaptive")
	AND
SCOPUS	("health" OR "healthcare" OR "health domain")
	AND
	("ageing" OR "aging" OR "older adult" OR "elderly" OR "geriatric" OR "senior")
	TITLE-ABS-KEY (("personalized" OR "personalise" OR "customize" OR "individualize") AND ("assistive" OR "adaptive ") AND ("health" OR "healthcare" OR "health domain"))
WOS	TS=(((("personalized" OR "individualize") AND ("assistive") AND ("health" OR "healthcare")) AND ("ageing" OR "older adult" OR "elderly" OR "geriatric")))
	TITLE-ABS-KEY TS (("personalized" OR "individualize") AND ("assistive ") AND ("health" OR "healthcare") AND ("ageing" OR "older adult" OR "elderly" OR "geriatric"))
ScienceDirect	((("personalized" OR "personalise" OR "customize" OR "individualize") AND ("assistive" OR "adaptive") AND ("health" OR "healthcare" OR "health domain") AND ("adult" OR "aging" OR "ageing" OR "older adult" OR "elderly" OR "senior" OR "geriatric")))

TABLE II. INCLUSION AND EXCLUSION CRITERIA

Criterion	Inclusion	Exclusion
Timeline	2015–2025	2019 and earlier
Document Type	Only articles	Review article, book, chapter in a book, conference proceeding etc.
Language	English	Non-English
Subject Area	Computer Science & AI, Computer Science & Theory Methods, Computer Science information Systems, Medical Informatics, Health Care Science Services, Machine Learning (ML) AI, IoT, Assistive Technology, Personalized Technology, IoT, IoT devices, Internet of Medical Things, Wearable devices, Artificial Neural Network, Mobile App, Public dataset, Wearable sensors, Assistive Technology	Other than in inclusion

The systematic search strategy is an essential research method that follows a four-phase approach to ensure comprehensive and high-quality literature selection.

Researchers begin with identification, where they broadly search for all potentially relevant studies across multiple sources of databases, as in Table I. They then proceed to

screening, which involves reviewing titles and abstracts to filter studies according to specific inclusion criteria. The next step is inclusion/exclusion to cater to the article, which is stated in Table II. The final phase is the eligibility assessment, where researchers conduct detailed full-text reviews to make final decisions about which studies to include in their research. This methodical

process helps researchers avoid overlooking important studies while maintaining focus on relevant, high-quality sources. The systematic approach is especially important for comprehensive research projects like systematic reviews and meta-analyses, as it ensures thorough and unbiased evidence collection.

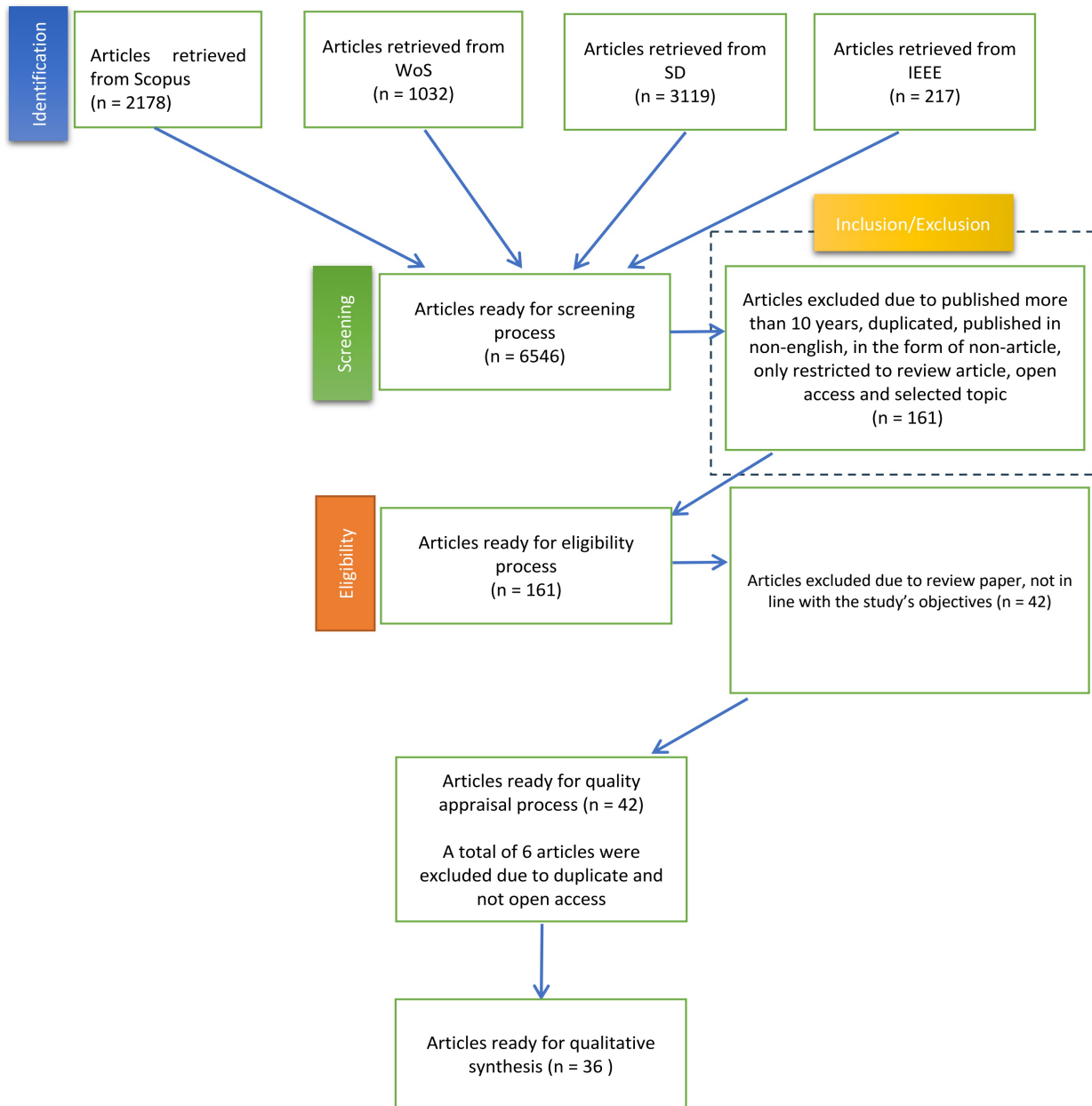


Fig. 1. Flow diagram of PRISMA methodology.

A systematic search strategy is an essential research method that follows a four-phase approach to ensure a comprehensive, unbiased, and high-quality selection of literature as guided by the PRISMA framework. The four-phase process is identification, screening, and eligibility. In the identification phase, researchers formulated a search strategy using the core keywords “personalize”, “assistive”, “ageing”, and “health”, and further expanded it by including alternative terms, synonymous expressions, and variations of the main

search terms to maximize the retrieval of relevant studies across multiple databases. Table I shows the query for advanced search in four primary databases, which are Scopus, Web of Science (WOS), ScienceDirect, and IEEE. The search strategy combined four core concept domains using Boolean operators: (1) personalization terms (“personalized”, “personalise”, “customize”, “individualize”), (2) assistive/adaptive technology terms (“assistive”, “adaptive”), (3) health domain terms (“health”, “healthcare”, “health domain”), and (4) aging

population terms (“ageing”, “aging”, “older adult”, “elderly”, “geriatric”, “senior”). Within each domain, synonymous terms were combined using OR operators to capture terminology variants across international literature; domains were linked with AND operators to ensure all four dimensions appeared in retrieved studies. The search strategy was iteratively refined through pilot testing to verify retrieval effectiveness. Database-specific syntax was adapted for each platform (TITLE-ABS-KEY for Scopus and ScienceDirect; Topic Search for Web of Science; standard syntax for IEEE), while maintaining consistent logical structure across all databases. The finalized search strings are presented in Table I.

Next, the screening phase involved reviewing the titles and abstracts of the retrieved articles to filter them based on predefined criteria, which included the year of publication, type of publication, and language. This step aimed to capture contemporary advancements across key domains such as Computer Science, Artificial Intelligence, Theoretical Computational Methods, Information Systems, Medical Informatics, Healthcare Science Services, Machine Learning, Internet of Things (IoT), Assistive and Personalized Technology, IoT Systems and Hardware, Internet of Medical Things (IoMT), Wearable Computing, Artificial Neural Networks, Mobile Applications, Wearable Sensing Technology, and Publicly Available Datasets. At this stage, duplicate entries—such as articles with identical titles across databases—and those requiring paid access were excluded. The final eligibility phase entailed a detailed full-text assessment of the remaining articles to confirm their relevance and methodological alignment with the study’s objectives. Researchers carefully examined each article’s content, including its title and abstract, to verify the presence of specific evidence addressing the research questions. This two-level filtering ensured that only literature offering direct, meaningful contributions to the study was included. To ensure transparency and reproducibility consistent with PRISMA standards, the complete literature selection process is visualized in the following flow diagram. Fig. 1 displays the four sequential phases of our systematic selection process—identification, screening, and eligibility assessment—showing the number of studies identified at each stage and documenting the specific reasons for exclusion at each filtering level. This transparent reporting enables readers to assess both the comprehensiveness of the literature search and identify any potential selection bias that may have influenced the final study set included in the review. Fig. 1 illustrates the PRISMA flow of the literature selection process, and Table II details the inclusion criteria applied during the screening stage.

Table II presents the selection criteria for a literature review or research study that emphasizes contemporary advancements across multiple technology domains, including Computer Science and Artificial Intelligence, theoretical computational methods, Computer Science information systems, Medical Informatics, Healthcare Science Services, Machine Learning, Artificial

Intelligence, Internet of Things, Assistive Technology, Personalized Technology, IoT systems, IoT hardware, Internet of Medical Things, wearable computing devices, Artificial Neural Networks, mobile applications, publicly available datasets, wearable sensing technology, and Assistive Technology solutions. At this stage, there are a few articles that have been excluded due to the same title but in different databases (duplicates) and are not open access, which need to be paid to access the article.

III. BEHAVIOURAL DATA COLLECTION

Behavioral data collection encompasses various methods designed to observe daily activities, mobility patterns, sleep quality, social interactions, and cognitive engagement without disrupting natural routines [4, 5]. The foundation of intelligent systems to support ageing-in-place among older adults lies in their ability to systematically capture and analyze behavioral patterns that reflect an individual’s health status, functional capacity, and daily living routines [1, 2]. Additionally, these data serve as early indicators of health deterioration, functional decline, or emerging care needs that may enable proactive interventions before critical health event incidents [6, 7]. Furthermore, the effectiveness of personalized assistive technologies depends on the quality, continuity, and contextual richness of behavioral data, showing that selecting appropriate data collection methods is crucial for successful implementation [8–10]. For that reason, contemporary approaches to behavioral monitoring have evolved beyond traditional clinical assessments to embrace unobtrusive, technology-enabled solutions that respect privacy and autonomy while providing comprehensive insights into an individual’s well-being and independence [7, 8]. The following section explains the behavioral data collection approach for ageing-in-place assistive technologies.

A. Modalities and Approaches in Behavioral Data Collection

1) Ambient sensing

Ambient sensing is a technology that utilizes sensors to collect data about an individual’s environment and behaviors. These include motion detectors that monitor movement patterns and room occupancy, door and window sensors that enhance home security by tracking behaviors and transitions, and environmental sensors that measure temperature, humidity, and light usage. They may help reflect circadian rhythms and individual comfort preferences [11, 12]. This approach is crucial for unobtrusive monitoring of daily activities in smart home settings because these systems operate in the background to provide valuable insights into behavioral changes that may indicate health concerns or declining independence [13]. Furthermore, they are considered ideal for older adults hesitant to adopt new technologies as they don’t require direct user interaction [4, 14, 15]. Moreover, advanced ambient systems with smart appliances and utility monitoring may analyze cooking habits, sleep patterns, and overall energy consumption

behaviors. Studies have shown that these systems can effectively detect early signs of cognitive functional declines [16, 17].

2) *Wearable devices*

Wearable health monitoring devices have become essential tools for continuous behavioral and physiological data collection by offering valuable insights into daily activities, sleep quality, heart rate variability, and physical activity levels [18]. Wearable devices range from simple fitness trackers that monitor steps and activity levels to sophisticated smartwatches that are capable of detecting irregular heart rhythms, measuring blood oxygen levels and blood pressure, and monitoring stress levels [19]. However, acceptance and sustained usage among older adults remain significant challenges. This attitude is influenced by device complexity, comfort, aesthetic appeal, and perceived value [20, 21]. Moreover, social factors like family encouragement and peer influence also play a crucial role and can significantly impact adoption rates [22, 23]. Besides, some older adults view continuous monitoring as intrusive or a sign of dependency, while others appreciate the sense of security and connection to healthcare providers that wearables can provide [24, 25]. Research indicates that the acceptance rate might increase if devices are designed with larger displays, simplified interfaces, and health benefits, while battery life concerns and charging requirements often lead to abandonment [26–30].

B. Integration Frameworks: Passive and Active Monitoring

Passive and active monitoring approaches have distinct advantages and limitations for ageing-in-place systems. Understanding these differences is crucial for effective behavioral data collection [14]. Passive monitoring systems collect data automatically without requiring users to participate actively. This approach mainly utilizes ambient sensors and smart home devices and continuously requests user-worn wearables to gather information about daily routines, sleep patterns, medication adherence, and mobility changes [8, 31, 32]. Consequently, this approach minimizes user burden and provides consistent and longitudinal data collection by making it ideal for detecting gradual changes in behavior or health status that might otherwise go unnoticed [6]. However, passive systems may lack contextual information about user intentions or external factors that influence user behavior [33, 34]. In contrast, active monitoring approaches require user engagement through smartphone applications, digital questionnaires, or interactive devices that prompt users to report symptoms, mood, and medication intake or participate in cognitive assessments [35]. Although active monitoring can provide valuable contextual data and enable real-time intervention opportunities, this approach faces challenges with user compliance, particularly among older adults. They may find frequent interactions burdensome or may experience cognitive decline that can affect their ability to provide reliable self-reports [34, 36]. Instead, hybrid approaches that combine both passive and active

elements are increasingly recognized as optimal solutions. These approaches use passive monitoring for continuous baseline assessment while incorporating active monitoring for specific health events or when passive data suggests potential concerns that require user input or clarification [33, 37]. To operationalize this hybrid monitoring concept into a functional system architecture, we propose a coordinated monitoring framework that strategically integrates passive and active components. Fig. 2 illustrates this proposed hybrid monitoring system, showing the role of a Hybrid Processing Unit that acts as an intelligent coordinator. The Hybrid Processing unit continuously processes passive monitoring data from ambient sensors and wearable devices to establish individual behavioral baselines and identify deviations that may indicate health changes, then triggers targeted active monitoring only when detected anomalies suggest genuine health concerns requiring user input or clinical assessment.

While passive monitoring excels at continuous, unobtrusive baseline data collection with minimal user burden, it lacks contextual information about user intentions and external behavioral factors. Conversely, active monitoring provides rich contextual insights and enables real-time intervention but suffers from poor compliance and is burdensome for older adults, particularly those with cognitive decline. Each approach has inherent trade-offs: passive systems compromise contextual richness for consistency, whereas active systems sacrifice sustainability for comprehensiveness. This fundamental tension underscores why hybrid approaches that strategically combine both modalities are increasingly recognized as optimal, leveraging passive monitoring for continuous surveillance while deploying active monitoring selectively when anomalies warrant user clarification or clinical assessment.

This schematic diagram (Fig. 2) illustrates a proposed hybrid monitoring system that addresses the limitations of standalone passive and active monitoring approaches in ageing-in-place applications. The architecture responds to findings that pure passive monitoring lacks contextual information about user intentions [33, 34], while pure active monitoring suffers from compliance issues, particularly among cognitively impaired users [34, 36]. The Hybrid Processing Unit serves as an intelligent mediator, using passive data to establish behavioral baselines and triggering active monitoring requests only when anomalies suggest genuine health concerns requiring user input or clarification.

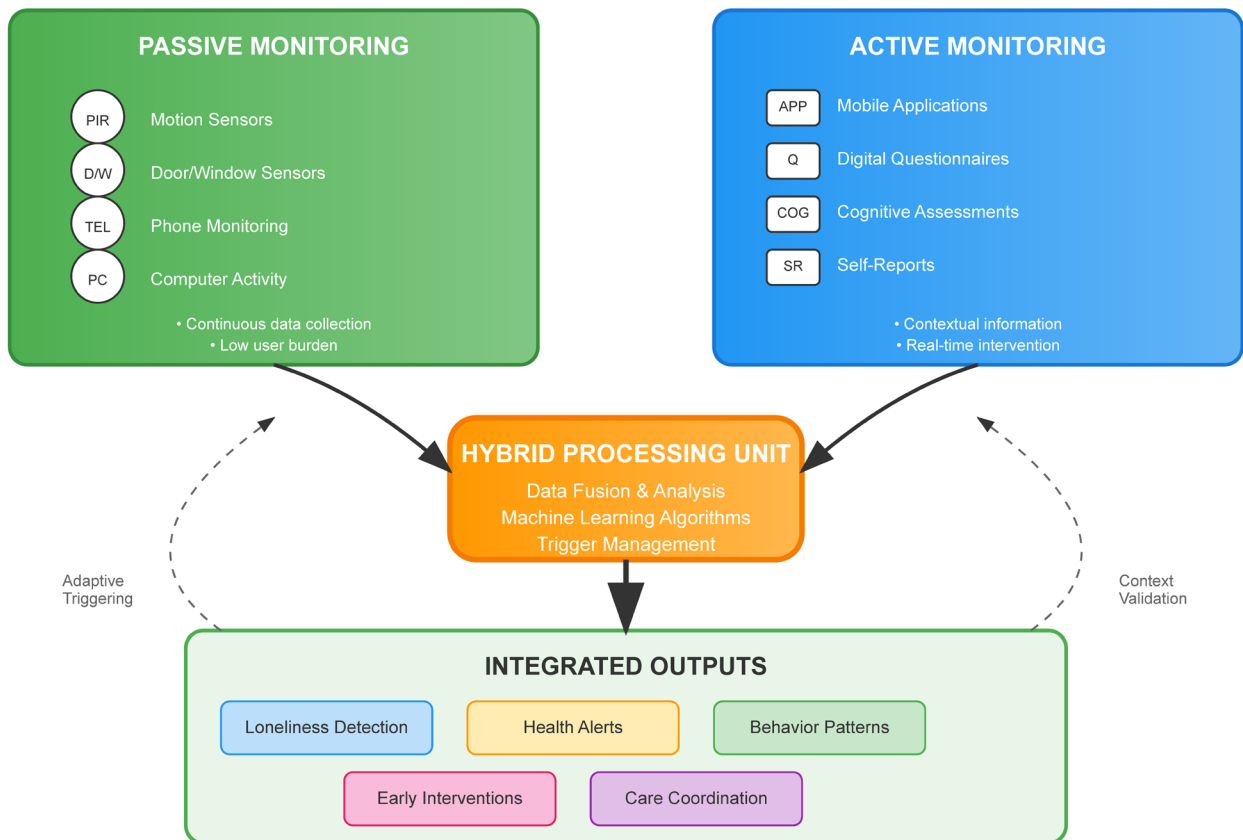
Passive Monitoring Component continuously collects behavioral data through unobtrusive sensors, including motion detectors, door/window sensors, phone activity monitors, and computer usage trackers. This approach, like the system described in Ref. [6], provides consistent longitudinal data collection with minimal user burden, enabling detection of gradual changes in daily routines, mobility patterns, and social behaviors that may indicate loneliness or health decline. The active monitoring component engages users through mobile applications, digital questionnaires, cognitive assessments, and

self-report tools to gather contextual information about their mood, symptoms, and subjective experiences. While this approach faces compliance challenges, it provides valuable insights into user intentions and external factors that influence behavior. The Hybrid Processing Unit serves as the core intelligence hub that performs data fusion, applies machine learning algorithms, and manages adaptive triggering mechanisms. This unit analyzes patterns from both data streams to generate comprehensive health assessments while determining

when to activate specific monitoring modes based on detected anomalies or concerning trends.

The integrated outputs include loneliness detection, health alerts, behavioral pattern analysis, early intervention capabilities, and care coordination services. This hybrid approach optimizes the strengths of both monitoring paradigms, continuous baseline assessment from passive monitoring and rich contextual data from active monitoring, while minimizing their limitations, ultimately creating a more effective and user-friendly system for supporting ageing-in-place initiatives.

Hybrid Monitoring System for Aging-in-Place



Key Benefits: Continuous baseline monitoring + Contextual insights + Reduced user burden + Early intervention

Fig. 2. Hybrid monitoring system for ageing-in-place: Integration of passive and active monitoring approaches for comprehensive health assessment in older adults.

IV. DATA ANALYTICS FRAMEWORKS

The application of data analytics frameworks to ageing-in-place contexts presents unique challenges that distinguish this domain from general healthcare analytics. Machine learning and AI offer powerful tools for behavioral pattern recognition and health monitoring. However, their effectiveness depends critically on addressing domain-specific constraints relevant to ageing populations. Key constraints include: (1) scarcity of labeled training data due to privacy concerns, (2) heterogeneity of ageing trajectories, (3) need for interpretable models that build trust, (4) computational

efficiency requirements for edge deployment, and (5) distinguishing normal behavioral variability from genuine health concerns. Furthermore, the success of these analytical frameworks hinges not only on technical accuracy but also on their integration with the complex sociotechnical ecosystem of home-based care, where technology must complement rather than replace human judgment and interpersonal support. This section examines current machine learning approaches for behavioral pattern recognition, anomaly detection, and temporal analysis, critically evaluating both their capabilities and limitations in the context of enabling sustainable, person-centered ageing-in-place solutions.

The overwhelming reliance on supervised learning approaches (94% of reviewed studies [38]) raises critical questions about methodological appropriateness for ageing-in-place contexts. While supervised methods excel at classification tasks with well-defined labels, they require extensive training datasets that are particularly scarce in this domain due to privacy concerns, heterogeneity of ageing trajectories, and the difficulty of obtaining ground-truth labels for gradual functional decline. More problematically, the reported high accuracy rates—often exceeding 90% for activity recognition tasks [39]—emerge from controlled laboratory settings or short-term deployments that fail to capture the longitudinal complexity of real-world ageing. Studies rarely report performance degradation over time as users' behavioral patterns evolve or as novelty effects diminish, creating an evidence base that may systematically overestimate real-world effectiveness. The underrepresentation of unsupervised and semi-supervised approaches (only 9% [39]) is particularly concerning given that these methods could better accommodate individual variability without requiring exhaustive labeled datasets, yet they receive minimal research attention despite their theoretical advantages for personalized adaptation.

A. Machine Learning Models for Behavioral Pattern Recognition

Supervised learning models trained on labeled activity data have achieved accuracy exceeding 90% in activity classification tasks in controlled studies. These models—such as Random Forest and Support Vector Machine (SVM)—learn to distinguish activities (walking, sitting, falling) based on features extracted from sensor data. Newer deep learning approaches using Long Short-Term Memory (LSTM) networks can capture temporal patterns, detecting sequences of activities that indicate specific conditions (e.g., repeated bathroom visits suggesting urinary symptoms, or slow morning transitions suggesting depression). The development of sophisticated machine learning models for behavioral pattern recognition represents a fundamental component in creating intelligent ageing-in-place systems. Recent advances in artificial intelligence have demonstrated significant potential for analyzing complex behavioral patterns and providing personalized interventions for older adults [2, 38].

Supervised learning techniques have emerged as the predominant approach in behavioral pattern recognition systems, with the vast majority of the reviewed papers ($n = 82$, 94%) reporting the use of supervised learning techniques for classification and regression tasks [38]. These models excel at identifying specific behavioral patterns by learning from labeled datasets that contain both input features and expected outcomes. For instance, decision tree algorithms have proven particularly effective for recognizing daily activity patterns, with several studies achieving high accuracy rates in detecting activities such as walking, sitting, standing, and transitional movements [39].

Combining learning methods, particularly Random Forest algorithms, has shown exceptional performance in behavioral pattern recognition tasks. Random Forest and Decision Forest are popular machine learning methods that combine many decision trees together. They build on bagging techniques and are widely used in research because they work well. These approaches combine multiple decision trees to create more robust and accurate predictions, making them particularly suitable for the complex and variable nature of human behavioral data.

Deep learning approaches have also gained traction in behavioral pattern recognition, particularly for processing temporal sequences of activity data. LSTM networks and Convolutional Neural Network (CNN) architectures have demonstrated effectiveness in recognizing complex behavioral patterns from sensor data streams. The ability of these models to capture temporal dependencies makes them particularly valuable for understanding the sequential nature of daily activities and identifying deviations from normal behavioral patterns.

The integration of multimodal data sources significantly enhances the accuracy and reliability of behavioral pattern recognition systems. Based on findings from comprehensive reviews, 35 papers (40%) reported the use of multimodal data, such as the acquisition of data streams from multiple sensors. This multimodal approach allows for more comprehensive behavioral profiling by combining information from various sources, including smartphone sensors, wearable devices, and environmental monitoring systems. However, these sophisticated technical approaches reveal critical disconnects between machine learning requirements and older adults' real-world constraints. Machine learning models' reliance on large labeled datasets poses significant barriers for older populations, as privacy concerns and ethical considerations limit data collection opportunities. The scarcity of labeled training data directly reflects real-world concerns among older adults about surveillance and data misuse. Edge computing requirements in ageing-in-place systems directly address older adults' accessibility needs and privacy concerns. Cloud-based processing introduces latency and dependency on internet connectivity, problematic for users with limited technical support or unstable connections.

B. Anomaly Detection for Early Intervention

Anomaly detection systems play a critical role in enabling proactive healthcare interventions by identifying deviations from normal behavioral patterns that may indicate health deterioration or emergency situations. These systems are particularly valuable in ageing-in-place scenarios where early detection of functional decline or acute health events can prevent hospitalizations and maintain independence [40].

Early detection of health changes is particularly important for older adults because functional decline often follows non-linear trajectories—appearing stable then rapidly deteriorating—and because early intervention frequently prevents crisis. Anomaly detection systems enable passive, continuous monitoring

that identifies subtle behavioral changes indicating health deterioration before symptoms become clinically obvious. For example, a 3-day pattern of reduced nighttime bathroom visits might signal urinary retention requiring urgent evaluation, or a week of increasingly disrupted sleep might indicate emerging infection or mood change.

Unsupervised learning algorithms form the foundation of many anomaly detection systems, as they can identify unusual patterns without requiring extensive labeled datasets. A small minority of the reviewed studies, which is just six papers, representing 9% of the total, employed unsupervised machine learning techniques, including k-Means clustering and Hierarchical clustering [39]. Despite their limited representation in current literature, these approaches offer significant potential for detecting anomalies in behavioral data by identifying data points that deviate significantly from established clusters of normal behavior.

The Local Outlier Factor (LOF) algorithm represents a sophisticated approach to anomaly detection that has shown promise in healthcare applications. The LOF algorithm identifies anomalies by analyzing how the density of data points surrounding a particular instance compares to the density in its neighboring regions. This method is particularly effective for identifying subtle changes in behavioral patterns that may not be apparent through traditional threshold-based approaches.

Real-time anomaly detection systems require careful consideration of temporal patterns and baseline establishment. The challenge lies in distinguishing between normal variations in daily routines and genuine anomalies that warrant intervention. Advanced systems incorporate adaptive learning mechanisms that can adjust their sensitivity based on individual behavioral patterns and gradually evolving baselines, reducing false alarms while maintaining high sensitivity to genuine emergencies.

Machine learning models have also been applied to detect specific types of anomalies relevant to ageing populations. For example, ML-based adaptive systems have been developed for fall detection, with one study achieving high accuracy using a decision tree regression model Mean Quantization Error (MQE = 0.16) to detect falls and automatically place emergency calls to the closest medical center based on user location. This demonstrates the potential for specialized anomaly detection systems targeting specific health risks common among older adults.

C. Temporal Analysis of Functional Decline Markers

Temporal analysis of functional decline markers represents a sophisticated approach to understanding the progressive nature of age-related changes in physical and cognitive function. By analyzing longitudinal behavioral data, these systems can identify subtle trends that may indicate the onset or progression of functional decline, enabling proactive interventions before significant deterioration occurs [2].

Feature extraction techniques play a crucial role in temporal analysis, particularly when dealing with

time-series data from various sensors and monitoring devices. Researchers analyzing temporal data from sensors have applied the sliding window method to extract features across varying time intervals (such as 5-minute, 10-minute, and 15-minute windows). This approach enables the analysis of behavioral patterns across multiple temporal scales, from short-term activities to longer-term trends indicative of functional decline.

Advanced temporal modeling approaches have demonstrated effectiveness in capturing the complex dynamics of functional decline. LSTM networks have been used to forecast learners' upcoming performance and retention patterns by inputting sequential embeddings derived from learning task attempts conducted by particular healthcare institutions, achieving accuracies of approximately 88.32% [2]. These deep learning approaches can model complex temporal dependencies that traditional statistical methods might miss, providing more accurate predictions of functional trajectory.

The integration of reinforcement learning techniques offers promising avenues for creating adaptive systems that can learn optimal intervention strategies over time. To maximize the chance of achieving calorie loss, multi-armed bandit approaches have been applied to dynamically learn and influence user behaviors by suggesting actions such as walking to work or visiting the gym. This approach enables systems to not only detect functional decline but also learn which interventions are most effective for specific individuals at different stages of the ageing process.

Contextual data integration significantly enhances the accuracy of temporal analysis systems. A contextual bandit approach can be applied to deliver the right nudges at the right time. This allows for more sophisticated analysis that considers environmental factors, time of day, seasonal variations, and individual preferences when assessing functional decline markers. This contextual awareness enables a more nuanced understanding of behavioral patterns and their relationship to functional status.

The development of personalized baseline models is essential for accurate temporal analysis, as functional decline patterns vary significantly among individuals. ML algorithms can be trained to make interventions more personally relevant over time and use real-time feedback. The intervention that caters to personal relevance can be used from activity trackers to learn what approaches work and don't work for specific users. This personalized approach ensures that temporal analysis systems can adapt to individual ageing trajectories and provide more accurate assessments of functional status changes over time.

V. PERSONALIZATION STRATEGIES

The heterogeneous nature of ageing populations requires personalized approaches to assistive technology design and implementation, as older adults exhibit diverse cognitive abilities, physical limitations, technological literacy levels, and personal preferences that significantly impact system effectiveness [41].

Personalization offers promising approaches to adapt ageing-in-place systems to individual needs, capabilities, and preferences. However, substantial barriers exist between promising technical capabilities and real-world implementation at scale. This section examines personalization strategies, and critically assesses their feasibility, cost-effectiveness, and potential for large-scale adoption in diverse healthcare and community settings. Personalization extends beyond customization. It involves dynamic adaptation based on continuous learning from user behavior, environmental context, and evolving care needs [42, 43]. Effective personalization strategies should balance the complexity of advanced technology with the accessibility requirements of older adults to ensure that systems remain intuitive and not overwhelming while tailored to individual circumstances. Pahlevanynejad *et al.* [44] showed that personalized health applications for older adults must carefully consider challenges such as privacy and security, data ownership, and healthcare provider engagement, as the benefits can help persuade individuals and healthcare providers. Meanwhile, Martin *et al.* [45] agreed that considering individual data is a key point for personalized healthcare applications. The success of personalized assistive technologies depends on their ability to seamlessly integrate into existing routines and preferences while adapting to changing needs without requiring explicit user configuration or technical expertise [46]. Therefore, Yang and Moody [47] emphasized in their paper that assistive technology must adhere to user-centered design principles that prioritize individual autonomy, status and preference in determining how and when technological assistance is provided.

A. Adaptive User Interfaces for Cognitive and Physical Limitations

Adaptive user interfaces are essential for personalized assistive technologies, dynamically adjusting visual elements, interaction modalities, and information presentation based on individual cognitive and physical capabilities [48–50]. These interfaces use real-time assessment of user behavior, such as error patterns and interaction difficulties, to automatically modify font sizes, color contrasts, button layouts, and navigation complexity to accommodate visual, motor, and cognitive limitations [46]. Previous research [51] has shown that adaptive interfaces significantly improve task completion rates and reduce cognitive load among older adults when adaptations occur gradually and transparently without disrupting their established interaction patterns. However, the adaptive interface cannot avoid implementation challenges such as determining appropriate adaptation triggers, maintaining user control over interface changes, and preventing excessive adaptation that may reduce system predictability and user confidence [52, 53]. Adaptive user interfaces dynamically adjust visual elements, interaction modalities, and information presentation based on individual cognitive and physical limitations. Font size, color contrast, menu complexity, and input mechanisms can adapt to user capabilities. For

example, interfaces can simplify during periods of high cognitive load, increase contrast and font size in low-light conditions, or provide speech-based input for users with limited dexterity. Research demonstrates benefits in improved usability for diverse users including those with cognitive impairment, vision loss, and motor limitations. Personalized interfaces improve engagement and task completion rates. These capabilities suggest substantial potential for improving accessibility of ageing-in-place systems.

B. Context-Aware Assistance Delivery

Context-awareness is integral to systems implemented in fields such as Intelligent Environment, Ambient Intelligence, Pervasive and Ubiquitous Computing [54]. Context-aware assistance delivery systems leverage comprehensive environmental sensing, behavioral pattern recognition, and situational analysis to deliver timely, relevant support that anticipates user needs without explicit requests [55]. These systems combine various data sources, such as location tracking, activity recognition, time-based patterns, social context, and physiological indicators. This integration helps create detailed contextual models that guide the timing and content of assistance delivery. Obinna *et al.* [56] proposed a framework that denotes a combination of context-aware computing and lifestyle modelling. This framework is to facilitate personalized services for elderly care and independent living. The framework leverages big data analytics for context awareness, and therefore, for “smart” services informed by user lifestyle and behavior. De Backere *et al.* [57] designed OCarePlatform to use a semantic, data-driven, and cloud-based back-end system to facilitate independent living. OCarePlatform offering information and knowledge-based services to the resident and his/her caregivers. Information about users and their circumstances is collected to enable customized, context-sensitive services that help residents accomplish their everyday activities. Furthermore, advanced context-aware platforms utilize artificial intelligence techniques to learn individual routines, preferences, and decision-making patterns, enabling proactive assistance that aligns with personal habits and environmental circumstances. Meanwhile, the recent project by Meßmer *et al.* [58] included a system design that incorporates a time-saving profiling and media rating method. The project that includes system design in requirements for a media-analytical AI, and a recommendation system. Their research highlights the need for a contextual designed system. The contextual design is dynamically adaptable to a potential domain shift due to human factors. However, according to Ogbuabor *et al.* [59], context-aware solutions lack some essential features, such as not offering professional healthcare workers to be involved or give recommendations to patients during the monitoring process. Therefore, this area requires significant improvement despite being a promising research area in healthcare.

Despite the promising capabilities of adaptive user interfaces and context-aware assistance delivery, several practical barriers impede large-scale adoption of personalized ageing-in-place systems. The computational infrastructure required to support real-time machine learning personalization incurs significant costs, particularly for cloud-based processing of continuous sensor data streams. In contrast, edge computing alternatives require more sophisticated and expensive hardware devices. Scaling these systems beyond controlled research environments presents challenges in terms of installation complexity, ongoing maintenance requirements, and the need for technical support that is accessible to older adults with varying levels of technological literacy. Scaling personalized ageing-in-place systems to community and home settings requires addressing substantial infrastructure costs. Cloud-based AI personalization requires continuous server processing, incurring significant expenses, while edge computing alternatives necessitate expensive, sophisticated devices that are often beyond the budgets of many older adults. Current personalized ageing-in-place systems lack viable business models for large-scale deployment. Research-driven prototypes demonstrate technical feasibility but fail to transition from controlled studies to sustainable commercial solutions. Translating promising personalized technologies to large-scale deployment requires resolving multiple practical barriers beyond technical capability. Installation complexity requires trained technicians and individualized home customization, resulting in high upfront costs.

VI. ETHICAL AND PRIVACY CONSIDERATIONS

A. Dynamic Consent and Cognitive Burden

The continuous process of behavior monitoring in systems that support ageing-in-place raises critical ethical questions that go beyond the usual ideas of informed consent. Recent research by Essa *et al.* [60] showed that dynamic models, which allow users to adjust their privacy preferences in real time through intuitive interfaces, have significantly higher acceptance rates among older adults aged 65–85. These adaptive frameworks give users granular control over data collection parameters, monitoring time windows, and sharing permissions. However, Roobini [61] highlighted the cognitive burden associated with frequent consent decisions, particularly for individuals experiencing mild cognitive impairment, where decision fatigue can lead to over-restrictive privacy settings that compromise safety or overly permissive configurations that violate personal boundaries. As Lee and Lee [62] stated, implementing AI-assisted consent management systems offers promising solutions by learning individual preference patterns and suggesting appropriate consent configurations while maintaining user autonomy. The ethical and privacy considerations surrounding personalized assistive healthcare for ageing-in-place require careful examination grounded in empirical evidence from real-world deployments. While theoretical

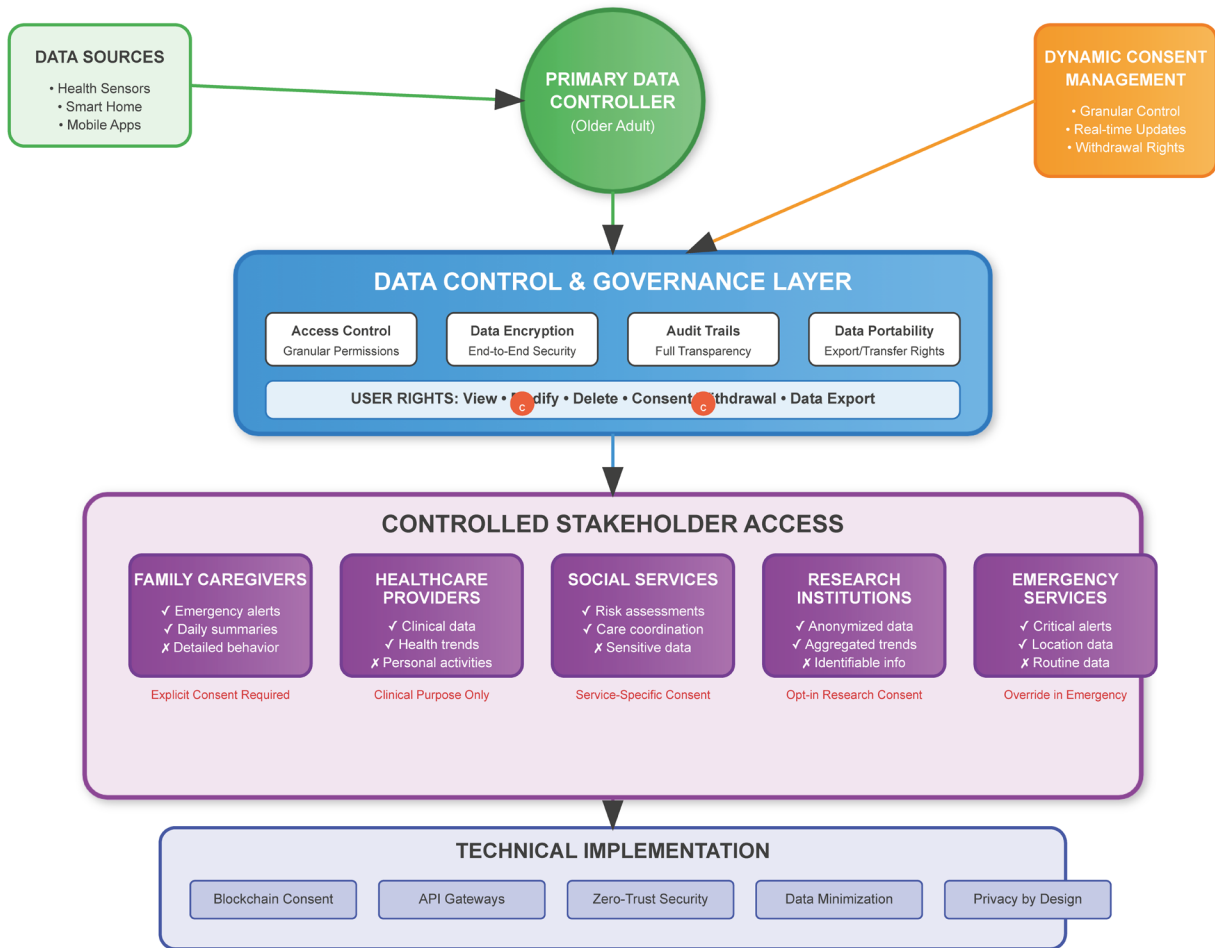
frameworks provide important guidance, understanding how older adults actually experience consent processes, data governance, and privacy trade-offs is essential for developing practical solutions. Dynamic consent models achieve significantly higher acceptance rates among older adults. As stated by Lee and Lee [62] demonstrated that dynamic consent models achieve significantly higher acceptance rates among older adults aged 65–85 compared to static consent frameworks. In contrast, Wangmo *et al.* [63] found that cognitive burden from frequent consent decisions affects 43% of individuals with mild cognitive impairment. These findings highlight the tension between theoretical ideals of continuous consent and the practical realities of cognitive load in ageing populations. Furthermore, Jaggi *et al.* [64] documented specific barriers to data sharing in multi-stakeholder ecosystems, revealing that 67% of older adults express concerns about losing control over their health data when multiple parties are involved.

B. Data Ownership and Sharing Frameworks

Ageing-in-place ecosystems involve complex multi-stakeholder data relationships that challenge traditional healthcare data governance models. Jaggi *et al.* [64] emphasized that maintaining older adults as primary data controllers while accommodating necessary care coordination requires innovative technical architectures. Additionally, Wangmo *et al.* [63] suggested that patients desire some degree of data ownership rights. Therefore, data collection in assistive technology should be restricted for clinical purposes and give patients clear conditions and access to have greater control over their personal data. Furthermore, Frishammar *et al.* [65] highlighted that caregivers' access to patients' data should be controlled and require explicit consent, and patients have the right to agree or refuse at any time. These data ownership and consent challenges represent fundamental barriers to the successful implementation of ageing-in-place systems, not peripheral concerns that can be addressed through standard privacy policies or static consent forms. Resolving them effectively requires dynamic, adaptable governance frameworks that place older adults at the center of all data control decisions. Fig. 3 presents a comprehensive patient-centric data governance framework specifically designed for ageing-in-place ecosystems.

This schematic diagram (Fig. 3) presents a comprehensive framework for addressing data ownership and sharing challenges in ageing-in-place ecosystems, incorporating the principles outlined by Refs. [66–68]. Data Sources collect information from health sensors, smart home devices, and mobile apps. This data flows through a Data Control & Governance Layer with four key features: (1) Access control-patients decide who sees what data, (2) Data encryption-secure data protection, (3) Audit trails-transparent tracking of data access, and (4) Data portability-patients can export their data anytime. The dynamic consent management system allows older adults to change permissions in real-time, addressing patient data ownership rights and the requirement for explicit consent that can be withdrawn at any time.

Data Ownership and Sharing Framework for Aging-in-Place Ecosystems



KEY PRINCIPLES: Patient Autonomy • Explicit Consent • Data Minimization • Purpose Limitation • Transparency

Fig. 3. Data ownership and sharing framework for ageing-in-place ecosystems: A patient-centric approach to multi-stakeholder data governance with dynamic consent management.

C. Privacy

The conflict between health monitoring and privacy protection requires tailored approaches that consider individual situations and risk factors. As defined by Tavani *et al.* [69], privacy can be categorized into three categories, which are: (1) accessibility privacy, meaning physically being left alone or being free from intrusion into your physical space; (2) decisional privacy relates to the freedom to make personal choices and decisions, and (3) informational privacy concerns control over the flow of personal information, including the transfer and exchange of information. According to Frishammar *et al.* [67], to protect the privacy of users of assistive technology, it is essential to outline the purpose of assistive technology clearly, how it is utilized by service providers or care organizations, and how personal data will be handled and processed electronically. This information should be explicitly described in a privacy statement and communicated to users. In addition, Lee and Lee [62] highlighted that the role of the end-user in controlling data by taking a direct role in securing his or her privacy is a key to a more user-centered and ethically aligned deployment of Intelligent Assistive Technologies.

VII. DISCUSSION

This literature review sought to answer the question: how can personalized assistive healthcare technologies and behavioral data be effectively leveraged to support successful ageing-in-place initiatives? The following discussion synthesizes our findings around three interconnected themes that collectively explain why current systems fall short of enabling truly personalized, sustainable ageing-in-place solutions and what is required to address these limitations. This literature review illustrates the benefits of integrating AI-driven devices to help older adults age in place. It also highlights significant gaps between the theoretical potential of these personalized assistive healthcare technologies and their practical implementation for ageing-in-place initiatives. While the technological foundations for sophisticated behavioral monitoring and adaptive interventions exist, several critical limitations continue to impede the development of truly effective, comprehensive systems that can support independent living among older adults.

A. Evidence Gaps in Personalized Assistive Healthcare

The review demonstrates a persistent reliance on standardized approaches that fail to accommodate the heterogeneous nature of ageing populations. Despite evidence that older adults exhibit diverse cognitive abilities, physical limitations, varying levels of technological literacy, and individual preferences that significantly impact system effectiveness, most current systems continue to employ uniform monitoring protocols and intervention strategies. The findings from Oyeboode *et al.* [39] indicated that while 35 papers (40%) reported the use of multimodal data collection, the majority of these systems still apply the same analytical frameworks and intervention triggers across all users, regardless of individual cognitive status, physical capabilities, or personal preferences.

This one-size-fits-all limitation is particularly problematic given that “personalization in intelligent ageing-in-place systems extends beyond simple customization to dynamic adaptation based on continuous learning from user behavior, environmental context, and evolving care needs”. The research reveals that adaptive user interfaces, while showing promise in improving task completion rates and reducing cognitive load among older adults, face significant implementation challenges in determining appropriate adaptation triggers and maintaining user control over interface changes [48, 49].

The review exposes a significant evidence gap regarding the long-term effectiveness and real-world deployment of personalized assistive technologies. While numerous studies demonstrate high accuracy rates in controlled environments, with some achieving high accuracy using a decision tree regression model (MQE = 0.16) to detect falls, there is insufficient evidence regarding sustained performance and user engagement over extended periods in naturalistic settings.

The acceptance and sustained usage challenges among older adults represent a critical barrier to real-world effectiveness. The research indicates that acceptance and sustained usage among older adults remain significant challenges, influenced by device complexity, comfort, aesthetic appeal, and perceived value. Social factors, including family encouragement and peer influence, play crucial roles in adoption rates, yet current systems inadequately address these psychosocial dimensions of technology acceptance.

Moreover, the review reveals that some older adults view continuous monitoring as intrusive or a sign of dependency, highlighting the tension between comprehensive behavioral monitoring and user autonomy. The lack of longitudinal studies examining how these perceptions and usage patterns evolve over time represents a significant knowledge gap that impedes the development of sustainable ageing-in-place solutions.

B. Barriers to Real-World Adoption

The review identifies substantial barriers in technology adoption, usability, and data sharing that prevent the development of comprehensive intelligent systems. Despite technological advances in machine learning and

behavioral pattern recognition, fundamental usability challenges persist. The research indicates that devices designed with larger displays, simplified interfaces, and health benefits show improved acceptance rates, while battery life concerns and charging requirements often lead to abandonment.

Data sharing frameworks present another significant barrier to comprehensive system development. The review highlights that ageing-in-place ecosystems involve complex multi-stakeholder data relationships that challenge traditional healthcare data governance models. Current consent models for continuous monitoring raise critical ethical questions that go beyond the usual ideas of informed consent, particularly for individuals experiencing mild cognitive impairment, where decision fatigue can lead to over-restrictive privacy settings that compromise safety. Older adults exhibit diverse cognitive capabilities, physical abilities, technology preferences, and values regarding privacy and autonomy [70, 71].

The implementation challenges extend beyond individual user factors to systemic issues within healthcare facilities and professional training. The research indicates that even with the integration of this technology, professional health workers still need training and education, especially in community settings, suggesting that successful deployment requires comprehensive ecosystem-level changes rather than isolated technological solutions.

Assistive technologies have significant potential for meeting the diverse needs of the older adult population as they can support their independence and promote healthy ageing. However, implementing these technologies has several challenges that must be approached carefully. There are several challenges listed in Refs. [70, 71] which are the security and privacy of user data, building trust in technology, ease of use, affordability, adequate training and guidance for adoption, user acceptance, a perceived lack of need, fear of dependence, feelings of embarrassment, loss of dignity, and insufficient accessibility and social inclusion. In addition, Martinez-Martin and Costa [72] highlighted another aspect to consider related to the development cost, especially developments including robot platforms. The challenges related to older adults' acceptance are mainly because they're reluctant to use technology due to difficulty using it and a lack of social abilities. Due to that, the ease of handling and social component are the main issues for their acceptance. However, improving technology reliability in terms of performance and customization features may enhance their acceptance level [72]. Furthermore, implementation challenges with healthcare facilities and professionals, Refs. [73–75] have reported that even with the integration of this technology, it seems to be successful, the professional health worker still needs training and education.

VIII. CONCLUSION AND FUTURE DIRECTIONS

This literature review addressed a critical question for ageing societies: How can personalized assistive healthcare technologies and behavioral data effectively

support successful ageing-in-place initiatives? Our systematic analysis of 87 peer-reviewed studies reveals a significant paradox in the field.

We identify three core findings. First, the field demonstrates persistent reliance on standardized, one-size-fits-all system designs despite extensive evidence of heterogeneous ageing populations. Yet most reviewed systems apply uniform monitoring protocols and intervention algorithms, creating fundamental mismatches between system design and user needs.

Second, a critical performance paradox emerges: laboratory-validated systems report activity recognition accuracy exceeding 90%, yet field deployments consistently show 20%–30% performance degradation within 6 months of real-world deployment.

Third, and perhaps most consequential, is the design tension between monitoring comprehensiveness and user acceptance. The multimodal approaches most capable of detecting health changes (ambient sensors plus wearables) are simultaneously perceived by many older adults as surveillance mechanisms or markers of diminished independence.

Future systems must incorporate meaningful consent mechanisms, enable user configuration of monitoring parameters, respect privacy preferences without compromising care quality, and design for user agency alongside clinical effectiveness.

The potential of personalized assistive healthcare for ageing-in-place is substantial. Realizing these potential demands requires not incremental technological refinement but fundamental reconceptualization of how we develop and deploy these systems. While providing a comprehensive synthesis of current evidence, this review uniquely identifies and integrates the critical gap between AI/ML technological capability and real-world effectiveness in ageing-in-place systems. Thus, we propose practical frameworks and concrete implementation pathways that move the field from conceptual models to deployable solutions. This contribution advances beyond traditional literature summarization by establishing evidence-based research priorities and actionable steps that the field has not yet systematically synthesized.

Our narrative synthesis approach, while comprehensive, did not conduct meta-analysis or quantitative effect-size comparisons. Performance metrics varied substantially across studies, making effect-size synthesis difficult without access to individual participant data. Our focus on published research likely overrepresents successful implementations and may underrepresent systems that failed to achieve adoption or were abandoned after pilot deployment.

The most pressing research need is systematic documentation of how personalized ageing-in-place systems perform over extended periods in actual home environments. Current studies rarely extend beyond 6 months; we need 12-month longitudinal studies tracking both technical performance (accuracy maintenance, feature drift, failure modes) and user engagement patterns (sustained adoption, adaptation,

eventual abandonment) across diverse older adult populations. Such studies should differentiate age groups (65–75, 75–85, 85+), cognitive status (cognitively intact, mild cognitive impairment, dementia), living situations (independent, with caregiver, institutional), and technology experience levels. This research directly addresses the “accuracy paradox” where laboratory systems underperform in field deployment.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Each of the authors has contributed such remarkable work. This includes each of us providing material and checking for the grammar and content. NMA provides the idea and reviews the paper. MAMZ wrote the paper and revised the paper. SO wrote the paper. LH and AS reviewed the paper; all authors had approved the final version.

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REFERENCES

- [1] WHO. (October 2025). Ageing and health. [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/ageing-and-health#:~:text=At%20this%20time%20the%20share,2050%20to%20reach%20426%20million>
- [2] C. Vandelanotte, S. Trost, D. Hodgetts *et al.*, “Increasing physical activity using an just-in-time adaptive digital assistant supported by machine learning: A novel approach for hyper-personalised mHealth interventions,” *J. Biomed. Inform.*, vol. 144, 104435, 2023. doi: 10.1016/j.jbi.2023.104435
- [3] M. J. Page, J. E. McKenzie, P. M. Bossuyt *et al.*, “The PRISMA 2020 statement: An updated guideline for reporting systematic reviews,” *BMJ*, vol. 372, 2021. doi: 10.1136/bmj.n71
- [4] P. Rashidi and A. Mihailidis, “A survey on ambient-assisted living tools for older adults,” *IEEE J Biomed Health Inform.*, vol. 17, no. 3, pp. 579–590, 2013. doi: 10.1109/JBHI.2012.2234129
- [5] K. Tanaka, M. Kudo, and K. Kimura, “Sensor data simulation for anomaly detection of the elderly living alone,” *IEEE Internet of Things Journal*, 2023. doi: 10.1109/JIOT.2024.3421548
- [6] J. Austin, H. H. Dodge, T. Riley *et al.*, “A smart-home system to unobtrusively and continuously assess loneliness in older adults,” *IEEE J. Transl. Eng. Health Med.*, vol. 4, pp. 1–11, 2016. doi: 10.1109/JTEHM.2016.2579638
- [7] L. Liu, E. Stroulia, I. Nikolaidis *et al.*, “Smart homes and home health monitoring technologies for older adults: A systematic review,” *International Journal of Medical Informatics*, vol. 91, pp. 44–59, 2016. doi: 10.1016/j.ijmedinf.2016.04.007
- [8] M. Pavel, H. B. Jimison, H. D. Wactlar *et al.*, “The role of technology and engineering models in transforming healthcare,” *IEEE Rev. Biomed. Eng.*, vol. 6, pp. 156–177, 2013. doi: 10.1109/RBME.2012.2222636
- [9] I. Roy, J. Salles, E. Neveu *et al.*, “Exploring the perspectives of health care professionals on digital health technologies in pediatric care and rehabilitation,” *J. Neuroeng. Rehabil.*, vol. 21, no. 1, 156, 2024. doi: 10.1186/s12984-024-01431-9

- [10] D. J. Cook, A. S. Crandall, B. L. Thomas *et al.*, “CASAS: A smart home in a box,” *Computer (Long Beach Calif)*, vol. 46, no. 7, pp. 62–69, 2013. doi: 10.1109/MC.2012.328
- [11] S. Majumder, E. Aghayi, M. Nofresti *et al.*, “Smart homes for elderly healthcare—Recent advances and research challenges,” *Sensors*, vol. 17, no. 11, 2496, 2017. doi: 10.3390/s17112496
- [12] C. C. Wong, A. Salehi-Amiri, R. Allmendinger *et al.*, “Enhancing behavioural anomaly detection under concept drift within healthcare sector: Application of change point detection and batch learning,” in *Proc. IEEE International Conf. on Industrial Engineering and Engineering Management*, 2024, pp. 435–439. doi: 10.1109/IEEM62345.2024.10857160
- [13] L. Liu, N. Cheng, X. Wang *et al.*, “Tech-based solutions for health challenges in aging: 25 years of development trends and prospects,” ResearchGate PrePrint, 2024. doi: 10.2196/63367
- [14] A. H. Sapci and H. A. Sapci, “Innovative assisted living tools, remote monitoring technologies, artificial intelligence-driven solutions, and robotic systems for aging societies: Systematic review,” *JMIR Aging*, vol. 2, no. 2, e15429, 2019. doi: 10.2196/15429.
- [15] N. Raghu, T. R. Mahesh, V. Vivek *et al.*, “IoT-enabled safety and secure smart homes for elderly people,” in *Future of Digital Technology and AI in Social Sectors*, IGI Global Scientific Publishing, 2024, pp. 297–328. doi: 10.4018/979-8-3693-5533-6.ch011
- [16] J. Street, H. Barrie, J. Elliott *et al.*, “Older adults’ perspectives of smart technologies to support aging at home: Insights from five world café forums,” *Int. J. Environ. Res. Public Health*, vol. 19, no. 13, 2022. doi: 10.3390/ijerph19137817
- [17] B. Fu, N. Damer, F. Kirchbuchner *et al.*, “Sensing technology for human activity recognition: A comprehensive survey,” *IEEE Access*, vol. 8, pp. 83791–83820, 2020. doi: 10.1109/ACCESS.2020.2991891
- [18] R. S. Ransing and M. Rajput, “Smart home for elderly care, based on Wireless Sensor Network,” in *Proc. 2015 International Conf. on Nascent Technologies in the Engineering Field (ICNTE)*, 2015. doi: 10.1109/ICNTE.2015.7029932
- [19] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, “Automated cognitive health assessment from smart home-based behavior data,” *IEEE J. Biomed. Health Inform.*, vol. 20, no. 4, pp. 1188–1194, 2016. doi: 10.1109/JBHI.2015.2445754
- [20] M. Schmitter-Edgecombe, C. Parsey, and D. J. Cook, “Cognitive correlates of functional performance in older adults: Comparison of self-report, direct observation, and performance-based measures,” *Journal of the International Neuropsychological Society*, vol. 17, no. 5, pp. 853–864, 2011. doi: 10.1017/S1355617711000865
- [21] S. Farivar, M. Abouzahra, and M. Ghasemaghahi, “Wearable device adoption among older adults: A mixed-methods study,” *Int. J. Inf. Manage.*, vol. 55, 2020. doi: 10.1016/j.ijinfomgt.2020.102209
- [22] V. Vijayan, J. P. Connolly, J. Condell *et al.*, “Review of wearable devices and data collection considerations for connected health,” *Sensors*, vol. 21, no. 16, 5589, 2021. doi: 10.3390/s21165589
- [23] J. Chen, T. Li, H. You *et al.*, “Behavioral interpretation of willingness to use wearable health devices in community residents: A cross-sectional study,” *Int. J. Environ. Res. Public Health*, vol. 20, no. 4, 2023. doi: 10.3390/ijerph20043247
- [24] K. Mercer, L. Giangregorio, E. Schneider *et al.*, “Acceptance of commercially available wearable activity trackers among adults aged over 50 and with chronic illness: A mixed-methods evaluation,” *JMIR Mhealth Uhealth*, vol. 4, no. 1, e4225, 2016. doi: 10.2196/mhealth.4225
- [25] R. Chandrasekaran, V. Katthula, and E. Moustakas, “Too old for technology? Use of wearable healthcare devices by older adults and their willingness to share health data with providers,” *Health Informatics Journal*, vol. 27, no. 4, 2021. doi: 10.1177/14604582211058073
- [26] Y. Gao, H. Li, and Y. Luo, “An empirical study of wearable technology acceptance in healthcare,” *Industrial Management & Data Systems*, vol. 115, no. 9, pp. 1704–1723, 2015. doi: 10.1108/IMDS-03-2015-0087.
- [27] K. Preusse, T. Mitzner, C. Fausset *et al.*, “Older adults acceptance of activity trackers,” *Journal of Applied Gerontology*, vol. 36, no. 2, pp. 127–155, 2016. doi: 10.1177/0733464815624151
- [28] Y. Zhang, C. Liu, S. Luo *et al.*, “Factors influencing patients’ intention to use diabetes management apps based on an extended unified theory of acceptance and use of technology model: Web-based survey,” *Journal of Medical Internet Research*, vol. 21, no. 8, e15023, 2019. doi: 10.2196/15023
- [29] A. Seifert, A. Schlomann, C. Rietz *et al.*, “The use of mobile devices for physical activity tracking in older adults’ everyday life,” *Digit Health*, vol. 3, 2017. doi: 10.1177/2055207617740088
- [30] S. L. Silveira, J. F. Baird, and R. W. Motl, “Rates, patterns, and correlates of fitness tracker use among older adults with multiple sclerosis,” *Disabil. Health Journal*, vol. 14, no. 1, 100966, 2021. doi: 10.1016/j.dhjo.2020.100966
- [31] J. Kaye, N. Mattek, H. Dodge *et al.*, “One walk a year to 1000 within a year: Continuous in-home unobtrusive gait assessment of older adults,” *Gait Posture*, vol. 35, no. 2, pp. 197–202, 2012. doi: 10.1016/j.gaitpost.2011.09.006
- [32] I. Susnea, E. Pecheanu, A. Cocu *et al.*, “Non-intrusive monitoring and detection of mobility loss in older adults using binary sensors,” *Sensors*, vol. 25, no. 9, 2755, 2025. doi: 10.3390/s25092755
- [33] H. Gokalp and M. Clarke, “Monitoring activities of daily living of the elderly and the potential for its use in telecare and telehealth: A review,” *Telemedicine and e-Health*, vol. 19, no. 12, pp. 910–923, 2013. doi: 10.1089/tmj.2013.0109
- [34] A. Papagiannaki, E. I. Zacharaki, G. Kalouris *et al.*, “Recognizing physical activity of older people from wearable sensors and inconsistent data,” *Sensors*, vol. 19, no. 4, 880, 2019. doi: 10.3390/s19040880
- [35] G. A. Wildenbos, L. Peute, and M. Jaspers, “Aging barriers influencing mobile health usability for older adults: A literature based framework (MOLD-US),” *Int. J. Med. Inform.*, vol. 114, pp. 66–75, 2018. doi: https://doi.org/10.1016/j.ijmedinf.2018.03.012
- [36] T. Heart and E. Kalderon, “Older adults: Are they ready to adopt health-related ICT?,” *Int. J. Med. Inform.*, vol. 82, no. 11, 2013. doi: 10.1016/j.ijmedinf.2011.03.002
- [37] R. H. Wang, T. Tannou, N. Bier *et al.*, “Proactive and ongoing analysis and management of ethical concerns in the development, Evaluation, and implementation of smart homes for older adults with frailty,” *JMIR Aging*, vol. 6, no. 1, e41322, 2023. doi: 10.2196/41322
- [38] O. Oyeboode, J. Fowles, D. Steeves *et al.*, “Machine learning techniques in adaptive and personalized systems for health and wellness,” *Int. J. Hum. Comput. Interact.*, vol. 39, no. 9, pp. 1938–1962, 2023. doi: 10.1080/10447318.2022.2089085
- [39] O. Oyeboode, F. Alqahtani, and R. Orji, “Exploring for possible effect of persuasive strategy implementation choices: Towards tailoring persuasive technologies,” in *Proc. International Conference on Persuasive Technology*, 2022, pp. 145–163. doi: 10.1007/978-3-030-98438-0_12
- [40] Q. Xie, M. Wang, Y. Zhao *et al.*, “A personalized beat-to-beat heart rate detection system from ballistocardiogram for smart home applications,” *IEEE Trans. Biomed. Circuits Syst.*, vol. 13, no. 6, pp. 1593–1602, 2019. doi: 10.1109/TBCAS.2019.2957571
- [41] T. L. Mitzner, J. Savla, W. R. Boot *et al.*, “Technology adoption by older adults: Findings from the PRISM trial,” *The Gerontologist*, vol. 59, no. 1, pp. 34–44, 2019.
- [42] L. Øksnebjerg, J. Janbek, B. Woods *et al.*, “Assistive technology designed to support self-management of people with dementia: User involvement, dissemination, and adoption. A scoping review,” *International Psychogeriatrics*, vol. 32, no. 8, pp. 937–953, 2020. doi: 10.1017/S1041610219001704
- [43] M. Donnelly, C. Nugent, S. McClean *et al.*, “A mobile multimedia technology to aid those with Alzheimer’s disease,” *IEEE Multimedia*, vol. 17, no. 2, pp. 42–51, 2010.
- [44] S. Pahlevanynejad, S. R. N. Kalthori, M. R. Katigari *et al.*, “Personalized mobile health for elderly home care: A systematic review of benefits and challenges,” *International Journal of Telemedicine and Applications*, vol. 2023, no. 1, 5390712, 2023. doi: 10.1155/2023/5390712
- [45] C. K. Martin, L. A. Gilmore, J. W. Apolzan *et al.*, “Smartloss: A personalized mobile health intervention for weight management and health promotion,” *JMIR Mhealth Uhealth*, vol. 4, no. 1, e5027, 2016. doi: 10.2196/mhealth.5027
- [46] N. Liappas, J. G. Terius-Padron, E. Machado *et al.*, “Best practices on personalization and adaptive interaction techniques in the scope of smart homes and active assisted living,” in *Proc.*

- 2019 *IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Internet of People and Smart City Innovation, SmartWorld/UIC/ATC/SCALCOM/IOP/SCI*, 2019, pp. 190–195. doi: 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00075
- [47] D. Yang and L. Moody, “Challenges and opportunities for use of smart materials in designing assistive technology products with, and for older adults,” *Fashion Practice*, vol. 14, no. 2, pp. 242–265, 2022. doi: 10.1080/17569370.2021.1938823
- [48] M. Awan, S. Ali, M. Ali *et al.*, “Usability barriers for elderly users in smartphone app usage: An analytical hierarchical process-based prioritization,” vol. 2021, no. 1, 2780257, 2021. doi: 10.1155/2021/2780257
- [49] S. Kuoppamäki, S. Tuncer, S. Eriksson *et al.*, “Designing kitchen technologies for ageing in place,” in *Proc the ACM Interact Mob Wearable Ubiquitous Technol.*, 2021, vol. 5, no. 2. doi: 10.1145/3463516
- [50] N. Mahasivam, I. Vithiya, S. Anantharshika *et al.*, “Personalized and adaptive user interface framework for mobile application,” in *Proc. 2013 International Conf. on Advances in Computing, Communications and Informatics (ICACCI)*, 2013. doi: 10.1109/ICACCI.2013.6637474
- [51] S. Raheel, “Improving the user experience using an intelligent Adaptive user interface in mobile applications,” in *Proc. 2016 IEEE International Multidisciplinary Conf. on Engineering Technology (IMCET)*, 2016, pp. 64–68. doi: 10.1109/IMCET.2016.7777428
- [52] M. Kowtko, “Using assistive technologies to improve lives of older adults and people with disabilities,” in *Proc. 2012 IEEE Long Island Systems, Applications and Technology Conf. (LISAT)*, 2012, pp. 1–6. doi: 10.1109/LISAT.2012.6223205
- [53] M. Peissner and R. Edlin-White, “User control in adaptive user interfaces for accessibility,” in *Proc. IFIP Conf. on Human-Computer Interaction*, 2013, pp. 623–640. doi: 10.1007/978-3-642-40483-2_44
- [54] U. Alegre, J. C. Augusto, and T. Clark, “Engineering context-aware systems and applications: A survey,” *Journal of Systems and Software*, vol. 117, pp. 55–83, 2016. doi: 10.1016/j.jss.2016.02.010
- [55] S. Singhal, A. Sinha, and B. Singh, “Context awareness for healthcare service delivery with intelligent sensors,” in *Frontiers of Data and Knowledge Management for Convergence of ICT, Healthcare, and Telecommunication Services*, 2022, pp. 61–83. doi: 10.1007/978-3-030-77558-2_4
- [56] A. Obinna, H. Tawfik, and E. L. Secco, “A context-aware architecture for personalized elderly care in smart environments,” in *Proc. 1st EAI International Conf. on Smart Grid Inspired Future Technologies*, 2016.
- [57] F. De Backere, P. Bonte, S. Verstichel *et al.*, “The OCarePlatform: A context-aware system to support independent living,” *Comput. Methods Programs Biomed.*, vol. 140, pp. 111–120, 2017. doi: 10.1016/j.cmpb.2016.11.008
- [58] L.-M. Meßmer, P. Held, A. Bejan *et al.*, “Designing a dementia caregiver-centered recommendation and context-aware AI media analytical application: A comprehensive system requirements analysis,” *Int. J. Hum. Comput. Interact.*, pp. 1–20, 2024. doi: 10.1080/10447318.2024.2344913
- [59] G. O. Ogbuabor, J. C. Augusto, R. Moseley *et al.*, “Context-aware system for cardiac condition monitoring and management: A survey,” *Behaviour and Information Technology*, vol. 41, no. 4, pp. 759–776, 2022. doi: 10.1080/0144929X.2020.1836255
- [60] S. G. Essa, T. Celik, and N. E. Human-Hendricks, “Personalized adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review,” *IEEE Access*, vol. 11, pp. 48392–48409, 2023. doi: 10.1109/ACCESS.2023.3276439
- [61] M. S. Roobini, B. B. Asish, S. Challa *et al.*, “Designing an MI-Powered assistive technology for people with cognitive and mental disabilities,” in *Proc. 9th International Conf. on Science, Technology, Engineering and Mathematics (ICONSTEM)*, 2024, pp. 1–7. doi: 10.1109/ICONSTEM60960.2024.10568651
- [62] H. Lee and U. Lee, “Dynamic consent for sensor-driven research,” in *Proc. 2021 Thirteenth International Conf. on Mobile Computing and Ubiquitous Network (ICMU)*, 2021, pp. 1–6. doi: 10.23919/ICMU50196.2021.9638790
- [63] T. Wangmo, M. Lipps, R. W. Kressig *et al.*, “Ethical concerns with the use of intelligent assistive technology: Findings from a qualitative study with professional stakeholders,” *BMC Med Ethics*, vol. 20, no. 1, 2019. doi: 10.1186/s12910-019-0437-z
- [64] I. Jaggi, R. Carli, B. Buzcu *et al.*, “Consent understanding and verification for personalized assistive systems,” in *Proc. 17th International Conf. on Agents and Artificial Intelligence*, 2025, pp. 694–701. doi: 10.5220/0013376300003890
- [65] J. Frishammar, A. Essén, F. Bergström *et al.*, “Digital health platforms for the elderly? Key adoption and usage barriers and ways to address them,” *Technol Forecast Soc Change*, vol. 189, 122319, 2023. doi: 10.1016/j.techfore.2023.122319
- [66] S. Martin, J. E. Bengtsson, and R.-M. Dröes, “Assistive technologies and issues relating to privacy, ethics and security,” in *Supporting People with Dementia using Pervasive Health Technologies*. London: Springer London, 2010, pp. 63–76. doi: 10.1007/978-1-84882-551-2_5
- [67] J. Frishammar, A. Essén, F. Bergström *et al.*, “Digital health platforms for the elderly? Key adoption and usage barriers and ways to address them,” *Technol. Forecast. Soc. Change*, vol. 189, 122319, 2023. doi: 10.1016/j.techfore.2023.122319
- [68] T. Wangmo, M. Lipps, R. W. Kressig *et al.*, “Ethical concerns with the use of intelligent assistive technology: findings from a qualitative study with professional stakeholders,” *BMC Med Ethics*, vol. 20, no. 1, 98, 2019. doi: 10.1186/s12910-019-0437-z
- [69] H. T. Tavani, *Ethics and Technology 2e WSE: Ethical Issues in an Age of Information and Communication Technology*, 2nd ed. John Wiley and Sons, 2007.
- [70] N. Thakur and C. Y. Han, “A review of assistive technologies for activities of daily living of elderly,” arXiv Preprint, arXiv:2106.12183, 2021.
- [71] S. Yusif, J. Soar, and A. Hafeez-Baig, “Older people, assistive technologies, and the barriers to adoption: A systematic review,” *Int. J. Med. Inform.*, vol. 94, pp. 112–116, 2016. doi: 10.1016/j.ijmedinf.2016.07.004
- [72] E. Martinez-Martin and A. Costa, “Assistive technology for elderly care: An overview,” *IEEE Access*, vol. 9, pp. 92420–92430, 2021. doi: 10.1109/ACCESS.2021.3092407.
- [73] E. Gkiolnta, D. Roy, and G. Fragulis, “Challenges and ethical considerations in implementing assistive technologies in healthcare,” *Technologies (Basel)*, vol. 13, no. 2, 48, 2025. doi: 10.3390/technologies13020048
- [74] N. F. M. Johari, N. M. Ali, M. H. M. Salim *et al.*, “Factors driving the use of mobile health app: insights from a survey,” *Mhealth*, vol. 11, 12, 2025. doi: 10.21037/mhealth-24-44.
- [75] M. A. M. Zuki, N. M. Ali, and C. J. Kit, “Reinforcement learning: Methods and recent applications,” *Journal of Information System and Technology Management*, vol. 9, no. 36, 67, 2024.

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