Multimodal Wearable Fall Risk Assessment for Independent People Living with Dementia

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Dedication

This thesis is dedicated to my awesome and supportive wife, Helen Elohor Orobor, and to my ever-encouraging mother, Mrs. Anna Orobor, whose unwavering sacrifices made my early education possible.

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Abstract

Older adults with dementia face a twice higher risk of falls compared to cognitively healthy peers, largely due to impaired cognition, reduced self-monitoring, and poorer balance and movement control. Traditional fall prevention strategies effective in cognitively healthy older adults have generally not reduced fall risk in People with Dementia (PwD) and individual with Mild Cognitive Impairment (MCI). While interventions such as home modifications may improve safety and independence, adherence can be challenging. Technology-based approaches, particularly Augmented Reality (AR) assistive tools, show promising potential; however, most existing AR solutions fail to adequately adapt to users' fluctuating or declining cognitive states. This thesis therefore, aims to develop an adaptive multimodal AR–based Assistive Technologies (AT) that leverages Deep learning (DL) and Hidden Markov Model (HMM) to assess fall risk for PwD and individual with MCI.

The thesis began with an extensive systematic review of 1,449 studies on AR–based AT for the safety of PwD and MCI, of which 31 met the final inclusion criteria. The review demonstrated the potential of AR technologies in enhancing safety, independence, and Quality of Life (QoL) for the target population. It also identified persistent challenges such as the need for more adaptive and intuitive interfaces, improved ergonomic design for prolonged use, and robust privacy protections, particularly in location and movement monitoring. This was followed by a cross-sectional survey involving 121 caregivers to examine their perspectives on PwD's attitudes toward home hazards and safety interventions, with the aim of identifying unmet needs. The findings indicate that PwD exhibited limited hazard avoidance and low adherence to existing home safety interventions, largely due to cognitive and behavioural impairments associated with the condition.

Based on insights obtained from the systematic review and cross-sectional survey, an adaptive multimodal AR–based AT for fall risk assessment system aimed at supporting safe mobility through personalised, context-aware notifications that align with the user's cognitive attention state was proposed. The proposed system employs wearable smart glasses equipped with an integrated camera to capture environmental images and an Inertial Measurement Unit (IMU) to collect motion data. DL techniques were employed to analyse visual data, enabling detection of potential environmental hazards and the identification of existing safety interventions within the environment, while HMM was applied to infer the user's cognitive attention state from

IMU sensor data. This approach enables the delivery of personalised safety alerts and guidance only when cognitive attention is reduced, thereby minimising unnecessary notifications that can lead to alert fatigue while preserving user autonomy.

The system was evaluated based on Unified Theory of Acceptance and Use of Technology (UTAUT) framework. To better capture the needs of individuals with cognitive impairment, the UTAUT framework was extended to include Social Sensitivity (SS), which reflects concerns related to stigma and social judgement, and Technology Anxiety (TA), both of which significantly influence technology acceptance. Findings from 68 participants emphasise that emotional and stigma-related factors strongly influence adoption, underscoring the need for socially sensitive, human-centred AT that provide functional benefits while minimising stigma and discomfort.

This thesis contributes to the field of AT by introducing a scalable, adaptive, and human-centred framework for fall risk assessment. It demonstrates that intelligent wearable multimodal systems can detect environmental hazards and integrate existing home safety interventions to provide real-time personalised support, enhancing safety, autonomy, and QoL for individuals with cognitive impairment.

List of Publications

Ise Anderson Orobor, Faiyaz Doctor, Ramy Hammady and Mary R. Kennedy (2026). Smart Glasses Augmented Reality Based Fall Risk Assessment System for People with Dementia Using Deep Learning and Hidden Markov Model. *Multimedia Systems*. [In Review]

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Ise Anderson Orobor, Ramy Hammady, Mary R. Kennedy and Faiyaz Doctor (2026). Augmented Reality Based Assistive Technologies for the Safety of People with Dementia and Related Mild Cognitive Impairment: A Systematic Review. *Virtual Reality*. [In Press]

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List of Abbreviations

AE	Aesthetics
AFRA	Attention-Aware Fall Risk Assessment
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
API	Application Programming Interfaces
AT	Assistive Technologies
AUC	Area Under the Curve
AUROC	Area Under the Receiver Operating Characteristic
AVE	Average Variance Extracted
AD	Alzheimer Disease
ANG	Adaptive Navigation Guidance
ASC	Attention-Aware Safety Cues
BI	Behavioural Intention
BiLSTM	Bidirectional Long Short-Term Memory
CART	Classification and Regression Trees
CBAM	Convolutional Block Attention Module
CHD	Context-Aware Hazard Detection
CIF	Conditional Inference Forest
CLAHE	Contrast Limited Adaptive Histogram Equalisation
CNN	Convolutional Neural Network
ConvLSTM	Convolutional Long Short-Term Memory
CR	Composite Reliability
CSM	Cognitive State Monitoring
CSO	Cognitive Service Orchestration
DAM	Dynamic Alert Management
DBN	Deep Belief Network
DCFS	Dementia Cognitive Fluctuation Scale
DCPAR	Device with Pico Projector for Augmented Reality
DL	Deep Learning
DSRM	Design Science Research Methodology
DT	Decision Trees

DWT	Dynamic Time Warping
EE	Effort Expectancy
EM	Expectation–Maximization
ENA	Environmental Adaptation
Faster-RCNN	Faster Region-based Convolutional Neural Network
FC	Facilitating Conditions
FD	Frontotemporal Dementia
FDR	Fall Detection and Reporting
FIM	Fisher Information Matrix
FOV	Field of View
FPS	Frames Per Second
FRPA	Feature Representation and Pattern Analysis
GASF	Gramian Angular Summation Field
GAN	Generative Adversarial Networks
GB	Gradient Boosting
GRU	Gated Recurrent Unit
HMD	Head Mounted Display
HMM	Hidden Markov Model
HMM-GAN	Hidden Markov Model Generative Adversarial Network
HMRNNs	Hidden Markov Recurrent Neural Networks
HOG	Histogram of Oriented Gradients
HTMT	Heterotrait–Monotrait
HWD	Head-Worn Displays
IM	Input Modalities
IMU	Inertial Measurement Unit
IN	Interactivity
IoT	Internet of Things
KNN	K-Nearest Neighbour
LBD	Lewy Body Dementia
LLM	Large Language Model
LR	Logistic Regression
LSTM	Long Short-Term Memory
mAP	mean Average Precision
MCI	Mild Cognitive Impairment

MCMC	Markov Chain Monte Carlo
MFA	Multimodal Feedback Adaptation
MMAT	Mixed Methods Appraisal Tool
NB	Naive Bayes
NHMM	Neutrosophic Hidden Markov Model
NN	Neural Network
OM	Output Modalities
P	Precision
PAR	Projection Augmented Reality
PE	Performance Expectancy
PIS	Personalised Interaction Support
PLV	People with Low Vision
POF	Point of Familiarity
POMA	Performance-Oriented Mobility Assessment
PR	Privacy
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PwD	People with Dementia
Q^2	Predictive Relevance
QoL	Quality of Life
R	Recall
R^2	Coefficients of Determination
RAA	Routine-Aware Assistance
RCT	Randomised Controlled Trial
RF	Random Forest
RNN	Recurrent Neural Networks
SAR	Spatial Augmented Reality
SBA	Service-Based Architecture
SEM	Structural Equation Modelling
SI	Social Influence
SRCNN	Super-Resolution Convolutional Neural Network
SS	Social Sensitivity
SVM	Support Vector Machines
TA	Technology Anxiety
TAM	Technology Acceptance Model

THLLOD	Transfer Hybrid Learning Low-Light Object Detection
TL	Transfer Learning
TPB	Theory of Planned Behaviour
TUG	Timed Up and Go
UTAUT	Unified Theory of Acceptance and Use of Technology
VD	Vascular Dementia
VGG	Visual Geometry Group
ViTs	Vision Transformers
$\chi 2$	Chi-Square
YOLO	You Only Look Once
Zero-DCE	Zero-Reference Deep Curve Estimation

Chapter 1

Introduction

This chapter presents the motivation behind the research and the problems investigated in this thesis. It outlines the research questions, aim and objectives, research contributions as well as the significance of the study. Additionally, it provides a brief overview of the upcoming chapters.

Contents

1.1 Motivation

Older adults with dementia have significantly higher fall risk than those without cognitive impairment. Impaired cognition and reduced self-monitoring contribute to poorer balance and movement control, leading to roughly two to three times more falls and a greater likelihood of sustaining injuries (Chantanachai et al., 2021; Racey et al., 2021; Zhang et al., 2022). Fall prevention approaches effective for cognitively healthy older adults have generally not reduced fall risk in people with cognitive impairment such as dementia (Guo et al., 2014; Racey et al., 2021), although emerging research indicates possible benefits from tailored strategies (Choi et al., 2025). Limited evidence means current guidelines offer no specific recommendations for this population (Montero-Odasso et al., 2021). Some studies suggest that interventions like home modifications may reduce fall risk and enhance safety and independence for People with Dementia (PwD) (Kahya et al., 2020; Chen et al., 2020). However, Bianco et al. (2016) and Nishchyk et al., (2021) argued that adherence to the intervention strategies can be an issue as older adults could find it challenging to follow and comply with fall prevention measures.

The application of technology-based interventions such as Augmented Reality (AR) assistive tools in the dementia continuum has shown great potential and promising results in recent times (Wolf et al., 2018; Rohrbach et al., 2019; Vona et al., 2020; Pillette et al., 2023). However, most of the existing AR-based Assistive Technologies (AT) for older adults and PwD often do not adequately account for users' cognitive state, especially given that cognition can fluctuate (Escandon et al., 2010; Lee et al., 2014) or decline over time (Gibson et al., 2015; Spalla et al., 2025). While many smart-home systems for older adults, including those with dementia can perform activity recognition and anomaly detection**,** they generally do not adapt dynamically to changes in cognitive function or evolving routines associated with progressive dementia (Moyle et al., 2021; Chimamiwa et al., 2022). Most safety-oriented AT for dementia focuses on monitoring or tagging, rather than dynamically adapting to real-time cognitive changes (Gagnon-Roy et al., 2017). These technologies are designed as static cognitive aids, usually based on "one-size-fits-all" design approach, which fails to adequately support the personalised, person-centred care needs of users (Hayhurst, 2018; Brookman et al., 2023). As a result, such technologies may be underutilised or used improperly**,** ultimately limiting their effectiveness in promoting independence, safety, and daily support for PwD (Sriram et al., 2022; Brookman et al., 2023). These limitations highlight the need for AT that can dynamically adapt to users' cognitive states**,** providing timely and context-aware support when attention or cognitive capacity is reduced.

This thesis therefore, developed an adaptive multimodal AR-based AT to enhance the safety of PwD through context-aware fall risk assessment. The system utilises wearable AR technology to continuously monitor user movement and surrounding environmental context through real-time camera feeds and inertial measurement unit (IMU) data captured from smart glasses. The proposed system integrates Deep Learning (DL) for detecting potential environmental hazards and recognising existing home safety interventions with a Hidden Markov Model (HMM) that infer the user's latent attention state from movement data and predicts periods of reduced cognitive engagement. By modelling the high-dimensional data collected from camera feeds and inertial sensors, the system delivers personalised safety alert and guidance that based on user's cognitive attention state. This approach supports engagement with home safety interventions and enhances safe, independent mobility while preserving user autonomy and minimising unnecessary notifications to reduce fatigue in real-world home environments.

1.2 Research Questions

Formally, based on the motivation of the research, the following research questions were addressed:

1. What is the current State-of-The-Art (SoTA) AR-based AT for enhancing the safety of PwD and individual with MCI?

2. What is the attitude of PwD towards potential home environment hazards and existing home safety interventions?

3. How can fall risk be reduced and the use of home safety interventions improved within home environments?

4. How can a fall risk assessment model be designed to dynamically adapt to users' cognitive fluctuations, particularly variations in attention and engagement?

5. How can AR-based AT support the safe mobility of PwD and individuals with MCI without generating unnecessary alerts or compromising their autonomy?

1.3 Aim and Objectives

This thesis aims to develop an adaptive multimodal AR–based AT that leverages DL and HMM to assess fall risk for PwD and individual with MCI. The system combines image analysis and IMU data captured in real-time from movement data, behavioural cues, and environmental factors associated with fall risk. By modelling these signals probabilistically, the system can deliver real-time safety alert and guidance based on users' cognitive attention level. This minimises unnecessary notifications, reducing user fatigue and supporting autonomy in real-world home environments. To achieve this aim, the following objectives have been developed:

Research Objective 1: To conduct an in-depth review of the existing literature to explore the current SoTA AR-based AT design towards the safety of PwD and related cognitive impairment.

Research Objective 2: To conduct an exploratory study using a caregiver-reported questionnaire to assess the attitude of PwD towards potential home environment hazards and existing home safety interventions.

Research Objective 3: To develop and evaluate a hybrid DL method for detecting potential home environment hazards and recognise safety interventions within home environments that AT can leverage.

Research Objective 4: To design and implement a fall risk assessment model based on DL and HMM to infer users' latent attention states from observed user movement pattern and environmental context through real-time device camera feeds and IMU data.

Research Objective 5: To design, develop, and validate an adaptive AR–based AT that delivers personalised context-aware notifications that align with the user's cognitive attention state.

1.4 Research Contributions

This thesis contributes to the advancement of AT for PwD and individuals with MCI through the development of an adaptive, context-aware AR-based fall risk assessment framework. The system integrates real-time detection of environmental hazards and safety interventions with IMU-based behavioural monitoring to infer users' latent cognitive attention states using an HMM. By combining environmental context with inferred attention levels, it delivers personalised safety guidance only when reduced attention is detected in the presence of potential risks. This approach minimises unnecessary alerts, reduces alert fatigue, preserves user autonomy, and supports safer navigation in everyday living environments. To achieve this, the thesis adopted a multi-method research approach that include systematic literature review, exploratory research, experimental investigation, and quantitative analysis.

The systematic literature review identified existing technological solutions, gaps, and design considerations related to AR-based AT for the safety of PwD and MCI. This was followed by exploratory phase which focused on understanding the challenges, needs, and environmental risks experienced by PwD through insights gathered from caregivers and relevant stakeholders. Building on these findings, an experimental phase was conducted to design, implement, and evaluate the proposed AR-based assistive system. The system was evaluated using quantitative methods to assess its effectiveness, usability, and overall performance. Together, these phases provided a comprehensive framework that informed the design and evaluation of the proposed system and led to the following key research contributions:

1. Augmented Reality-Based Assistive Technologies Systematic Literature Review

This research advances AR-based AT by identifying key design gaps in existing solutions aimed at supporting the safety of PwD and individuals with MCI. Through a systematic review, it proposes a structured framework to enlighten the understanding and design of such systems for these target populations. The review highlights the potential of AR-based AT to enhance safety and categorises current applications into three main domains: mobility, medication management, and home safety and control. It also emphasises the need to align system design with users' cognitive capabilities, noting that many existing approaches fail to account for cognitive fluctuations. To address this limitation, the study advocates for adaptive, context-aware AR systems that tailor safety alerts and guidance to users' attention states, enabling a shift from static solutions to more personalised and responsive interventions.

2. Cross Sectional on the Perspectives of Caregivers on PwD Attitude Towards Home Environment Hazards and Safety Interventions

To understand the unmet need of PwD, a cross sessional survey was conducted based on caregivers' perspective. Unmet needs refer to problems experienced by individuals that require intervention but are not adequately addressed by available services or support systems. This research found that PwD often experience difficulties navigating uneven surfaces and avoiding obstacles in their home environments. Although various safety interventions are available to support mobility, many individuals struggle to recognise when and how to use these measures effectively. As a result, adherence to existing home safety modifications remains relatively low. These findings suggest that traditional home adaptations, while beneficial, may not be sufficient on their own, particularly for individuals living alone who may face greater risks. This gap highlights the need to view home safety intervention not only as an environmental design issue but also as a behavioural and cognitive engagement challenge. Accordingly, this research suggests a model of care in which conventional home modifications are enhanced by intelligent AT that support users in engaging with safety interventions in everyday life.

3. Transfer Hybrid Low-Light Object Detection Framework for Potential Home Fall Hazards and Safety Interventions Detection

This research makes a significant contribution through the development of a domain-specific object detection framework designed to identify potential fall hazards and safety interventions within real-world home environments. Unlike existing object detection models that rely on general-purpose datasets, the proposed Transfer Hybrid Learning Low-Light Object Detection (THLLOD) framework is designed to recognise context-relevant hazards and safety interventions that directly impact the safety of older adults and individuals with cognitive impairment. By integrating a pretrained You Only Look Once (YOLO)-based detector with the Zero-Reference Deep Curve Estimation (Zero-DCE) algorithm, the framework enhances visual perception under low-light and degraded conditions, which are common in everyday environments. This integration improves the reliability and robustness of detection across diverse indoor and outdoor scenarios. As a result, the proposed framework advances the capability of AT to deliver accurate and context-aware environmental insights, forming a critical component for proactive fall risk assessment systems capable of supporting safer and independent living.

4. Attention-Aware Fall Risk Assessment Framework for Real-Time Safety Alert

This research advances fall risk assessment by developing a DL and HMM framework that infers users' latent attention states from observed behavioural patterns and environmental context. The framework integrates real-time device camera feeds and IMU data to capture user movement data and environmental context, enabling continuous monitoring of user behaviour during Activities of Daily Living (ADL). Potential environmental home fall hazards and existing safety interventions are identified through the DL-based perception module, while the HMM models' temporal patterns of safety adherence behaviour to estimate underlying user's attention states that are not directly observable. By analysing these multimodal data, the framework provides a more comprehensive and context-aware assessment of fall risk. This enables the delivery of adaptive safety alerts tailored to the user's current attention state and level of situational risk.

5. Smart Glass Augmented Reality Based Assistive Technology for Fall Risk Assessment

This research contributes to AT by demonstrating the design and development of an adaptive, multimodal AR-based system for personalised fall risk assessment amongst PwD and individual with MCI using smart glasses. The system combines environmental image perception with IMU-based motion data to infer the user's attention state and provide real-time, context-aware safety cues. By leveraging multimodal sensing, the system moves beyond static assistance toward a dynamic framework that adapts to fluctuating cognitive conditions, selectively triggering safety cues only when reduced attention is detected. This approach reduces unnecessary notifications, mitigates alert fatigue, and supports user autonomy.

6. Extend Unified Theory of Acceptance and Use of Technology (UTAUT) Framework

This study makes a significant contribution to the understanding of technology acceptance in AT for PwD by extending the UTAUT framework to better reflect the psychosocial and cognitive characteristics of this population. Specifically, the integration of Social Sensitivity (SS) and Technology Anxiety (TA) provides a more nuanced perspective on how stigma, emotional responses, and apprehension toward technology influence adoption decisions. The study highlights the role of design-related factors, such as interactivity, privacy, and aesthetics as indirect determinants of behavioural intention through their impact on users' emotional and social perceptions. By examining these factors from the caregivers' perspective, the research offers valuable insights into the contextual and relational dynamics that shape acceptance in dementia care. The study advances theoretical models of technology adoption for cognitively vulnerable populations and provides practical design implications for developing AT that are not only functional but also socially acceptable, emotionally supportive, and aligned with the dignity and autonomy of PwD.

1.5 Significance of the Study

1. The study's findings provide researchers with insights into the present state and challenges within the current design approach of AR-based AT for PwD, along with potential improvement solutions.

2. This research contributes to the ongoing body of knowledge by critically analysing evidence obtained through cross-sectional surveys to assess the perceptions of PwD towards fall prevention home safety interventions.

3. The study produces an object detection framework capable of detecting potential environmental fall hazards and existing home safety interventions in varied lighting conditions.

4. The research demonstrates a fall risk assessment approach that integrates DL and HMM to provide safety cues based on the user's cognitive attention state.

5. The study develops an adaptive multimodal AR–based assistive tool to enhance the safe mobility of PwD and individual with MCI.

1.6 Thesis Outline

This thesis is organised as follows:

Chapter 2 provides the relevant background and an overview of related work.

Chapter 3 presents augmented reality based assistive technologies for people with dementia.

Chapter 4 reports caregiver perspectives of digital interventions for people with dementia.

Chapter 5 presents system development methodology.

Chapter 6 reports the system evaluation based on the unified theory of acceptance and use of technology model.

Chapter 7 presents the thesis conclusion, limitation and future work.

Chapter 2

Background and Related Work

This chapter provides an overview of dementia and cognitive impairment and introduces the technologies employed in this research, examining their applications across the dementia continuum.

Contents

2.1 Dementia

Dementia is a progressive syndrome caused by various brain diseases or injuries, characterised by deterioration in memory, thinking, behaviour, and the ability to carry out ADL (Rose et al., 2018; Chia-Fen et al., 2021). It is a major global health concern, ranking as the seventh leading cause of death and a leading cause of disability and dependency among older adults (World Health Organisation, 2023). Although age increases risk, dementia is not an inevitable part of ageing. Its symptoms can include memory loss, reduced spatial awareness, difficulty concentrating or organising, language and communication problems, misinterpretation of visual information, and disorientation in time or place (National Health Service, 2020; Javeed et al., 2023). There are four (4) forms of dementia based on these symptoms. They are Alzheimer’s disease (AD), Vascular Dementia (VD), Lewy Body Dementia (LBD) and Frontotemporal Dementia (FD) (Duong et al., 2017; National Health Service, 2020; Alzheimer's Society, 2023a).

Dementia affects people differently, as varying symptoms are exhibited between the mild stage and the severe stage (Kort, 2014; Hayhurst, 2018). The effects have substantial societal and economic impacts that are steadily increasing as the population ages, significantly burdening caregivers, healthcare systems, and society at large (Spalla et al., 2022). As of 2019, there are 120,000 People with Dementia (PwD) living alone, and this number is predicted to double to around 240,000 by 2039. With this growing number, 85% of the people in a survey report express the desire to stay at home for as long as possible if diagnosed with dementia (Alzheimer's Society, 2019). This desire can be concerning because living alone with cognitive impairment is associated with increased risks and unmet needs (Emma et al, 2016; Clare et al., 2025).

Given the absence of a cure for dementia, recent studies have shown a growing interest in developing non-pharmacological interventions aiming to improve the Quality of Life (QoL) for individuals with dementia (Cammisuli et al., 2016; Algar et al., 2016; Akintola et al., 2019; Peterson et al., 2012; Ienca et al., 2017; Yaddaden et al., 2022; Makhataeva et al., 2023). Some technology-based safety interventions are examined in detail in Chapter 3 of this thesis.

2.1.1 Cognitive Decline and Fluctuation

Cognitive decline can impair judgment and risk assessment, causing individuals to engage in unsafe mobility behaviours and increasing their likelihood of falls (Robinson and Kiely, 2017; Appeadu and Bordoni, 2023; Minta et al., 2023). Cognitive abilities generally experience some decline as part of the normal aging process. (Wisdom et al. 2012; Murman, 2015; Randhawa and Varghese, 2023). However, the level of cognitive decline differs significantly from person to person. If this becomes more severe, it can lead to MCI or potentially progress to major neurocognitive disorder or dementia (Murman, 2015; Randhawa and Varghese, 2023).

Cognitive abilities encompass several domains including memory task, visuospatial ability, and attention states with each showing measurable age-related decline (Lezak et al., 2012; Harada et al., 2013). Effective performance in these domains requires perceiving a stimulus, processing the information, and producing a response. Because both sensory perception and processing speed diminish with age, they negatively affect performance across many cognitive tasks (Murman, 2015). Several studies show that declines in any of these cognitive domains increase the risk of falls in both healthy older adults and individuals with dementia (Robinson and Kiely, 2017; Appeadu and Bordoni, 2023; Minta et al., 2023).

I. Memory Task

Age-related memory changes may result from slower processing speed (Luszcz and Bryan, 1999), a reduced ability to filter out irrelevant information (Darowski et al., 2008), and diminished use of strategies that enhance learning and memory. Declines in processing speed can affect multiple cognitive domains (Harada et al., 2013). While some aspects of memory remain stable with normal ageing, the ability to acquire new information and retrieve recently learned material consistently declines with age (Lezak et al., 2012). Learning is further impaired in older adults when tasks require mental manipulation of information or simultaneous performance of multiple activities. In contrast, procedural memories such as knowing how to play an instrument or ride a bike are generally preserved with age (Murman, 2015).

II. Visuospatial Ability

Visuospatial ability refers to the capacity to perceive, analyse, and mentally manipulate visual and spatial information, such as recognising objects, judging distances, and navigating environments (Hegarty and Waller, 2005; Pal et al., 2016; Cardillo et al., 2020). There are age-related declines in aspects of visuospatial processing and constructional praxis (Lezak et al., 2012). Visual recognition of objects, shapes, gestures, and conventional signs remains stable into advanced age. However, visuoperceptual judgment and the ability to perceive spatial orientation decline with age (Murman 2015). In PwD, visuospatial functioning can be impaired at the beginning of the disease, and it gradually declines with deterioration of cognition over time (Pal et al., 2016). These deficits can manifest as difficulty with tasks like reading maps, assembling objects, dressing appropriately, or judging spatial relationships. The severity and pattern of visuospatial impairment can vary depending on the type of dementia. For example, individuals with Alzheimer’s disease often show early deficits in spatial navigation and object recognition, while those with LBD may experience pronounced visuoperceptual disturbances, including visual hallucinations.

III. Attention States

Attention plays a central role in all cognitive processes (Balota and Faust, 2001). In dementia, it is generally believed that attention is typically the second cognitive domain to be affected, following initial memory impairment (Perry and Hodges, 1999; Balota and Faust, 2001).

Attention can be divided into three main types: sustained attention, selective attention, and divided attention (Perry and Hodges, 1999; Balota and Faust, 2001). Sustained attention is the capacity to maintain focus and remain engaged with task goals over extended periods, especially during monotonous or repetitive activities (Unsworth and Robison, 2020). Robertson and colleagues (1997) described it as the ability to consciously sustain processing of stimuli that are repetitive and non-arousing, which would otherwise lead to habituation. Selective attention is the ability to focus on specific information in an environment while at the same time ignoring irrelevant information (Murman 2015). Divided attention is the ability to manage multiple pieces of information at once, either simultaneously or by rapidly switching between tasks. Impairments in divided attention arise from the brain's limited cognitive processing capacity (McKanna et al., 2010; Murman, 2015) and are evident in the early stages of Alzheimer's disease (Mirahadi et al., 2018). Impaired attention is also an important factor increasing the risk of falls (Robinson and Kiely, 2017).

Collectively, these studies suggest that cognitive decline is a heterogeneous, multi-domain process that reflects underlying neuropathological changes and varies in trajectory depending on disease stage and individual differences. Building on this understanding of progressive impairment, it is also important to consider the role of cognitive fluctuation (Escandon, et al., 2010; Lee et al. 2014).

Cognitive fluctuation describes transient and often unpredictable variations in attention, alertness, and overall cognitive performance occurring over short time frames (Escandon et al., 2010). These fluctuations are particularly characteristic of certain dementias, notably Lewy body dementia, where individuals may alternate between periods of relative cognitive clarity and episodes marked by confusion, reduced responsiveness, or diminished awareness (Lee et al., 2014). Such variability is not solely attributable to external influences like fatigue or environmental change, but instead reflects underlying neuropathological processes affecting brain function. Clinically, tools such as the Dementia Cognitive Fluctuation Scale (DCFS) have been developed to capture the frequency, severity, and functional consequences of these changes, thereby supporting more accurate diagnosis and assessment. Cognitive fluctuations can manifest in diverse forms, including brief lapses in consciousness, shifts in arousal, and extended intervals resembling sleep states (Escandon et al., 2010). Neurobiological explanations attribute these phenomena to disruptions in large-scale neural networks involved in attention and arousal regulation, including cholinergic system deficits, impaired neuronal synchronisation, and disturbances in sleep–wake mechanisms (Matar et al., 2020). The temporal pattern of these fluctuations is highly variable, ranging from seconds and minutes to days or even weeks (Matar et al., 2020). Importantly, this instability has significant functional implications, as it can lead to inconsistent decision-making capacity, whereby an individual may demonstrate adequate reasoning ability at one moment but be unable to do so shortly thereafter (Trachsel et al., 2015). Consequently, cognitive fluctuations in dementia can profoundly affect judgement and self-awareness by producing a dynamic and unstable cognitive state in which decision-making capacity and insight continually wax and wane in unpredictable ways (Mainland et al., 2017).

2.1.2 Mild Cognitive Impairment

Mild Cognitive Impairment (MCI) is a diagnostic classification describing individuals who exhibit measurable cognitive decline without significant impairment in daily functioning (Gerstenecker and Mast, 2015). It is a clinically recognised neurocognitive condition characterised by cognitive deficits that exceed normal age-related changes but do not substantially interfere with basic ADL. As such, MCI is considered an intermediate stage on the continuum between normal ageing and dementia (Anand and Schoo, 2024). It precedes and leads to dementia in many cases (Albert et al., 2011).

MCI may also be categorised according to the specific cognitive domains involved. Impairment can occur in one or more of six domains, including learning and memory, language, complex attention, executive functioning, social cognition, and visuospatial abilities (Sanford et al., 2017). Based on the pattern of deficits, MCI is classified as either amnestic or non-amnestic, affecting single or multiple domains. Amnestic MCI is characterised by prominent memory impairment and carries an increased risk of progression to Alzheimer's disease. In contrast, non-amnestic MCI involves relatively preserved memory, is less prevalent, and may progress to non-Alzheimer's dementias (Sanford et al., 2017; Kasper et al., 2020).

2.1.3 Interventions for Dementia

Dementia interventions range from traditional home modifications to reduce fall risks (Taylor et al., 2021; Georlee et al., 2020) to technology-based solutions that support independence and safety (Peterson et al., 2012; Ienca et al., 2017; Yaddaden et al., 2022; Makhataeva et al., 2023).

Home modification interventions involve making changes to a person's home environment to improve safety, accessibility, and overall QoL (McCullagh et al., 2006). These modifications are typically aimed at reducing the risk of accidents and injuries, particularly for older adults and individuals with disabilities (Georlee et al., 2020). Examples of home modification interventions include installing grab bars in bathrooms, adding ramps or stairlifts for accessibility, improving lighting, removing tripping hazards, and adapting kitchen and bathroom fixtures for ease of use (Taylor et al., 2021; Georlee et al., 2020; National Institutes of Health, 2017); Alzheimer’s Association, 2023b). Zhang et al. (2022) revealed that PwD has a higher incidence of injurious falls starting four years before diagnosis, with rates peaking in the year of diagnosis. This suggests the need for fall prevention strategies immediately after a dementia diagnosis.

Traditionally, the National Institutes of Health (2017) and Alzheimer’s Association (2023b) recommend home modification strategies to enhance independence and safety for PwD. These modifications encompass installing grab bars, handrails, clearing walkways, and implementing auto shut-off devices, among other safety features. Home modification safety-based interventions can help to decrease fall risk and improve independence and safety (Kahya et al., 2020; Chen et al., 2020). It is important to note that the effectiveness of fall prevention interventions may vary depending on individual circumstances and the specific interventions implemented (Nguyen et al., 2021). The strategy aims to create a living environment that supports independence, improves mobility, and reduces the risk of falls and other accidents. Bianco et al. (2016) highlighted the importance of older adults understanding fall prevention home modifications, noting that current design methods often do not align with the goals of older individuals, which hinders compliance with these interventions. However, PwD generally exhibit mixed attitudes toward existing home safety interventions for fall prevention, such as grab bars, handrails, non-slip surfaces, and visual cues. In the mild stages of dementia, many individuals may recognise these features but often forget to use them, misunderstand their purpose, or overlook them entirely during ADL (Marquardt et al., 2011; Mulliner et al., 2025). As cognitive impairment progresses, PwD may show reduced awareness, low motivation, or resistance toward environmental modifications, especially if the interventions are unfamiliar, visually intrusive, or perceived as signalling dependency. Some individuals may even view these safety features as unnecessary or disruptive to their usual routines (Marquardt et al., 2011). In all, the effectiveness of traditional home safety interventions is limited not by the physical design of the features themselves but by memory difficulties, reduced hazard awareness, and variability in acceptance, which influence how consistently PwD use or respond to these interventions.

Technology-based interventions can significantly improve the effectiveness of home safety measures for PwD by providing timely, personalised, and context-aware support (Rossi et al., 2020; Miura et al., 2023; Dylan et al., 2023; Su et al., 2024). Unlike passive safety features such as grab bars or handrails, digital systems such as sensors, reminders, AR cues, and intelligent monitoring tools can actively guide PwD during daily activities. These technologies can deliver real-time prompts to remind individuals when and how to use safety features, compensate for memory lapses, and enhance awareness of environmental hazards (Saracchini et al., 2015; Rossi et al., 2020; Mettouris et al., 2021). They can also detect unsafe movement patterns, identify increased fall risk, and alert caregivers when intervention is needed. By adapting to the user's cognitive state and behaviour, technology-based solutions promote greater independence, support safer navigation within the home, and bridge the gap between existing safety interventions and the cognitive limitations that hinder their consistent use. Ultimately, these tools enhance both the usability and effectiveness of traditional home modifications for fall prevention in dementia care.

Several studies have shown that technology interventions are increasingly being implemented as assistive tools to help PwD and those with MCI (Peterson et al., 2012; Ienca et al., 2017; Yaddaden et al., 2022; Makhataeva et al., 2023) as well as maintain their independence (Bauernschmidt et al., 2023). However, non-adherence to technology intervention prompts poses a significant barrier to the effectiveness of the interventions (Leslie et al., 2005; Glasgow, 2007; Trompetter et al. 2015) and this has been attributed to a lack of user engagement and interaction with the systems (MacEa et al., 2010; Kassinopoulos et al., 2023). Since non-adherence to intervention undermines its effectiveness, researchers have attempted to delve into the various reasons why individuals may not adhere to prescribed interventions. In the context of PwD, studies have investigated how AT can offer multiple interventions to enhance adherence.

2.1.4 Fall Risk Assessment and Prevention

Falls are a significant threat to the health and independence of elderly people and represent an enormous burden on the healthcare system. Successfully predicting falls could be of great help, yet this requires a timely and accurate fall risk assessment (Kiprijanovska et al., 2020). Fall risk assessment is essential to predict and prevent falls in geriatric populations, especially patients with life-long conditions like neurological disorders (Tunca et al., 2020). It aims to identify individuals who are more likely to fall, determine the contributing risk factors, and guide the selection of the most effective prevention strategies (Aicha et al., 2018; Minta et al., 2023). Many clinical practice guidelines for fall risk assessment are derived from studies that have either deliberately or inadvertently excluded older adults with cognitive impairment (Dolatabadi et al., 2018; Lim et al., 2017; Montero-Odasso and Speechley, 2017). Consequently, standard fall risk screening and assessment tools are often unsuitable for PwD, who may struggle to comprehend instructions, maintain attention, or engage with the assessment process.

Conventional fall risk assessment methods vary according to care settings. In clinical environments, tools such as the Morse Fall Scale and the Hendrich II Fall Risk Model are widely used, whereas assessments including the Berg Balance Scale and the Timed Up and Go (TUG) test are commonly applied in rehabilitation and geriatric medicine (Karen et al., 2001). These assessments are typically conducted in clinical settings and rely on questionnaires and standardised functional mobility tests, such as the TUG (Podsiadlo and Richardson, 1991), the Performance-Oriented Mobility Assessment (POMA) (Tinetti et al., 1986), and the Berg Balance Scale (Berg et al., 1989). However, despite their ease of administration, these methods are often subjective and dependent on assessor judgment, which may limit their reliability and consistency (Liang et al., 2015; Shumway-Cook et al., 2000).

Although traditional clinical assessments provide useful information about an individual's mobility and balance under controlled conditions, their ability to predict future falls remains limited (Barry et al., 2014). This limitation is particularly relevant for people living with dementia, whose cognitive impairment may affect task comprehension, consistency of performance, and real-world mobility behaviour, making clinical test outcomes less representative of daily life function (Aicha et al., 2018). In contrast, recent advances in wearable and sensor technologies enable continuous and unobtrusive monitoring of daily activities, offering more ecologically valid insights into fall risk by capturing natural movement patterns over time (Rajagopalan et al., 2017; Lara and Labrador, 2013). Sensors integrated with Artificial Intelligence (AI) models can predict simple and complex falls with good accuracy (Tang and Romero-Ortuno, 2022; Capodici et al., 2025). Based on the growing promise of AI and Machine Learning (ML) in fall risk assessment, recent research has increasingly focused on the development of advanced, data-driven systems to improve the accuracy and applicability of fall risk identification (Zhai et al., 2021; Agrawal et al., 2023; Velusamy et al., 2023; Capodici et al., 2025). These technologies leverage diverse data sources, including wearable sensors, gait analysis, computer vision, and electronic health records, to model complex patterns associated with fall risk that may not be captured by traditional clinical assessments.

Velusamy et al. (2023) analysed various ML algorithms used for fall prediction in older adults, including those based on gait analysis from sensor data. Gait analysis is an essential tool for predicting fall risk and preventing falls. Wearable sensors such as accelerometers, gyroscopes, and pressure sensors can be used to obtain gait-related data and extract features that can be used to predict falls. The study included 16 studies employing several ML algorithms, including Support Vector Machines (SVM), Decision Trees (DT), Convolutional Neural Network (CNN), K-Nearest Neighbour (KNN), Naive Bayes (NB), Random Forest (RF), and Logistic Regression (LR). The algorithm's accuracy ranges from 0.87 to 0.98. Additionally, it describes the challenges and limitations associated with wearable sensor-based fall prediction, and it identifies the possible future research directions in this field and provides a comprehensive narrative review of the recent research on fall risk assessment using wearable sensors.

Since not all clinical settings are able to provide patients with high-tech devices and sensors, Capodici et al.'s (2025) review provides evidence that falls can be predicted using ML without using sensors if the amount of data and its quality are adequate. The review explored 19 studies that used different ML, including DT, Adaptive Neuro-Fuzzy Inference System (ANFIS), Lasso LR, Artificial Neural Network (ANN), RF, LR, Markov Chain Monte Carlo (MCMC), DT, Bagging + SVM, eXtreme Gradient Boosting (GB), CatBoost, Conditional Inference Forest (CIF) and SVM + NB. The Neural Network (NN) models, LR variants and RF were the most used. However, further studies are needed to validate these models in diverse groups and populations. Metric performances reported by authors were commonly high in terms of accuracy, above 0.70. However, these ML model results were not directly comparable to each other, as they were fitted on different datasets, with potentially different distributions. Some studies have explored the use of pressure sensors for fall prediction. Zhai et al. (2021) used a pressure sensing insole to predict falls in real-time. The authors extracted features such as plantar pressure distribution and centre of pressure displacement, and used the DT algorithm to predict falls with an accuracy of 0.92. Agrawal et al. (2023) investigated fall risk prediction using wireless pressure-sensor–embedded insoles and ML models trained on dynamic walking data collected from 1,101 participants. The study evaluated six classifiers, SVM, RF, LR, NB, DT, and KNN, demonstrating that LR with oversampling achieved the highest AUC (0.82), while RF with oversampling attained the highest accuracy (0.81) and specificity (0.88). Although these methods can indicate fall risk, they are often inefficient for fall prediction due to reliance on manual feature engineering, which is time-consuming and human experience dependent. In contrast, DL enables data-driven feature learning, overcoming these limitations and improving predictive efficiency (Liang et al., 2019).

In recent years, researchers have begun to shift their focus from an ML approach to a DL approach in predicting falls using sensor data. Table 2.1 presents a summary review of selected state-of-the-art DL based fall risk assessment systems.

Table 2.1. Summary of Recent Studies on Fall Risk Assessment Using Wearable Sensors and AI Models for Older Adults and PwD

Study	Participants / Data	Sensors / Data Type	Method / Model	Key Features / Inputs	Performance / Results
Mohan et al., (2025)	66–71 older adults, aged 65–87, ADL datasets from PhysioNet	ADLs, medical history	Cooperative AI: Fuzzy Logic (vital signs) + DBN (ADLs), meta-model	Behavioural and physiological markers	Accuracy 0.93, Sensitivity 0.92, Specificity 1.00 (DBN-FRPA)
Chiang et al., (2025)	120 community-dwelling older adults, aged 65–90	Plantar pressure insoles	Hybrid CNN-BiLSTM	Tinetti scores, Centre of Pressure (COP)	Accuracy 0.94 with 8 sensors/foot; LOGO cross-validation used
Kravchenko et al., (2024)	Nursing home residents; MDS dataset and drug records	Clinical and prescription data	RNN, LSTM, GRU	Delirium scale, antipsychotic use, psychotropic exposure, cumulative days in facility	AUROC ≈ 0.74; all outperformed CART-logit (AUROC = 0.67)
Maiora et al., (2024)	106 older adults, ages 70–104	IMU sensors during TUG test	CNN, RNN, BLSTM	TUG test features	BLSTM: Accuracy 0.83, AUC 0.73
Li et al., (2023)	24 older adults, ≥65 years	Foot-mounted pressure sensors	CBAM-EfficientNet (CNN + attention module)	GASF-transformed plantar pressure data	Accuracy 0.98, Sensitivity 0.99

Suzuki et al., (2020)	42 nursing home residents with Alzheimer's	Clinical, age, dementia severity	CNN	MMSE scores, knee extension strength, FIM locomotion	Accuracy 0.66
Liang et al., (2019)	85 older adults, aged 65+	Footscan® plantar force sensors	ConvLSTM	Raw plantar force data	Sensitivity 0.93, Specificity 0.94, Accuracy 0.94; outperformed DTW-KNN
Aicha et al., (2018)	296 older adults	Accelerometers	CNN, LSTM, ConvLSTM, multi-task learning	Raw accelerometer data, age and gender (auxiliary tasks)	Best AUC 0.75 with multi-task learning and pre-processing
Tunca et al., (2020)	60 patients with neurological disorders (training), 16 patients (testing)	Inertial sensor–based gait analysis system	LSTM network	Sequential spatiotemporal gait parameters	Accuracy 0.92
Kiprijanovska et al., (2020)	18 participants performing normal and simulated abnormal gait	Wrist-worn IMU sensors (accelerometer, gyroscope, rotation vector)	Deep neural network combining CNN and BiLSTM	Multimodal IMU sensor signals; spatiotemporal gait features	Accuracy 0.89, sensitivity 0.91, specificity 0.86
Potluri et al., (2019)	7 participants with normal gait; simulated abnormal gaits	Plantar pressure insoles and IMUs (thigh and shank)	Stacked LSTM RNN	Gait parameters, pressure distribution, stance ratio	Successfully distinguished normal and abnormal gait patterns

Table acronyms: RNN (Recurrent Neural Networks); LSTM (Long Short-Term Memory); DBN (Deep Belief Network); DBN-FRPA (Deep Belief Network - Feature Representation and Pattern Analysis); BiLSTM (Bidirectional Long Short-Term Memory); GRU (Gated Recurrent Unit); CART (Classification and Regression Trees); ConvLSTM (Convolutional LSTM); DTW-KNN (Dynamic Time Warping - K-Nearest Neighbours); AUROC (Area Under the Receiver Operating Characteristic); AUC (Area Under the Curve); CBAM (Convolutional Block Attention Module); GASF (Gramian Angular Summation Field); FIM (Fisher Information Matrix);

Summary of Table 2.1 shows that DL has significantly advanced fall risk assessment in older adults, particularly those with dementia, by exploiting complex data sources such as gait sensors, electronic health records, and daily activity patterns to develop personalised and predictive models. Approaches including convolutional and RNN enable the detection of subtle gait and behavioural changes, allowing falls to be predicted earlier than with traditional methods. Given the heightened vulnerability of older adults to serious injury from falls, these advances highlight the need for stable and cost-effective e-health technologies to support independent living. DL and ML further enhance fall prediction through real-time monitoring, adaptive learning, and smart system integration, offering superior accuracy and adaptability compared to conventional approaches (Mohan et al., 2025).

2.2 Artificial Intelligence

Artificial Intelligence (AI) has emerged as a transformative technology in healthcare, enabling the development of intelligent systems capable of learning from complex datasets, identifying hidden patterns, and supporting evidence-based decision-making across a wide range of clinical applications (Vagvala, 2022). Within dementia care, AI has demonstrated considerable potential to improve diagnosis, monitoring, risk prediction, and personalised intervention by analysing diverse sources of data, including neuroimaging, speech, behavioural observations, physiological signals, and wearable sensor streams (Ranson et al., 2023). Recent studies have shown that AI-based approaches can facilitate earlier and more accurate identification of dementia-related conditions through automated analysis of speech characteristics (Fristed et al., 2022), brain imaging biomarkers, and cognitive assessment data. Furthermore, AI-driven technologies such as socially assistive robots, digital assistants, and personalised therapeutic interventions have shown promise in supporting daily living, enhancing quality of life, and reducing caregiver burden among people living with dementia (PwD) (Wu et al., 2025; Morris et al., 2026; Steijger et al., 2025).

Particularly relevant to this research is the growing application of AI and Deep Learning (DL) in fall risk assessment and prevention. By automatically extracting complex temporal, spatial, and behavioural features from multimodal data sources, including wearable sensors, gait measurements, and environmental observations, DL models have demonstrated superior capability for recognising subtle indicators of mobility decline and elevated fall risk that may not be readily detectable through conventional clinical assessment methods (Tunca et al., 2020). Similarly, predictive AI models have shown the ability to outperform traditional approaches in forecasting dementia progression, with studies reporting classification accuracies exceeding 80% when distinguishing stable Mild Cognitive Impairment (MCI) from cases likely to progress to Alzheimer's disease using cognitive and neuroimaging data (Lee et al., 2024a). These advances highlight the potential of AI to support precision medicine approaches that can adapt interventions according to an individual's evolving cognitive, functional, and behavioural profile.

Despite these promising developments, significant scientific, ethical, and practical challenges continue to constrain the widespread deployment of AI systems in dementia care. One of the most persistent limitations relates to data bias and representativeness. AI models are inherently dependent on the quality and diversity of their training datasets, and models trained on unrepresentative populations may generate biased predictions that disproportionately disadvantage underrepresented demographic groups, including ethnic minorities, socioeconomically disadvantaged populations, and older adults with complex comorbidities (Habbal et al., 2025). Such biases may arise from sampling bias, measurement bias, or algorithmic bias, potentially resulting in inequitable healthcare outcomes and reduced model reliability when deployed across diverse real-world populations. This concern is particularly important in dementia research, where significant heterogeneity exists across disease subtypes, severity levels, cultural contexts, and living environments.

Another critical challenge concerns transparency, explainability, and trustworthiness. Many high-performing AI systems, particularly deep neural networks, operate as "black-box" models whose decision-making processes are difficult to interpret or explain to clinicians, caregivers, and end users (Zhang and Zhang, 2023). In safety-critical applications such as fall risk assessment, the inability to understand why a system generated a particular prediction or intervention recommendation may limit clinical acceptance and raise concerns regarding accountability and patient safety. Consequently, there is increasing recognition that explainable and interpretable AI approaches are necessary to support informed decision-making, enhance user trust, and facilitate regulatory approval within healthcare environments (Weiner et al., 2024).

Ethical and governance considerations represent an additional barrier to adoption. Dementia populations are particularly vulnerable due to cognitive impairment, fluctuating decision-making capacity, and increased dependency on caregivers, raising complex questions regarding informed consent, autonomy, privacy, data ownership, and surveillance (Nouis et al., 2025). The collection of continuous behavioural and physiological data through wearable and ambient sensing technologies introduces further concerns regarding data security and potential misuse of sensitive health information. As AI systems become increasingly embedded within assistive technologies, robust ethical frameworks and governance mechanisms are required to ensure that principles of fairness, transparency, privacy, accountability, and human-centred design are incorporated throughout the system lifecycle (Zhang and Zhang, 2023; Weiner et al., 2024).

Furthermore, many AI-based dementia studies continue to suffer from limited external validation and poor generalisability. A substantial proportion of published models are evaluated using relatively small, homogeneous datasets collected under controlled research conditions, which may not accurately reflect the variability encountered in real-world clinical and home environments (Veronese et al., 2025). Consequently, model performance often degrades when applied to different populations, sensing platforms, geographical regions, or healthcare settings. This challenge is particularly relevant for fall risk assessment, where behavioural patterns, environmental hazards, and cognitive characteristics vary considerably across individuals and contexts. Without rigorous multicentre validation and longitudinal evaluation, confidence in the clinical utility and scalability of AI-driven dementia interventions remains limited.

The availability of high-quality training data also continues to represent a significant bottleneck for AI development. Obtaining large-scale, well-annotated datasets involving PwD is often difficult due to recruitment challenges, ethical restrictions, privacy concerns, and the relatively low frequency of critical events such as falls (Habbal et al., 2025). These constraints increase the risk of overfitting, reduce model robustness, and limit the development of reliable predictive systems. The challenge is further compounded when attempting to model complex interactions between cognitive state, environmental context, and behavioural responses, all of which contribute to fall risk in dementia populations.

Collectively, these limitations highlight that the successful integration of AI into dementia care extends beyond algorithmic performance alone. Future progress will require the development of inclusive and representative datasets, explainable and transparent AI methodologies, robust ethical governance frameworks, and comprehensive real-world validation studies involving diverse dementia populations. Addressing these challenges is essential for ensuring that AI-enabled assistive technologies are not only technically effective but also trustworthy, equitable, clinically meaningful, and capable of delivering sustainable benefits for people living with dementia, their caregivers, and healthcare providers (Ueda et al., 2025).

2.2.1 Deep Learning

Deep learning (DL) has shown strong performance in detecting pre-fall and fall events from wearable accelerometer and gyroscope data, indicating their effectiveness in real-time fall risk assessment systems that could support timely intervention (Mohammad et al., 2023; Chiang et al., 2025; Mohan et al., 2025). DL architectures have the potential to produce models that can operate directly on the raw data, thus alleviating the need for feature engineering (Tunca et al., 2020). The algorithm uses hierarchical learning process to extract complex, high-level abstractions from data. Each level of the hierarchy builds on simpler abstractions learned at the previous level to develop more complex representations (Munappy, et al., 2022). Its frameworks provide a high-level programming interface with essential tools for designing, training, and validating DL models. Some of these frameworks include TensorFlow (Abadi et al., 2015), PyTorch (Paszke et a., 2019), MXNet (Chen et al., 2015), CNTK (Seide and Agarwal, 2016), Caffe (Jia et al., 2014), Ultralytics (Sapkota and Karkee, 2025) etc.

Convolutional Neural Network (CNN) is the most famous and commonly employed algorithm used in the field of DL (Zhou, 2020; Jhong et al., 2020). CNN which is also called ConvNets is one type of feedforward Neural Networks (NN) that is a popular choice for different computer vision tasks such as image recognition (Alzubaidi, et al., 2021). CNN is a kind of DL network architecture whose goal is to learn higher-order features in the data via convolutions (Gu et al., 2018).

In CNN, the network receives input. Each input (for instance, an image) passes through a series of convolution layers with various filters. The control layer controls how the signal flows from one layer to the other. Next, the output is flattened and fed into the fully connected layer where all the layers of the network are connected with every neuron from a preceding layer to the neurons from the subsequent layer. As a result, the output can be classified (Alom, et al., 2018). Figure 2.1 shows the overall architecture of the CNN, which includes an input layer, multiple alternating convolutions, and max-pooling layers, one fully connected layer and one classification layer.

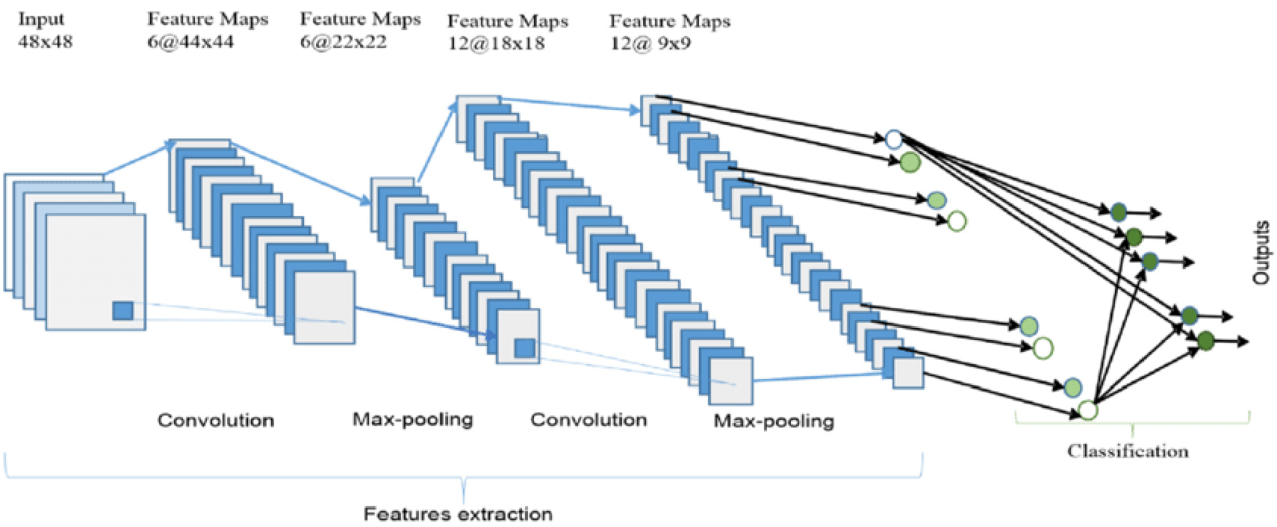

Figure 2.1. Architecture of a Convolutional Neural Networks (CNN). Source: Alom et al., (2018).

Recent benchmarks have shown that CNNs show remarkable performance on image classification, which makes them an excellent approach for object recognition and detection (Patil et al., 2022). In the proposed work of Kumar and Srivastava (2020), CNN was used to develop a model which is composed of multiple layers to detect, label, and classify objects into any of the defined classes, and it attained a good performance in both static and video images. Galvez et al., (2018) compared Single Shot Multi-Box Detector (SSD) with MobileNetV1 and a Faster Region-based CNN (Faster-RCNN) with InceptionV2, which are two state-of-the-art CNN models for object detection and result showed that one model is ideal for real-time application because of speed and the other can be used for more accurate object detection.

DL and other AI techniques have been extensively applied in fall risk assessment research for older adults and individuals with neurological disorders, including dementia, by analysing wearable sensor data to uncover movement patterns predictive of fall risk and improve identification and mitigation strategies (Potluri et al., 2019; Suzuki et al., 2020; Li et al., 2023). However, further research is required to strengthen clinical validity, particularly through dementia-specific cohorts and evaluation in real-world settings, to ensure the robustness and generalisability of these approaches (Chen et al., 2023).

2.2.2 Transfer Learning

Deep learning (DL) methods rely on vast amounts of accurately labelled training data, which are often sensitive to domain shifts (LeCun et al., 2015). However, collecting and labelling massive amounts of data is very time consuming and monotonous (Zhang et al., 2023a). Transfer Learning (TL) has emerged as a viable approach to addressing the challenge of data scarcity and circumvents the necessity of constructing models from scratch. TL is an ML paradigm in which knowledge acquired from a source task is leveraged to improve learning performance on a related but distinct target task (Pan and Yang, 2010).

In neuroimaging, this approach facilitates the study of progression from MCI to dementia by transferring knowledge from related classification tasks, such as MCI versus cognitively unimpaired individuals, to target tasks such as dementia versus cognitively unimpaired individuals (Bae et al., 2021; Cheng et al., 2015). The overarching objective of TL is to furnish a framework for leveraging pre-existing knowledge to solve novel but related problems more expediently and efficiently.

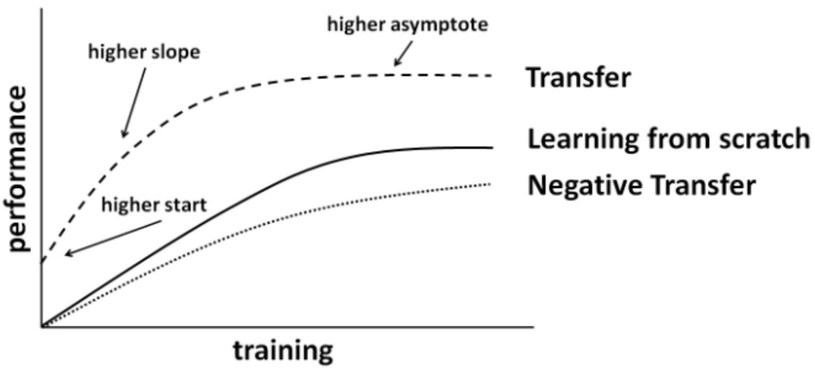

Figure 2.2. Positive and Negative Effects of Transfer Learning on Performance. Source: Torrey and Shavlik, (2019).

TL can lead to a higher asymptote -a higher performance level- in the target task, a greater slope (a shorter learning curve), or a higher start (a higher performance level) in the target task (Torrey and Shavlik, 2019). However, a case of negative transfer, in which the knowledge acquired from a source domain adversely impacts the performance of a target learner, may arise (Zhang et al., 2023b). These are illustrated in Figure 2.2. The source task and its relationship to the target task determine the effectiveness of a transfer learning strategy.

Pan and Yang (2010), introduced some notations that formed the basis of their definition of TL. A domain is defined as:

$$D = \{X, P(X)\}, \tag{2.1}$$

where χ denotes the feature space and $P(X)$ represents the marginal probability distribution over χ. A task is defined as:

$$T = \{y, f(.)\}, \tag{2.2}$$

where y is the label space and $f: x \rightarrow y$ is the predictive function, typically learned from training data.

In TL, we consider a source domain-task pair (D_s, T_s) and a target domain-task pair (D_T, T_T), where either the domain differs $(Ds \neq D_T)$, the task differs $(T_s \neq T_T)$, or both. The objective of TL is to learn the target predictive function ft(.) by exploiting knowledge embedded in Ds and Ts, even when labelled data in the target domain are scarce.

From an optimisation perspective, conventional supervised learning seeks to minimise the empirical risk:

$$\min_{\theta} \mathbb{E}_{(x,y)\sim P_T(X,Y)} [\mathcal{L}(f_\theta(x), y)], \tag{2.3}$$

where $\mathcal{L}(.)$ is a loss function and θ denotes model parameters. In contrast, TL introduces an inductive bias by initialising or constraining θ using θ_s learned from the source task.

In fall risk assessment research, this paradigm enables models to recognise environmental hazards (Hsiao, et al., 2025), human poses, or motion patterns from images or sensor-derived representations with improved efficiency and accuracy compared to models trained solely on small, task-specific datasets.

TL is commonly implemented through the use of pre-trained models, which are initially trained on large-scale datasets and subsequently adapted to domain-specific tasks with limited data. This approach is particularly valuable in fall risk assessment, where collecting extensive labelled datasets, especially from older adults and individuals with cognitive impairment, is often challenging. By leveraging learned representations from pre-trained models, researchers can improve model performance, reduce training time, and enhance generalisation in fall risk assessment systems. The following section reviews several commonly used pre-trained models that have been explored in the literature for fall risk assessment applications.

2.2.2.1 Pretrained Models

Pre-trained models originally trained on large datasets such as ImageNet (Deng et al., 2009) have been shown to capture generic visual features that can be effectively repurposed for related tasks, including object detection and activity recognition via fine-tuning (Canziani et al., 2016). A pre-trained model is a NN that has already been trained on a large benchmark dataset to solve a task similar to the one targeted in a new application, providing learned feature representations that can be adapted to downstream tasks through TL (Iman et al., 2022). This approach is widely used because training Deep Neural Networks (DNN) from scratch on domain-specific data is computationally expensive and often infeasible when labelled data are limited (Pan and Yang, 2010), as is common in fall risk assessment for older adults and clinical populations.

Several of these pretrained architectures have significantly advanced computer vision tasks such as image classification, feature extraction, and object detection. VGG-16, proposed by Simonyan and Zisserman (2014), demonstrated that increasing network depth using small 3×3 convolution filters improve image recognition performance. The model consists of 13 convolutional layers, two fully connected layers, and a SoftMax classifier, and is widely used for transfer learning due to its strong low-level feature extraction capabilities (Tammina, 2019). To address degradation problems in deeper networks, ResNet introduced residual learning blocks that enable easier optimisation and improved accuracy in very deep architectures (He et al., 2016). Similarly, MobileNet employed depthwise separable convolutions to reduce computational complexity, making it suitable for mobile and embedded applications (Howard et al., 2017). Inception improved computational efficiency through the use of 1×1 convolutions for dimensionality reduction within multi-scale convolution modules (Szegedy et al., 2014), while Xception extended this concept using depthwise separable convolutions, achieving superior performance on benchmark datasets such as ImageNet and JFT (Chollet, 2017). In object detection, YOLO (You Only Look Once) introduced by Redmon et al. (2016) transformed detection into a single regression problem, enabling real-time object detection with high accuracy and speed. Its later versions further improved efficiency and detection performance across various computer vision applications.

2.2.2.2 Object Detection

Falls arise from the interaction of intrinsic and extrinsic risk factors. Intrinsic factors include impairments in gait, balance, vision, reaction time, and muscle strength (Lord and Dayhew, 2001) and extrinsic factors primarily relate to environmental hazards such as uneven or slippery surfaces, obstacles, and poor lighting (Appeadu and Bordoni, 2023). Object detection techniques play an increasingly crucial role in fall risk assessment by enabling the automated identification of environmental hazards and safety features in living environments, thereby supporting proactive, context-aware interventions tailored to the needs of cognitively impaired older adults. It involves identifying the class of an object instance and estimating its location by providing a bounding box around the object (Zhao et al., 2019b).

The construction of a robust object detector model highly depends on the design of a DL backbone network. The primary function of the backbone network is to extract features from images before proceeding to subsequent steps, such as the localisation phase in object detection (Liu et al., 2020). Most of the recent successful object detection methods have been based on

CNN backbone. These backbones, a pretrained or randomly initialised feature extractor (Goldblum, et al., 2023) include YOLO (Redmon et al., 2016), AlexNet (Krizhevsky et al., 2012), VGG (Simonyan and Zisserman, 2014), ResNet (He et al., 2016), Inception (Szegedy et al., 2014), Efficientnets (Tan and Le, 2019), CSPNet (Chien-Yao et al., 2019), DenseNet (Huang et al., 2017), and Xception (Chollet, 2017). Some of these backbones are trained on very large datasets, with some popular examples summarised in Table 2.2.

The quantity and quality of the dataset as well as the type of NN architecture used determines the accuracy of an object detection model (Zhou et al., 2017). Deng et al. (2009) posit that by utilising large-scale image datasets, more complex and reliable models and algorithms can be developed.

Figure 2.3. Snapshot of Two Image Categories in ImageNet. Source: Deng et al., (2019).

Table 2.2. Common Datasets for Object Detection

Dataset	Description	Authors
ImageNet	Large-scale image dataset built upon the backbone of the WordNet structure. It consists of 3.2 million images having 12 subtrees – “mammal, bird, fish, reptile, amphibian, vehicle, furniture, musical instrument, geological formation, tool, flower, fruit” and 5247 synsets. Each synset consist of an average of 500-1000 images.	Deng et al., (2009)
COCO	Large-scale object detection, segmentation, key-point detection, and captioning dataset. The dataset consists of 2.5 million labelled instances in 328k image.	Lin et al., (2014)
Scene UNderstanding (SUN) database	It consists of 130,519 images of different scene which are categorised into 899. This scene includes access road, grassland, stream, ditch, alleyway, skyscraper, mountain, cathedral etc. The images are 200 × 200 pixels or larger.	Xiao et al., (2010)

PASCAL Visual Object Classes (VOC)	It contains of 20 object categories including vehicles, household, animals, and other: aeroplane, bicycle, boat, bus, car, motorbike, train, bottle, chair, dining table, potted plant, sofa, TV/monitor, bird, cat, cow, dog, horse, sheep, and person. Each image in this dataset has pixel-level segmentation annotations, bounding box annotations, and object class annotations.	Everingham et al., (2009)
LabelMe	It consists of 30369 images with 111 490 annotations ground truth labels. The images belong to 180 categorises.	Russell et al., (2008)
Lotus Hill dataset	Large-scale general-purpose image database with human annotated ground truth. It consists of 636,748 annotated images and video frames which are organised into 13 categories.	Yao et al., (2007)
TinyImage	A dataset of 80 million 32 × 32 low resolution images, collected from the Internet by sending all words in WordNet as queries to image search engines.	Torralba et al., (2008)
Caltech101	Consist of 8677 labelled images belonging to 101 categories. Each categories having 40-800 images. The size of each image is roughly 300 x 200 pixels.	Fei-Fei et al., (2004)
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)	The ILSVRC is a benchmark in object category classification and detection on hundreds of object categories and millions of images. ILSVRC2012 consist of 1000 object classes and 1,431,167 annotated images.	Russakovsky et al., (2015)
Open Images	Open Images is a computer vision dataset covering approximately 9 million images with labels spanning thousands of object categories (annotations -30,113,078 image-level labels, 15,440,132 bounding boxes, 374,768 visual relationship triplets).	Kuznetsova e al., (2018)

In recent years, YOLO has become a widely adopted object detection model, demonstrating state-of-the-art performance across multiple benchmark datasets (Redmon et al., 2016; Bochkovskiy et al., 2020; Yin et al., 2020). The method is based on a deep CNN architecture, as illustrated in Figure 2.4, which enables efficient feature extraction and object localisation. Unlike traditional two-stage detection pipelines, YOLO reframes object detection as a single regression problem, directly predicting bounding box coordinates and class probabilities from raw image pixels in one forward pass (Redmon et al., 2016). This unified design removes the need for separate region proposal mechanisms, thereby significantly improving inference speed while maintaining competitive accuracy when compared with two-stage detectors (Redmon et al., 2016; Liu et al., 2016).

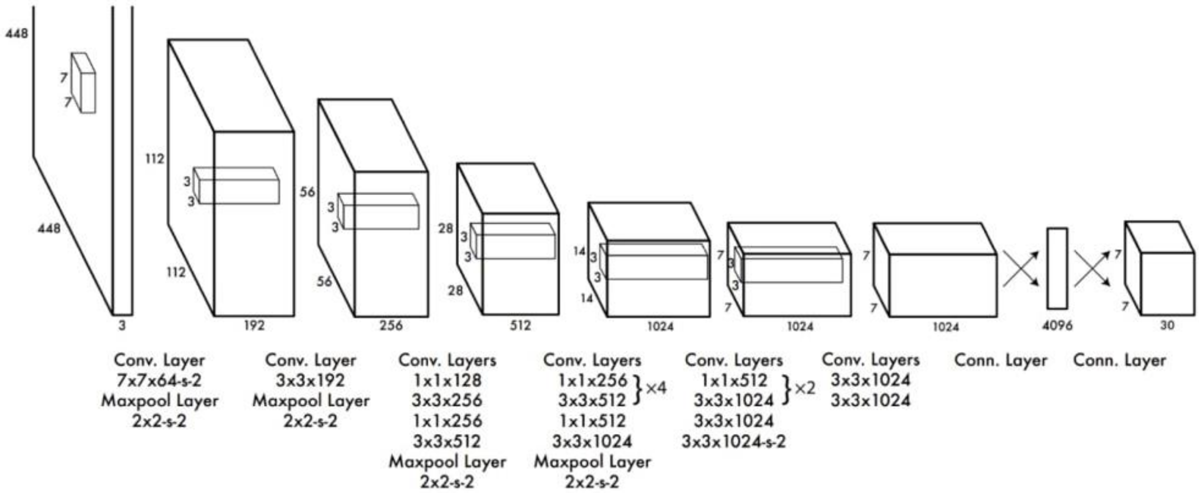

Figure 2.4. YOLO Architecture. Source: Redmon et al., (2016)

In this thesis, YOLO was selected over other CNN-based object detection frameworks primarily for its architectural efficiency, real-time performance, and competitive accuracy (Redmon et al., 2016; Reddy et al., 2024). CNN-based object detection models such as Faster R-CNN and SSD have demonstrated strong capabilities in visual recognition tasks; however, they differ fundamentally in their detection paradigms. Two-stage detectors like Faster R-CNN first generate region proposals and then classify them, which introduces additional computational overhead and latency (Reddy et al., 2024). In contrast, YOLO reframes object detection as a single regression problem, predicting bounding boxes and class probabilities directly from the full image in a single forward pass, thereby enabling end-to-end optimisation (Redmon et al., 2016). This unified architecture eliminates the need for separate region proposal stages and significantly simplifies the detection framework. Empirical studies consistently demonstrate that YOLO achieves substantially higher frame rates compared to traditional CNN-based detectors. For instance, the original YOLO model achieved up to 45 frames per second (FPS), with lightweight variants reaching as high as 155 FPS, making it suitable for real-time applications such as surveillance, autonomous driving, and robotics (Redmon et al., 2016). Comparative analyses further confirm that YOLO outperforms Faster R-CNN in terms of speed due to its single-stage design, while Faster R-CNN typically operates at significantly lower frame rates because of its region proposal mechanism (Redmon and Farhadi, 2016; Alkentar et al., 2021; Reddy et al., 2024; Wang et al., 2025a). This makes YOLO particularly advantageous in scenarios where low latency is critical.

2.2.2.3 Image Enhancement

Image enhancement encompasses a broad class of techniques aimed at improving the visual quality of images or making them more suitable for specific applications such as medical diagnosis, remote sensing, and computer vision tasks (Maini and Aggarwal, 2010; Sargun and Rana, 2015). Traditional image enhancement methods primarily rely on deterministic, hand-crafted algorithms that operate in either the spatial or frequency domain. Spatial domain techniques include contrast stretching, histogram equalisation, and filtering operations designed to directly manipulate pixel intensities (Gonzalez and Woods, 2018). Histogram equalisation, for instance, redistributes pixel intensity values to enhance global contrast, while adaptive variants such as Contrast Limited Adaptive Histogram Equalisation (CLAHE) improve local contrast and mitigate over-amplification of noise (Pizer et al., 1987). In the frequency domain, methods such as Fourier transform-based filtering and homomorphic filtering are used to enhance images by attenuating or amplifying specific frequency components, often to suppress noise or highlight structural details (Gonzalez and Woods, 2018). Additionally, wavelet transform-based enhancement techniques enable multi-resolution analysis, allowing selective enhancement of image features at different scales (Mallat, 1989). Despite their effectiveness in controlled scenarios, traditional methods often struggle with generalisation and require manual parameter tuning, making them less robust to diverse and complex real-world conditions.

With the advent of ML, early data-driven approaches began to surpass traditional methods by learning mappings from low-quality to high-quality images using statistical models and shallow architectures. However, the most significant advancements in image enhancement have been driven by DL techniques, particularly CNN, which automatically learn hierarchical feature representations from large datasets (LeCun et al., 2015). Among these, CNNs serve as the core framework, enabling effective modelling of spatial structures through layered convolutional operations that capture both low-level features (e.g., edges and textures) and high-level semantic information, making them highly suitable for tasks such as denoising, deblurring, and super-resolution (Dong et al., 2014). A notable early DL-based method is the Super-Resolution Convolutional Neural Network (SRCNN), which introduced an end-to-end learning paradigm for mapping low-resolution images to high-resolution counterparts, eliminating the need for traditional multi-stage processing pipelines (Dong et al., 2014).

Building on standard CNNs, advanced architectures such as residual networks and densely connected networks further enhance performance by improving gradient flow and encouraging feature reuse, thereby enabling deeper and more efficient models (He et al., 2016; Huang et al., 2017). Encoder–decoder architectures, particularly U-Net, incorporate skip connections to fuse multi-scale contextual information with fine spatial details, making them especially effective for image restoration tasks where both global structure and local precision are critical (Ronneberger et al., 2015). In parallel, autoencoder-based approaches learn compact latent representations of degraded images and reconstruct enhanced outputs by minimising reconstruction errors, offering efficient solutions for noise reduction and feature learning, especially in scenarios with limited labelled data (Vincent et al., 2008).

Generative Adversarial Networks (GAN) introduce a fundamentally different paradigm by employing an adversarial training process in which a generator produces enhanced images and a discriminator evaluates their realism, leading to visually sharper and more perceptually convincing results than traditional pixel-wise optimisation methods (Goodfellow et al., 2014; Ledig et al., 2017). Variants such as SRGAN further improve perceptual quality by integrating adversarial, content, and perceptual losses, enabling the generation of high-frequency details that closely resemble natural images (Ledig et al., 2017).

Diffusion model-based techniques have also become a powerful approach for image enhancement by formulating the task as a probabilistic denoising process. These models progressively corrupt an image by adding noise in a forward process and then learn a reverse process to iteratively reconstruct a clean, high-quality image from the noisy input. This iterative refinement enables diffusion models to capture complex data distributions and generate high-fidelity outputs with strong perceptual quality, making them particularly effective for tasks such as super-resolution, denoising, and image restoration. Compared to adversarial methods, diffusion models offer more stable training dynamics and reduced risk of artefacts, albeit at the cost of higher computational complexity due to multiple sampling steps (Ho et al., 2020; Dhariwal and Nichol, 2021).

In parallel, transformer-based techniques have emerged as a strong complementary approach by leveraging self-attention mechanisms to model long-range dependencies and global context within images. Vision Transformers (ViTs) process images as sequences of patches to capture global interactions (Dosovitskiy et al., 2021), while hierarchical designs such as Swin Transformer balance efficiency and feature representation through localized attention mechanisms (Liu et al., 2021). These models are often integrated into encoder–decoder frameworks or combined with CNNs to exploit both global and local feature learning, with additional enhancements such as multi-scale and cross-attention further improving performance in complex restoration scenarios (Wang et al., 2022a; Chen et al., 2021; Zamir et al., 2022).

Furthermore, in scenarios where paired training data is scarce or unavailable, zero-reference and self-supervised methods provide an effective solution by learning enhancement mappings directly from input images using loss functions based on natural image priors such as exposure consistency, colour constancy, and spatial coherence (Guo et al., 2017; Guo et al., 2020). A representative example is Zero-DCE, which estimates pixel-wise enhancement curves and optimises them without requiring ground-truth references, making it highly practical for real-world low-light enhancement tasks (Guo et al., 2020). Additionally, zero-shot methods exploit internal image statistics by training models on a single test image, enabling adaptive, image-specific enhancement without external datasets and demonstrating strong performance in data-scarce environments (Shocher et al., 2018).

In this thesis, zero-reference techniques was selected as the preferred approach for image enhancement due to their practicality and adaptability in real-world scenarios where high-quality paired training data is often unavailable or expensive to obtain (Guo et al., 2020; Zhu et al., 2017). Unlike supervised methods that rely on ground-truth reference images, zero-reference approaches learn enhancement mappings directly from degraded inputs by leveraging carefully designed non-reference loss functions based on natural image priors, such as exposure consistency, colour constancy, and spatial coherence (Guo et al., 2020; Jiang et al., 2021). This makes them particularly suitable for unconstrained environments, including low-light and adverse imaging conditions, where collecting aligned datasets is infeasible (Lore et al., 2017; Guo et al., 2017). Furthermore, zero-reference methods offer greater flexibility and generalisation, as they are not tightly bound to specific paired datasets and can adapt to diverse degradation patterns (Zhang et al., 2021). Their relatively lightweight architectures and reduced dependency on large annotated datasets also contribute to lower computational and data collection costs (Guo et al., 2020; Wang et al., 2013).

More specifically, this thesis adopts Zero-DCE (Guo et al., 2020), which introduces several key advancements within the zero-reference paradigm. Zero-DCE formulates image enhancement as a task of estimating pixel-wise high-order curves that iteratively adjust image illumination, enabling fine-grained and adaptive enhancement without over-amplifying noise or introducing artefacts (Guo et al., 2020). Unlike many DL approaches, it does not require paired or even unpaired datasets, relying instead on a set of carefully designed non-reference loss functions that enforce perceptual quality and visual consistency. Additionally, Zero-DCE employs a lightweight network architecture, making it computationally efficient and suitable for real-time applications. Its ability to preserve colour fidelity, avoid overexposure, and generalise well across diverse lighting conditions represents a significant advancement over earlier enhancement techniques. Consequently, the adoption of Zero-DCE in this thesis aligns with the objective of developing an efficient, scalable, and practically deployable image enhancement solution.

2.3 Hidden Markov Model

Hidden Markov Models (HMM) are statistical models based on Markov processes in which the underlying states are not directly observable (Franzese and Iuliano, 2019). HMM are well suited for capturing temporal dynamics in sequential data, as they incorporate the history of previous states and observations when making decisions about the current sequence (Shehroz et al., 2017). It is commonly defined by the parameter set triple $\lambda = (A, B, \pi)$, where A is the state transition probability matrix, B denotes the observation probability matrix, and π is the initial state probability distribution. A sequence of observations, denoted by O, is available and is probabilistically linked to the hidden state sequence X through the observation matrix B (Franzese and Iuliano, 2019; Sánchez et al., 2020; Rabiner, 1989). Figure 2.5 illustrates the high-level structure of an HMM.

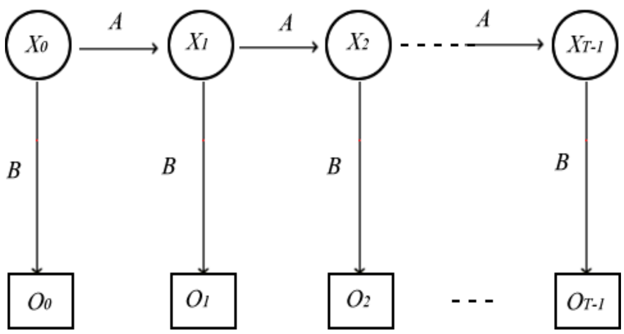

Figure 2.5. Hidden Markov Model Structure.

The components of HMM structure is defined as follows:

State: The model comprises a finite number of hidden states $X = \{X_0, X_1, X_2, \ldots, X_T\}$, representing various underlying conditions. The T denote the number of hidden states in the model and the state at time t is denoted by x_t.

Observations*:* The observations are given as a sequence $O = \{ O_1, O_2, \ldots, O_T\}$, where each observation is produced by a hidden state. T denotes the total number of observations and each O_t corresponds to the observation at time step t, for $t=1, 2, \ldots, T$.

Transition Probabilities: The transition probabilities between states are defined as:

$$P(S_t|S_{t-1}) = P_{ij} = P(Z_t = S_j \,|Z_{t-1} = S_i) \tag{2.6}$$

where P_{ij} is the probability of transitioning from state S_i to state S_j.

Emission Probabilities: The emission probabilities describe the likelihood of observing a particular output given a state:

$$P(O_t \,|S_t) = b_j(O_t) = P(X_t = O_t \,|Z_t = S_j) \tag{2.7}$$

where $b_j(O_t)$ is the probability of observing O_t when in state S_j.

Initial State Distribution: The distribution of the initial state is defined as:

$$P(Z_1 = S_i) = \pi_i \tag{2.8}$$

where π_i is the probability of starting in the state S_i.

In fall-related assessment and detection systems, a sequence of observed measurements O, such as accelerometer or motion sensor data, is used to infer a corresponding hidden sequence of activity or physiological states X (e.g., walking, stumbling, falling) (Yu et al., 2018). Because these observable signals are probabilistically related to the hidden states through the observation matrix B, HMMs can classify or predict fall events or fall-risk behaviours from time-series sensor data. Researchers have applied HMM classifiers to wearable and environmental sensor inputs to distinguish normal activities from fall events with high sensitivity and predictive value, demonstrating HMMs' practical value in automated fall monitoring (Yu, 2024; Wang et al., 2022b; Htet et al., 2022).

2.3.1 Applications in Dementia Continuum

Hidden Markov Models (HMMs) and their variants have been widely adopted in healthcare research for modelling latent disease states, behavioural patterns, and temporal dynamics where the true underlying state is not directly observable (Baucum et al., 2020; Canavan et al., 2021).

In particular, HMM-based approaches have shown strong potential in dementia recognition, disease progression modelling, and activity or fall detection in elderly populations. Early work by Chen and Pham (2013) proposed a computational framework for modelling MRI-based structural complexity of the brain using HMMs for dementia recognition. Their approach successfully distinguished individuals with mild Alzheimer's disease and achieved superior classification accuracy compared to other machine learning classifiers, demonstrating the suitability of HMMs for capturing complex neurodegenerative patterns from imaging data.

Beyond diagnosis, HMMs and Markov-based models have also been employed for risk prediction and disease progression. A Markov prediction model was developed to estimate the risk of developing dementia in elderly individuals while accounting for mortality as a competing risk. Validation using 515 participants from the ADNI dataset showed that the probability of dementia decreases at advanced ages due to increasing mortality risk, achieving an area under the ROC curve of 0.78 (0.95 CI: 0.73–0.82). Similarly, Canavan et al. (2021) proposed a Gaussian HMM to model dynamic disease trajectories in patients with MCI. Their unsupervised model trained using the Baum–Welch algorithm, incorporated non-invasive cognitive and functional markers and demonstrated meaningful alignment between inferred HMM states and clinical ground-truth labels.

Recent studies have extended traditional HMMs by integrating DL techniques to enhance predictive performance. Baucum et al. (2020) introduced Hidden Markov Recurrent Neural Networks (HMRNNs), which combine the interpretability of HMMs with the flexibility of NN. Applied to Alzheimer's disease data, the HMRNN improved disease forecasting by incorporating patient covariates and estimating parameters jointly via gradient descent. In a similar direction, Nagarajan et al. (2023) proposed Neutrosophic HMM (NHMM) to better capture uncertainty and ambiguity in disease progression, showing that NHMMs can simulate disease development more realistically than traditional clinical staging.

HMMs have also been extensively used in fall detection and activity recognition, which are closely related to dementia care and independent living. Yu et al. (2018) developed an HMM-based fall detection system using a single motion sensor, addressing real-world challenges such as sensor misplacement through orientation calibration. Their system achieved high sensitivity and positive predictive value on both experimental and real-world datasets. Building on this, Yu (2024) proposed a fall prevention framework combining HMMs with Generative Adversarial Networks (HMM-GAN) and LR. This framework automatically extracts temporal features from sensor data, handles sequential dependencies, and supports both supervised and semi-supervised learning.

In the domain of human activity and behaviour modelling, Wang et al. (2022b) integrated smartphone sensors with positioning systems and proposed an attention-based Convolutional Neural Network Long Short-Term Memory (CNN–LSTM) model for action recognition, followed by an HMM to model daily behaviour states. Their approach achieved high precision, recall, and F1-score, and the behavioural HMM was able to detect changes in individual activity patterns. Similarly, Htet et al. (2022) developed a real-time action recognition system using depth cameras and HMMs, incorporating privacy-preserving depth data, YOLO-based person detection, and Histogram of Oriented Gradients (HOG) features, achieving promising accuracy in care-centre environments.

Several studies have focused on long-term behavioural monitoring and abnormality detection in elderly populations. AlBeiruti and Al-Begain (2014) used HMMs with simple binary sensors to detect sudden and gradual behavioural changes that may indicate dementia, leaving final decision-making to caregivers. Fletcher-Lloyd et al. (2023) applied Markov modelling to Internet of Things (IoT)-based in-home monitoring data to detect behavioural changes in PwD. Their analysis revealed significant changes in kitchen activity patterns during the COVID-19 pandemic, highlighting the sensitivity of Markov-based approaches to real-world behavioural shifts.

HMMs have also been applied to multimodal and wearable data for activity indexing and recognition. Karaman et al. (2014) proposed a hierarchical two-level HMM for analysing activities of daily living from wearable camera videos, combining visual, audio, and mid-level features such as motion and location. Their results demonstrated the challenges of real-world activity recognition and the effectiveness of hierarchical HMM structures.

The above existing literature demonstrates that HMMs and their extensions provide a powerful and interpretable framework for modelling dementia-related processes, including diagnosis, disease progression, behavioural monitoring, and fall detection.

2.4 Multimodal Wearable Devices

Recent advances in multimodal wearable technologies have transformed the monitoring and assessment of PwD, offering new opportunities for the development of objective, continuous, and personalised digital health solutions. Research has increasingly focused on the use of digital biomarkers, including heart rate, electrodermal activity, skin temperature, sleep patterns, and movement characteristics, combined with AI algorithms to detect early cognitive decline, predict episodes of agitation, and monitor behavioural and psychological symptoms of dementia (Nair et al., 2025; Dieffenderfer et al., 2023; Iaboni et al., 2022). In particular, wearable sensor systems have demonstrated the ability to capture physiological and behavioural changes that may not be observable during routine clinical assessments, enabling earlier identification of deteriorating cognitive and functional status and supporting more proactive interventions (Dieffenderfer et al., 2023; Petersen et al., 2019). Recent work by Nair et al. (2025) further highlights the importance of stakeholder-informed and co-designed wearable technologies, including hearable devices, emphasising that successful implementation in dementia care requires solutions that are acceptable, unobtrusive, and responsive to the needs of people with dementia, caregivers, and healthcare professionals.

The application of multimodal wearables for behavioural monitoring has shown particularly promising results. Iaboni et al. (2022) demonstrated that wearable sensors measuring physiological and movement-related signals, combined with personalised machine learning models, can accurately detect agitation and aggression in individuals with dementia. Their findings revealed substantial inter-individual variability in sensor-derived behavioural signatures, suggesting that personalised approaches may outperform generic population-based models in identifying escalating behavioural symptoms and facilitating timely, tailored interventions. Such findings support the broader movement towards precision dementia care, where digital health technologies are used to deliver individualised monitoring and management strategies.

Beyond behavioural assessment, wearable sensing technologies have emerged as valuable tools for fall risk assessment and mobility monitoring in older adults and neurological populations. Continuous monitoring of daily activities through wearable devices provides objective insights into movement patterns associated with declining mobility and increased fall risk (Rajagopalan et al., 2017; Lara and Labrador, 2013). Wearable systems incorporating IMU, pressure sensors, and electromyography have enabled reliable quantification of spatiotemporal gait characteristics, including gait speed, cadence, stride length, and gait variability, all of which are recognised indicators of fall risk (Fang et al., 2017; Liu et al., 2012; Guan et al., 2025). Studies have consistently demonstrated that changes in these biomechanical parameters reflect impairments in motor control and gait stability that often precede falls (Liang et al., 2019; Lara and Labrador, 2013). Among available technologies, IMU-based systems have gained particular attention due to their portability, affordability, and ability to capture detailed movement data during everyday activities outside controlled laboratory environments (Kobsar et al., 2020; Maiora et al., 2024). Their capacity for unobtrusive, long-term monitoring allows subtle changes in gait regularity, balance, and stability to be detected in real-world settings, providing clinically meaningful information that may not be evident during episodic assessments (Kiprijanovska et al., 2020).

The relevance of these technologies is especially pronounced in PwD, who frequently experience progressive gait impairments, postural instability, and reduced mobility that substantially increase their risk of falling (Kiprijanovska et al., 2020). Emerging evidence suggests that wearable sensor-based approaches, including low-burden wrist-worn devices, can effectively identify gait abnormalities associated with elevated fall risk while maintaining usability and comfort for long-term monitoring (Chen et al., 2022). Consequently, integrating multimodal wearable sensing with advanced data-driven modelling techniques offers a promising approach for delivering accurate, affordable, and user-centred fall risk assessment. This aligns closely with the broader vision of personalised dementia care, whereby continuous monitoring of physiological, behavioural, and mobility-related biomarkers can support earlier intervention, improve clinical decision-making, and ultimately enhance safety, independence, and quality of life for people living with dementia (Nair et al., 2025; Iaboni et al., 2022; Chen et al., 2022).

2.5 Conclusion

This chapter explored a range of technologies investigated to support PwD and individuals with MCI, highlighting the growing role of intelligent AT in addressing the progressive cognitive, behavioural, and functional decline associated with these conditions. Dementia is characterised by deterioration in memory, attention, executive functioning, and spatial awareness, all of which significantly affect independence and the ability to perform ADL. Due to the complex, heterogeneous, and progressive nature of dementia, conventional one-size-fits-all interventions are often insufficient, motivating the development of adaptive technology-driven solutions capable of providing personalised support over time.

Among these technologies, AR has emerged as a promising assistive approach due to its ability to overlay context-aware digital information directly onto the physical environment. Existing studies demonstrated the potential of AR systems to provide real-time safety guidance, navigation assistance, memory support, and task prompting while reducing cognitive load and supporting autonomy in familiar environments. These findings informed the use of wearable AR smart glasses within the proposed system to deliver unobtrusive, real-time safety guidance tailored to the user's environmental and cognitive context.

The review also highlighted the increasing application of AI techniques in dementia care to support adaptive and personalised interventions. AI-driven systems can analyse behavioural, physiological, and contextual information to dynamically tailor assistance according to users' changing cognitive and functional abilities. Within this broader AI framework, probabilistic models such as HMM were identified as particularly suitable for modelling latent cognitive and behavioural states over time. Prior studies demonstrated the effectiveness of HMM in dementia recognition, disease progression modelling, activity recognition, behavioural monitoring, and fall detection using sequential sensor data. These findings directly informed the development of an attention-aware fall risk assessment framework, which infers users' latent attention states from IMU-derived behavioural observations to enable context-aware and adaptive safety interventions.

The chapter further explored advances in wearable sensing technologies and multimodal monitoring systems for fall risk assessment. Existing research established that wearable sensors, particularly IMU-based systems, can reliably capture gait abnormalities, movement instability, and behavioural changes associated with elevated fall risk in older adults and PwD. These findings supported the integration of multimodal wearable sensing within the framework to enable continuous and unobtrusive monitoring of user behaviour in real-world environments.

In addition, the review of image enhancement and object detection literature provided the foundation for the environmental perception component of the proposed system. Studies on DL-based image enhancement demonstrated the effectiveness of CNN-based approaches for improving image quality under degraded visual conditions, while research on object detection highlighted the suitability of YOLO architectures for fast and accurate real-time hazard detection. Since environmental hazards such as poor lighting, obstacles, uneven surfaces, and unsafe walking conditions significantly contribute to fall risk, these findings informed the development of THLLOD framework, which integrates Zero-DCE low-light enhancement with a lightweight YOLO-based detector to improve hazard recognition under challenging illumination conditions.

Chapter 3

Augmented Reality Based Assistive Technologies for the Safety of People with Dementia

This chapter presents an in-depth systematic review of the existing literature that examines the current state-of-the-art augmented reality based assistive technologies aimed at enhancing the safety of people with dementia and related mild cognitive impairments.

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Contents

3.1 Introduction

Augmented Reality (AR) is an interactive technology that overlays computer-generated sensory information onto a user’s real-world environment in real time (Lee, 2012). It enhances the real world by integrating computer-generated content such as images, text, audio, or three-dimensional objects into the user’s physical surroundings in real time (Azuma, 1997). By combining real and virtual elements across multiple sensory channels, AR enhances perception and interaction, making it useful in various domains including healthcare, education, navigation, and assistive technologies (Billinghurst et al., 2015). A key component of AR systems is the display device, which allows users to visualise augmented content within their physical environment. These devices are commonly classified into three main types based on their physical placement relative to the user and the surrounding real-world environment:

Head-Worn Displays (HWD) (Dylan et al., 2023; Htike et al., 2023; Rossi et al., 2020; Blusi and Nieves, 2019; Ingeson et al., 2018), handheld displays (Hervas et al., 2014; Bianco et al., 2016; Połap et al., 2017; Kanno et al., 2018; Miura et al., 2023), and spatial displays (Guerrero et al., 2019; Ro et al., 2019; Park et al., 2019). HWD, also referred to as head-mounted displays, present digital content directly within the user’s field of view through optical see-through mechanisms, enabling hands-free interaction and immersive alignment of virtual elements with the physical world (Cheng et al., 2021). Figure 3.1 presents some prominent HWD widely used in research and practice. These include Microsoft HoloLens, Magic Leap, Epson Moverio, and Vuzix Blade (Vagvala, 2022).

Figure 3.1. Head-Worn AR Display Devices

Handheld displays, typically implemented via smartphones or tablets, overlay virtual information onto live camera feeds of the real environment on a screen, offering a portable and widely accessible form of AR that leverages existing mobile hardware (Achilleos et al., 2023; Franzén, 2023). In contrast, spatial displays, sometimes described as projective displays or Spatial Augmented Reality (SAR) systems, project digital content directly onto physical surfaces or into the surrounding space using external projectors or fixed installations, eliminating the need for users to wear or hold a device and allowing shared, collaborative AR experiences within an environment (Guerrero et al., 2019; Ro et al., 2019; Park et al., 2019). This tripartite classification is well established in AR literature and provides a foundational framework for analysing AR system design, usability, and application contexts across domains such as healthcare, education, and rehabilitation.

Recently, AR has emerged as a promising innovation within Assistive Technologies (AT) for older adults, PwD, and individuals with MCI (Kanno et al., 2018; Su et al., 2024; Ball et al., 2023; Mettouris et al., 2021). AT refers to devices and systems designed to help individuals maintain or enhance their independence, safety, and wellbeing while performing ADL (Social Care Institute for Excellence, 2019). These technologies range from simple assistive aids, such as walking canes, to more advanced technological solutions (Garçon et al., 2016). Both healthy older adults and individuals with cognitive impairments can benefit from AT to remain safe and well within their homes (Peterson et al., 2012; Bennett et al., 2017; Hayhurst, 2018; Sriram et al., 2020). In the early stages of dementia, AT can support continued independent living while simultaneously alleviating caregiver burden and reducing pressure on healthcare systems (Ienca et al., 2017; Berrett et al., 2022).

Within the dementia continuum, AR-based AT is gaining attention for its potential to provide real-time assistance while reducing caregiver workload (Zhao et al., 2019a; Achilleos et al., 2023). Unlike fully immersive technologies, AR allows users to remain engaged with their physical surroundings while integrating digital support into everyday routines. By delivering real-time warnings and safety alerts in an intuitive manner, AR-based AT can enhance situation awareness and support safer decision-making in daily activities (Połap et al., 2017; Li, 2024a). Compared to traditional visually centric interfaces, AR enables novel forms of interaction and engagement (Li, 2024a), potentially extending the period during which cognitively impaired individuals can live independently before transitioning to assisted living facilities (Rossi et al., 2020; Dickinson et al., 2023). Figure 3.2 presents representative use-case scenarios demonstrating the application of AR across diverse contexts. These use-cases are explored in details in subsequent section.

(a) Fall Prevention (b) Wayfinding (c) Medication Adherence (d) Home Safety

Figure 3.2. Augmented Reality Use-Case Scenarios

Although both conventional and technology-enabled safety interventions can improve independence and safety among older adults (Nguyen et al., 2021; Rose et al., 2018; Kahya et al., 2020; Chen et al., 2020), their effectiveness depends largely on user adherence (Rose et al., 2018). Adherence remains a significant challenge, as some older adults may struggle to understand, remember, or consistently follow recommended safety measures (Nishchyk et al., 2021). The ability to comprehend and engage with safety interventions is, therefore, crucial for achieving empowering outcomes. However, existing design approaches often fail to reflect older adults' personal goals and lived experiences within safety services, which can reduce compliance and contribute to feelings of disempowerment (Bianco et al., 2016).

The strong preference of older adults, particularly those with cognitive impairment living alone, raises concerns for families and caregivers. While many home-based interventions prioritise fall prevention, other household hazards and the need for monitoring and reporting dangerous situations are frequently overlooked, leaving critical safety needs unmet. AR-based AT shows promise in addressing these gaps by providing timely hazard detection and alerts to individuals with cognitive impairments and their caregivers, thereby preventing or mitigating accidents.

This thesis examines the current state of AR-based AT aimed at improving safety for PwD and individuals with MCI. Specifically, this review explores: (1) the domains of safety targeted by AR-based AT; (2) the interaction modalities employed to facilitate user engagement; and (3) the types of situation awareness cues used to draw vulnerable users' attention to potential dangers. Given that cognitive decline can further complicate technology use (Hervas et al., 2014; Rossi et al., 2023), identifying interaction modalities that best support this population is essential for improving usability and engagement. As many existing studies overlook the distinct interaction preferences of older adults, particularly those with cognitive impairments, this thesis highlights current limitations and offers recommendations to guide the development of more effective AR-based safety interventions. Furthermore, some key adaptive design considerations that should inform the development of AT for old adults with cognitive impairment are also presented.

3.2 Methodology

A comprehensive understanding of how prior research has addressed the safety needs of PwD is essential for designing more adaptive and personalised interventions that align with individual preferences and capabilities. Emerging evidence indicates that AR can effectively support activities of daily living among individuals with MCI. This review aims to investigate the role of AR-based AT in supporting the safety and independence of PwD and individuals with MCI. First, the study examines the types of safety support currently provided by AR-based AT solutions, categorising existing approaches to identify the safety needs most effectively addressed in the literature. Second, it explores the interaction modalities used in AR-based AT systems to determine which approaches are most suitable for enhancing user engagement when designing safety interventions for individuals with age-related cognitive impairment. Finally, the study analyses the situation awareness capabilities offered by AR-based AT, identifying the types of environmental hazards and safety risks that these technologies can help communicate to PwD and MCI in order to improve their awareness and mitigate potential dangers. To ensure methodological rigour and transparency, the review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). Figure 3.3 presents the PRISMA flow diagram outlining the study selection process used in this systematic review. Figure 3.1 illustrates the PRISMA flow diagram detailing the study selection process for the systematic review.

3.2.1 Search Strategy

A systematic search was conducted across three major electronic databases: IEEE Xplore, PubMed, and Scopus. To ensure comprehensive coverage, supplementary searches were conducted in additional databases to identify potentially relevant studies. The search included publications from January 2014 to December 2024. Only peer-reviewed studies published in English and indexed within the selected databases were considered eligible for inclusion.

The complete search strategy was structured using a Boolean combination of three concept groups (Set1) AND (Set2) AND (Set3) as detailed in Table 3.2.

Table 3.1. Search Keywords

Search Set	**Keywords**
Set1	Augmented Reality OR Mixed Reality OR Assistive Technology OR Ambient Assisted Living
Set2	Alzheimer OR Old Adults OR Dementia OR Mild Cognitive Impairment
Set3	Mobile Phone OR Smartphones OR Tools OR Systems OR Smart Glasses OR Head Mounted Display

3.2.2 Selection Criteria

Studies satisfying the criteria outlined in Table 3.3 were either included or excluded from the systematic review.

Table 3.2. Inclusion and Exclusion Criteria

Inclusion criteria	**Exclusion criteria**
Studies including some or all participants who are older adults with dementia, MCI, or age-related cognitive decline Written in the English language	Studies that did not undergo peer-review Addressing conditions that are not dementia, MCI or age-related cognitive decline Whose methodology are not based on AR

Published in journals and conferences between the year January 2014 to December 2024 Utilising qualitative, quantitative or mixed method study design	Addressing outcomes that are not safety related

3.2.3 Study Screening

All retrieved journal and conference records were imported into Zotero to facilitate the initial screening process, and duplicate entries were removed. The remaining titles and abstracts were screened against the inclusion and exclusion criteria outlined in Table 3.2. Subsequently, full-text articles that met the preliminary criteria were assessed for eligibility.

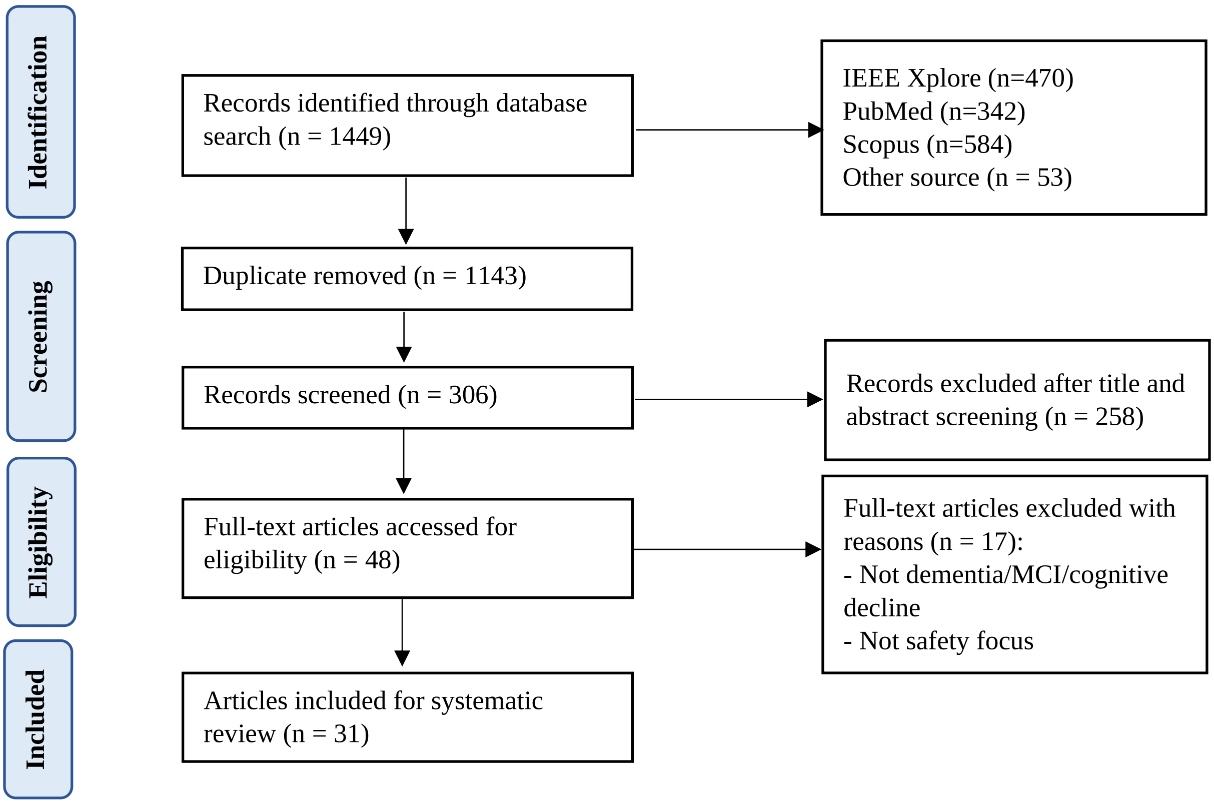


Figure 3.3. PRISMA Flowchart for Systematic Review

3.2.4 Quality Assessment

To ensure the validity and minimise bias in this review, the methodological quality of the 31 included studies was assessed using the Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2018). The MMAT is a critical appraisal instrument designed to evaluate the quality of empirical studies employing qualitative, quantitative, or mixed-methods research designs

(Hong et al., 2018). The results of the quality assessment are summarised and presented in Appendix I.

3.3 Classification Analysis of AR-based AT for the Safety of PwD and MCI

The classification process involved extracting and synthesising relevant data aligned with the scope of this review. Through a detailed analysis of the AR-based AT interventions reported in the eligible full-text studies, five key elements were identified. These elements are summarised in Table 3.3 and they include: (1) Safety Support – the approaches employed by AR-based AT to promote safety and independence among individuals with cognitive impairments; (2) Features – the specific safety-related functionalities embedded within the interventions; (3) Interaction Modalities – the input and output mechanisms that facilitate user interaction and system feedback; (4) Situation Awareness – the contextual information provided to cognitively impaired individuals and caregivers to enhance awareness of their environment; and (5) Risk Mitigated – the potential hazards or adverse events the interventions are designed to reduce.

Together, these elements formed a structured framework for analysing AR-based safety interventions. They support the identification of appropriate system features, interaction methods, feedback strategies, and awareness mechanisms tailored to the cognitive needs of PwD and individuals with MCI, while explicitly addressing safety-related risks to enhance overall user protection.

The review further grouped the identified AR-based interventions into three overarching categories of safety support as depicted in Figure 3.4: (1) Mobility, (2) Medication Management, and (3) Home Safety and Control. Within this context, safety is defined as any system function that directly contributes to hazard prevention, including medication reminders, user monitoring, and fall prevention strategies (Gross et al., 2011).

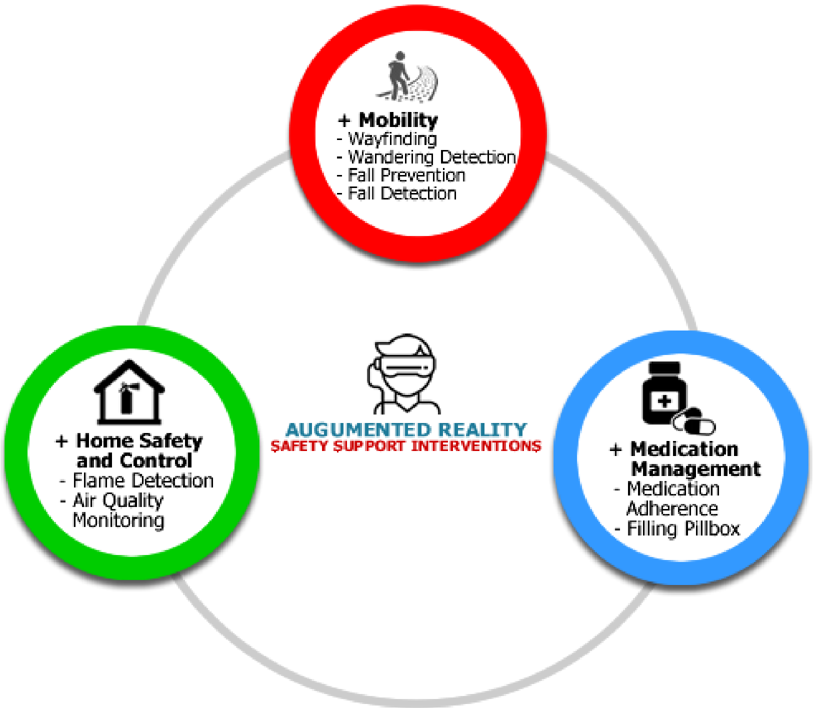


Figure 3.4. Categories of AR-based AT for the Safety of PwD and Related MCI

The safety support categories are mainly based on the features provided by the AR-based AT interventions to enhance the safety of PwD and related MCI. First, interventions that target fall prevention, fall detection, wandering detection and wayfinding were categorised as offering mobility safety support because these features emanate from user mobility activities. Mobility refers to the ability to move between positions, including sitting, standing, walking, and transitioning between postures (Tyson and Connell, 2009). Maintaining independent mobility for PwD is crucial, as mobility loss can increase fall risk, reduce participation in meaningful activities, and lead to other negative effects (Hauger et al., 2019; Ooteghem et al., 2019).

Secondly, AR-based AT interventions that focus on medication management were also considered to offer safety related outcome. This is because more complex medical issues or life-threatening situations might result from missed medications or improper dosage administration (Taghian et al., 2023). For PwD, their health condition might deteriorate unprecedently, hence, medication management becomes a significant safety issue, especially for vulnerable populations living alone. Poor medication management can lead to serious risks such as overdosing or underdosing, drug interactions, insufficient health outcomes, and missed doses etc (Yadav and Kirit, 2024; Taghia et al., 2023). Effective medication management is vital for maintaining safety and wellbeing; as such, AR-based tools that function as medication reminders, manage regimens, and assist with filling pillboxes (Guerrero et al., 2019; Blusi and

Nieves, 2019; Franzén, 2023; Yadav and Kirit, 2024) were categorised as offering medication management safety support.

The third safety-related support is categorised as home safety and control. This category includes AR-based AT that connects with smart home embedded devices to provide safety information to cognitively impaired users by monitoring hazardous situations, atmospheric conditions, and controlling smart home devices (Mettouris, et al. 2021; Ghorbani et al., 2023). Monitoring the homes of individuals with PwD and MCI is essential, as they may need reminders to complete critical tasks, like turning off the stove, avoiding hazardous areas or needing ventilation in the home (Ghorbani et al., 2022; Ghorbani et al., 2023). AR-based AT with the capability of connecting with smart home devices can be beneficial in providing real-time and precise information to cognitively impaired users.

Table 3.3. Five Key Elements of AR-based AT Safety Interventions

Authors	**Safety Support**	**Features**	**Interaction Modalities**	**Situation Awareness**	**Risk Mitigated**
Hervas et al. (2014)	Mobility	Wayfinding	IM: Visual (Touch) OM: Visual (Text)	User Location	Getting Lost
Lera et al., (2014)	Medication Management	Medication Adherence	IM: * OM: Visual	- Medication Time - Medication Regimen	- Missing/Delayed Medication - Incorrect Medication Dosage
Saracchini et al., (2015)	Home Safety and Control	Flame Detection	IM: * OM: Visual (Text, Sign)	Presence of Fire	Burn and Scald
Bianco et al., (2016)	Mobility	Fall Prevention	IM: * OM: Visual	Object on Pathway	Falling
Połap et al., (2017)	Mobility	Fall Prevention	IM: * OM: Visual (Sign)	- Object on Pathway	Falling
Kanno et al., (2018)	- Mobility - Medication Management	- Wayfinding - Medication Adherence	IM: Auditory (Voice) OM: Auditory (Voice), Visual (Text), Tactile (Vibration)	- User Location - Medication Time - Medication Regimen	- Getting Lost - Missing/Delayed Medication - Incorrect Medication Dosage
Ingeson et al., (2018)	Medication Management	- Medication Adherence - Filling Pillbox	IM: Auditory (Voice), Gesture OM: Visual (Text), Auditory (Voice)	- Medication Time - Medication Regimen - Medication Distribution	- Missing/Delayed Medication - Incorrect Medication Dosage - Mixing Medication

Liang (2018)	Medication Management	Pillbox	IM: Visual (Touch) OM: Visual (Text, Image, Audio)	Medication Regimen	- Incorrect Medication Dosage
Gacem et al., (2019)	Mobility	Wandering Detection	IM: Visual (Touch), Auditory (Voice) OM: Visual (Text, Image), Auditory (Voice)	User Location	Getting Lost
Ro et al., (2019)	- Mobility - Medication Management	- Fall Detection - Medication Adherence	IM: Visual (Touch), Auditory (Voice) OM: Visual (Text) and Auditory (Sound)	- User Position - Medication Time - Medication Regimen	- Falling - Missing/Delayed Medication - Incorrect Medication Dosage
Park et al., (2019)	- Mobility - Medication Management - Home Safety and Control	- Fall Detection - Medication Adherence - Air Quality Detection	IM: Visual (Touch), Auditory (Voice) OM: Visual (Text) and Auditory (Sound)	- User Location - Medication Time - Environment Condition	- Getting Lost - Falling - Incorrect Medication Dosage - Missing/Delayed Medication - Poor Ventilation - Respiration Issue
Liu et al., (2019)	Mobility	- Wayfinding - Wandering Detection	IM: * OM: Visual (Text, Arrow), Auditory (Sound)	User Location	Getting Lost
Guerrero et al., (2019)	Medication Management	- Medication Adherence - Filling Pillbox	IM: Gesture (Hand) OM: Visual (Text)	- Medication Time - Medication Distribution	- Missing/Delayed Medication - Mixing Medication
Zhao et al., (2019a)	Mobility	Fall Prevention	IM: * OM: Auditory (Sound, Voice)	Uneven Surface	Falling
Blusi and Nieves (2019)	Medication Management	Filling Pillbox	IM: Auditory (Voice), Gesture (Body) OM: Visual (Text), Auditory (Voice)	Medication Distribution	Mixing Medication
Younis et al., (2019)	Mobility	Fall Prevention	IM: * OM: Visual (Arrow), Tactile (Vibration)	Object on Pathway	Falling
Rossi et al., (2020)	Home Safety and Control	Flame Detection	IM: * OM: Visual (Text, Image) - Auditory (Voice)	Presence of Fire	Burn and Scald
Yang et al. (2021)	Medication Management	Medication Adherence	IM: Visual (Touch) OM: Visual (Text)	Medication Time	Missing/Delayed Medication
Mettouris et al., (2021)	Home Safety and Control	Air Quality Monitoring	IM: Visual (Touch)	Environment Condition	Respiratory Issue

			OM: Visual (Text), Auditory (Sound)		
Varghese et al., (2021)	Mobility	- Wandering Detection - Fall Detection	IM: Visual (Touch) OM: Visual (Text)	- User Location - User Position	- Getting Lost - Falling
Ghorbani et al., (2022)	- Home Safety and Control - Medication Management	- Flame Detection - Medication Adherence	IM: * OM: Visual (Image) and Auditory (Voice)	- Presence of Fire - Medication Time	- Burn and Scald - Missing/Delayed Medication
Htike et al., (2023)	Mobility	Fall Prevention	IM: Gesture (hand), Auditory (Voice) OM: Visual (Line, Color, Comic overlay)	Object on Pathway	Falling
Taghian et al., (2023)	- Medication Management - Mobility	- Medication Adherence - Wayfinding	IM: Visual (Touch) OM: Visual (Text), Auditory (Voice)	- Medication Time - User Location	- Missing/Delayed Medication - Getting Lost
Miura et al. (2023)	Mobility	Fall Prevention	IM: * OM: Visual (Text)	Absence of Safety Intervention	Falling
Ball et al., (2023)	Mobility	Fall Prevention	IM: * OM: Visual (Arrow)	- Object on Pathway - User Position	Falling
Franzén (2023)	Medication Management	- Medication Adherence - Filling Pillbox	IM: Visual (Touch) OM: Visual (Text) Auditory (Voice)	- Medication Regimen - Medication Distribution	- Incorrect Medication Dosage - Mixing Medication
Achilleos et al., (2023)	- Mobility - Medication Management - Home Safety and Control	- Wayfinding - Medication Adherence - Air Quality Monitoring	IM: Visual (Touch) OM: Visual (Text, Arrow)	- Medication Time - Presence of Smoke/Gases	- Getting Lost - Missing/Delayed Medication - Respiratory Issue - Poor Ventilation
Dylan et al., (2023)	Mobility	Fall Prevention	IM: * OM: Visual (Arrow)	Object on Pathway	Falling
Ghorbani et al., (2023)	- Mobility - Home Safety and Control	- Fall Prevention - Flame Detection	IM: * OM: Visual (Text, Image) and Auditory (Voice)	- User Position - Presence of Fire	- Falling - Burn and Scald
Su et al., (2024)	Mobility	Fall Prevention	IM: * OM: Visual (Text)	- Absence of Safety Intervention - Object on Pathway	Falling
Yadav and Kirit (2024)	Medication Management	- Medication Adherence - Filling Pillbox	IM: * OM: Auditory	- Medication Time - Medication Regimen - Medication Distribution	- Missing/Delayed Medication - Mixing Medications

Table Acronym/Symbols: IM: Input Modalities; OM: Output Modalities; *: Not reported by author in the study

The analysis presented in Table 3.3 informed the development of an AR-based AT conceptual framework, illustrated in Figure 3.5. This framework synthesises the core elements identified across existing AR-based safety intervention systems, with particular emphasis on applications designed for individuals with dementia and related MCI. Although the framework is not exhaustive, it provides a structured representation of the key components underpinning AR-based safety interventions and offers guidance for understanding and designing such systems for these target populations.

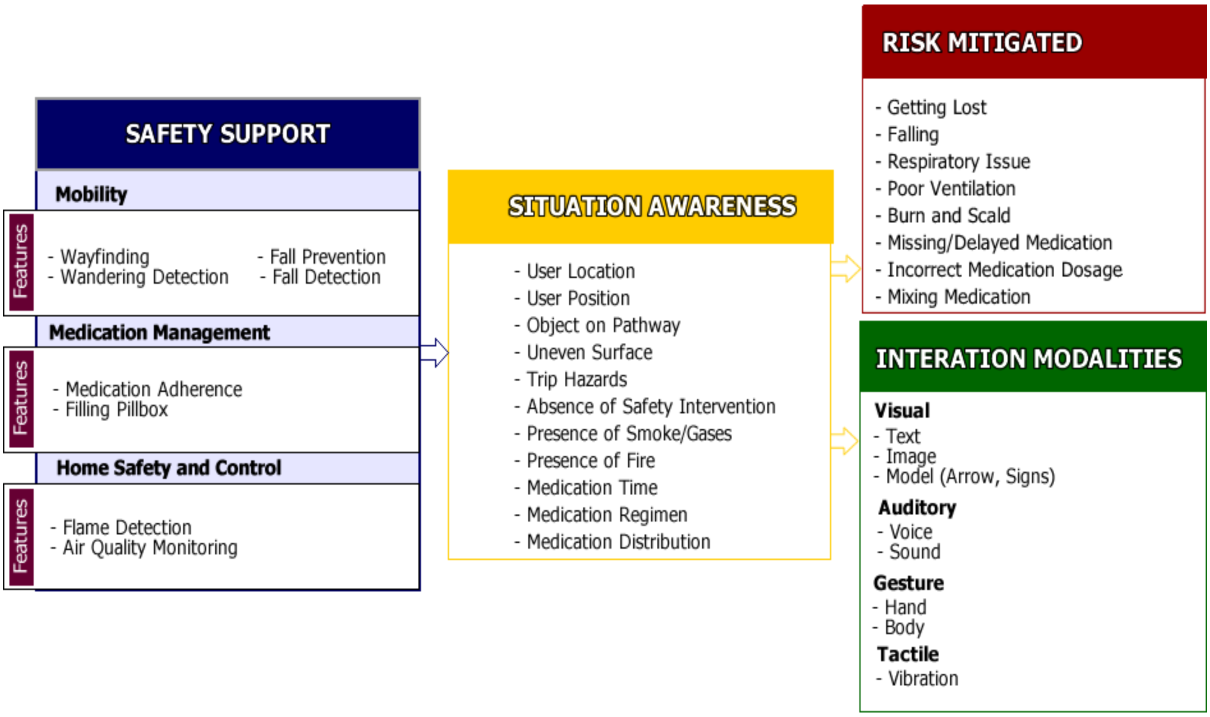


Figure 3.5. AR-based AT Applications Framework for the Safety of People with Dementia (PwD) and Mild Cognitive Impairment (MCI).

3.4 Adaptive Features of AR-based AT for the Safety of PwD and MCI

Adaptive features are increasingly recognised as a critical component of AR–based AT for enhancing the safety and independence of PwD. These features enable systems to dynamically adjust their behaviour based on users' cognitive state, environmental context, and interaction patterns (Velusamy et al., 2023; Dada, et al., 2024), moving beyond static "one-size-fits-all" solutions (Hayhurst, 2018; Brookman et al., 2023). In AR-based systems, this adaptability is often achieved through real-time sensing, multimodal data integration, and decision-making mechanisms (Tunca et al., 2020; Kiprijanovska et a., 2020).

This review highlights some key adaptive design considerations that should guide the development of AT for older adults with cognitive impairment, as outlined in Table 3.4. These features may also be applicable across a wider range of AT domains, including technologies designed to support individuals with visual impairments.

Table 3.4. Adaptive Features Relevant to AT for Mobility Related Safety Support

Adaptive Feature	Function	Adaptive Mechanism	Benefits	Studies
Cognitive State Monitoring	Tracks user attention or cognitive engagement	Uses behavioural data, gaze, movement patterns, or probabilistic models to infer cognitive state	Enables timely guidance when attention is reduced	Gibson et al., (2015); Spalla et al., (2025)
Attention-Aware Safety Cues	Delivers alerts only when user attention declines	System triggers cues based on predicted attentional states	Reduces fall risk and avoids unnecessary notifications	Hedman et al., (2019)
Context-Aware Hazard Detection	Identifies environmental fall hazards	Computer vision models detect obstacles, stairs, clutter, and slippery surfaces	Improves environmental awareness and safety	Younis et al., (2019); Crandall et al., (2023); Su et al., (2024)
Adaptive Navigation Guidance	Provides route or movement guidance	Adjusts guidance based on location, obstacles, and user movement	Supports safe mobility and navigation	Crandall et al., (2023)
Dynamic Alert Management	Controls frequency and timing of notifications	Suppresses alerts when user is cognitively stable and increases support when needed	Reduces alert fatigue and improves usability	Michels et al., (2025); Crandall et al., (2023)
Routine-Aware Assistance	Recognises daily behaviour patterns	Learns user routines and detects deviations	Supports independent living and early anomaly detection	Moyle et al., (2021)
Environmental Adaptation	Adjusts system performance based on lighting or surroundings	Uses sensor data to adapt detection algorithms or visual guidance	Maintains reliability in real-world conditions	Su et al., (2024)
Multimodal Feedback Adaptation	Delivers information through multiple channels	Dynamically switches between visual, audio, and haptic cues	Improves accessibility and comprehension	Pillette et al., (2023)
Personalised Interaction Support	Adjusts interface complexity and guidance level	Learns user preferences and interaction patterns	Enhances usability and user engagement	Brookman et al., (2023)
Fall Detection and Reporting	Detects and reports falls in real time	Uses wearable sensors and computer vision algorithms to identify fall events; triggers immediate alerts to caregivers or emergency services	Enables rapid response, reduces injury severity, improves safety and caregiver awareness	Chantanachai et al., (2021); Wolf et al., (2018); Appeadu and Bordoni, (2023)

Based on Table 3.4, several adaptive features have been identified that could support the independent living of PwD. However, Table 3.5 shows that these capabilities are fragmented across different AT solutions, with no single system integrating them into a unified framework. Consequently, existing AR-based AT tend to address only isolated aspects of user support, rather than offering a comprehensive solution that can respond to the complex and dynamic needs of PwD.

Table 3.5. AR-based AT for Fall Risk Assessment and Prevention for Individual with Cognitive Impairment

	Adaptive Features									
Studies	**CSM**	**ASC**	**CHD**	**ANG**	**DAM**	**RAA**	**ENA**	**MFA**	**PIS**	**FDR**
Połap et al., (2017)			*							
Ro et al., (2019)			*							*
Younis et al., (2019)			*							
Varghese et al., (2021)									*	*
Htike et al., (2023)			*							
Ball et al., (2023)			*							
Dylan et al., (2023)			*							
Crandall et al., (2023)			*	*	*					
Su et al., (2024)			*				*			
Proposed system	*	*	*	*			*	*	*	

Table Acronyms: CSM: Cognitive State Monitoring; ASC: Attention-Aware Safety Cues; CHD: Context-Aware Hazard Detection; ANG: Adaptive Navigation Guidance; DAM: Dynamic Alert Management; RAA: Routine-Aware Assistance; ENA: Environmental Adaptation; MFA: Multimodal Feedback Adaptation; PIS: Personalised Interaction Support; FDR: Fall Detection and Reporting.
Asterisk (*) denote features present in studies.

Existing studies lack mechanisms to infer or continuously monitor users' cognitive or attention states in real time, despite the known fluctuations in cognitive functioning among PwD (Escandon et al., 2010; Lee et al., 2014). Consequently, many assistive systems deliver prompts and alerts in a static, non-adaptive manner that may not correspond to the user's current cognitive capacity or level of attention (Hayhurst, 2018; Brookman et al., 2023). Additionally, important adaptive features, such as Routine-Aware Assistance (RAA) and Multimodal Feedback Adaptation (MFA), remain largely unexplored.

3.5 Summary of Existing AR-based AT for the Safety of PwD and MCI

The studies reviewed demonstrate significant potential for AR-based AT to enhance the safety of PwD and individuals with MCI. This review identifies and summarises key limitations in existing solutions, as presented in Table 3.6, to inform the development of more robust and effective future interventions. The identified limitations are derived from the core elements outlined in Table 3.3, alongside a broader critical analysis of the reviewed interventions.

Table 3.6. Summary of Existing AR-based AT for the Safety of PwD and Related MCI

Studies	**Study Design**	**Target Population / Condition**	**Benefits**	**Display Devices**	**Limitations**
Hervas et al., (2014)	Qualitative Study	10 participants including old adults / Alzheimer, MCI, Asperger syndrome	A navigation system that utilises well-known locations and monitors user activities to identify potentially risky situations	Smartphone	- Raises privacy concern - Requires activation of navigation mode, which might be difficult for the cognitive impaired individual
Lera et al., (2014)	Qualitative Study	Old adults / Needing help with medications	A general assistance system and drug dosage management system for the elderly	Robot	- Expensive - Indoor use only
Saracchini et al., (2015)	Qualitative Study	35 participants including 9 old adults / Cognitive impairment	Alert user of potential hazards, such as fire from the stove	- Tablet - DCPAR	- Devices is bulky and uncomfortable to use - Willingness to wear device
Bianco et al., (2016)	Qualitative Study	10 old adults who may need home modification/fall prevention.	Recommends suitable position for the installation of safety bar	Smartphone	- Only recommendation made
Połap et al., (2017)	Qualitative Study	Adults / Low vision impairment	AR obstacle detection system based on deep learning methods that can helps older people to walk in the city and cross streets.	Smartphone	- Use of smartphone on busy environment could be a distraction.
Kanno et al., (2018)	Qualitative Study	2 old adults / MCI	- Reminds users to take their medications - Helps locate and identify the correct medication - Assists in tracking the location of user	Smartphone	- Raises privacy concern - The need to wear a tracker may make users uncomfortable
Ingeson et al., (2018)	Qualitative Study	15 participants including 11 old adults / Age-related cognitive decline	Medication coach intelligent system that enables users to maintain self-management and medication adherence	HMD	- Unclear how gesture can be used - Could be stigmatising - Bulky and uncomfortable to use
Liang (2018)	Mixed Method	50 participants including old adults / Memory deficits	Provide additional information to user on medication regimens	Smartphone	- User might not remember to scan medication.
Gacem et al., (2019)	Qualitative Study	Old adults / Alzheimer	Monitor if the user has lost their way, displaying directions home on the AR interface while simultaneously sending the user's location to the caregiver	Smart glass Smartphone	- Raises privacy concern - Text output can be unclear under certain lighting conditions - False alert user location - Depending on a smartphone to operate may cause inconvenience

Younis et al., (2019)	Qualitative Study	5 participants/ Low vision impairment	An egocentric indoor and outdoor hazard recognition dataset is created using a wearable camera and classified using DL object detector and Kalman Filter tracker to be used in the hazard detection and classification for people with vision defects	Smart glass	Difficulty detecting small objects.
Liu et al., (2019)	Qualitative Study	5 participants / MCI	POF based navigation system for people with MCI based on wandering detection	Smartphone	- Raises privacy concern - False alert user location
Zhao et al., (2019a)	Qualitative Study	12 participants including old adults / Low vision impairment	Facilitate stair navigation by leveraging PLV's residual vision	HMD	- No input modality - Could be stigmatising - Bulky and uncomfortable to use
Blusi and Nieves (2019)	Qualitative Study	15 participants including 8 old adult / Needing help with medications	Helps in organising medications in a pillbox	HMD	- Tested only in lab settings - Device is inconveniencing. - Text only output - Could be stigmatising
Ro et al., (2019)	Descriptive Study	Old adults / Dementia	A projection-based AR system robot that can cover 360 degrees of space of the user environment	PAR	- Requires hardware - Expensive - Less interactive - Can only monitor indoor
Park et al., (2019)	Qualitative Study	Old adults / Age-related cognitive decline, MCI	- 3D space reconstruction of a pervasive PAR space for elderly support - Prevent accidents using DL pose estimation in detecting abnormal conditions, such as falling and tripping	PAR	- Requires hardware - Expensive - Less interactive - Can only monitor indoor - Fall related activities could trigger false alerts (Abbate et al., 2012) - No cue to environmental hazards
Guerrero et al., (2019)	Qualitative Study	5 old adults / Needing help with medications	Helps older adults manage their medications through a smart medicine cabinet	PAR	- Expensive - Limited ecological validity
Rossi et al., (2020)	Qualitative Study	Old adults / Age-related cognitive decline, Cognitive Impairment	Notify users about potentially dangerous situations such as stove flame, by providing cues in real time	HMD	- Did not mention the situation detected. - No input interaction - Could be stigmatising - Bulky and uncomfortable to use
Yang et al., (2021)	Qualitative Study	Old adults / Dementia, Needing help with medications	Recognises medication pack and track Medication Management	Smartphone	- Requires user to interact by pressing buttons - Adherence feature only shows medication details.

Mettouris et al., (2021)	Qualitative Study	39 old adults / Age-related cognitive decline	AR app that allows users to control their home environment and detect the presence of smoke or carbon monoxide using smart home service	Smartphone	Usability and user experience was not evaluated
Varghese et al., (2021)	Qualitative Study	Older adults / Dementia	Ensure the safety of the PwD through wandering and fall detection	Smartphone	False alarm when user genuinely enter dangerous zone
Ghorbani et al., (2022)	Quantitative RCT	37 older adults / MCI	Monitors user location and identifies dangerous areas such as near a fireplace in AR serious game simulation environment	Smartphone	- Tested in laboratory setting which might not be realistic - Wearable localisation tag. - False alert in dangerous place
Htike et al., (2023)	Quantitative Study	18 participants including old adults / Low vision impairment	Mobility aid for PLV in avoiding the obstacle	HMD	- Device is bulky and uncomfortable to use - Could be stigmatising - Bulky and uncomfortable to use
Taghian et al., (2023)	Qualitative Study	Old adults / Age-related cognitive aging, Needing help with medications	- Medication reminder - Helps users navigate back home if they get lost	Smart glass Smartphone	- Depends on smartphone - Required user to confirm medication taken
Miura et al., (2023)	Qualitative Study	Old adult / Age-related cognitive aging	Identifies indoor areas in a home where falls are likely to occur, and overlays fall prevention measures. Check for the need of fall prevention measures	Smartphone	- Only text output - No input interaction - Lower detection accuracy in some home settings
Ball et al., (2023)	Quantitative Non-Randomised Studies	170 participants including old adults / Vision Acuity and Colour Vision	Obstacle detection during navigation in pseudo-natural environments	Laptop	Experimented only in lab settings
Franzén (2023)	Qualitative Study	4 older adults / Needing help with medications	Provided an augmented way of accessing and consuming medication information	Smartphone	Does not remind the user when to take medication
Achilleos et al., (2023)	Qualitative Study	22 old adults / Age-related cognitive aging, Needing help with medications	Enables user in medication management, smart home device control and wayfinding	Smartphone	- Text only output - Required user to tick checkbox when medication is taken
Dylan et al., (2023)	Qualitative RCT	20 participants including old adults / Low vision impairment	Displaying multiple kinds of visual cues for obstacles on an optical see-through HMD	HMD	- No input modality shown - Could be stigmatising - Bulky and uncomfortable to use
Ghorbani, et al., (2023)	Qualitative Study	Old adult / MCI	Presents an IoT-based fuzzy decision-making system designed to manage user interactions and environmental factors	Smartphone	- False alarm when user genuinely enters dangerous zone - Interaction with dangerous zone was based on laboratory settings

					- No primary input modality - The need to wear a localisation tag may make users uncomfortable.
Su et al., (2024)	Qualitative Study	18 participants including old adults / Accessibility and safety issues	Helps identify, localise, and visualise indoor accessibility and safety issues such as throw rug	Smartphone	Misclassification due to several similar indoor objects
Yadav and Kirit (2024)	Qualitative Study	Dataset of old adults / Needing help with medications	Assist patients in tracking their medications and promoting adherence to prescriptions.	Smart glasses	No implementation

Table Acronyms: HMD: Head Mounted Display; DCPAR: Device with Pico Projector for Augmented Reality); PLV: People with Low Vision; POF: Point of Familiarity; IoT: Internet of Things; DL: Deep Learning; 3D: Three Dimensional; PAR: Projection Augmented Reality; RCT: Randomised Controlled Trial

3.6 Results

This section presents the findings of the systematic review supported by visual representations of the results. Figure 3.3 illustrates the number of records retrieved from each database and the screening procedure used to identify eligible studies.

A total of 1,449 records were initially identified. After removing duplicates, 306 records remained. Screening based on the exclusion criteria resulted in the removal of 258 records, leaving 48 articles for further assessment against the inclusion criteria. Application of the inclusion criteria excluded an additional 17 records, leaving 31 studies ultimately included in the review and used to address the research questions.

The included studies employed a range of methodological designs, comprising qualitative studies (n = 26), quantitative randomised controlled trials (RCTs) (n = 2), non-randomised controlled trials (n = 1), descriptive studies (n = 1), and mixed-methods research (n = 1).

3.6.1 AR-based AT Safety Support for PwD and MCI

As shown in Figure 3.6, AR-based AT interventions presented in 31 studies were classified into three types of safety support, as shown in Figure 2. 46% of the studies applied AR for mobility-related safety support. 39% focused on medication management. Only 15% used AR for home safety and control.

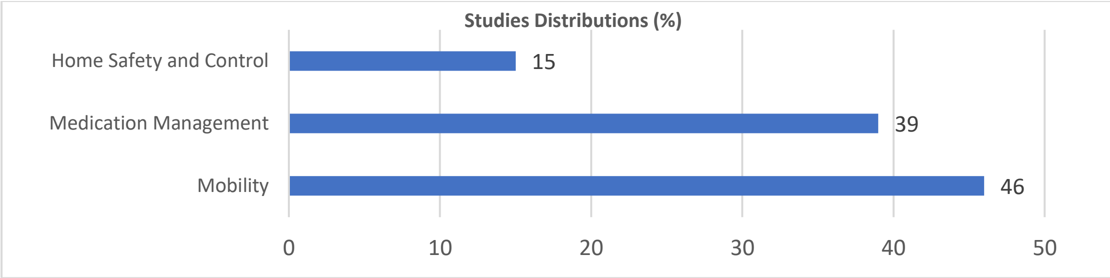


Figure 3.6. Bar Chart with Percentages Showing Studies Distributions Based on Safety Supports Categories.

The findings reveal that a substantial portion of research has focused on mobility-related support, highlighting features such as wayfinding assistance, wandering detection, fall prevention, and fall detection, all aimed at enhancing user safety and promoting independence. Mobility is particularly critical for PwD and individuals with MCI, as it supports autonomy, encourages social engagement, and helps reduce the risk of falls and further cognitive decline.

Medication management also emerged as a key area of focus, reflecting the challenges cognitive impairments pose for consistent medication adherence among older adults. PwD and individuals with MCI often experience memory lapses and executive function deficits, which can compromise their ability to follow complex medication regimens. Non-adherence can result in serious health consequences. However, evidence from the reviewed studies demonstrates that digital reminders, structured schedules, and organisational aids can improve adherence, minimise medication errors, and enhance overall safety for users.

In contrast, home safety and control received relatively less attention, despite their importance for cognitively impaired individuals, who face elevated risks of accidents and threats to independence. Most interventions targeting home safety were implemented through smart home systems rather than AR-based AT.

Figure 3.7 presents the distribution of features across the three safety support categories. Within mobility-related safety, wayfinding accounted for 11%, wandering detection 6%, fall prevention 22%, and fall detection 6%. Medication management features focused on adherence (28%) and pillbox filling (11%), while home safety and control included air quality monitoring (7%) and flame detection (9%). Among these, fall prevention and medication adherence emerged as the most prominent features within mobility-related safety and medication management, respectively.

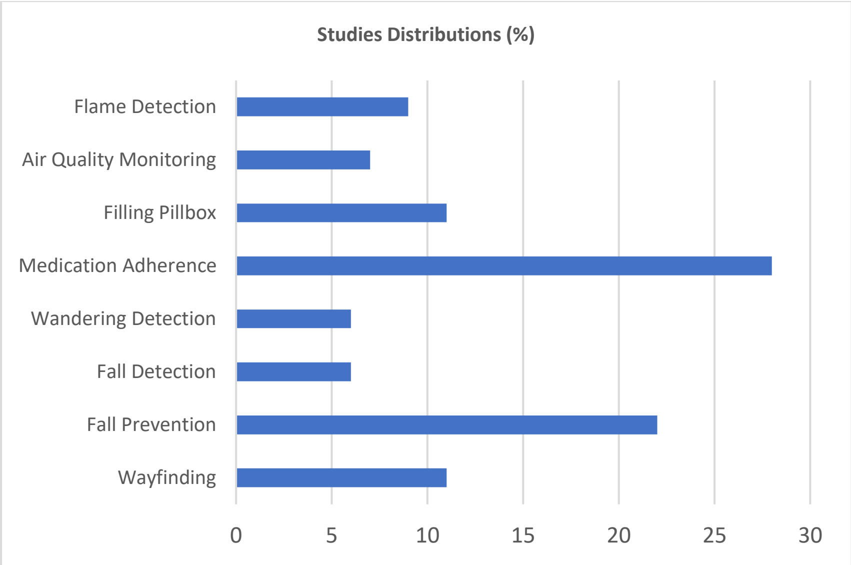


Figure 3.7. Bar Chart with Percentages Showing Studies' Distributions Based on Safety Features.

Furthermore, Figure 3.8 shows that 77% of the studies interventions targeted specific safety support such as, mobility (Hervas et al., 2014; Bianco et al., 2016; Połap et al., 2017; Liang 2018; Gacem et al., 2019; Liu et al., 2019; Zhao et al., 2019a; Younis et al., 2019; Varghese et al., 2021; Htike et al., 2023; Miura et al., 2023; Ball et al., 2023; Franzén, 2023; Dylan et al., 2023; Su et al., 2024), medication management (Lera et al., 2014; Ingeson et al., 2018; Guerrero et al., 2019; Blusi and Nieves 2019; Yang et al., 2021; Yadav and Kirit 2024) and home safety and control (Saracchini et al., 2015; Rossi et al., 2020; Mettouris et al., 2021). While only 23% targets two or more safety support combined (Kanno et al., 2018; Ro et al., 2019; Park et al., 2019; Ghorbani et al., 2022; Taghian et al., 2023; Achilleos et al., 2023; Ghorbani et al., 2023) to address the safety concerns of cognitive impaired individuals, as shown in Table 3.3.

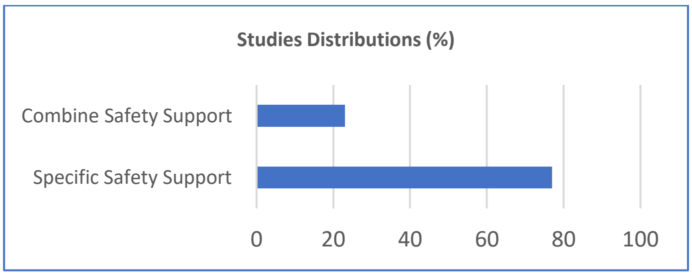
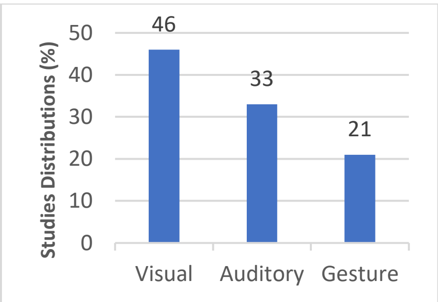


Figure 3.8. Bar Chart with Percentages Showing Studies' Distributions Based on Safety Support Targets.

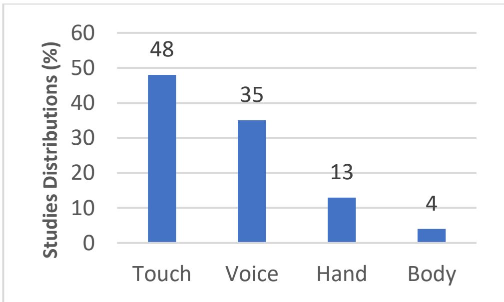
3.6.2 AR-Based AT Interaction Modalities for User Engagement

Interaction modalities allow users to engage with a system and receive feedback, playing a critical role in enhancing user engagement with AT. However, their effectiveness is highly context-dependent. The results of this review, illustrated in Figure 3.9A, indicate that AR-based AT for PwD and individuals with MCI employ three primary input modalities: visual, auditory, and gesture-based. Visual inputs are the most commonly used (46%), followed by auditory (33%) and gesture-based inputs (21%). Within the visual category, touch-based input is predominant (48%), followed by voice input (35%), while gesture-based inputs such as hand gestures (13%) and full-body gestures (4%) are less frequently utilised, as shown in Figure 3.9B.

Despite the widespread use of touch input, PwD and older adults often experience difficulties with technology use and menu navigation (Hervas et al., 2014; Rossi et al., 2020). To mitigate these challenges, Rossi et al. (2020) removed input modalities from their intervention; however, this approach may inadvertently reduce user engagement. A more effective strategy is to prioritise usability, intuitive interaction, and ease of learning, ensuring that systems are accessible and engaging while accommodating the specific preferences and capabilities of users (Hervas et al., 2014).



(A)

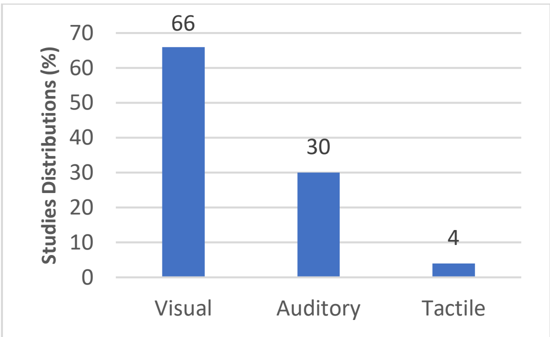


(B)

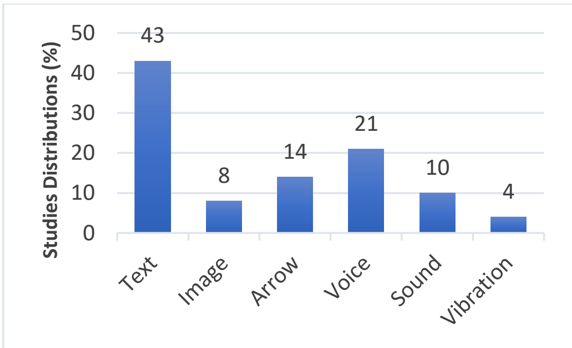
Figure 3.9. Pie Chart with Percentages Showing Studies Distributions Based on Input Modalities. A) Modalities Categories B) Modalities Forms

In contrast, output modalities in AR-based AT were categorised as visual (66%), auditory (30%), and tactile (4%), as illustrated in Figure 3.10A. Among these, text (43%) is the most frequently used visual output modality, followed by voice (21%), while vibration is the least utilised (4%) as shown in Figure 3.10B. Some studies employed text-only output (Miura et al., 2023); however, this may be insufficient for PwD, particularly those with low vision. Older adults often encounter difficulties reading small text on smartphones (Park et al., 2019), and text visibility can be further compromised under certain lighting conditions (Taghian et al., 2023).

Auditory feedback, including voice and sound, is increasingly recognised as a valuable modality in interactive technologies. Older adults often prefer voice feedback, as it allows them to remain engaged in activities, such as walking, without needing to constantly monitor a screen (Achilleos et al., 2023). Additionally, Ghorbani (2023) suggests that using voice messages instead of visual images may reduce battery consumption and enhance system performance. While this claim requires further empirical validation, it highlights the need for additional research on the performance and resource implications of different input and output modality formats.



(A)



(B)

Figure 3.10. Pie Chart with Percentages Showing Studies' Distributions Based on Output Modalities. A) Modalities Categories B) Modalities Forms

The review indicates that AR-based interventions utilise a range of interaction modalities to support safety and accommodate the needs of individuals with cognitive impairments. However, a heavy reliance on dominant modalities, such as visual and text-based feedback, may not align with all users' preferences. While several studies incorporated multiple modalities, none implemented a fully integrated multimodal output system. Adopting a broader multimodal approach could improve personalisation, increase flexibility, and offer greater user choice, while also minimising the risk of cognitive overload.

3.6.3 Situation Awareness Provided by AR-based AT

Understanding how older adults perceive and interact with their environment is critical for designing solutions that enhance safety, reduce confusion, and support independence. AR has the potential to provide contextual cues, alert users to hazards, and guide navigation in both familiar and unfamiliar settings. The studies reviewed demonstrate that AR-based AT can significantly improve safety and independence for individuals with PwD and MCI by mitigating risks in both indoor and outdoor environments. Table 3.4 summarises the types of situational awareness these systems can provide and the associated risks they help reduce.

However, a major challenge in designing effective interventions is the limited information available regarding the physical environments of the target population (Miura et al., 2023). This review highlights the need for further research to explore the full range of hazards and situational awareness capabilities that AR-based AT can offer for PwD and MCI. While some studies (e.g., Mettouris et al., 2021; Taghian et al., 2023) incorporate multiple contextual cues or hazard detection features, broader situational awareness is necessary to develop more robust interventions across the dementia continuum. Designing applications that provide risk-prevention feedback tailored to the user's physical characteristics and living environment could further enhance autonomy, safety, and independent living.

3.7 Discussion

This section discusses the review findings in relation to existing literature, highlights ethical concerns associated with AR-based AT for PwD and MCI, and outlines the strengths and limitations of the review.

3.7.1 AR-based AT Intervention for PwD and MCI

AR-based AT interventions for PwD and individuals with MCI are designed to enhance daily functioning, improve safety, and promote independence by providing real-time, context-aware guidance that mitigates challenges associated with memory loss, attentional deficits, and executive dysfunction. This review categorises safety-focused interventions into three main areas: mobility, medication management, and home safety and control.

The findings indicate that mobility support is the most commonly implemented safety feature, with fall prevention being the most frequently used function. This emphasis reflects the significantly higher risk of falls among PwD, who are approximately twice as likely to experience falls compared to cognitively healthy older adults (Shaw, 2007; Panel on Prevention of Falls in Older Persons, 2011). Falls most commonly occur at home, and older adults living alone often experience heightened anxiety about such incidents (Kim, 2015). Fall risk is influenced by a combination of factors, including ageing, dementia, depression, dizziness, and visual or balance impairments (Al-Aama, 2011; Gazibara et al., 2014; Htike et al., 2023), as well as environmental conditions (Tinetti, 2003; Ambrose et al., 2013). Assessing both individual physical characteristics and environmental contexts is therefore critical. While conventional safety features, such as handrails, are commonly installed, tailoring these interventions to the specific needs of cognitively impaired individuals is essential (Miura et al., 2023). AR-based AT shows strong potential in this area by overlaying fall-prevention cues in real environments (Miura et al., 2023), providing virtual guidance to avoid hazards when users are disoriented (Yordanova et al., 2017), and supporting navigation and orientation skills (Htike et al., 2023).

Most AR-based interventions for wayfinding and wandering detection involve tracking the user's location and sharing it with caregivers or family members. A common approach is to define a safety zone and trigger alerts if the individual leaves this area (Ko et al., 2014; Liu et al., 2019). However, this method can generate false alarms when a person leaves the zone while cognitively stable (Ko et al., 2014; Gacem et al., 2019; Liu et al., 2019). Given the complexity and variability of wandering behaviours (Hammoud et al., 2018), systems must adopt adaptive models that can detect states of disorientation (Yordanova et al., 2017; Taghian et al., 2023). While monitoring movement and location provides valuable safety information and reassurance to caregivers (Yusif et al., 2020; Ionescu and Enescu, 2022), it also raises privacy concerns, a limitation noted in many of the reviewed interventions and echoed in studies by Wangmo et al. (2019), Bhargava and Baths (2022), and Ong et al. (2023). Future AR-based safety systems should address these privacy issues.

Fall detection, in contrast, is one of the least frequently implemented mobility features. Although such systems can alert caregivers or family members to a fall by transmitting the user's location (Park et al., 2019; Ro et al., 2019; Varghese et al., 2021), they are inherently reactive rather than preventive, as the incident has already occurred. These systems are also prone to false alerts triggered by fall-like activities, such as sitting, lying down, walking, or running. To improve accuracy, Abbate et al. (2012) employed machine learning techniques to differentiate actual falls from similar movements.

Interaction modalities in AR-based AT must account for the cognitive limitations of users, ensuring usability, intuitiveness, and minimal cognitive load. Hayhurst (2018) notes that as PwD experience cognitive decline, their ability to engage with AT may diminish. Designing systems that require minimal prior knowledge or training is therefore recommended (Avilés-López et al., 2010). Natural interaction methods, such as voice commands, are particularly effective, as they reduce user effort and are generally preferred by older adults over other interaction forms (Kanno et al., 2018; Li, 2024a; Avilés-López et al., 2010; Yang et al., 2022). Gesture-based and speech interactions can also support more natural engagement, though they may appear awkward to observers (Lazaro et al., 2022). Gesture inputs allow users to interact without wearing devices, but their functionality is often limited to specific indoor locations (Chen et al., 2020).

Many studies fail to clearly report the input modalities used, creating uncertainty about how users interact with these systems. Prioritising intuitive, user-friendly interaction is critical for engagement. Low adherence to digital prompts remains a major barrier to AT effectiveness (Leslie et al., 2005; Glasgow, 2007; Trompetter et al., 2015), often due to insufficient user engagement (Kassinopoulos et al., 2023). Evidence suggests that technological interventions have nearly twice the dropout rate of traditional face-to-face interventions, likely because they fail to provide meaningful opportunities for active participation and interaction (MacEa et al., 2010).

Some studies combined multiple input modalities to enhance interaction and feedback (Ingeson et al., 2018; Gacem et al., 2019; Ro et al., 2019; Park et al., 2019; Blusi and Nieves, 2019; Htike et al., 2023). Lazaro et al. (2022) emphasises that combining modalities can improve user engagement. This review concludes that multimodal interaction, tailored to user preferences and incorporating natural forms of input and output, can significantly enhance engagement. In particular, voice commands are well-suited for both indoor and outdoor applications.

Most reviewed interventions focus on a single safety domain, such as mobility, medication management, or home safety and control, with only a few addressing multiple safety domains simultaneously. Studies integrating two or more safety supports (Kanno et al., 2018; Ro et al., 2019; Park et al., 2019; Ghorbani et al., 2022; Taghian et al., 2023; Achilleos et al., 2023; Ghorbani et al., 2023) produced the most promising results. These findings support Guthrie et al.'s (2018) recommendation that addressing the safety needs of PwD and MCI is most effective when multiple safety supports are combined, despite the associated increases in cost and system complexity.

3.7.2 Preferred Intervention Devices for AR-based AT for PwD and MCI

The suitability of AR intervention devices depends on both the intervention goal, such as communication, safety, or social support and the characteristics of the target users, including older adults or individuals with MCI. The reviewed studies indicate that AR is most commonly deployed on smartphones (55%) for safety-related applications, compared to head-mounted displays (HMDs, 19%) and smart glasses (13%). However, prolonged use of smartphone-based AR can lead to fatigue and discomfort due to sustained visual attention, postural strain, and cognitive load, particularly among older adults (Liang, 2018; Farshid et al., 2018; Park et al., 2019; Gacem et al., 2019; López et al., 2024). Most studies focus on a single device type, and direct comparisons of device preference among this population are lacking.

Wearable AR headsets remain an emerging technology for enhancing safety among older adults and cognitively impaired individuals. Current HMDs and smart glasses are often perceived as bulky, heavy, expensive, and ergonomically uncomfortable, limiting prolonged use and acceptability (Juan et al., 2018; Liang, 2018; Lee et al., 2019; Dickinson et al., 2023; Mikhailova et al., 2024). In contrast, smartphones remain widely adopted due to their familiarity, ease of use, affordability, commercial availability (Lancioni et al., 2019), and non-stigmatising nature compared to traditional AT devices (Wilson et al., 2022). Despite these advantages, smartphones have limitations in supporting spatial aspects of mobility-related safety. While they can provide reminders, alerts, and location information (Achilleos et al., 2023; Taghian et al., 2023; Yadav and Kirit, 2024; Liu et al., 2019; Gacem et al., 2019; Varghese et al., 2021), they offer limited hands-free, gaze-aligned, or context-aware guidance for real-world mobility tasks such as fall prevention, which can reduce safety for users with cognitive impairments.

In contrast, smart glasses offer hands-free, immersive experiences and have shown promising acceptance among older adults in some studies (Gacem et al., 2019; Hellec et al., 2023). The development of lightweight and more affordable AR smart glasses, such as the Vuzix Blade (Vuzix, 2024), enhances their feasibility and accessibility. Further miniaturisation into conventional eyeglass designs may improve acceptability, particularly for older adults accustomed to wearing spectacles.

Although other technologies, such as sensors (Weizman et al., 2021; Tiersen et al., 2021), robotics (Lera et al., 2014; Ro et al., 2019), and Virtual Reality (VR) (Afifi et al., 2021; Flynn et al., 2022), are also employed in assistive interventions for older adults and individuals with cognitive impairments, AR is particularly valued for its ability to enhance real-world experiences across diverse platforms (Zhao et al., 2019a; Achilleos et al., 2023; Li, 2024a). AR-based AT can deliver real-time, context-aware safety cues that support safer decision-making within users' environments. Compared to conventional visual interfaces, AR provides more intuitive, immersive, and engaging interactions, overlaying contextual information, data visualisations, or virtual objects onto real-world environments to enhance perception and understanding (Połap et al., 2017; Li, 2024a).

Evidence suggests that older adults with age-related cognitive decline, PwD, and individuals with MCI are generally willing to adopt AR-based AT (Saracchini et al., 2015; Bianco et al., 2016; Kanno et al., 2018; Ingeson et al., 2018; Blusi and Nieves, 2019). However, technology acceptance was inconsistently measured across studies. Where assessed, participants reported high ratings for usefulness, ease of use, performance, and interactivity (Su et al., 2024; Guerrero et al., 2019; Achilleos et al., 2023), indicating a generally positive attitude toward AR-based AT, provided these systems are carefully designed to meet the specific needs of older adults and individuals with cognitive impairments.

3.8. Comparison Between the Proposed System and Existing Fall Prevention Approaches

Based on the limitations identified in existing fall prevention approaches for PwD and individuals with MCI, this research proposes a more adaptive, context-aware, and cognitively responsive assistive approach. Unlike conventional systems that primarily rely on static alerts or passive environmental modifications, the proposed approach integrates real-time environmental fall hazard and safety intervention detection with attention-aware adaptive guidance to better align with users' fluctuating cognitive states and behavioural needs. Table 3.7 presents a comparative overview of the proposed system and existing fall prevention approaches, highlighting their respective advantages, trade-offs, scalability, adaptability, and practical applicability.

Table 3.7. Comparison Between the Proposed System and Existing Fall Prevention Approaches

System/Approach	Expected Advantages	Trade-offs / Limitations	Scalability	Adaptability	Practical Applicability	Authors
Traditional Home Safety Modifications (e.g., grab bars, handrails, lighting improvements)	Low cost, simple implementation, immediate environmental support	Passive interventions; rely heavily on user memory, awareness, and adherence	High scalability due to low technological requirements	Limited adaptability to changing cognitive states or contexts	Widely applicable in domestic environments but less effective for PwD with cognitive impairments	Kahya et al., 2020; Chen et al., 2020); Bianco et al. (2016); Nishchyk et al., (2021)
Wearable Sensor-Based Monitoring Systems	Continuous physiological and movement monitoring	May generate excessive alerts; limited environmental understanding	High scalability with wearable technologies	Limited contextual and cognitive adaptation	Practical for long-term monitoring but may affect user compliance	Kiprijanovska et al. (2020); Chen et al. (2022); Maiora et al. (2024); Guan et al. (2025)
Existing AR-Based Assistive Systems	Provides visual guidance and navigation support	Often static and non-personalised; limited consideration of fluctuating cognitive attention	Moderate scalability due to hardware dependency	Partial adaptability depending on system complexity	Promising for assisted navigation but limited by cognitive responsiveness	Miura et al. (2023); Ball et al., (2023); Bianco et al., (2016); Połap et al., (2017); Dylan et al., (2023); Su et al., (2024)
Proposed Adaptive Multimodal AR Assistive System	Delivers adaptive safety cues tailored to the user's cognitive attention level, minimising unnecessary alerts and promoting independence	Increased system complexity; requires multimodal sensing and wearable smart glasses	High scalability through modular AI and wearable integration	Highly adaptive to both environmental context and users' cognitive attention states	Strong practical applicability for independent living support and proactive fall risk mitigation in PwD and individuals with MCI	

3.9. Conclusion

In conclusion, AR-based AT demonstrates considerable potential to enhance safety, independence, and QoL for PwD and individuals with MCI. However, their application in this context is still in its early stages and remains relatively underexplored. Existing studies underscore the capacity of AR to provide real-time, context-aware guidance, fall prevention support, wayfinding assistance, and medication reminders, yet they also reveal significant challenges related to design, usability, and ethical considerations. Key limitations include the need for adaptive and intuitive interaction modalities that accommodate cognitive decline, device ergonomics and comfort for prolonged use, and effective mechanisms for protecting user privacy, particularly when monitoring location or movement.

These gaps point to clear avenues for future research, including the development of context-responsive AR systems that can tailor interventions to the individual's physical abilities, cognitive status, and environmental conditions. There is also a pressing need for robust evaluation methodologies that go beyond user perceptions to quantify safety outcomes, such as reductions in falls, wandering incidents, or medication errors. Moreover, the review highlights the critical importance of embedding ethical principles at every stage of AR design and implementation. Ensuring transparency, safeguarding privacy, and minimising cognitive or physical burden are essential to protect vulnerable users and foster trust in these technologies.

Adopting a human-centred design approach, as highlighted in the literature (Wolff et al., 2021), is essential for the responsible development of AR-based AT. In this study, the perspectives of caregivers and family members of PwD were examined to gain a deeper understanding of the needs, challenges, and everyday experiences of individuals living with dementia. Given their close and continuous interaction with PwD, caregivers offer valuable insights into the practical difficulties encountered in home environments, particularly those related to mobility, navigation, and safety (Hurt et al., 2008; Jorm, 2004). The following chapter describes the procedures and methodological approach used to collect these insights, including the research design, data collection methods, participant recruitment, and analytical techniques employed to systematically capture and interpret the perspectives of these stakeholders.

Chapter 4

Attitude of People with Dementia Towards Potential Home Environment Hazards and Safety Interventions

This chapter presents a cross-sectional study, which gathers the perspectives of caregivers and family members who provide care or support to individuals in the mild stages of dementia using a questionnaire. The results and findings are discussed, while possible limitations of the study are also mentioned.

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Contents

4.1 Introduction

Gathering the perspectives of caregivers and family members who support individuals in the mild stages of dementia is essential for understanding how early cognitive and behavioural changes manifest in everyday life. Because caregivers interact with individuals in natural environments over extended periods, their observations often capture subtle symptoms and functional changes that may not be immediately evident during clinical assessments (Jorm, 2004; van Vliet et al., 2011).

Research shows that informant reports from relatives or caregivers play a crucial role in identifying and differentiating neurodegenerative conditions, as structured caregiver questionnaires can reveal patterns of changes in memory, reduced independence in daily activities, or emerging behavioural symptoms that assist clinicians in diagnosis and monitoring disease progression (Sikkes et al., 2012; Murley et al., 2024). Caregiver accounts are particularly valuable in the early or pre-diagnostic phase, when symptoms are often ambiguous or misinterpreted. Qualitative studies of family caregivers describe noticing gradual personality and behavioural changes, disruptions in family roles, and difficulties obtaining recognition of the problem from healthcare professionals or social networks. These early observations help explain why diagnosis can be delayed and highlight the importance of including caregivers' insights in the diagnostic process (van Vliet et al., 2011). Integrating caregiver perspectives into research and clinical practice supports a more comprehensive understanding of how dementia affects QoL and daily functioning. Studies comparing patient and caregiver assessments show that behavioural and psychological symptoms strongly influence perceived QoL and care needs, emphasising the importance of caregiver-reported information in care planning (Hurt et al., 2008).

Therefore, this cross-sectional study aims to explore the perspectives of caregivers and family members who provide care or support to individuals in the mild stages of dementia, particularly regarding their attitudes toward potential home environmental hazards and the use of safety interventions. The insights gained from this investigation provide an important empirical foundation for the subsequent phases of the research. By examining the experiences of caregivers who often have the most frequent and sustained interaction with PwD, this chapter offers valuable context for understanding the practical needs, everyday challenges, and potential opportunities for improving dementia care within the home environment. Furthermore, the findings contribute to informing the development and refinement of technological support systems designed to enhance safety and support independent living for individuals with dementia in domestic settings.

4.2 Method

A cross-sectional survey method was employed in this study to obtain an overview of caregivers' perspectives at a single point in time. This observational design collects and analyses data from a population at one time, capturing a snapshot of characteristics, behaviours, or opinions within the target group (Setia, 2016; Levin, 2006). It is commonly used to measure the prevalence of health outcomes, examine associated factors, and describe population characteristics (Mann, 2003). Unlike longitudinal studies, cross-sectional surveys do not involve follow-up and are generally inexpensive, easy to conduct, and useful for providing preliminary evidence for future research (Hall, 2008; Wang et al., 2020). They are particularly effective for descriptive and exploratory studies, allowing efficient data collection from diverse participants and analysis of associations between categorical variables (Capili, 2021). In this study, the method enabled quantitative data collection from professional caregivers and family members of PwD, offering valuable insight into the mobility challenges and risks associated with cognitive impairment.

4.2.1 Ethical Approval

This study received ethics approval from the University of Essex Ethics Sub Committee 2 (Reference numbers: ETH2324-0711). Submission of the online questionnaire was taken as implied consent for all participants in this research.

4.2.2 Participants

Participants aged 18 and above were eligible for the survey. The participants were either professionals or family members/friends with at least 1 year of experience in providing care or support for PwD.

4.2.3 Recruitment and Data Collection

Participants were recruited by posting study information on healthcare workers' WhatsApp groups and through word-of-mouth. The recruitment was between February 2024 and April 2024 across England, United Kingdom. Those interested in participating were directed to a Google Form to complete the online form which was designed with the questionnaire sample in Appendix II. Participants were provided information about the research with an additional links to the consent and participant information sheet before accessing the online form. The sample of the participant consent form and information sheet are in Appendix III and IV respectively. The survey was designed to take approximately 10 minutes and was entirely anonymous and voluntary.

4.2.4 Survey Development

The survey materials were developed in accordance with the University of Essex guidelines for the ethical approval of research involving human participants (University of Essex, 2021).

The survey was online and was divided into four sections: Introduction, Demographics, PwD Safety Intervention and Adherence, and Perception of Digital Intervention. The questionnaire items were developed through an iterative process, and a total of 25 questions were created as shown in Appendix II. Completeness checks were implemented to ensure all mandatory questions were answered before progressing to the next survey page. Participants had the option to review and revise their answers before submitting the survey. No identifiable information was collected.

4.2.5 Data Analysis

The survey was closed from accepting input from participants by April 30, 2024. The raw data were exported into Excel with all mandatory questions fully completed. The file was saved in CSV format to ensure compatibility with any statistical analysis tool.

Survey responses were analysed using the statistical software package R. Descriptive statistical techniques were employed to summarise and interpret participants' responses, including frequency distributions, percentages, cross-tabulations, and graphical representations. The use of descriptive statistics is widely recognised as a fundamental step in quantitative research because it enables researchers to systematically organise, summarise, and present data in a clear and interpretable manner (Cooksey et al., 2020). Through these techniques, large volumes of raw data can be condensed into meaningful summaries that facilitate the identification of patterns and trends within the dataset. Descriptive analysis also serves both exploratory and communicative purposes, allowing researchers to clearly present the characteristics of the data and support evidence-based interpretation prior to further statistical analysis (de Vaus, 2014). In this study, the application of these methods provided clearer insight into the distribution, central tendencies, and variability of participants' responses, thereby supporting a structured and transparent analysis of the survey data. The chi-square (χ^2) test (McHugh, 2012) was used to determine the statistical significance of the correlation between variables with significance level α, derived from the threshold of 5% ($\alpha=0.05$) and *p-value* < 0.05.

If p-value $< 0.05 \rightarrow H_0$ is unlikely, hence the null hypothesis is rejected.
Otherwise, p-value $\geq 0.05 \rightarrow H_1$ is likely, and do not reject the null hypothesis.

4.3 Results

A total of 121 participants who were caregivers or family members providing care or support to PwD in the United Kingdom took part in the survey. The participants were female 80 (61.1%), 30 – 39 years of age 67 (55.4%) and of African ethnicity 82 (67.8%). The majority of the participants were healthcare assistants/ caregivers, 91 (75.2%), and provided care or support to PwD in residential or nursing care facilities, 99 (81.8%). Table 4.1 presents a comprehensive data distribution of the survey.

Table 4.1. Summary of Participants' Demographic Characteristics.

Participant demographic characteristic (n=121)	**N**	**(%)**
Age Range (Years)		
18-29	4	3.3
30-39	67	55.3
40-49	47	38.8
50+	3	2.5
Gender		
Male	41	33.9
Female	80	66.1
Other	0	0
Prefer not to say	0	0
Ethnicity		
White/White British	23	19
Black/Black British	6	5
Asian/Asian British	8	6.6
African	82	67.8
Other	2	1.7
Occupation		
Healthcare Assistant/ Caregiver	91	75.2
Other	30	24.8
Category		
Professional	79	65.3
Family member/Friend	42	34.7
Experience (Years)		
1-3	53	43.8
4-7	60	49.6
8-11	5	4.1
12+	3	2.5
Place of care or support		
Residential or Nursing care facility	99	81.8
Domiciliary care	22	18.2
Number of PwD cared for or supported		
1-3	56	46.3
4-6	36	29.8
7-9	8	6.6
10+	21	17.4
Daily hours spent with PwD		
1-8	43	35.5
9-16	38	31.4
17-24	40	33.1

To evaluate the attitudes of PwD toward home hazards and safety interventions, caregivers' responses regarding the individuals they have cared for or supported were analysed. Table 4.2 summarises these responses, while the corresponding graphical representations are presented in Figures 4.1 and 4.2 to illustrate the distribution and patterns observed in the data.

Table 4.2. Summary of Participant Response on the Attitude of PwD Regarding Home Environment Hazards and Safety Interventions

Participant response on the attitude of people with dementia towards potential home hazards and safety interventions (n=121)	**N**	**(%)**
Are there any home safety interventions where you provide care or support to assist people living with dementia?		
Yes Sometime No	95 23 3	78.5 19 2.5
Do the person or people living with dementia consistently maintain awareness of their surroundings, avoiding collisions with objects or unsafe environment?		
Yes Sometime No	36 67 18	29.8 55.4 14.9
Assuming there is no physical mobility impairment, are people living with dementia always able to navigate staircases, uneven surfaces, obstacles, etc., safely without assistance?		
Yes Sometime No	14 61 46	11.6 50.4 38
Do the person or people living with dementia able to recognise when to use home safety interventions (e.g., holding handrails, grab bars etc) without being reminded?		
Yes Sometime No	11 76 34	9.1 62.8 28.1
Do the person or people living with dementia always able to utilise home safety interventions without being guided?		
Yes Sometime No	12 723 7	9.9 59.5 30.6

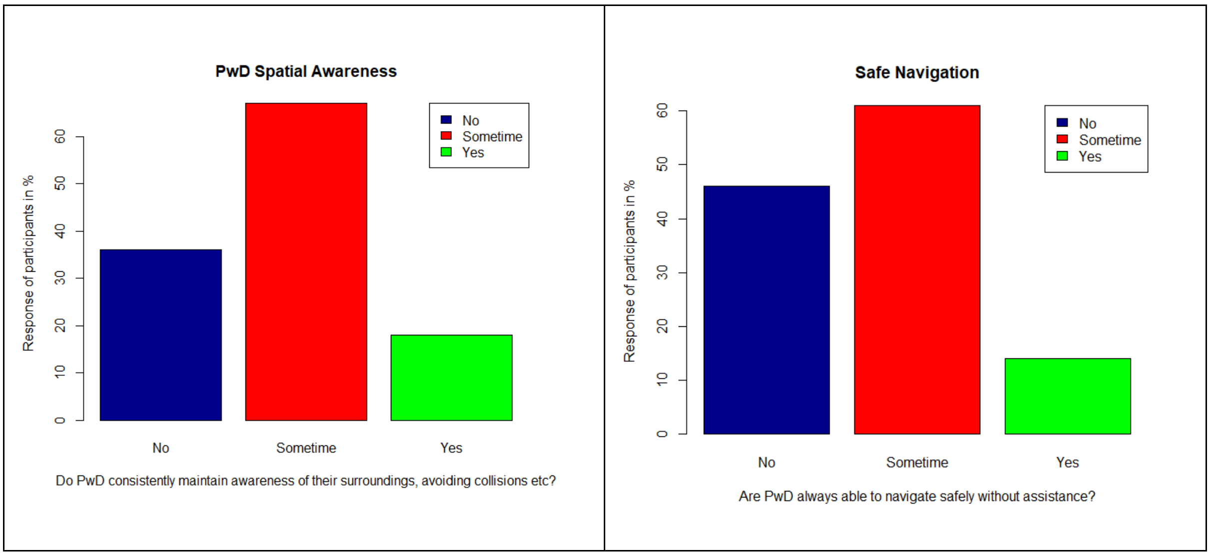

Figure 4.1. Participant Response on Safe Mobility

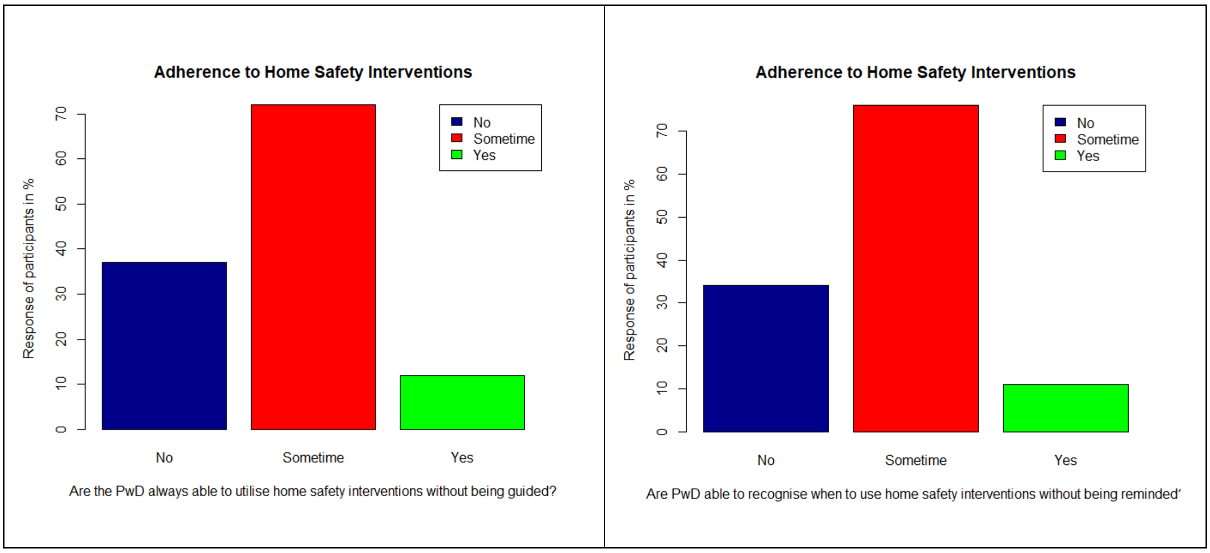

Figure 4.2. Participant Response on Home Safety Interventions Usage

Other relevant characteristics measured as part of the survey are presented in Table 4.3.

Table 4.3. Summary of Other Characteristics Measured.

Participant response on other characteristics measured for people with dementia (n=121)	**N**	**(%)**
Do the person or people living with dementia you care for or support use glasses?		
Yes	59	48.8
Sometime	38	31.4
No	24	19.8
Do the person or people living with dementia use any wearable electronic interventions or devices?		
Yes	12	9.9
Sometime	45	37.2
No	64	52.9
Do you think wearable electronic devices can help improve the safety of people living with dementia?		
Yes	873	71.9
Maybe	2	26.4
No	2	1.7
Do you think combining wearable electronic devices, alongside the current home safety interventions, would be advantageous for people living with dementia?		
Yes	98	81
Maybe	23	19
No	0	0
Would you be happy to take part in the assessment of the proposed system that is been developed once it's completed?		
Yes	53	43.8
Sometime	15	12.4
No	53	43.8

This study formulates the following hypotheses to guide the investigation:

Null Hypothesis (H_0): *People with dementia (PwD) do not require additional digital interventions to effectively utilise existing home safety interventions and to navigate their home environment safely.*

Alternative Hypothesis (H_1): *People with dementia (PwD) require additional digital interventions to effectively utilise existing home safety interventions and to navigate their home environment safely.*

Table 4.4. Chi-square Test for Questionnaire Variables

Measure	Q14	Q15	Q16	Q17
Home Hazards and Safety Intervention	$\chi 2$ = 21.062 df = 4 p-value = 3.078 e-04	$\chi 2$ = 27.597 df = 4 p-value = 1.505e-05	$\chi 2$ = 25.971, df = 4 p-value = 3.208e-05	$\chi 2$ = 27.005 df = 4 p-value = 1.983e-05

Table acronyms: Q14: Do the person or people living with dementia consistently maintain awareness of their surroundings, avoiding collisions with objects or an unsafe environment? Q15: Assuming there is no physical mobility impairment, are people living with dementia always able to navigate staircases, uneven surfaces, obstacles, etc., safely without assistance? Q16: Are the people living with dementia able to recognise when to use home safety interventions (e.g., holding handrails, grab bars, etc.) without being reminded? Q17: Are the people living with dementia always able to utilise home safety interventions without being guided?

The results in Table 4.4 demonstrated statistically significant associations across all four items. In each case, the p-value is substantially lower than the predetermined significance level of $\alpha = 0.05$. The chi-square test evaluates whether there is a statistically significant association between categorical variables. A small p-value indicates that the observed distribution of responses differs significantly from what would be expected if the variables were independent.

Given that all p-values are well below 0.05, the null hypothesis of independence can be rejected for Q14 through Q17. This suggests that perceptions of home hazards and safety interventions are significantly associated with the factors related to mobility and navigation challenges among PwD.

The strength and consistency of these statistically significant findings across multiple survey items provide robust evidence that existing home safety measures may not be fully sufficient on their own. Instead, the results support the alternative hypothesis that additional digital interventions are necessary to enhance the effectiveness of current home safety strategies and to improve safe navigation for PwD within their home environments. These findings strengthen the empirical argument for integrating digital assistive technologies into dementia home care frameworks to address mobility and safety-related challenges more comprehensively.

4.4 Discussion and Findings

This study explored caregivers' perspectives to assess the attitudes of PwD toward home environment hazards and home safety interventions. Data were collected through self-report questionnaires administered to participants who were either professional caregivers or family members actively involved in supporting PwD with ADLs. The majority of respondents were professional caregivers (n = 79, 65.3%) with between four and seven years of caregiving experience (n = 60, 49.6%). Most participants (n = 99, 81.8%) provided care within residential or nursing care facilities, indicating that the findings are grounded in substantial practical experience within structured care environments.

The findings of this study indicate that 95 participants (78%) reported that home safety interventions aimed at preventing fall hazards are commonly implemented in the homes of PwD, with most strategies focusing on environmental modifications. These results are consistent with existing literature highlighting the critical role of home modification strategies in promoting safety for PwD. Studies by Taylor et al. (2021), Georlee et al. (2020), the National Institutes of Health (2017), and the Alzheimer's Association (2023b) emphasise that environmental adaptations such as removing trip hazards, improving lighting, and installing supportive fixtures can significantly reduce fall risks and enhance safety within domestic environments. Similarly, research conducted by Kahya et al. (2020), Chen et al. (2020), and Nishchyk et al. (2021) demonstrates that well-designed home modifications not only improve safety but also support functional independence and overall QoL for individuals living with dementia.

Despite the widespread implementation of home safety interventions, this study found that PwD often demonstrate low adherence to these measures, potentially limiting their effectiveness in reducing domestic risks. One contributing factor appears to be impaired spatial awareness, a common cognitive deficit in dementia. Impairments in spatial orientation and navigation can significantly hinder an individual's ability to move safely within both familiar and unfamiliar environments, reducing their capacity to recognise hazards or utilise environmental modifications effectively (Coughlan et al., 2018; Zanco et al., 2018; Tragantzopoulou and Giannouli, 2024). The study also highlighted that PwD frequently experience difficulties navigating uneven surfaces and avoiding obstacles. These findings align with the observations of the American Psychiatric Association (2010), which note that PwD often lack the necessary judgment to identify and respond appropriately to potentially hazardous situations. Given the substantial risks identified, particularly for PwD who may live alone, the findings suggest that traditional home modifications, while beneficial, may not be sufficient on their own. There is a strong need to explore digital interventions that can support and improve the usability and effectiveness of current safety measures. This study, therefore, proposes a digital solution designed to augment current home safety interventions by providing context-aware support that assists PwD in recognising and appropriately utilising installed safety features.

Encouragingly, a majority of participants (n = 87, 71.9%) indicated that digital interventions could improve safety outcomes for PwD and expressed willingness to participate in testing and evaluating the proposed system. This positive perception among caregivers strengthens the feasibility and acceptability of integrating digital technologies into dementia continuum.

Furthermore, nearly half of the reported PwD population (n = 59, 49%) use glasses. Given that eyewear is commonly used among older adults, integrating the proposed digital system into wearable devices such as glasses could offer a practical, unobtrusive delivery method. Embedding AT within familiar personal accessories could enhance user acceptance, reduce stigma, and promote consistent utilisation, thereby maximising the potential safety benefits of the intervention.

4.5 Conclusion

This study explored caregivers' perspectives to better understand the attitudes of PwD toward home environment hazards and existing home safety interventions, and the findings directly informed the design and development of the proposed wearable smart glasses-based adaptive AR assistive system. The study revealed that, despite the widespread implementation of home safety interventions, PwD often demonstrate low adherence to these measures due to cognitive impairments associated with dementia, particularly deficits in spatial awareness, navigation, memory, and situational judgment. These impairments reduce the ability of PwD to recognise environmental hazards, remember to use installed safety features, or appropriately engage with safety interventions during daily activities. Consequently, the continued risk of falls and domestic accidents, especially among individuals living alone, highlighted the limitations of relying solely on passive environmental modifications.

This study posits a new perspective by shifting the focus from merely installing environmental modifications to enhancing their usability through digital assistive technologies. While existing safety strategies predominantly emphasise passive environmental adaptations, they often assume that individuals can recognise, remember, and correctly utilise these features. This study challenged this assumption and provided empirical evidence supporting the need for complementary digital interventions that actively support engagement with existing safety measures. The findings established the need for an intelligent assistive approach capable of actively supporting cognitive engagement with home safety interventions in real time. As a result, the proposed system was designed to integrate real-time environmental hazard detection with an adaptive framework that responds dynamically to users' cognitive states. The observation that PwD frequently experience difficulties navigating uneven surfaces and avoiding obstacles informed the incorporation of computer vision-based hazard detection capable of identifying potential environmental fall risks and safety interventions within the user's surroundings.

Furthermore, the identified variability in users' awareness and engagement with safety measures motivated the integration of a HMM-based attention state prediction mechanism. By modelling fluctuations in user attention through behavioural and multimodal sensory data, the system can selectively provide context-sensitive AR guidance and safety alerts only when reduced attention or elevated fall risk is inferred. This adaptive decision-making approach was specifically designed to minimise unnecessary notifications, reduce alert fatigue, and preserve user autonomy while enhancing situational awareness and safer navigation within the home environment.

Importantly, the findings also indicated that most PwD regularly use prescribed glasses, which informed the decision to implement the proposed assistive technology through wearable smart glasses. Embedding the AR system within a familiar and socially acceptable accessory provides a practical and unobtrusive delivery platform for continuous support. This design choice has the potential to improve usability, encourage consistent utilisation, reduce stigma associated with assistive devices, and enhance user acceptance. Collectively, the study findings provided the conceptual, behavioural, and practical foundations for the development of a personalised, wearable, and cognitively adaptive AR assistive system aimed at improving fall risk mitigation and supporting safer independent living for PwD.

Chapter 5

System Development Methodology

This chapter outlines the various stages involved in the development of an adaptive augmented reality-based assistive technologies for fall risk assessment among people with dementia and individuals with mild cognitive impairment. The proposed system, named PwDAT (People with Dementia Assistive Technology), was designed to support fall risk assessment through adaptive and interactive augmented reality-based functionalities.

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In review as: Ise Anderson Orobor, Faiyaz Doctor, Ramy Hammady and Mary R. Kennedy (2026). Smart Glasses Augmented Reality Based Fall Risk Assessment System for People with Dementia Using Deep Learning and Hidden Markov Model. *Multimedia Systems.*

Contents

5.1 Design Science Research Methodology

The research utilises Design Science Research Methodology (DSRM) as it aims to present an innovative approach to address the identified problem in existing system design. DSRM framework involves six main steps: problem identification and motivation, setting solution objectives, design and development, demonstration, evaluation, and communication (Peffers et al., 2007).

Based on this framework, Figure 5.1 presents a comprehensive system design that outlines the methodology adopted for developing an adaptive AR-based assistive technology for fall risk assessment.

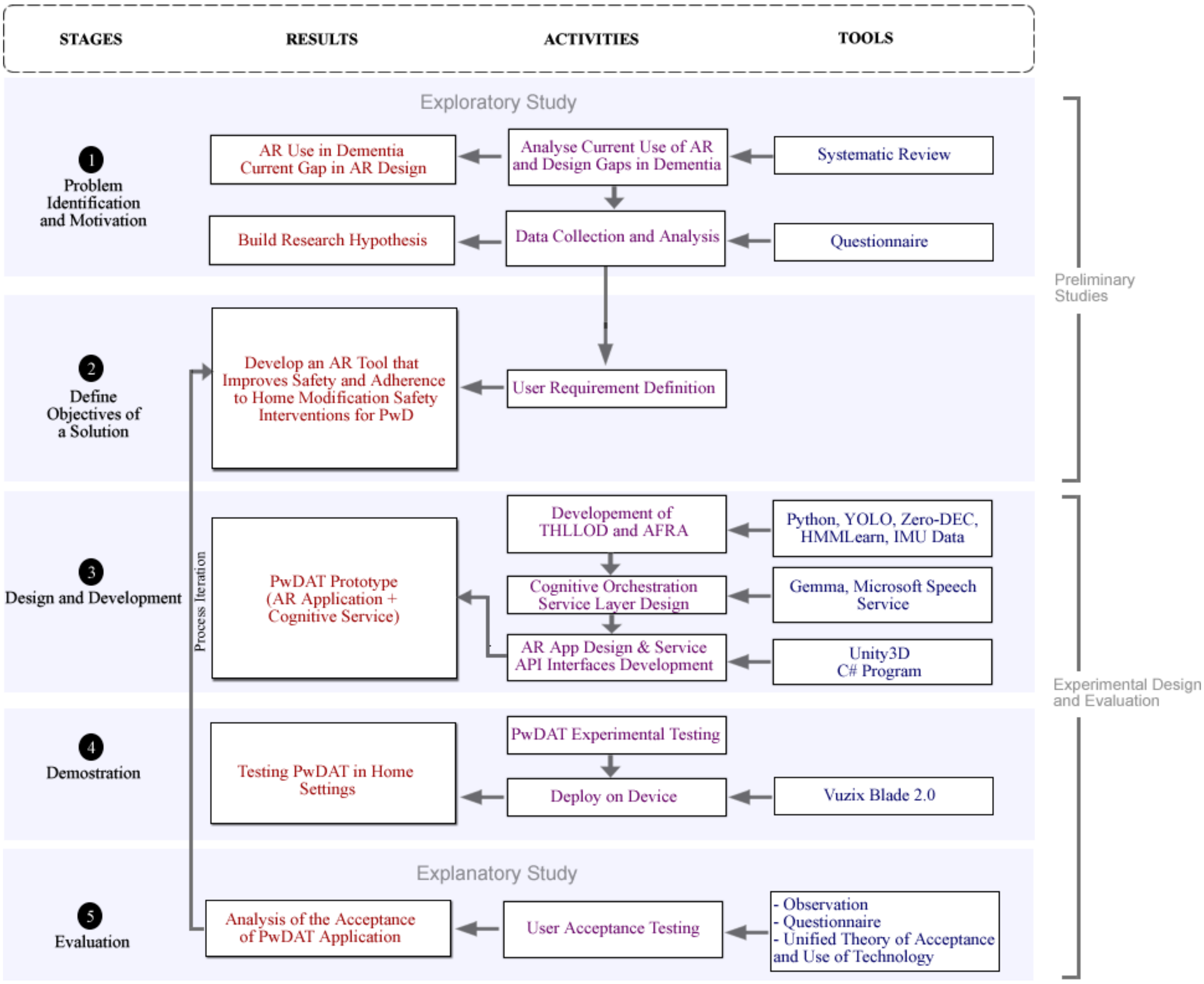


Figure 5.1. Adaptive Multimodal AR-based System Methodology

Stage 1: In this stage, a literature review was conducted to identify the problem. The review explores the current application of AR-based AT in dementia, as presented in Chapter 3, and the design gap in the existing application. The findings from the literature were used to formulate research questions for the research. In addition, a cross-sectional survey using a questionnaire was conducted to gain more understanding of the problem from caregivers as presented in Chapter 4. The analyses of the information collected are used to define the user requirements of the system proposed.

Stage 2: Based on the user requirements identified in Stage 1, clear solution objectives were defined. Hence, an adaptive AR–based AT to support safe mobility amongst PwD and individual with MCI was proposed. The system focused on fall risk assessment, leveraging AR to deliver intuitive guidance, real-time feedback, and enhanced environmental awareness, with the aim of reducing fall risk and supporting safe, independent performance of ADL.

Stage 3: At this stage, the design and implementation of the proposed system were initiated, beginning with the development of the Transfer Hybrid Learning Low-Light Object Detection (THLLOD) framework. The framework integrates Zero-DCE for low-light image enhancement with YOLO-based object detection to identify environmental hazards and safety interventions, with model training and experimentation conducted in Python.

This was followed by the development of the Attention-Aware Fall Risk Assessment (AFRA) framework, which uses DL and HMM to infers users' latent attention states from real-time IMU-derived behavioural observations, enabling the assessment of safety adherence behaviour and supporting adaptive intervention delivery. The integration of this attention modelling component with the DL-based detection module forms a unified fall risk assessment framework capable of delivering context-aware safety guidance aligned with the user's cognitive state.

Finally, an AR client application was developed using Unity3D and C# programming language, which leverages the THLLOD and AFRA services alongside Large Language Models (LLMs) and Microsoft Speech Services, coordinated through the Cognitive Orchestration Service (COS) layer, to deliver real-time adaptive safety guidance to end users.

Stage 4: At this stage, the core functionalities of the prototype were systematically tested to verify performance, reliability, and usability. Following successful validation, the prototype was deployed on smart glasses to enable real-world interaction and evaluation. This deployment supported user acceptance testing, allowing assessment of the system's practicality, comfort, and effectiveness in delivering AR-based safety guidance, as well as gathering user feedback to inform further refinement and optimisation of the solution.

Stage 5: In this stage, participants were recruited to evaluate the proposed system in a user study. The assessment involved direct observation of participants as they interacted with the application, allowing insights into usability, engagement, and real-world effectiveness. Following system use, participants provided structured feedback through a questionnaire developed based on the UTAUT framework. This approach enabled a comprehensive evaluation of user perceptions, including usefulness, ease of use, acceptance, and intention to adopt the system, thereby informing the overall effectiveness and user readiness of the solution.

5.2 Transfer Hybrid Learning Low-light Object Detection Framework

In this thesis, a Transfer Hybrid Learning Low-Light Object Detection (THLLOD) framework is developed to enable automated object detection in both indoor and outdoor environments, with the aim of identifying potential fall hazards and recognising home safety interventions for individuals with cognitive impairment. The framework integrates pretrained CNN architectures for image enhancement and object detection, enabling the recognition of context-specific objects and environmental risk factors that may contribute to falls. By leveraging TL, the system benefits from knowledge embedded in large-scale image datasets while enabling fine-tuning to the unique characteristics of domestic settings. This approach provides a robust model for detecting safety-critical objects and conditions in real time, thereby facilitating more effective monitoring and personalised intervention strategies for cognitively impaired users. The following section outlines the various stages involved in the development of the framework.

5.2.1 Object Detection Data Collection and Annotation

In this stage, images were collected and annotated to create a dataset for training the object detection model. The dataset specifically focused on environmental hazards that contribute to fall risk, as well as home safety interventions designed to prevent falls in older adults and individuals with cognitive impairment. Careful annotation ensured that each object of interest was accurately labelled, providing the model with the necessary information to recognise both potential risks and safety features in real-world environments. A total of 3049 images were collected from different sources. The images were organised based on WordNet (Miller, 1995), and its hierarchical structure is defined using a tree structure shown in Figure 5.2.

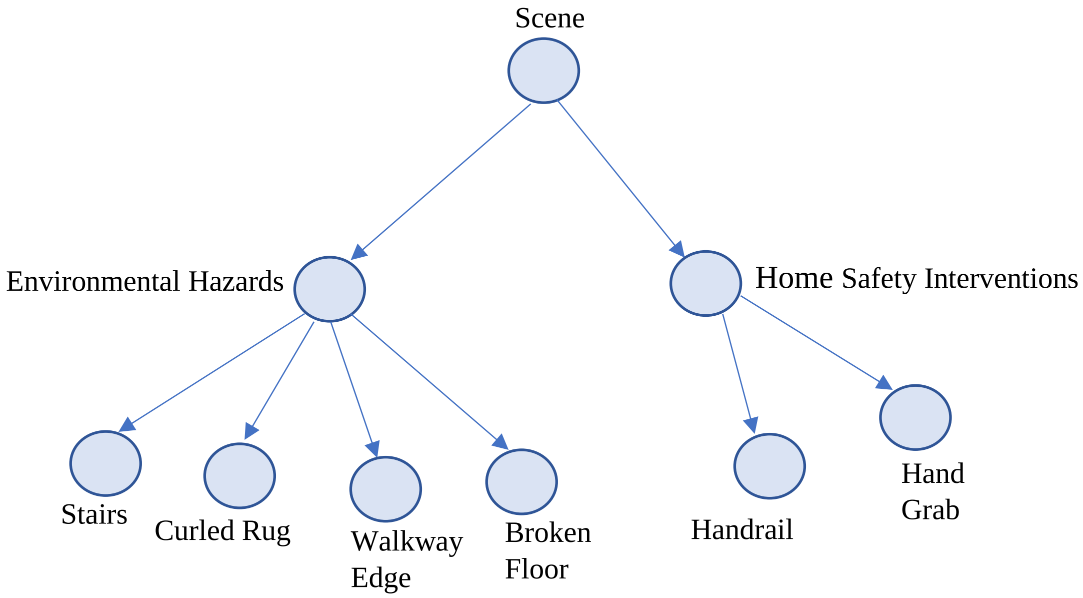


Figure 5.2. Image Synset for Potential Home Environment Hazards and Safety Interventions Object Detection

Based on the above, two synsets (hazards and safety interventions) with 6 subclasses (stairs, broken floor, walkway edge, curled rug, handrail, and hand grab) were constructed.

I. Dataset

Three complementary data collection methods were employed to assemble the datasets called HomeFall, used in this project. These approaches were necessary because the target objects, particularly those related to fall hazards and home safety interventions, are not in large publicly available datasets. The first method was through publicly available datasets. A subset of images from the StairNet dataset (Kurbis et al., 2022), an open-source collection of labelled staircase images, was used.

Secondly, images were manually collected using a smartphone. Smartphones come with an enormous array of functionality, including high-resolution inbuilt cameras adequate for large-scale images and video data collection through crowdsourcing (Hunt et al., 2021). Specifically, Samsung A02 with a rear camera of 13MP, F1.9, Macro: 2MP, F2.4 was utilised to collect scene images in the raw image domain, covering both daytime and night-time scenes with different noise levels.

Thirdly, web scraping, a technique that became necessary in gathering a portion of the data in instances where there was a lack of publicly available data and insufficient manual data collection (Rennie, 2020; Khder, 2021). To achieve this, a script was written to retrieve images from the internet by querying image search engines with all the words found in the WordNet graph in Figure 5.2. On average, each synset within the dataset comprises around 500 clean images. However, the script occasionally returns irrelevant images along with those exhibiting high levels of noise, duplicates and low resolution, which are unsuitable for model training. Consequently, all undesired images were removed to preserve only high-quality synsets, typically above 800 × 650 pixels. Table 5.1 shows the classes data distributions.

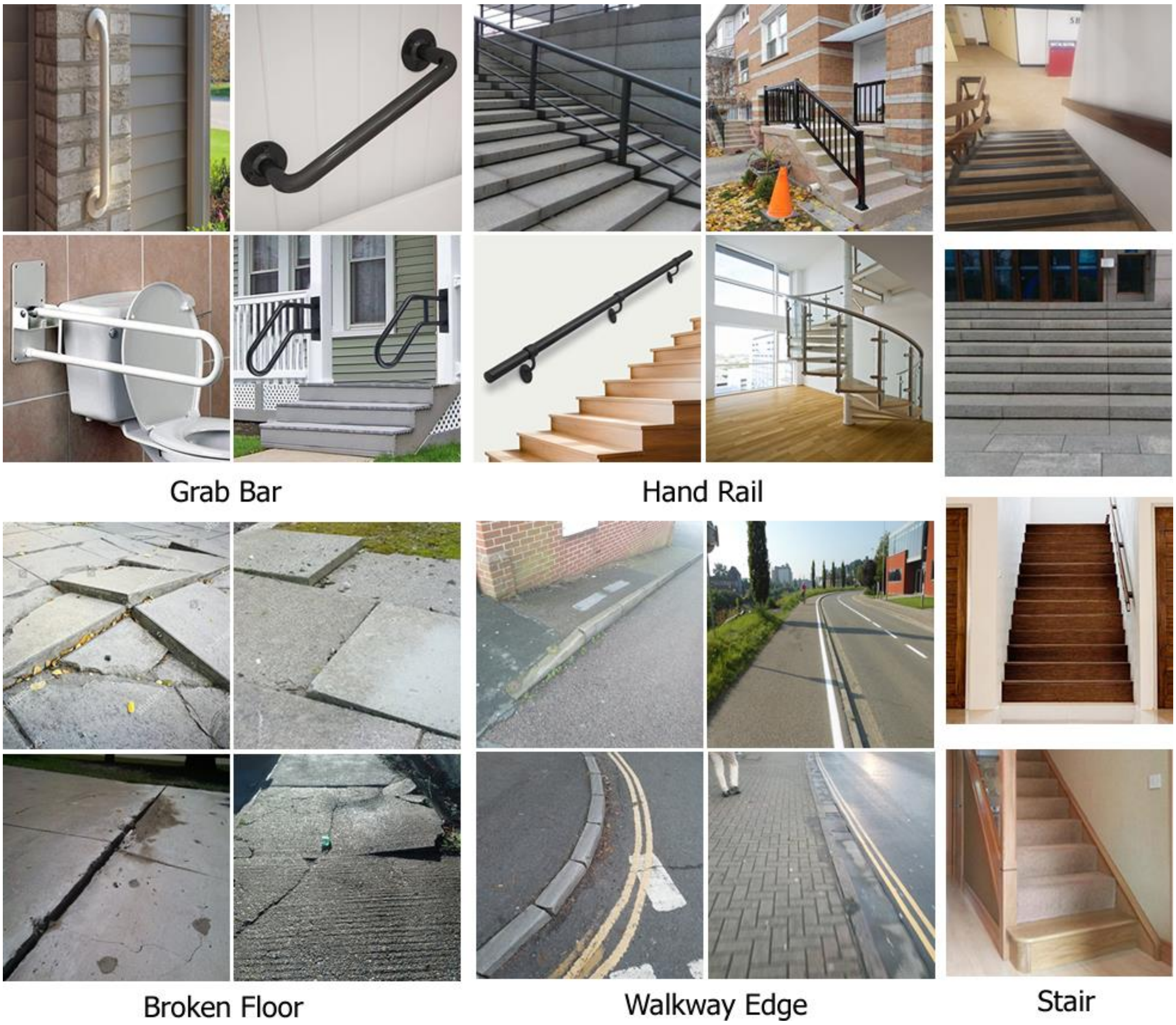


Figure 5.3. Sample Dataset with Randomly Selected Image Classes

Table 5.1. Details of Classes Distribution in the Dataset

Type of Class	Grab Bar	Hand Rail	Broken Floor	Walkway Edge	Stair	Curled Rug
Number	501	512	503	507	516	510

II. Annotation

The data collection task was followed by image annotation. The images were manually labelled by drawing a bounding box around the object of interest. Figure 5.4 shows an illustration of bounding box around a stair as determined by the x and y axis coordinates in the top-left corner of the rectangle.

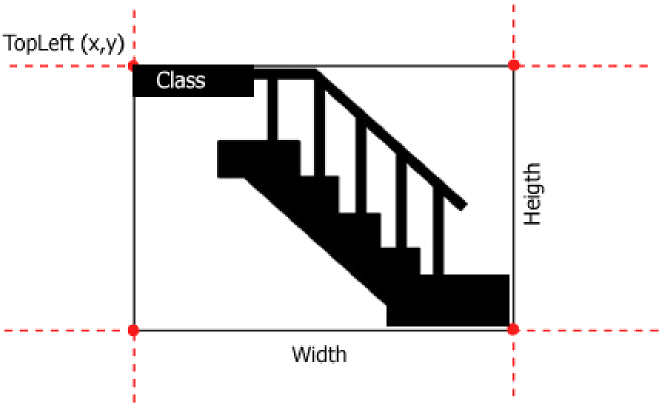


Figure 5.4. Object Bounding Box Representation with Class Label

The entire annotation task was done using Makesense.AI (Make Sense AI, 2024), a user-friendly annotation tool that runs directly from a browser. This process is time-consuming because it requires carefully going through each data point and labelling it with the appropriate annotation. Manual annotation approaches have been employed in small to large-scale image annotation, including popular ImageNet (Deng et al., 2009), COCO (Lin et al., 2014) and Visual Genome (Krishna et al., 2017) datasets, as images often show complex scenes with several objects, which makes it complex for machines (Zhu & Liu, 2024).

Figure 5.5. Image Annotation Using Makesense.AI

After the image annotation, a total of 3,932 bounding boxes for 6 object classes on 3049 images were created.

5.2.2 Low-light Image Synthesis

Low-light environments heighten fall risk in older adults, particularly those with dementia or visual impairments, by reducing postural stability and spatial awareness. Research shows that insufficient lighting adversely affects postural stability in older adults, leading to greater sway and instability that can precipitate falls in low-light conditions compared with normal lighting levels (Dev et al., 2021). Older adults with cognitive impairment such as dementia are already at substantially higher risk of falling due to compromised gait, balance, and executive function, and environmental hazards like poor lighting further exacerbate this risk by reducing visibility of obstacles and decreasing environmental cues needed for safe navigation. (Racey et al., 2021). Therefore, low-light conditions are a critical environmental hazard that increases fall risk among older adults with dementia or low vision, underscoring the need for improved lighting and environmental design as part of fall prevention strategies.

To address the above issue, the THLLOD framework incorporates low-light image synthesis in the data preparation framework. By augmenting training data with synthetic low-light images, the model learns to handle varied illumination conditions, enhancing detection accuracy, generalisation, and reliability in safety-critical scenarios. Since real-world low-light datasets are often difficult and costly to obtain, gamma correction provides an efficient and reproducible approach for simulating reduced illumination while preserving scene structure (Jeon et al., 2024). Applying gamma correction to existing images enables realistic low-light synthesis without altering spatial or structural content, which is essential for training models to recognise objects under varying lighting conditions (Wang et al., 2023). Such synthetic low-light augmentation increases dataset diversity and enhances model generalisation to real-world low-illumination scenarios (Reis et al., 2025). Moreover, the parameterised and computationally lightweight nature of gamma correction makes it a practical and scalable technique for low-light simulation in computer vision data preparation pipelines (Wang et al., 2023). To illustrate this, given an input image $I(x,y) \in [0,1]$, the gamma transformation generates a modified image $I\gamma(x,y)$ according to

$$I_{\gamma}(x,y)=I(x,y)^{\gamma}, \tag{5.1}$$

where γ determines the degree of intensity compression. We applied γ=[0.3, 0.5, 0.7] to generate a significantly darker image that effectively models varying low-light conditions as shown in Figure 5.6. The gamma transformation is applied uniformly across all colour channels after normalising pixel intensities to the range [0,1]. This ensures that the luminance adjustment is consistent and does not introduce colour distortions.

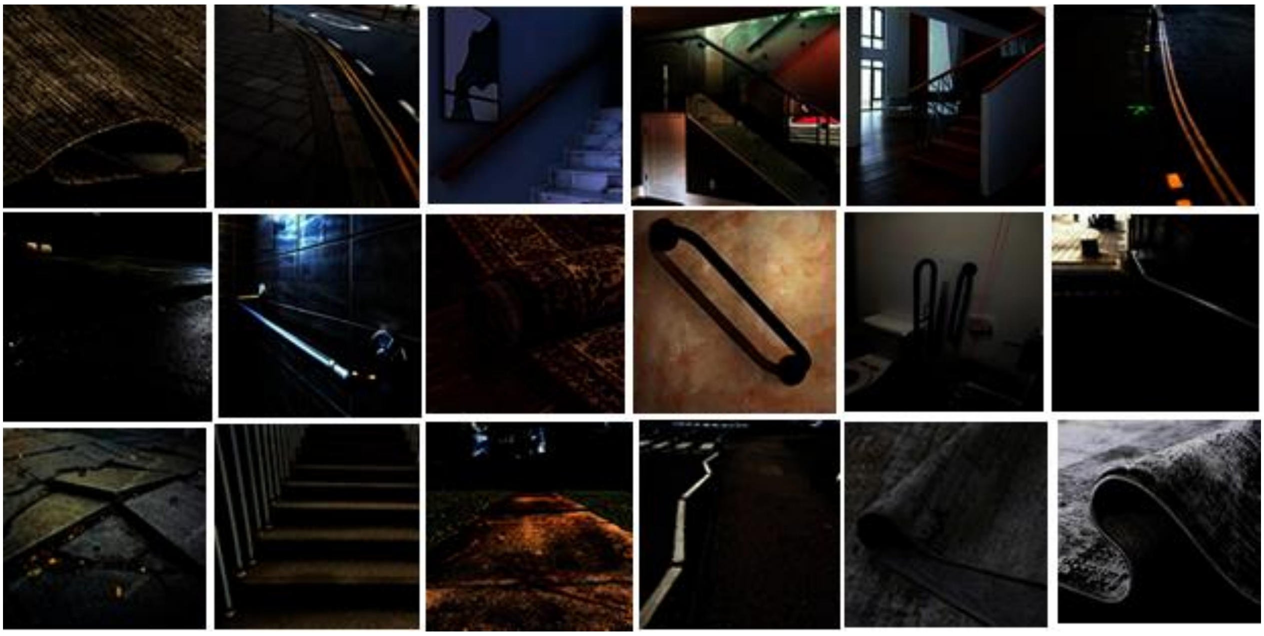


Figure 5.6. Gamma Synthesised Low-light Images

The process generates paired datasets consisting of original images and their gamma correction low-light counterparts, which are used for both training and evaluating the detection model (Guo et al., 2020). A key advantage of this approach is its computational efficiency and scalability, as gamma correction can be applied to large datasets without specialised hardware or complex calibration procedures (Wei et al., 2018). The procedure for generating gamma-corrected low-light images from the original dataset is presented in Algorithm 1.

Algorithm 1: Gamma-Based Low-Light Image Synthesis

Input: Image dataset D, Gamma values Γ = [0.3, 0.5, 0.7]
Output: Set of low-light images L

```
Initialize empty set L
For each image I in dataset D do
  For each gamma value γ in Γ do
    inv_gamma = 1 / γ  #Compute inverse gamma
    For i = 0 to 255 do
      table[i] = ((i / 255)^inv_gamma) × 255  #Create lookup table
    Convert LUT into uint8 format
    Ig = LUT(I, table)  #Apply LUT transformation:
    Store generated low-light image Ig in L
  End For
End For
Return L
```

Gamma-corrected synthetic low-light datasets are widely used for training and evaluating low-light image enhancement models because they are inexpensive to generate and provide paired low-normal-light image samples (Yadav et al., 2021; Wang et al., 2023; Liu et al., 2021). However, these datasets exhibit significant limitations compared with real-world low-light imaging conditions because gamma correction primarily applies a global nonlinear intensity transformation rather than modelling the physical image acquisition process (Rasheed et al., 2022). Real low-light images are affected by photon shot noise, read noise, sensor quantization, demosaicing artifacts, color distortion, and reduced dynamic range, all of which arise from camera hardware and exposure limitations that cannot be reproduced accurately using simple gamma transformations (Wang et al., 2019; Pais et al., 2026).

One major limitation of gamma-corrected data is the unrealistic representation of sensor noise. In real imaging systems, low-light noise is signal-dependent and varies according to sensor characteristics and exposure settings (Wang et al., 2019). Synthetic gamma-darkened images typically preserve the noise statistics of the original bright image instead of generating illumination-dependent degradation patterns (Pais et al., 2026). Consequently, models trained on synthetic data may learn enhancement mappings that perform well on benchmark datasets but fail to generalise effectively to real noisy environments (Rasheed et al., 2022). Previous studies have shown that noise suppression and contrast enhancement are strongly coupled tasks in real low-light enhancement pipelines, whereas gamma-corrected datasets often underestimate this interaction (Wang et al., 2019).

Another important discrepancy is the absence of realistic motion blur and temporal degradation effects. Real low-light photography commonly requires long exposure times to compensate for insufficient illumination, thereby increasing susceptibility to camera shake and object motion blur (Zheng et al., 2011). Gamma correction does not simulate these temporal acquisition artifacts because it only modifies pixel intensity distributions without modelling exposure dynamics (Yadav et al., 2021). As a result, models trained solely on synthetic gamma-corrected images may perform poorly in dynamic nighttime applications such as surveillance, autonomous driving, and mobile imaging systems (Burdziakowski and Bobkowska, 2021).

Gamma-corrected synthetic data also inadequately represents uneven or spatially varying illumination conditions observed in natural scenes. Real low-light environments often contain localised light sources, shadows, reflections, and illumination gradients caused by streetlights, vehicle headlights, or indoor lighting (Jia et al., 2023). Conventional gamma correction generally applies a uniform transformation across the entire image, resulting in unrealistically homogeneous darkness distributions (Rasheed et al., 2022). Research has demonstrated that enhancement methods trained on simplified illumination distributions frequently suffer from halo artifacts, color inconsistencies, and over-enhancement when exposed to nonuniform real-world lighting conditions (Jia et al., 2023).

These limitations introduce several forms of bias into DL models. First, networks may become biased toward learning brightness amplification rather than robust modelling of physical sensor degradation processes (Pais et al., 2026). Second, synthetic datasets often overrepresent clean textures and underrepresent severe noise, blur, and compression artifacts, leading models to prioritise perceptual brightness improvement over structural fidelity preservation (Wang et al., 2019). Third, benchmark evaluations performed exclusively on synthetic gamma-corrected datasets may produce overly optimistic performance estimates because the training and testing distributions remain artificially similar (Rasheed et al., 2022). Researchers have therefore emphasised the importance of physics-based raw image synthesis and sensor-aware augmentation methods for improving dataset realism and robustness (Pais et al., 2026).

The implications for model generalisation are substantial. Models trained predominantly on gamma-corrected synthetic data often exhibit significant domain shift when deployed on real-world low-light images (Wang et al., 2023). This domain gap may manifest as amplified noise, color distortion, unstable enhancement, poor edge preservation, and loss of structural details under varying illumination conditions (Wang et al., 2019; Jia et al., 2023). In safety-critical applications such as autonomous driving, UAV imaging, and surveillance systems, poor low-light generalisation can reduce object detection reliability and scene interpretation accuracy (Burdziakowski and Bobkowska, 2021). Recent research therefore advocates combining real low-light datasets with physics-grounded raw synthesis, illumination-aware degradation modelling, and adaptive sensor simulation strategies to bridge the gap between synthetic and real-world data distributions (Pais et al., 2026).

5.2.3 Hybrid Object Detection Framework Development

The proposed framework integrates a pretrained YOLO-based object detector with the Zero-DCE low-light enhancement algorithm to improve object detection performance under low-light and degraded imaging conditions, as illustrated in Figure 5.7. The hybrid architecture is specifically designed to enhance the visibility and discriminability of environmental hazards and safety interventions prior to detection, thereby improving detection robustness in challenging illumination environments. At the same time, the framework maintains the lightweight computational efficiency required for real-time AR deployment on wearable smart devices, enabling responsive and reliable hazard detection within safety-critical assistive living environments.

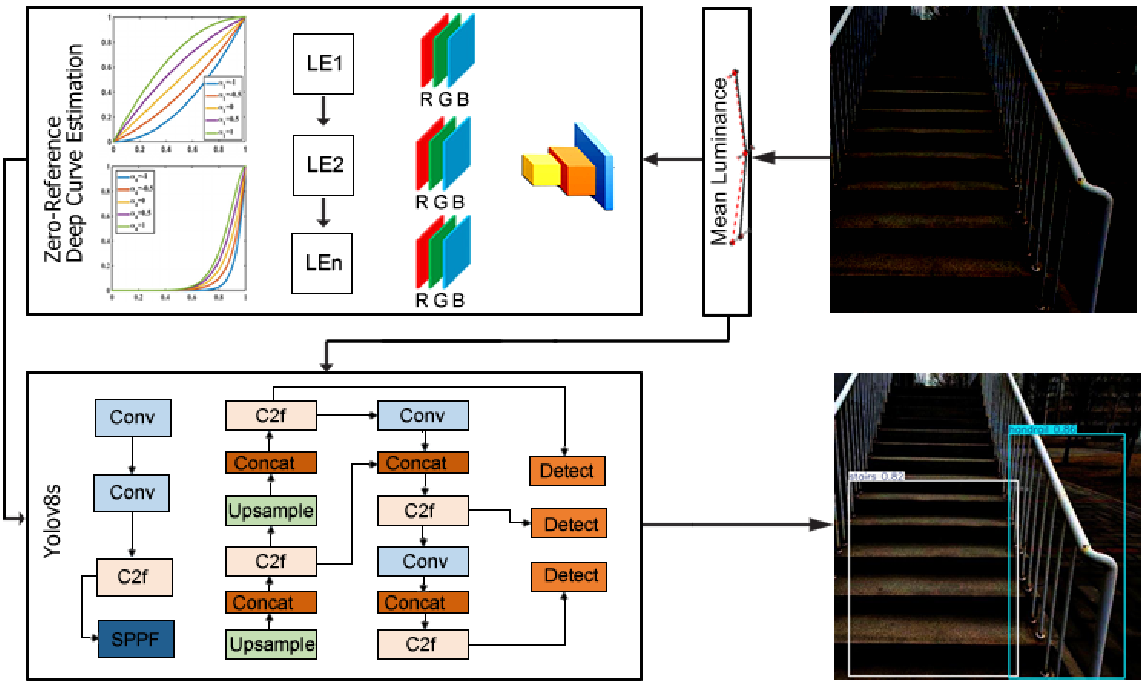


Figure 5.7. Transfer Hybrid Learning Low-Light Object Detection (THLLOD) framework

To improve robustness to illumination variability, multiple lightweight YOLO variants were trained using a combined dataset consisting of original images and synthetically generated low-light images. The low-light samples were produced using gamma-based augmentation with $\gamma \in \{0.3, 0.5, 0.7\}$, enabling the model to learn invariant features across a wide range of lighting conditions. All images were resized to a fixed resolution of 640×640 pixels, which represents a trade-off between spatial detail preservation and computational efficiency suitable for real-time AR inference.

YOLO formulates object detection as a single regression problem that predicts bounding boxes and class probabilities directly from an input image. Given an input image $I \in \mathbb{R}^{H \times W \times 3}$, the YOLO detector predicts a set of bounding boxes $B=\{b_i\}$, where each bounding box is represented as:

$$b_i = (x_i, y_i, w_i, h_i, c_i, p_i), \tag{5.2}$$

with (x_i,y_i) denoting the centre coordinates, (w_i,h_i) the width and height, c_i the object confidence score, and p_i the class probability vector.

The training objective is defined as a composite loss function:

$$\mathcal{L}_{YOLO} = \mathcal{L}_{box} + \mathcal{L}_{obj} + \mathcal{L}_{cls} \tag{5.3}$$

where $\mathcal{L}_{box}$ penalises localisation error (using IoU-based regression), $\mathcal{L}_{obj}$ measures objectness confidence error, and $\mathcal{L}_{cls}$ represents classification loss. The network parameters θ are optimised as:

$$\theta * = \frac{arg\ min}{\theta} \sum_{(I_j,Y_j)\epsilon Ɗ_{train}} \mathcal{L}_{YOLO}\ (f_\theta(I_j), Y_j), \tag{5.4}$$

where $Ɗ_{train}$ includes both original and gamma-augmented low-light images.

Training was conducted using the hyperparameters listed in Table 5.1. Following comparative evaluation of the YOLO variants, the model achieving the highest mAP was selected as the detection backbone for integration into the proposed framework.

Although the trained YOLO models demonstrated strong robustness to illumination variations due to low-light data augmentation, Zero-DCE was incorporated into the inference framework to handle extremely dark or noisy conditions that exceeded the illumination range represented in the training data. Zero-DCE enhances image brightness through adaptive curve estimation without requiring paired reference images, producing an enhanced image $I_{enh}=ZeroDCE(I)$ that preserves structural details critical for detection. This reduces the likelihood that low-intensity regions are misclassified as background or entirely missed during inference.

To maintain real-time performance, a selective enhancement strategy is applied prior to Zero-DCE processing. As described in Algorithm 2, each incoming image is first evaluated using its mean luminance:

$$\mu_L = \frac{1}{HW} \sum_{x=1}^{H} \sum_{y=1}^{W} L(x,y), \tag{5.5}$$

where $L(x,y)$ represents pixel luminance. Zero-DCE is only applied when μ_L it falls below a predefined threshold, ensuring that computationally intensive enhancement is used selectively. This adaptive pre-processing strategy preserves efficiency while maintaining high detection reliability in safety-critical AR scenarios. The Zero-DCE enhancement process is illustrated as: Let $I \in \mathbb{R}^{H\times W\times 3}$ denote the input image. Zero-DCE learns a set of curve parameters $\theta = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ that iteratively refine the illumination of I. The enhanced image I' is obtained through a deep curve mapping function $f_\theta(\cdot)$, expressed as

$$I' = f_\theta(I) = I + \sum_{k=1}^{n} \alpha_k . (I^k - I) \tag{5.6}$$

The enhanced output I′, whose quality is optimised using zero-reference loss functions expressed as:

$$\mathcal{L}_{total} = \lambda_E \mathcal{L}_E + \lambda_{cons}\mathcal{L}_{cons} + \lambda_{col}\mathcal{L}_{col} + \lambda_{ill}\mathcal{L}_{ill} \tag{5.7}$$

where

$$\mathcal{L}_E = \frac{1}{N} \sum_{j=1}^{N} || \mathrm{P}(I')_j - E_t ||_1 \tag{5.7.1}$$

$$\mathcal{L}_{cons} = \sum_{(p,q) \in N} || (I'_p - I'_q) - (I_p - I_q) ||_1 \tag{5.7.2}$$

$$\mathcal{L}_{col} = \sum_{(u,v) \in \{(R,G),(G,B),(B,R)\}} || u(I') - v(I') ||_1 \tag{5.7.3}$$

$$\mathcal{L}_{ill} = \sum_{k=1}^{n} (||\nabla_x \alpha_k||_1 + ||\nabla_y \alpha_k||_1) \tag{5.7.4}$$

These losses jointly supervise the enhancement process without requiring ground-truth references, enabling fully self-supervised optimisation of the Zero-DCE model.

The enhanced I' is then passed to the pretrained YOLO network $\mathcal{Y}(.)$, which predicts bounding boxes $B=\{bi\}$, confidence scores $C=\{c_i\}$ and class probabilities $P=\{p_i\}$ expressed as:

$$(B,C,P) = \mathcal{Y}(I') \tag{5.8}$$

Algorithm 2: Selective Low-Light Enhancement Based on Mean Luminance
Input: Image I, Luminance threshold τ Output: Enhanced image I′ 1: Read input RGB image I 2: L(x,y) = 0.299R(x,y) + 0.587G(x,y) + 0.114B(x,y) # Compute luminance map L(x,y) 3: $\mu_L = \frac{1}{HW} \sum_{x=1}^{H} \sum_{y=1}^{W} L(x,y)$, # Compute mean luminance µL 4: If $\mu_L < \tau$ then 5: I′ = ZeroDEC(I) #Apply Zero-DEC enhancement 6: Else 7: I′ = I #Keep original image 8: End If 9: Return I′

This hybrid framework improves feature visibility and thus increases detection accuracy in visually challenging environments as shown in Table 5.4.

5.2.4 Object Detection Experimental Setup

The experimental framework was executed on a Linux operating system utilising an NVIDIA A40 GPU with 48 GB of VRAM to support the computational demands of model training. The software environment was built on Python 3.8, with PyTorch 2.0 and Ultralytics serving as the DL framework and CUDA 11.4 providing GPU compute support. Each model was trained for a total of 200 epochs. To ensure methodological rigor and fairness in comparative analysis, all experiments were conducted under uniform hardware conditions and identical training configurations. The specific training hyperparameters are shown in Table 5.2.

Table 5.2. Training Hyperparameter

	Hyperparameter	**Value**
Training Setup	Optimizer	Stochastic Gradient Descent (SGD)
	Learning rate	0.001
	Momentum	0.937
	Weight Decay	0.0005
	Batch size	16
	Number of epochs	200
	Image size	640 × 640
	Train/Val/Test split ratio	80:10:10
Data Augmentation	Translate	0.1
	scale	0.5
	fliplr	0.5
Detection Settings	Confidence Threshold	0.30
	IoU Threshold	0.45

5.2.5 Object Detection Evaluation Metrics

Accurate evaluation metrics are essential for objectively assessing the performance and reliability of object detection models, particularly in safety-critical applications such as environmental fall hazard detection for PwD and individuals with MCI. Object detection tasks require models not only to correctly classify objects but also to precisely localise them within an image, making comprehensive evaluation metrics necessary for measuring both detection accuracy and spatial localisation performance (Padilla et al., 2021). In this thesis, standard object detection evaluation metrics including Intersection over Union (IoU), Precision (P), Recall (R), and mean Average Precision (mAP), were employed to evaluate the performance of both the baseline model and the proposed THLLOD framework.

IoU is a widely adopted metric used to quantify localisation accuracy by measuring the overlap between the predicted bounding box and the ground truth bounding box (Rezatofighi et al., 2019). IoU is calculated as:

$$IoU = \frac{Area(B_{pred} \cap B_{gt})}{Area(B_{pred} \cap B_{gt})} \tag{5.9}$$

where B_{pred} represents the predicted bounding box and B_{gt} represents the ground truth bounding box. A higher IoU value indicates better localisation accuracy and stronger agreement between predicted and actual object locations.

Precision (P) and Recall (R) were also utilised to evaluate classification effectiveness and detection robustness. Precision measures the proportion of correctly identified positive detections relative to all predicted detections, thereby assessing the model's ability to minimise false positives (Saito and Rehmsmeier, 2015). Precision is calculated as:

$$Precision = \frac{TP}{TP + FP} \tag{5.10}$$

where TP denotes True Positives and FP denotes False Positives.

True Positive (TP): Occurs when the model correctly detects and classifies an object that is actually present in the image (Padilla et al., 2021).

False Positive (FP): Occurs when the model incorrectly predicts an object that is not actually present, leading to incorrect detections or false alarms (Zou et al., 2023).

Recall measures the proportion of actual objects correctly detected by the model and reflects the system's ability to minimise false negatives, which is particularly critical in safety-sensitive fall hazard detection applications. Recall is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5.11}$$

where FN represents False Negatives.

False Negative (FN): Occurs when the model fails to detect an object that is actually present, resulting in missed detections (Rezatofighi et al., 2019).

To provide a comprehensive assessment of detection performance, Average Precision (AP) was computed from the Precision–Recall curve for each object class. AP summarises the trade-off between Precision and Recall across varying confidence thresholds and is calculated as:

$$AP = \int_0^1 Precision(Recall)\, d(Recall) \tag{5.12}$$

The overall detection performance was then evaluated using mean Average Precision (mAP), which represents the mean of *AP* values across all object classes (Everingham et al., 2010). mAP is calculated as:

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \tag{5.13}$$

where N is the total number of object classes and AP_i is the Average Precision for class i.

mAP is widely regarded as the standard benchmark metric in modern object detection research because it jointly evaluates localisation accuracy and classification performance across multiple classes and IoU thresholds (Zou et al., 2023). The combined use of IoU, Precision, Recall, AP, and mAP enabled a rigorous multidimensional evaluation of the THLLOD framework under varying illumination and environmental conditions. These metrics provided important insight into the robustness, reliability, and generalisation capability of the proposed framework for deployment in real-world safety-critical assistive technology environments where accurate environmental hazard detection is essential for proactive fall risk mitigation.

5.2.6 Object Detection Performance Evaluation

Performance evaluation is essential for assessing the effectiveness of object detection models, as it quantitatively measures both localisation and classification performance. In this thesis, the standard evaluation metrics presented in Section 5.2.5 were employed to comprehensively evaluate model performance. Five lightweights YOLO variants, namely YOLOv8s, YOLOv9s, YOLOv10s, YOLO11s, and YOLO12s, were experimentally compared to identify the most suitable architecture for integration into the proposed hybrid framework. As shown in Table 5.3, YOLOv8s achieved the highest overall detection performance and was therefore selected for integration with the Zero-DCE low-light enhancement module within the proposed THLLOD framework.

Figure 5.8 illustrates the training performance of the integrated Zero-DCE and YOLOv8s model, showing the progression of box loss, classification loss (cls loss), precision, recall, and mean Average Precision (mAP) throughout the training process. The loss plots demonstrate the convergence behaviour of the models, where progressively decreasing and closely aligned training and validation losses indicate stable learning and good generalisation, while divergence between the curves would suggest overfitting.

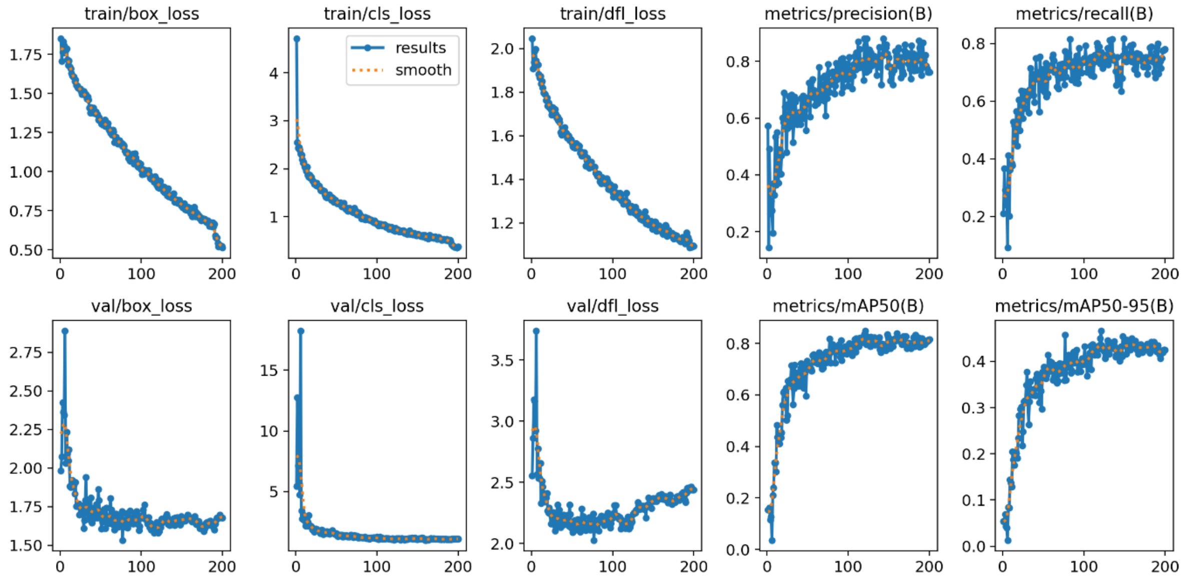
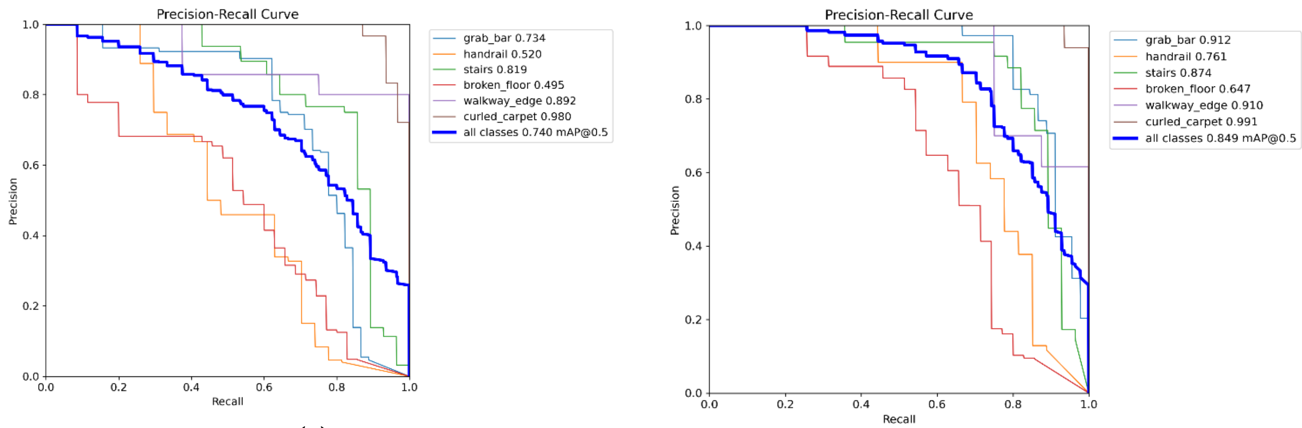


Figure 5.8. Training and Validation Results of Zero-DEC+YOLOv8s Model

The Precision–Recall (P–R) curves for the baseline YOLOv8s detector and the proposed Zero-DCE+YOLOv8s framework is presented in Figure 5.9. The proposed framework demonstrates consistently higher precision across a wider recall range, resulting in improved mAP@0.5 performance compared to the baseline model. This improvement indicates that the Zero-DCE enhancement module effectively improves feature visibility and object discriminability under low-light conditions while reducing false detections. The enhancement is particularly evident for safety-critical object classes such as grab_bar, handrail, and broken_floor, where poor illumination often obscures important edge, texture, and structural features. These findings suggest that integrating low-light enhancement strengthens feature representation and improves detection robustness for environmental hazards and safety interventions commonly encountered in indoor assistive living environments.



(a)

(b)

Figure 5.9. Comparison of P-R curves before and after improvement (mAP@0.5). (a) Precision-Recall (P-R) curve of the baseline model YOLOv8s. (b) Precision-Recall (P-R) curve of the proposed Zero-DEC+YOLOv8s

Intersection over Union (IoU), illustrated in Figure 5.10, measures the degree of overlap between predicted and ground-truth bounding boxes, thereby evaluating localisation accuracy. Precision (P) and Recall (R) quantify the correctness and completeness of detections, respectively, while mAP, particularly mAP@0.5, summarises overall detection performance across classes and serves as the principal benchmark for model comparison as shown in Table 5.3.

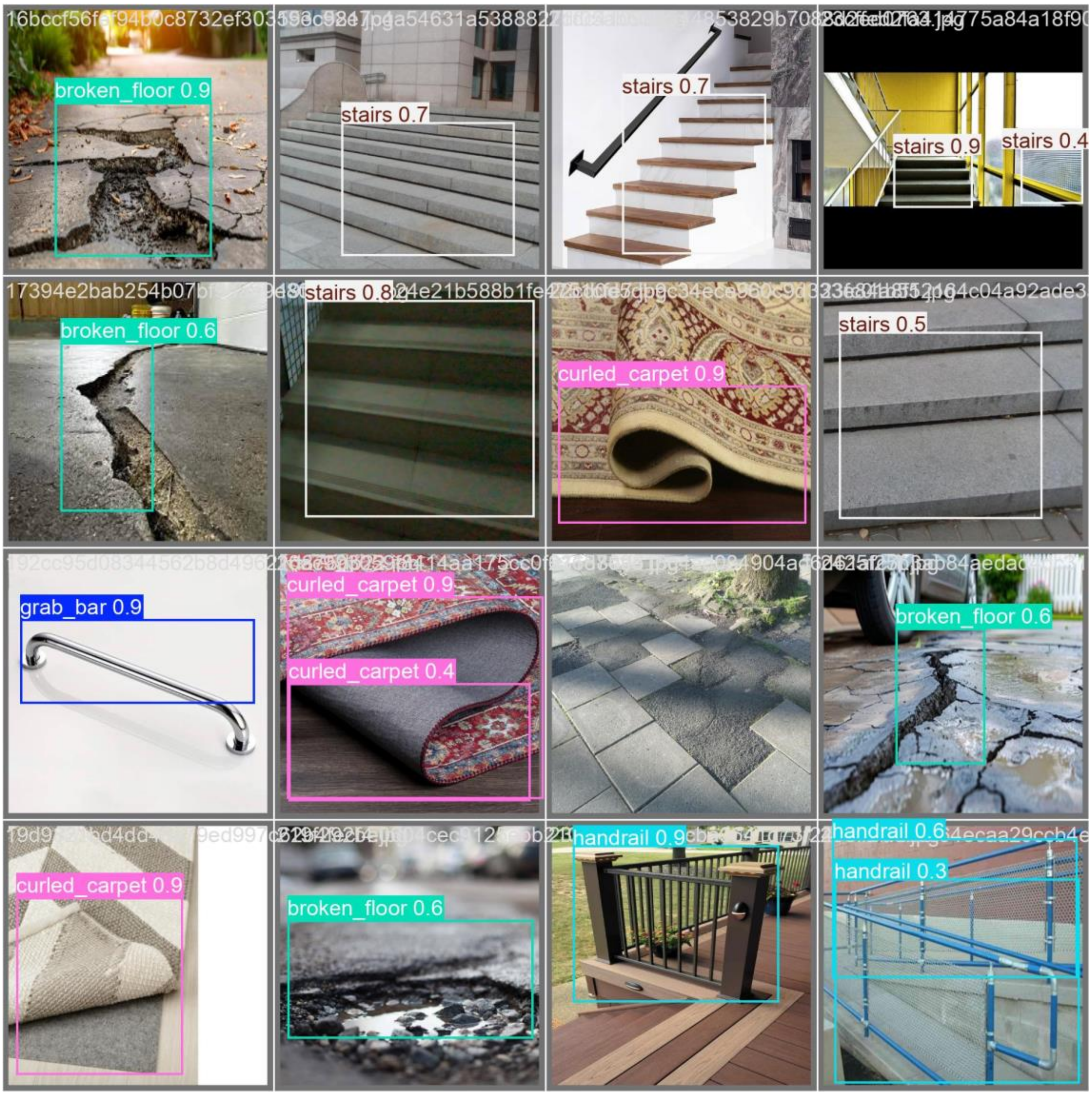


Figure 5.10. (a) Predicted Labels and Confidence Scores Bounding Box During Day Time

Figure 5.10. (b) Predicted Labels and Confidence Scores Bounding Box During Night Time

The confusion matrix, which provides a comprehensive class-wise evaluation of the detection performance of the model, is presented in Figure 5.11. The confusion matrix illustrates the distribution of predicted labels against the corresponding ground-truth labels, thereby enabling detailed analysis of true positives, false positives, false negatives, and inter-class misclassifications.

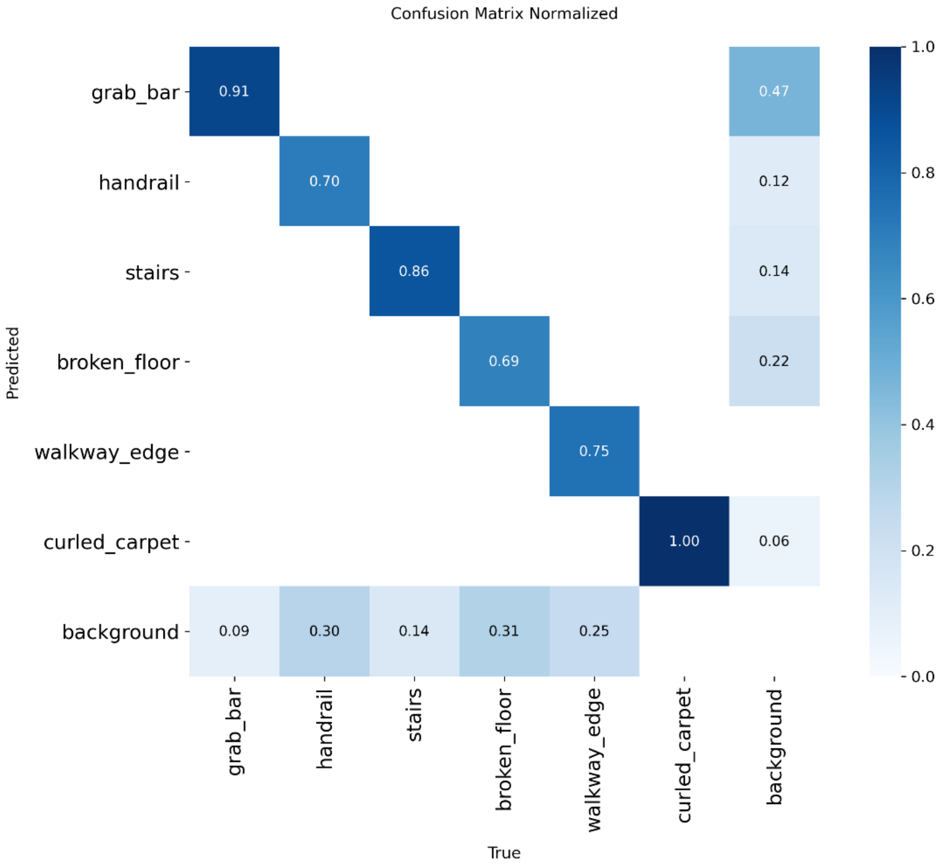


Figure 5.11. The Confusion Matrix for HomeFall Dataset Classes using Zero-DEC+YOLOv8s

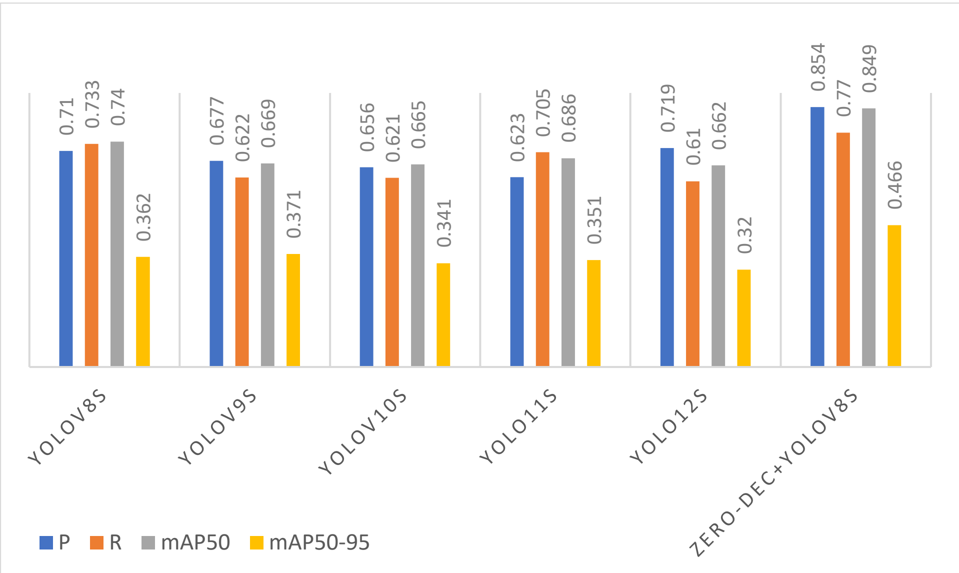


Figure 5.12. Result Comparison of Different YOLO Variants and Proposed Model

Table 5.3. Comparison of Different Methods Based on Precision, Recall, and mAP Values with the Proposed Model.

Model	**P**	**R**	**mAP50**	**mAP50-95**
YOLOv8s	0.71	0.733	0.740	0.362
YOLOv9s	0.677	0.622	0.669	0.371
YOLOv10s	0.656	0.621	0.665	0.341
YOLO11s	0.623	0.705	0.686	0.351
YOLO12s	0.719	0.610	0.662	0.320
Zero-DEC+Yolov8s	0.854	0.770	0.849	0.466

Figure 5.12 and Table 5.3 showed that YOLOv8s achieved the strongest overall baseline performance among the evaluated lightweight YOLO variants, attaining a mAP@50 of 0.740 while maintaining balanced precision and recall values. The model also achieved stable localisation performance under stricter Intersection over Union (IoU) thresholds, obtaining an mAP@50–95 score of 0.362. Compared with the newer lightweight YOLO variants, including YOLOv9s, YOLOv10s, YOLO11s, and YOLO12s, YOLOv8s provided a more effective balance between detection accuracy, localisation robustness, computational efficiency, and feature representation capability for the HomeFall dataset. This performance suggests that the architectural design of YOLOv8s, particularly its lightweight backbone and efficient feature aggregation mechanisms, is better suited for detecting structurally ambiguous environmental hazard objects under varying indoor illumination conditions.

The superior baseline performance of YOLOv8s may also reflect its ability to preserve discriminative spatial and texture features required for recognising safety-critical objects such as grab bars, stairs, uneven surfaces, and curled carpets, which often exhibit subtle visual characteristics and irregular geometric structures. In low-light environments, these features can become significantly degraded due to reduced contrast, shadowing, and loss of edge information, making reliable object detection considerably more challenging. Despite these conditions, YOLOv8s demonstrated comparatively stable performance, indicating stronger robustness to illumination variability and complex indoor environmental contexts.

Following integration with the Zero-DCE low-light enhancement module, the THLLOD framework achieved substantial improvements across all major evaluation metrics. Specifically, mAP@50 increased from 0.740 to 0.849, while mAP@50–95 improved from 0.362 to 0.466, demonstrating enhanced localisation accuracy and improved detection consistency across stricter IoU thresholds. Precision also increased significantly from 0.710 to 0.854, indicating that the enhancement module effectively improved feature visibility and object discriminability while substantially reducing false-positive detections in low-light conditions.

These improvements suggest that the integration of Zero-DCE enhancement strengthens the visual quality of degraded input images by improving illumination balance, contrast, and edge visibility prior to object detection. As a result, the detector is able to extract more reliable feature representations from safety-critical objects that may otherwise be partially obscured under poor lighting conditions. The enhanced framework therefore demonstrates improved robustness and generalisation capability for real-world indoor assistive environments where illumination variability commonly affects object visibility. The findings validate the effectiveness of combining low-light enhancement with lightweight object detection models to improve environmental hazard recognition performance in safety-critical assistive technology applications for older adults, people living with dementia, and individuals with mild cognitive impairment.

5.3 Attention-Aware Fall Risk Assessment Framework

This section presents an Attention-Aware Fall Risk Assessment (AFRA) framework that integrates DL and HMM to support the delivery of real-time, context-sensitive safety alerts based on user cognitive attention state. The DL component employs THLLOD framework to identify potential environmental fall hazards and safety interventions within the user's surroundings. Concurrently, the HMM component estimates users' latent cognitive attention states from observable behavioural patterns inferred through a rule-based mechanism. This mechanism combines contextual information derived from object detection with movement characteristics extracted from real-time IMU data. Specifically, the framework continuously analyses the spatial relationship between the user and detected environmental hazards, such as stairs, curled rugs, broken floors, walkway edges, and obstacles, together with recognised safety interventions including handrails and grab bars. IMU-derived features, including movement direction and velocity variation are evaluated to determine whether the user is demonstrating safe and appropriate navigation behaviour. By integrating environmental perception with behavioural analysis, the framework enables continuous assessment of both situational risk and user attentiveness, supporting adaptive fall risk assessment and the timely delivery of personalised safety alert. The following section describes the key stages involved in the development of the framework.

5.3.1 Inertial Measurement Unit Data Collection

Real-time multimodal data were collected using a smartphone, as summarised in Table 5.4, to train the proposed framework. The dataset comprised IMU measurements, including accelerometer, gyroscope, and magnetometer data, together with environmental images captured by the device camera. The image data were used to identify object classes and their spatial positions within the environment, while the IMU data captured user movement characteristics. These data streams were subsequently combined through a rule-based inference mechanism to derive behavioural observations based on users' movement patterns relative to detected hazards and safety interventions.

Smartphone-based methods are more cost-effective and easier to use than traditional wearable IMU systems (Lee et al., 2024b). While wearable IMUs often rely on specialised equipment and trained personnel, limiting their use to controlled environments, smartphones integrate inertial sensors into a single consumer-grade device, eliminating the need for external hardware and complex setup (Gikas and Perakis, 2016). Modern smartphones integrate accelerometers, gyroscopes, and magnetometers with sufficient accuracy and reliability for gait pattern recognition. Moreover, multiple studies have demonstrated the clinical validity of these built-in sensors, reporting that smartphone accelerometers can perform comparably to, or even outperform, external IMU devices across a range of activities and body placements (Ruiz-Zafra et al., 2015; Mourcou et al., 2015; Shahar and Agmon, 2021).

Table 5.4. Sample Smartphone Multimodal Sensor Dataset

Day	Time (ms)	Acc X	Acc Y	Acc Z	Gyro X	Gyro Y	Gyro Z	Mag X	Mag Y	Mag Z	M_D	O_D	O_P	M_T_O
1	5214	0.262	-0.100	9.836	0.035	0.025	0.045	33.55	-4.15	42.91	Forward	stairs	Center	Yes
1	5436	0.277	-0.125	9.845	0.064	0.037	0.01	31.83	-4.73	41.54	Forward-left	handrail	Right	No
1	10682	0.46	-0.149	9.61	0.01	0.053	0.058	35.17	-4.22	43.18	Forward-left	curl_rug	Left	Yes
1	20916	0.081	0.244	9.609	0.079	0.019	0.053	34.17	-5.09	40.68	Forward	grab_bar	Right	No
1	35131	-0.377	-0.012	9.819	0.062	0.023	0.065	32.64	-2.95	40.77	Backward	handrail	Right	No
2	6339	0.415	0.132	9.551	0.07	0.082	0.043	30.51	-3.82	41.64	Forward-right	curl_rug	Right	Yes
2	11579	-0.279	0.087	10.047	0.063	0.081	0.025	31.39	-3.75	42.03	Backward-right	stair	Right	No
2	6794	-0.199	0.074	9.945	0.001	0.101	0.042	32.97	-4.65	42.47	Backward-right	grab_bar	Center	No
2	7033	-0.059	0.029	9.827	0.058	0.004	0.002	31.53	-5.96	40.43	Backward	stairs	Center	No
2	7266	0.186	-0.071	9.702	0.053	0.103	0.039	31.18	-2.06	41.74	Forward-left	handrail	Left	Yes

Table acronyms: Acc X (accelerometer x-axis); Acc Y (accelerometer y-axis); Acc Z (accelerometer z-axis); Gyro X (gyroscope x-axis); Gyro Y (gyroscope y-axis); Gyro Z (gyroscope z-axis); Mag X (magnetometer x-axis); Mag Y (magnetometer y-axis); Mag Z (magnetometer z-axis); M_D (movement direction); O_D (object detected); O_P (object position); M_T_O (movement towards object)

To further scale AFRA framework, a larger synthetic dataset of 1,000 observations was generated, enabling a more rigorous evaluation of the model’s ability to recover hidden states over extended sequences. This approach assessed the consistency of decoding accuracy, posterior probabilities, and log-likelihood, while also examining model robustness and scalability. The use of simulated data is a well-established practice in the literature, allowing controlled, repeatable evaluation of algorithm performance under defined motion characteristics and noise profiles, and has been successfully applied in prior studies (Brunner et al., 2015; Li et al., 2021; Hao et al., 2022).

5.3.2 Mapping the Problem to Hidden Markov Model

Users' cognitive attention state prediction was formulated as HMM problem to capture the temporal relationship between observable safety behaviours and unobservable cognitive attention states. In this formulation, the hidden states as shown in Table 5.5 represent the user's latent attention states, which cannot be measured directly, while the observation states correspond to behavioural outcomes classified as Adherence or Non-Adherence as shown in Table 5.6. These observations are generated from a rule-based analysis that combines environmental context obtained from hazard and safety-intervention detection with IMU-derived movement characteristics. The HMM models the probabilistic transitions between attention states over time and the likelihood of observing particular behaviours under each state as shown in Figure 5.13.

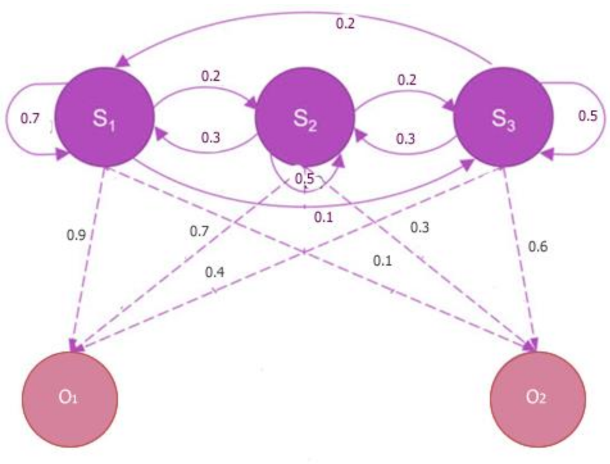


Figure 5.13. Fall Risk Assessment HMM Structure

The HMM is defined by the parameter set:

$$\lambda = (A, B, \pi) \tag{5.14}$$

where $A=\{a_{ij}\}$ denotes the state transition probability matrix, $B=\{b_i(o)\}$ represents the observation probability matrix, and $\pi=\{\pi_i\}$ defines the initial state probability distribution.

The hidden state space consists of three cognitive attention states:

$$S = \{S_1, S_2, \ldots, S_N\} \tag{5.15}$$

where $S = \{Sustained, Selective, Divided\}$.

Table 5.5. Cognitive Attention States

States	**Meaning**
Sustained	User is consistently attentive.
Selective	User focuses intermittently, attention shifts.
Divided	User is distracted or multitasking.

Since cognitive attention cannot be directly observed, these states are inferred from behavioural evidence collected through wearable sensors data computation.

The observation sequence is defined as:

$$O = \{O_1, O_2, \ldots, O_T\} \tag{5.16}$$

where $O = \{Adherence, Non\text{-}Adherence\}$. To generate the observation sequence, a rule-based behavioural inference mechanism combines contextual information from the THLLOD object detection framework with IMU-derived movement features, including movement direction and velocity changes described in Section 5.3.3. The detected object class and its spatial location are analysed alongside user movement behaviour to assess interactions with environmental hazards (e.g., stairs, curled rugs, broken floors, walkway edges, and obstacles) and safety interventions (e.g., handrails and grab bars). Based on these interactions, the system continuously classifies user behaviour as either Adherence or Non-Adherence.

Table 5.6. Safety Behaviours

Observation	**Actions**
Adherence	User follows safety interventions (uses handrail, use grab bar, stops before stairs, avoids broken floor, walkway edge or curl rug).
Non-Adherence	User ignores or forgets to use safety interventions.

Within this formulation, the HMM models both the temporal evolution of cognitive attention through the transition probabilities A and the relationship between attention states and observed behaviours through the observation probabilities *B*. Given an observed sequence of adherence-related behaviours, the model estimates the most probable hidden state sequence as:

$$X = \{x_1, x_2, \ldots, x_T\} \tag{5.17}$$

thereby enabling continuous estimation of user attentiveness during ADL. This probabilistic framework effectively captures the temporal dependencies between behavioural responses and cognitive attention, providing an interpretable mechanism for attention-aware fall risk assessment and adaptive safety intervention.

5.3.3 Rule-Based Behavioural Inference

A rule-based behavioural inference mechanism was developed to classify user actions as either Adherence or Non-Adherence with respect to environmental hazards and safety interventions detected by the THLLOD framework. The inference process combines contextual information obtained from object detection with behavioural features extracted from real-time IMU measurements. Let the environmental context at time *t* be represented as:

$$Et = \{c_t, p_t\} \tag{5.18}$$

where $c_t \in \{hazard, safety\ intervention\}$ denotes the detected object class and $p_t \in \{left, centre, right\}$ denotes the object's spatial position relative to the user. The behavioural feature vector derived from the IMU is defined as:

$$F_t = \{v_t, h_t, m_t, s_t\} \tag{5.19}$$

where v_t represents walking velocity, h_t denotes head orientation, m_t represents movement direction, and s_t indicates stopping behaviour.

The user's movement direction relative to the detected environmental cue is estimated given the lateral velocity component v_x, the degree of movement towards and away from the detected object or safety intervention is computed as:

$$(\mu_{towards}(t), \mu_{away}(t)) = \begin{cases} (\mu_L(v_x), \mu_R(v_x)), & p_t = left \\ (\mu_R(v_x), \mu_L(v_x)), & p_t = right \\ (\mu_C(v_x), max(\mu_L(v_x), \mu_R(v_x))), & p_t = centre \end{cases} \tag{5.20}$$

where μ_L, μ_C, and μ_R denote the functions corresponding to leftward, stationary, and rightward motion, respectively.

The adherence observation is subsequently determined by evaluating whether the user's behaviour corresponds to the expected safety response associated with the detected object class. Let $O_t \in \{Adherence, Non\text{-}Adherence\}$ denote the observation generated at time t. The adherence rule is formally defined as:

$$O_t = \begin{cases} Adherence, & c_t = hazard \wedge \mu_{away}(t) > \mu_{towards}(t) \\ Adherence, & c_t = safety\ intervention \wedge \mu_{towards}(t) > \mu_{away}(t) \\ Adherence, & v_t < \boldsymbol{\tau_v} \wedge s_t = 1 \wedge c_t = hazard \\ Non-Adherence, otherwise & \end{cases} \tag{5.21}$$

where τ_v represents a predefined velocity threshold used to identify cautious behaviour such as slowing down or stopping near a detected hazard.

Formally, the rule can be interpreted as a set of conditional decision criteria:

1. Hazard avoidance behaviour (safe response):

   When the detected object is a hazard (c_t = hazard), the user is classified as Adherence if the inferred movement away from the object is stronger than movement towards it, that is, $\mu_{away}(t) > \mu_{towards}(t)$.

   This captures situations where the user actively avoids hazards such as curled rug, walkway edge, or broken floor.

2. Safety intervention engagement (safe response):

   When the detected object is a safety intervention (c_t = safety intervention), the user is classified as Adherence if the movement towards the object is dominant, that is, $\mu_{towards}(t) > \mu_{away}(t)$

   This reflects correct usage of assistive structures such as handrails or grab bars.

3. Low-velocity or stationary hazard-aware behaviour (safe pause response):

Even when facing a hazard, if the user exhibits controlled motion characterised by low velocity and stable movement state, then adherence is also assumed as $v_t < \tau_v \wedge s_t = 1 \wedge c_t = hazard$

where $s_t = 1$ indicates a stable or stopping state. This captures behaviours such as pausing before stairs or obstacles.

4. Otherwise (unsafe or ambiguous behaviour):

   Any condition not satisfying the above criteria is classified as Non-Adherence, representing unsafe navigation such as moving towards hazards, failing to slow down, or ignoring safety interventions.

The resulting sequential observations provide indirect evidence of the user's underlying cognitive attention state and serve as inputs to the attention state prediction model.

5.3.4 Attention State Model Training

The attention state model was trained to learn the temporal relationships between object detected and the corresponding user safety adherence behaviour. Model parameters as shown in Equation x was estimated using the Baum–Welch algorithm, an Expectation–Maximisation (EM) approach. During training, the algorithm iteratively maximised the likelihood of the observed sequences by updating the HMM parameters until convergence.

The trained model was then used to infer the most probable sequence of activities from unseen observations using the Viterbi decoding algorithm. In the HMM model definition, a higher self-transition probability was assigned during initialisation to reflect the temporal persistence of cognitive states, consistent with theoretical expectations that attentional modes exhibit short-term stability. These are defined as follows:

A = [[0.7, 0.2, 0.1],
[0.3, 0.5, 0.2],
[0.2, 0.3, 0.5]]

B = [[0.9, 0.1],
[0.7, 0.3],
[0.4, 0.6]]

π = [0.6, 0.3, 0.1]

Following initialisation, model parameters were refined using the Baum–Welch algorithm shown in Algorithm 3, an Expectation–Maximization (EM) procedure that iteratively maximises the likelihood of the observed sequence. In the E-step, forward–backward recursions compute posterior state occupancy probabilities and expected state transitions. In the M-step, these expectations are used to update A, B, and π by normalised expected counts, thereby producing maximum-likelihood estimates under the assumed model structure. Iterative refinement continues until convergence of the log-likelihood function.

The forward variable can be represented as:

$$\alpha_t(i) = P(O_1, \ldots, O_t, S_t = S_i \,/\, \lambda) \tag{5.22}$$

and backward variable

$$\beta_t(i) = P(O_{t+1}, \ldots, O_T \,/\, S_t = S_i, \lambda) \tag{5.23}$$

The posterior probabilities of being in state S_i at time t and transitioning from S_i to S_j at time t are:

$$\gamma_t(i) = P(S_t = S_i \mid O, \lambda) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{k=1}^{N} \alpha_t(k)\beta_t(k)}, \tag{5.24}$$

$$\xi_t(i,j) = P(S_t = S_{i,} S_{t+1} = S_j \mid O, \lambda) = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)}{\sum_{k=1}^{N} \alpha_t(k)\beta_t(k)}, \tag{5.25}$$

The model parameters are then updated iteratively as:

$$\pi_i^{new} = \gamma_1(i), \tag{5.26}$$

$$a_{ij}^{new} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)}, \tag{5.27}$$

$$b_i^{new}(o_k) = \frac{\sum_{t=1}^{T} \gamma_t(i) 1_{\{o_t = o_k\}}(j)}{\sum_{t=1}^{T} \gamma_t(j)}. \tag{5.28}$$

When the HMM parameters λ was learned, the Viterbi algorithm as shown in Algorithm 4 was applied to decode the most likely sequence of hidden attention states $\hat{S} = (\hat{S}_1, \hat{S}_2, \ldots, \hat{S}_T)$ that best explains the observed adherence and non-adherence behaviour:

$$\hat{S} = arg \max_{s} P(S \mid O, \lambda), \tag{5.29}$$

where the Viterbi recursion computes:

$$\delta_1(i) = \pi_i b_i(O_1), \; \delta_t(j) = \max_{i} [\delta_{t-1}(i)\, a_{ij}]\, b_j(O_t), \tag{5.30}$$

and backtracking through the $\delta_t(j)$ values yields the most probable state sequence.

Algorithm 3: Baum–Welch Algorithm (for learning optimised parameter)

Input: Observation sequence $O_{1:T;}$ Initial parameters A, B, π
Output: Updated parameters A, B, π

Initialize A, B, π
Initialize log_likelihood_old ← −∞
Initialize convergence_flag ← FALSE
while convergence_flag = FALSE do
    #E-Step
    Compute α_t(i) using Forward algorithm
    Compute β_t(i) using Backward algorithm
    For each time t:
        $\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{k=1}^{N}\alpha_t(k)\beta_t(k)}$,
        $\xi_t(i,j) = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)}{\sum_{k=1}^{N}\alpha_t(k)\beta_t(k)}$,
        # M-STEP
        #Update initial distribution

        $\text{pi}_i = \gamma_1(i)$
        #Update transition probabilities
        $A_{ij} = \frac{\sum_{t=1}^{T-1}\xi_t(i,j)}{\sum_{t=1}^{T-1}\gamma_t(i)}$
        #Update emission probabilities:
        $B_{jk} = \frac{\sum_{t=1}^{T}\gamma_t(i)1_{\{o_t=o_k\}}\gamma_t(j)}{\sum_{t=1}^{T}\gamma_t(j)}$.
        #Compute log-likelihood
        log_likelihood_new ← log P(O | A, B, π)
        if |log_likelihood_new − log_likelihood_old| < ε then
            convergence_flag ← TRUE
        else
            log_likelihood_old ← log_likelihood_new
return A, B, pi

Algorithm 4: Viterbi Algorithm (for decoding hidden states)

Input: Observation sequence $O_{1:T}$
Output: Most likely state sequence Q*

For i = 1..N:
    δ[1][i] = π[i] * B[i][o1]
    ψ[1][i] = 0
For t = 2..T:
    For j = 1..N:
        δ[t][j] = max_i (δ[t-1][i] * A[i][j]) * B[j][ot]
        ψ[t][j] = argmax_i (δ[t-1][i] * A[i][j])
Q*[T] = argmax_j δ[T][j]
For t = T-1 downto 1:
    Q*[t] = ψ[t+1][Q*[t+1]]
return Q*

5.3.5 Attention State Prediction Performance Evaluation

The performance of the proposed fall risk assessment framework was evaluated through a series of experiments designed to examine its ability to capture the temporal dynamics of latent cognitive attention states. A synthetically generated sequence of 1,000 observations was employed to train and validate the framework. The results demonstrated that the framework effectively captured the temporal dynamics of attentional behaviour, enabling the differentiation of distinct cognitive states corresponding to varying levels of fall risk. Specifically, the framework successfully identified periods of low fall risk associated with Sustained Attention, moderate fall risk associated with Selective Attention, and elevated fall risk associated with Divided Attention.

The model achieved a decoding accuracy of 0.75, indicating that the Viterbi algorithm correctly recovered the underlying hidden cognitive states in approximately 75% of the observation sequence. This result demonstrates the model's ability to reliably infer latent attention states from observed behavioural patterns and suggests that the learned state transitions and emission probabilities effectively capture the temporal dependencies embedded within the data. An accuracy of this magnitude has been reported as practically informative in related HMM-based inference applications (Li et al., 2021). This is considered especially when supported by strong discrimination such as Figure 5.14 and a plausible model fit as indicated by log likelihood. The log-likelihood of the observed sequence was -549.86, reflecting a good fit of the model to the data.

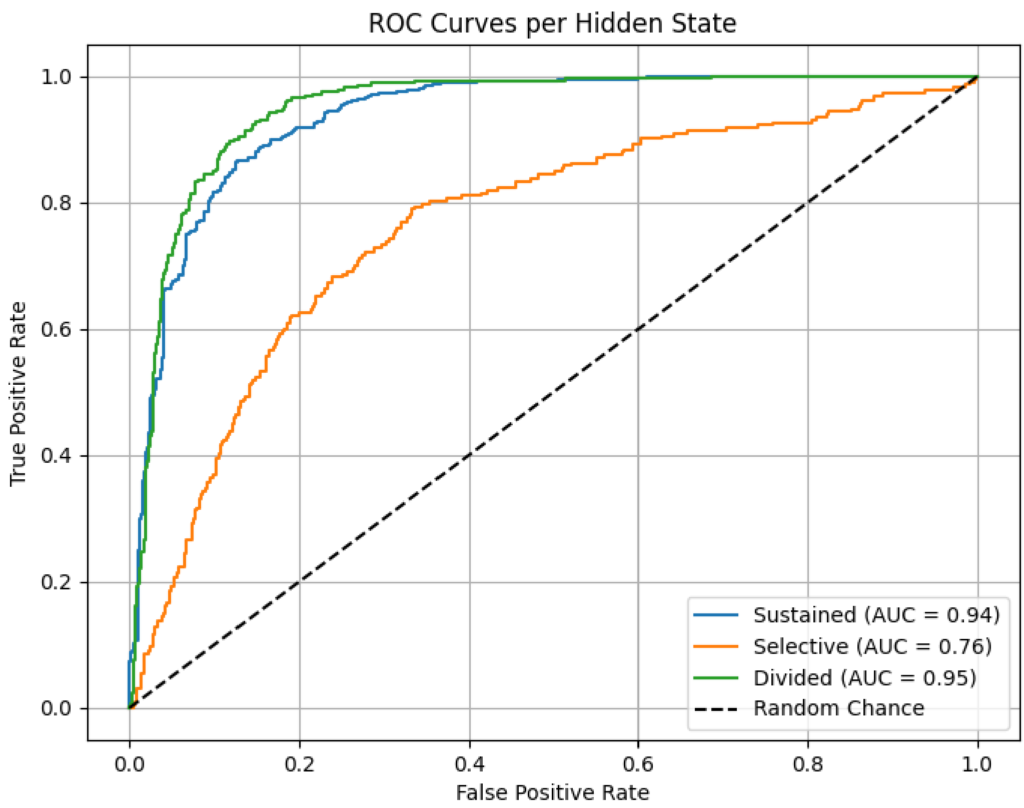


Figure 5.14. ROC Curve of Attention States

Posterior probability analysis and ROC curves showed high discriminative performance for Sustained (AUC = 0.94) and Divided (AUC = 0.95) states, while Selective exhibited moderate separability (AUC = 0.76).

This result indicates that the trained HMM provides a plausible probabilistic explanation of the observed data under the assumed model structure. Together, the satisfactory decoding accuracy, strong state discrimination, and converged log-likelihood value provide complementary evidence that the proposed framework effectively models latent cognitive attention dynamics and can serve as a robust foundation for attention-aware fall risk assessment.

The framework performance was further assessed for robustness and generalisability through evaluation of state classification consistency shown in the confusion matrix in Figure 5.15. The confusion matrix compares the ground-truth attention states with those predicted by the HMM, offering a detailed view of the model's classification performance across different attentional levels. Based on this matrix, performance metrics such as precision, recall, and F1-score were calculated for each class, along with the overall classification accuracy. The results demonstrate that the AFRA is effective in capturing temporal variations in user attention, with relatively low levels of misclassification between states.

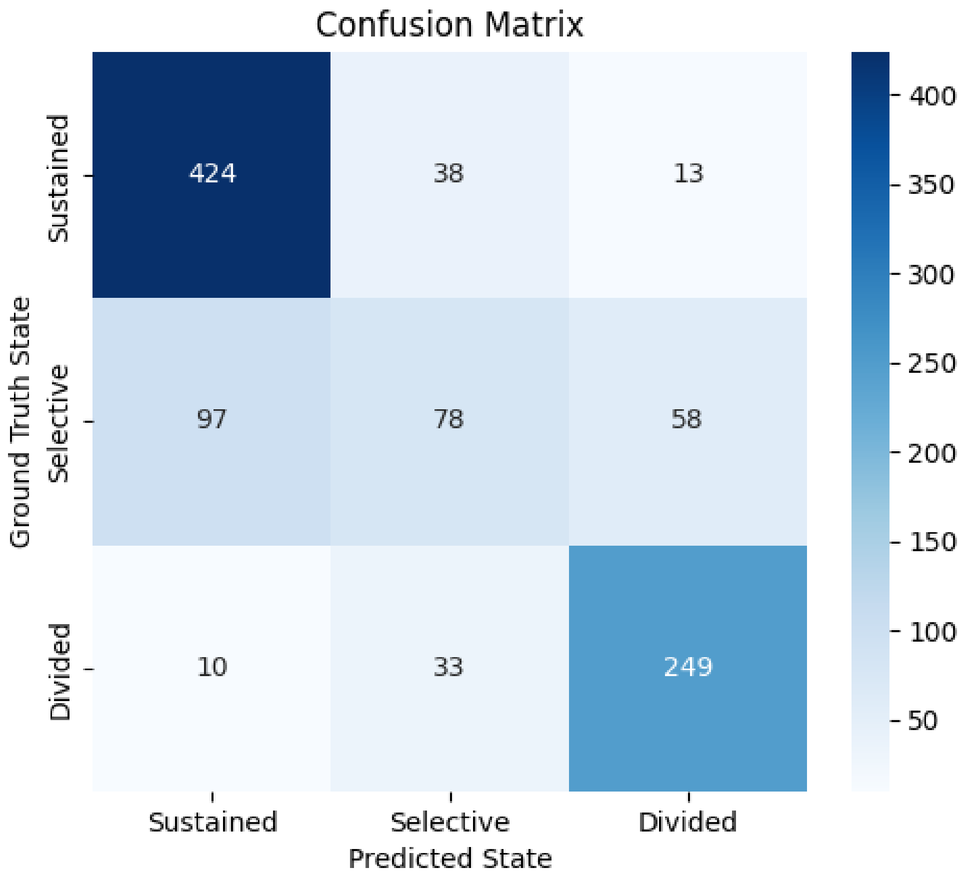


Figure 5.15. Confusion Matrix Showing Ground Truth and Predicted State

Figure 5.16 presents the state probabilities over time, illustrating the likelihood of the user being in a particular cognitive or adherence state at each moment. This visualisation can inform interventions by highlighting periods of elevated risk, such as non-adherence or divided attention, in real time.

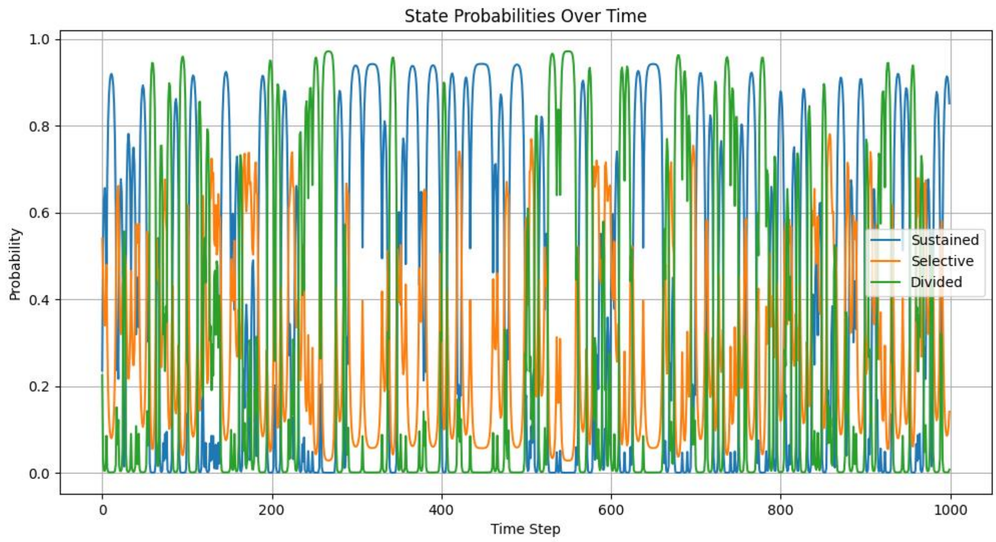


Figure 5.16. State Probabilities Over Time (duration of movement activities)

The risk assessment model further demonstrated the ability to continuously assess and monitor users' adherence behaviour toward hazards and safety interventions throughout the duration of movement activities, as shown in Figure 5.17.

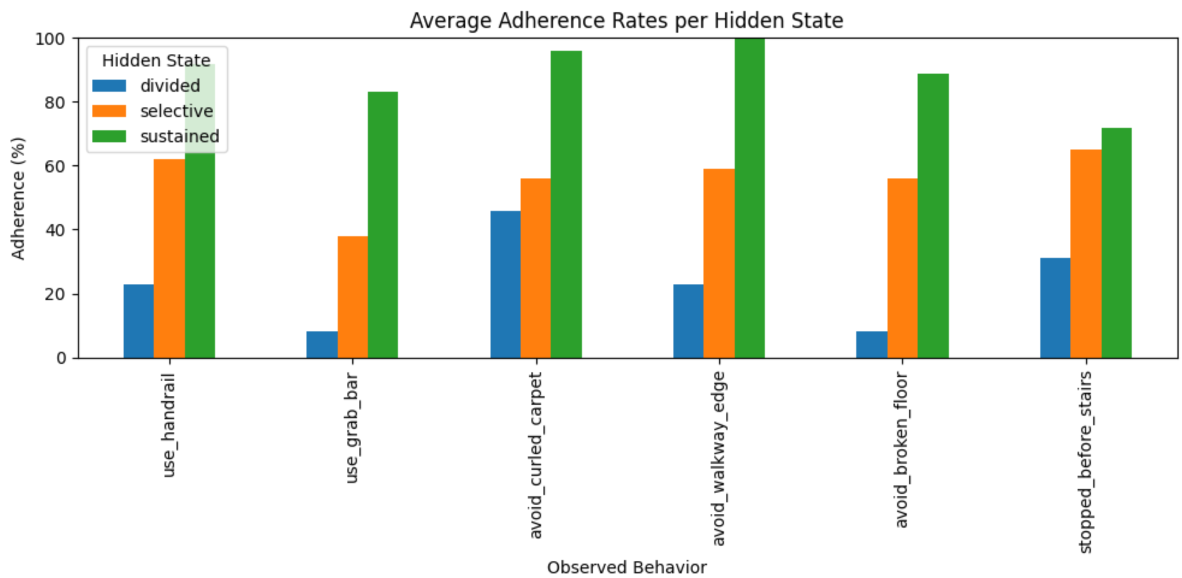


Figure 5.17. Observed Behaviour Towards Hazards and Safety Interventions

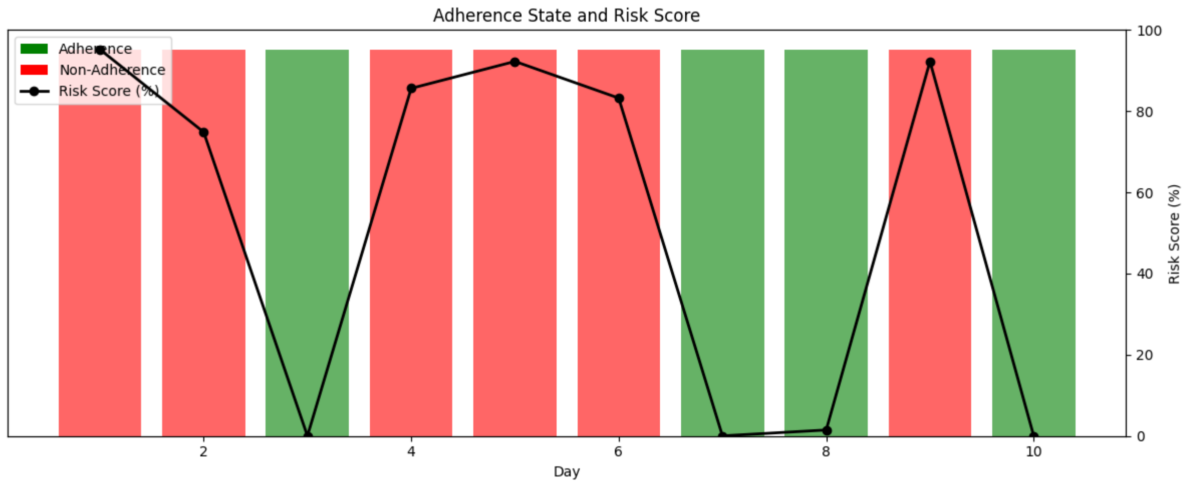


Figure 5.18. Safety Behaviour and Risk Scores Over Time

Figure 5.18 illustrates risk scores that monitor PwD adherence to safety precautions towards environmental hazards and home safety interventions. It reveals behavioural patterns over time that can indicate sustained independence or signal the need for timely, proactive interventions. This demonstrates the suitability of the framework for real-time fall risk monitoring. Longitudinal monitoring using this approach provides meaningful insights into individual patterns of mobility, safety behaviour, and engagement with care routines.

5.4 Smart Glass Augmented Reality Based Assistive Technology Development

A smart glass AR-Based AT was developed to provide adaptive, real-time support for PwD and individuals with MCI during ADL. Implemented on a Vuzix blade smart glasses platform, the system integrates environmental perception, attention state prediction, and multimodal interaction to deliver context-aware safety guidance directly within the user's environment. The architecture combines the THLLOD framework for detecting potential environmental hazards and safety interventions with the AFRA framework that estimating users' latent attention states from behavioural data for real-time safety alert. These components are coordinated through a Service-Based Architecture (SBA) and Cognitive Service Orchestration (CSO) layer, enabling scalable integration of AI services, speech processing, and AR interfaces. By dynamically adapting safety alerts according to both environmental risk and user attentiveness, the proposed smart glasses solution aims to enhance fall risk assessment, reduce unnecessary notifications, and support safer, more independent living. The following sections present the various stages of the system development and testing process.

5.4.1 System Architecture

The proposed system adopts a SBA as shown in Figure 5.19. SBA organises system functionality into independent services that communicate through Application Programming Interfaces (APIs). This enables components to operate, update, and scale independently without creating tight interdependencies (Dragoni et al., 2017). This approach enhances flexibility by supporting the seamless integration of heterogeneous technologies, sensors, ML models, and wearable devices, which is particularly important in adaptive AT environments requiring multimodal sensing and real-time processing (Alshuqayran et al., 2016).

The loose coupling inherent in SBA improves maintainability, extensibility, and system resilience by allowing services such as hazard detection, attention-state prediction, and sensor processing to be independently modified or replaced while containing failures within individual components (Newman, 2021; Balalaie et al., 2016). It supports scalability by enabling computationally intensive services to be distributed across cloud resources according to workload demands, thereby improving real-time responsiveness and resource efficiency (Pahl and Jamshidi, 2016). The architecture promotes interoperability and facilitate integration with third-party systems, wearable devices, and emerging AI-driven services (Bucchiarone et al., 2018), making it well suited for long-term deployment in adaptive AR-based AT for home care environments.

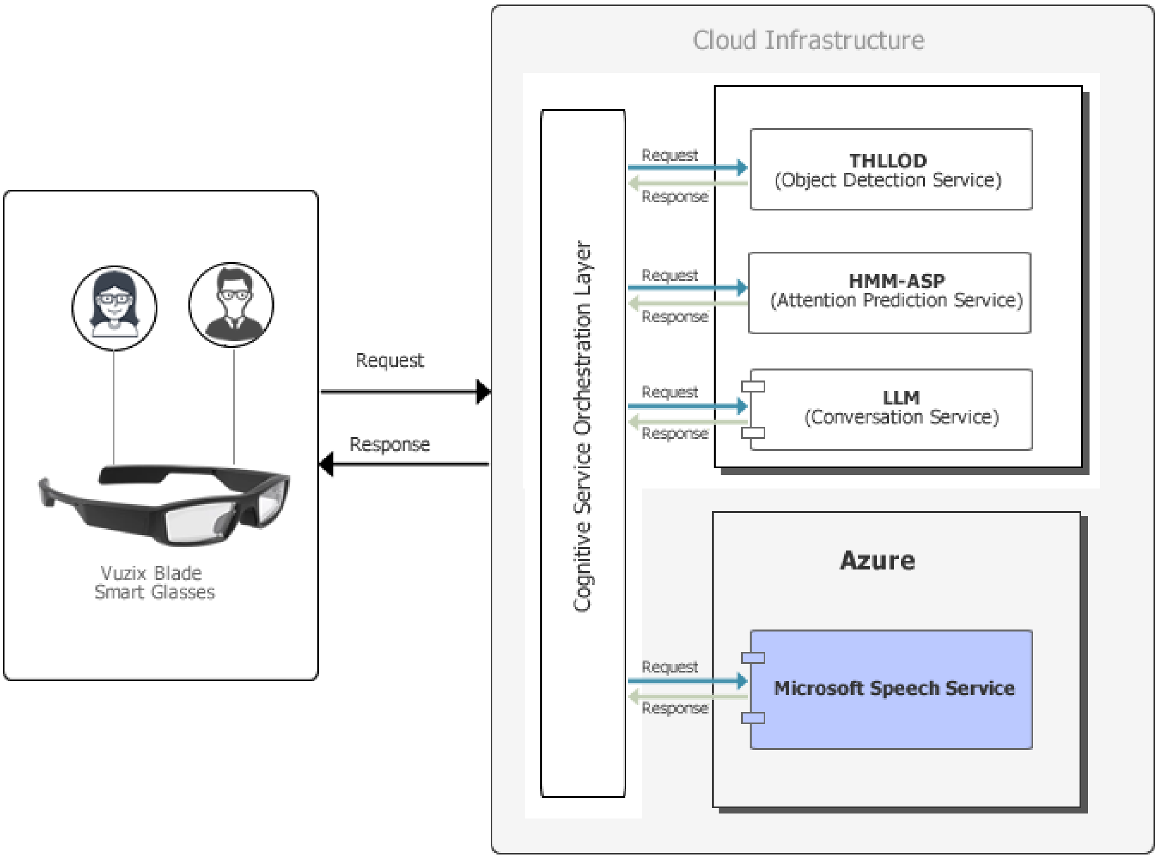


Figure 5.19. Service-Based Architecture of the System

In this architecture, the client application runs on the smart glasses, which continuously capture environmental images and IMU data. The data are transmitted at five-second intervals to the CSO layer. Within the CSO layer, services are logically organised and invoked according to contextual relevance. Incoming multimodal data first triggers the THLLOD object detection service, which analyses the camera stream feed to identify environmental features in the image.

Upon successful detection of an object of interest, the associated semantic and spatial information is returned to the COS layer, which subsequently invokes the AFRA service. The AFRA service probabilistically estimates the user's cognitive attention state by analysing behavioural and contextual cues derived from environmental observations and IMU data. The inferred attention state is then returned to the COS layer, where it is evaluated against predefined risk and attention thresholds. When reduced or insufficient attention is detected, the COS layer combines the outputs of the THLLOD and AFRA services and forwards them to the LLM-based conversational service. The LLM then generates personalised, context-aware safety guidance that communicates the identified risk and recommends appropriate actions to support safe navigation and hazard avoidance. The system delivers this guidance to the user either as textual AR content or auditory feedback, depending on individual user preferences.

Microsoft Speech Services (Azure Speech, 2026) was integrated to support bidirectional conversational interaction, providing speech-to-text for user input and text-to-speech for system responses. This architectural design ensures modular intelligence, real-time adaptability, and personalised assistive support within the AR application.

The smart glasses communicate with the cloud architecture, leveraging wireless internet connectivity and secure, low-latency protocols to balance performance, power consumption, and user experience. Latency typically ranges from 20ms to 150ms, depending on network conditions and deployment configuration.

5.4.2. Cognitive Orchestration Service Layer Design

The COS layer addresses the critical need for adaptive, interoperable, and user-centred assistive systems capable of responding to the cognitive fluctuations and evolving functional needs of PwD and individual with MCI. As illustrated in Figure 5.20, this design supports modularity, scalability, and personalisation through the orchestration of the THLLOD Service, AFRA Service, Microsoft Cognitive Services, and LLM capabilities, with the shaded components representing the services developed in this thesis.

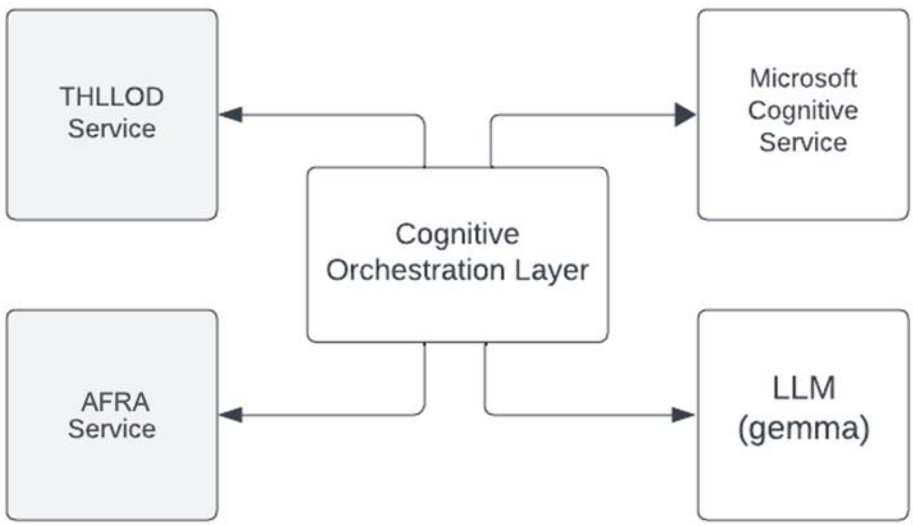


Figure 5.20. Cognitive Orchestration Service Layer

The need for such an orchestration layer is motivated by growing evidence that AI-powered AT can address key cognitive, communication, and safety challenges experienced by PwD, although many existing solutions remain isolated prototypes with limited adaptability and integration capabilities (Dada et al., 2024). Traditional AT often operate as standalone systems, providing static functionality that does not adequately adapt to changes in users' cognitive abilities, environmental context, or support requirements, thereby limiting long-term usability and engagement (Mohapatra et al., 2026). In contrast, the COS enables dynamic coordination between multiple specialised services, allowing the system to respond intelligently to multimodal inputs derived from environmental sensing, behavioural monitoring, speech interaction, and contextual reasoning.

By functioning as a service orchestrator, the COS determines how and when individual AI services are invoked, ensuring that outputs from one service can inform the operation of others without creating tightly coupled dependencies. This orchestration mechanism enables context-aware adaptation and supports more sophisticated decision-making than would be possible through a single AI model alone. The approach is consistent with findings from multi-agent AI research, which demonstrate that coordinated groups of specialised AI components can solve more complex tasks than individual models, provided that communication and coordination mechanisms are carefully designed (Li et al., 2024b).

Furthermore, dementia care research increasingly highlights the value of adaptive and personalised AI interventions across cognitive, emotional, and independence-support domains, demonstrating their potential to improve engagement, safety, and QoL (Mohapatra et al., 2026). Similarly, AI-based cognitive support interfaces have shown promise in assisting memory, self-management, and daily functioning by tailoring support to individual cognitive profiles (Maddali et al., 2022).

By leveraging pre-built, API-accessible services, the orchestration layer facilitates rapid development, architectural flexibility, scalability, and future extensibility. New AI models, healthcare services, IoT devices, or assistive modules can be integrated with minimal changes to the overall system architecture, supporting the long-term evolution of adaptive assistive technologies for dementia care. Table 5.7 provides a detailed description of external services integrated within the orchestration layer.

Table 5.7. External Cognitive Orchestration Service Components

Services	Description	Supporting Research
Microsoft Cognitive Service	A collection of pre-built AI services that allow capabilities such as speech processing, language understanding, and translation to be seamlessly integrated into applications.	Demonstrates a pilot use of an Azure voice-bot built with Azure Speech Service and related cloud services to screen for cognitive impairment in older adults (Moret-Tatay et al., 2022).
		Investigates using automatic speech recognition and linguistic/acoustic features to classify AD and MCI via mobile speech tasks (Yamada, et al., 2023).
		Microsoft research conducted studies using speech and its corresponding transcripts to detect Alzheimer's disease, employing automatic speech recognition within the analysis pipeline (Mittal et al., 2020)
LLM (Gemma)	Gemma is a family of lightweight, state-of-the-art open models built from the same research and technology used to create the Gemini models (Gemma, 2024).	Researchers developed a novel chain-of-thought (CoT) reasoning approach that integrates LLMs and vision-language models to improve Alzheimer's classification (Park and Kim, 2025).
		Demonstrates how the semantic knowledge encoded in an LLM can capture language degradation related to dementia (Agbavor and Liang, 2022).
		This research integrates LLM derived linguistic features with self-supervised speech representations to improve dementia and cognitive decline detection. The approach shows that LLM outputs can highlight linguistic patterns that correlate with cognitive impairment (Chlasta et al., 2025).

5.4.3 User Interface and Service API Design

The development of the AR application prototype and its user interface is implemented using the Unity 3D engine. Unity 3D provides a robust and flexible platform for building interactive, real-time AR experiences. Unity 3D was selected due to its strong support for cross-platform AR development, seamless integration with wearable and mobile AR frameworks, and efficient handling of real-time sensor data streams. Its real-time rendering capabilities support stable spatial anchoring of virtual objects within the physical environment, which is critical for maintaining user orientation and reducing cognitive confusion among PwD and MCI users.

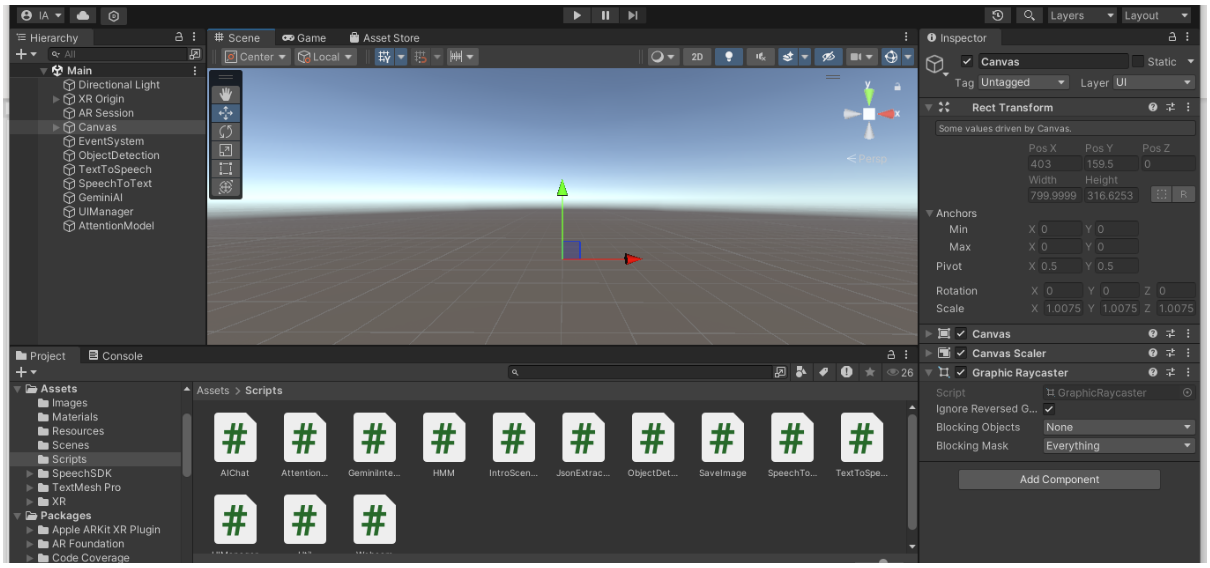


Figure 5.21. Unity 3D Engine

Furthermore, the Unity engine as shown in Figure 5.21 provides a scriptable execution environment using the C# programming language. This facilitates the design of an API service gateway capable of invoking multiple orchestration-layer services, as illustrated in Figure 5.22. Service responses are exchanged in JSON format to support interoperability and structured data representation. This design facilitates reliable aggregation, transformation, and downstream processing of multimodal AI outputs within the cognitive orchestration layer.

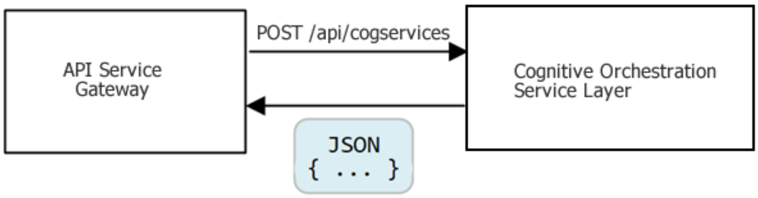


Figure 5.22. API Services Gateway for Cognitive Orchestration Service Layer

5.4.4 Experimental Testing

Experimental testing of the AR application was conducted to evaluate its usability, adaptability, and effectiveness in supporting safe mobility for PwD and MCI within realistic environments. The evaluation was carried out in controlled and semi-naturalistic home-like settings during both daytime and night-time conditions to ensure the system’s ability to reliably detect environmental hazards and deliver appropriate safety interventions under varied lighting conditions. The application demonstrated the capability to detect potential fall-related hazards, such as obstacles, uneven surfaces, and poor lighting. It provides timely AR prompts that remind users to utilise existing safety interventions, including handrails and grab bars, when these are identified in the environment. The system processes multimodal data from mobile phone or smart-glasses IMU sensors and AR-based visual perception in real time, enabling the inference of users' cognitive and attentional states. This real-time processing supports robust object and hazard detection and the generation of context-aware, adaptive AR UI cues, ensuring reliable performance across varying lighting conditions. Figure 5.23 – 5.29 shows the different scenario during the experimental testing with their corresponding states.

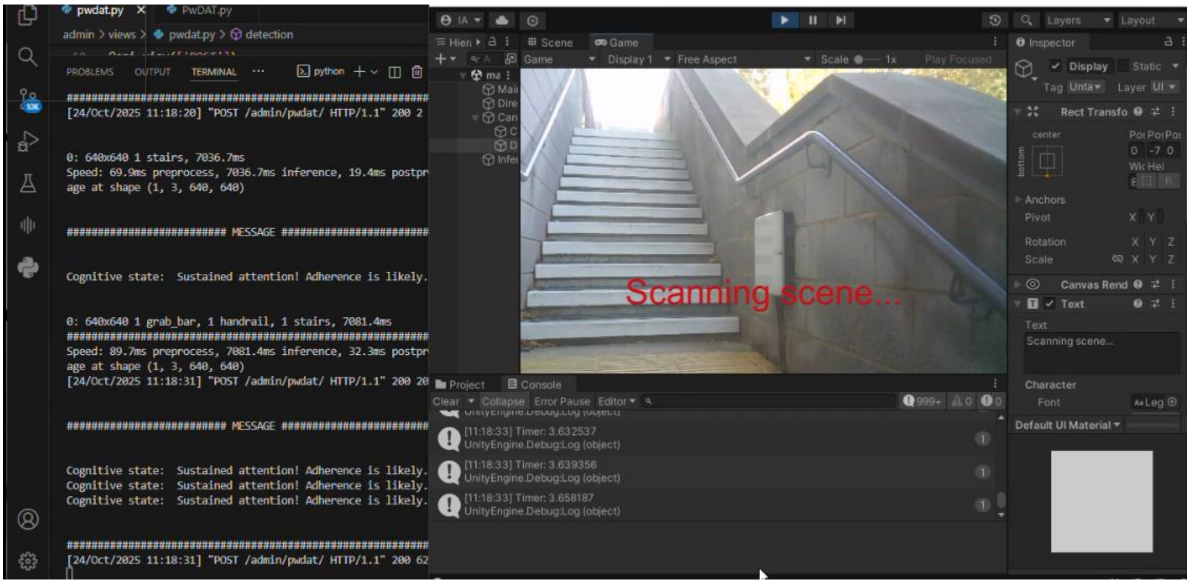


Figure 5.23. Walking on Stairs in Day Time

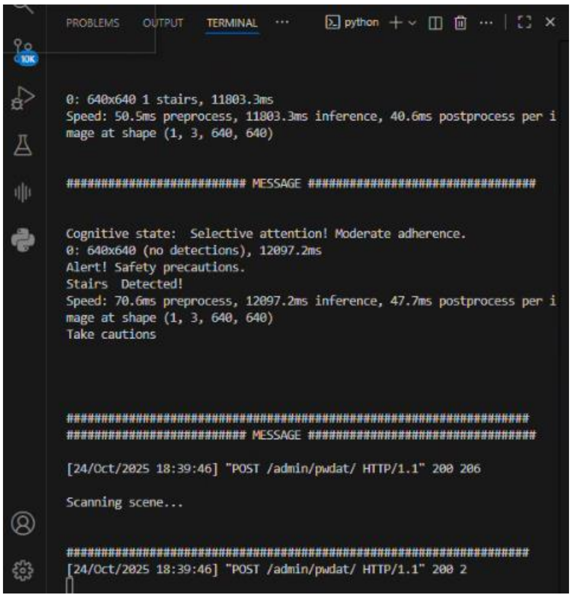


Figure 5.24. Sample Output Inference

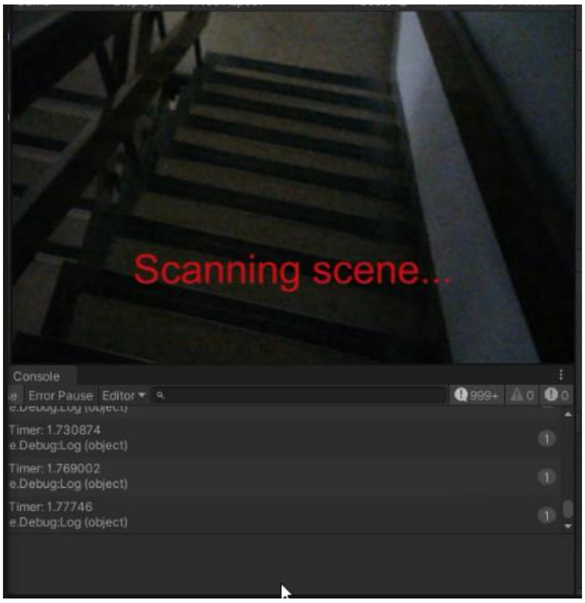


Figure 5.25. Stairs at Night Time with Low Light

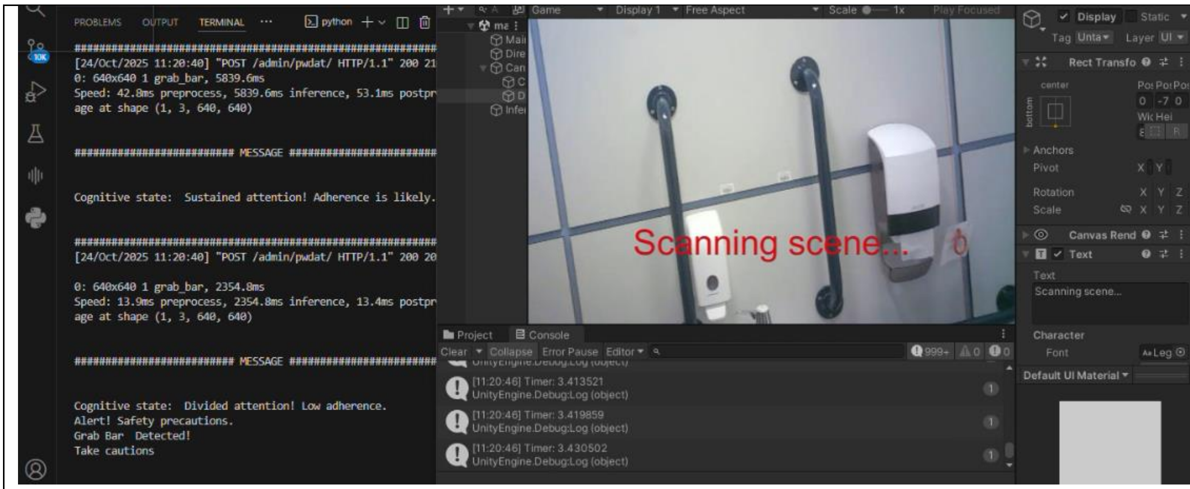


Figure 5.26. Toilet Grab Bar at Night Time

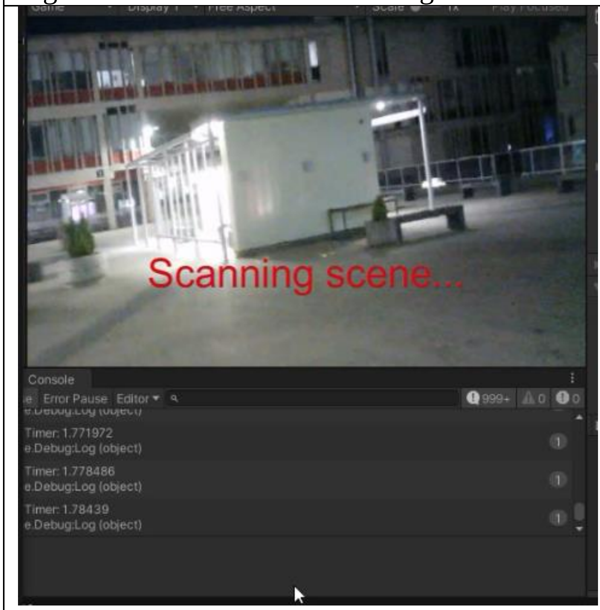


Figure 5.27. Outdoor Environment at Night

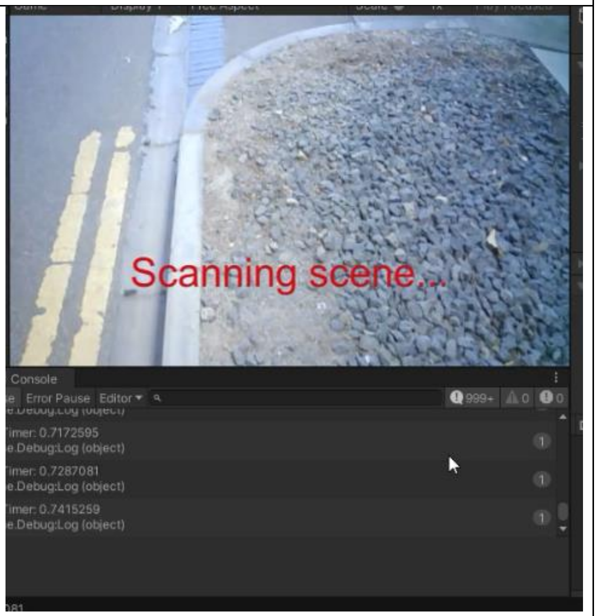


Figure 5.28. Walkway at Day Time

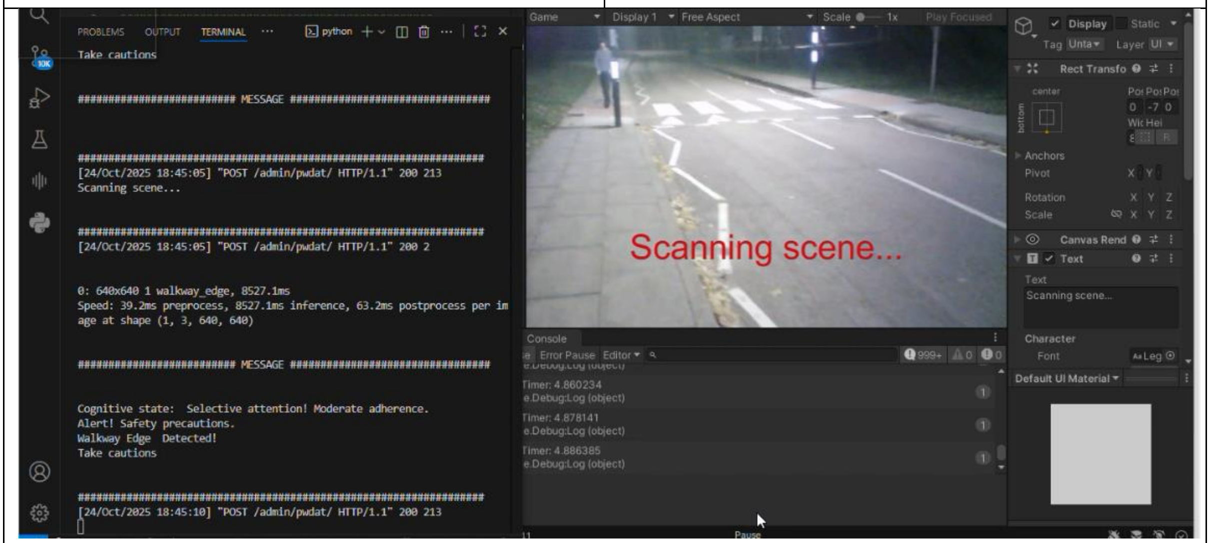


Figure 5.29. Walkway at Night Time

5.4.5 Hardware Specification

This thesis used Vuzix Blade 2.0 smart glasses to demonstrate the potential of an adaptive multimodal fall assessment risk application for PwD and MCI. Vuzix Blade is a wearable AR smart glasses designed to deliver contextual digital information through a see-through display while preserving the wearer's view of the real world. Its architecture integrates computing, sensing, communication, and human-machine interaction components in a compact form (Vuzix, 2024). Vuzix hardware and software specifications relevant to the proposed application are presented in Table 5.8.

Table 5.8. Vuzix Hardware and Software Specification

Feature	Specification	Use
Optics		
Display type	Waveguide based see-through	A transparent piece of glass that lets you see the real world while also guiding projected digital images into your eye.
Display resolution	480x480 colour display	Capture small size images that the application client easily transmitted over the internet to the cloud services.
Field of View (diagonal):	20 degrees	Present small slice of the scene, objects look closer and larger. Use information as part of object distance estimation.
Connectivity		
Wireless	5.0 and 2.4GHz WiFi	Enable application to connect to internet source to facilitate data transmission.
Input and Interaction		
Touch Control	Two-axis side touchpad supporting gesture input (swipe, tap)	Use to lunch application. However, this might be difficult for PwD and MCI to use. The application uses very minimal UI design.
Voice Control	Multilingual voice recognition for hands-free commands	User can interact with the application using voice in a natural manner.
Sensors		
IMU	Orientation sensors including gyroscope, accelerometer, and magnetometer for motion and head tracking.	Collect user movement pattern for the application determine their adherence to safety intervention.
System		
Features	Andriod 11 OS 40GB internal storage Quad Core ARM CPU 1 GB RAM memory	The application was successfully supported despite the minimal system configuration, as the computationally intensive processing was offloaded to the cloud.

5.4.6 Hardware and Architecture Constraints

The deployment of the proposed system on the Vuzix Blade 2.0 demonstrated the feasibility of delivering adaptive AR-based safety guidance through wearable smart glasses, while also highlighting several challenges related to connectivity, reliability, latency, responsiveness, interaction design, and hardware limitations.

The current system architecture relies on a stable Wi-Fi connection, either through tethering to a smartphone or connection to an external wireless network, to support data transmission, cloud-based processing, and communication between sensing and inference components. This dependency introduces important usability and reliability concerns, particularly for PwD, who may experience difficulty troubleshooting connectivity issues or re-establishing disrupted network connections independently. Under poor or intermittent network conditions, delays in communication between sensing, processing, and AR rendering components may introduce latency in the delivery of safety alerts and contextual guidance. Because the proposed framework involves computationally intensive tasks such as computer vision-based hazard detection and multimodal attention-state inference, network instability may result in delayed responses, temporary loss of hazard detection capability, or interruptions in adaptive AR guidance. In safety-critical situations such as fall risk mitigation, these delays may reduce system reliability, compromise situational awareness, and negatively affect user trust and confidence in the assistive system.

These limitations are particularly significant for PwD, whose cognitive impairments may increase reliance on immediate, predictable, and continuous feedback. Inconsistent responsiveness or abrupt interruption of AR cues could potentially increase confusion, cognitive burden, or frustration during navigation tasks. Furthermore, dependence on continuous internet connectivity may reduce ecological validity and practical usability in real-world domestic environments where wireless coverage and network stability vary considerably.

In addition, the interactive capabilities of the system are constrained by the hardware limitations of the smart glasses, particularly the restricted diagonal field of view (FOV) of approximately 20° as shown in Table 5.1. Compared to the human horizontal FOV of around 180°, the device projects information within a small, rectangular display area, resulting in a "letterbox" effect where virtual elements can quickly move out of view with slight head movements (Pavlovich, 2025). This limitation restricts the use of complex AR visualisations, such as large-scale overlays or spatial dashboards, as users can only engage with a limited portion of the augmented content at any given time (Hoogendoorn et al., 2024). Furthermore, visual interfaces and interactions may present additional challenges for older adults, as small text can be difficult to read (Park et al., 2019) and may become less legible under varying lighting conditions (Taghian et al., 2023). Given the age-related decline in physical and cognitive abilities, traditional graphical user interfaces are often less effective for this population (Vacher et al., 2015), with several studies reporting difficulties in reading and interacting with screen-based text among older adults and PwD (Portet et al., 2013; Blair and Abdullah, 2019; Kowalski et al., 2019).

To address these interaction constraints, the system design prioritised minimal visual interaction and relied more heavily on audio-based input and output modalities to support intuitive and cognitively accessible user interaction. This design decision aligns with findings presented in Chapter 3, which indicate that audio interaction is increasingly preferred among older adults and PwD because it reduces reliance on fine motor skills, visual attention, and complex menu navigation (Achilleos et al., 2023; Yu et al., 2023). However, while audio-based interaction reduces visual and cognitive demands, it may introduce additional challenges in noisy environments or for users with hearing impairments, highlighting the need for flexible multimodal interaction strategies.

Another significant limitation relates to battery capacity and operational duration. The Vuzix Blade 2 smart glasses typically offers a limited battery life of approximately 2–3 hours under typical usage conditions, extending to around 5–6 hours depending on workload intensity and system utilisation (Kumari and Hammady, 2026). Continuous use of computer vision, wireless communication, real-time AR rendering, and multimodal sensing substantially increases power consumption, which may further reduce operational duration. Consequently, battery limitations may restrict prolonged daily use, reduce overall system reliability, and necessitate frequent recharging, which may not be practical or manageable for PwD in everyday settings. Frequent charging interruptions could also negatively affect continuous monitoring and reduce adherence to long-term use.

The deployment also highlighted broader trade-offs associated with wearable AR platforms, including limited onboard computational resources, thermal constraints, and the balance between local processing and cloud-assisted inference. While cloud-based processing enables more advanced hazard detection and attention-state modelling, it introduces additional latency and dependency on network availability. Future system development should therefore investigate edge computing and on-device processing strategies to improve responsiveness and resilience under degraded connectivity conditions. Lightweight and optimised inference models could be deployed locally on the smart glasses or associated edge devices to maintain essential safety functions during network interruptions. Hybrid architectures combining local and cloud-assisted processing may provide a more robust solution by allowing simplified hazard detection, cached environmental context, or rule-based alerts to continue operating offline when connectivity is unavailable.

Future work should also explore adaptive communication management, latency-aware AR rendering, battery-efficient model optimisation, and fault-tolerant fallback strategies that prioritise critical safety notifications during unstable connectivity or low-power conditions. Evaluating the system under real-world network variability and prolonged daily usage scenarios would provide important insight into operational robustness, usability, and long-term feasibility for PwD and individuals with MCI living independently in home environments.

5.5 Conclusion

This chapter presented the design, development, and experimental implementation of the proposed adaptive AR-based AT for PwD and individuals with MCI. The system integrates the THLLOD model for robust potential home fall hazard and safety intervention detection under low-light conditions with the AFRA model for inferring users' latent attention states from behavioural data. Together, these components form an integrated fall risk assessment framework that combines environmental perception with cognitive state modelling to enable personalised and context-aware safety guidance that adapt to users' attention state. These capabilities are orchestrated within a SBA, supported by a COS layer that coordinates services, including LLMs and speech processing hosted on a cloud server and consumed by the AR client application.

The proposed system is specifically designed to address challenges associated with cognitive impairment and age-related visual decline, including low vision. Conventional AR interfaces can impose substantial perceptual and cognitive demands, particularly when presenting complex visual overlays, small text, or cluttered layouts, which have been shown to reduce usability and task performance in older adult and clinical populations (Owsley, 2011; Portet et al., 2013; Park et al., 2019; Hoogendoorn et al., 2024). In addition, the restricted FOV of wearable AR smart glasses may further limit the visibility of virtual content, requiring frequent head movement and potentially increasing visual strain for users with low vision. Cognitive impairments associated with dementia may compound these challenges by reducing the ability to interpret and respond to visual cues effectively, while prior research indicates that poorly designed or overly complex interfaces can increase cognitive load and negatively impact usability in elderly users (Vacher et al., 2015; Blair and Abdullah, 2019).

To mitigate these limitations, the proposed system adopted a simplified visual design strategy that reduces on-screen complexity and prioritises essential contextual information. This is complemented by an audio-first multimodal interaction approach that leverages speech-based guidance and auditory feedback to reduce reliance on continuous visual attention and fine motor control. This design is supported by prior evidence indicating that voice- and audio-based interfaces are more accessible and cognitively appropriate for users with declining visual and motor abilities (Achilleos et al., 2023; Yu et al., 2023). Collectively, these design choices aim to reduce cognitive and perceptual load while maintaining situational awareness and supporting user autonomy.

The proposed system demonstrated strong potential for delivering real-time safety alerts and guidance tailored to users' cognitive attention states. By integrating environmental hazard detection with HMM-based attention-state prediction, the system is capable of adapting the timing and delivery of interventions according to the user's current behavioural and cognitive context. Rather than issuing continuous or static alerts, the framework selectively provides guidance only when reduced attention, unsafe navigation behaviour, or elevated environmental risk is detected. This adaptive approach minimises unnecessary notifications and reduces the likelihood of alert fatigue, a common limitation in conventional assistive and monitoring systems where excessive prompts can overwhelm users, reduce compliance, and negatively affect usability.

Furthermore, the attention prediction design supports user autonomy by avoiding excessive system intrusion and allowing individuals to maintain independence while still receiving assistance when needed. The integration of multimodal interaction strategies, including simplified AR visual cues and audio-based feedback, further enhances accessibility and usability for people living with dementia and individuals with age-related sensory decline. In real-world home environments, where cognitive attention and environmental conditions may fluctuate dynamically, the proposed framework provides a more personalised, context-sensitive, and responsive assistive approach compared to static rule-based safety systems. Collectively, these capabilities demonstrate the feasibility of combining cognitive state modelling, wearable sensing, and AR-based guidance to support safer navigation, improve engagement with safety interventions, and promote independent living among cognitively vulnerable populations.

Chapter 6

System Evaluation Based on Unified Theory of Acceptance and Use of Technology Model

This chapter presents a comprehensive evaluation of the proposed system alongside considerations of technology adoption by PwD. Additionally, the chapter outlines the proposed research model and hypothesis formulation. Analysis of participant feedback is provided, followed by a detailed discussion of the results.

Contents

6.1 Introduction

This chapter presents the evaluation of the proposed adaptive AR-based AT for PwD and individual with MCI using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework (Venkatesh et al., 2003). The UTAUT was chosen for its comprehensive approach in assessing factors that influence user acceptance and Behavioural Intention (BI) to adopt new technologies, through constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). In this study, the evaluation emphasises key aspects of the system, including its ability to enhance safety, deliver real-time guidance, and provide adaptive support for PwD. The chapter examines users' intention to use the proposed system, satisfaction, and perceived reliability, offering insights into its practical effectiveness and potential adoption in home care settings. To better address the needs of older adults and individuals with cognitive impairments, this study extends the UTAUT framework by introducing Social Sensitivity (SS) as a construct to capture concerns about stigma, embarrassment, and social judgment (Greenhalgh et al. 2013; Peek et al. 2014), as well as Technology Anxiety (TA), a factor shown in prior research that influences technology acceptance among vulnerable populations (Dai et al., 2020; Bults et al., 2024; Chen et al., 2024). Furthermore, design choices such as interactivity (IN), privacy (PR), and aesthetics (AE) are considered for their direct impact on SS and TA, highlighting their role in shaping user acceptance and sustained use of assistive technologies. This study investigates the factors influencing the acceptance of wearable assistive technology among PwD from the caregivers' perspective by extending the UTAUT model to include two additional constructs: TA and SS.

6.2 Theoretical Framework

A wide variety of AR-based AT exist to support the safety of PwD, including mobility, medication, and home safety assistance, as previously discussed in Chapter 3. These technologies aim to enhance the independence of PwD, enabling them to remain at home longer before moving to nursing facilities. Supporting older adults with declining physical functions through technology is essential for promoting health, comfort, safety, and dignity (Dai et al. 2020; Yadav and Kirit, 2024; Su et al., 2024). Although AT offer significant potential to support independent living among older adults, its practical implementation continues to face substantial challenges (Bertolazzi et al., 2024). A key obstacle for the industry is not merely the ongoing development of innovative solutions but rather ensuring the effective adoption and integration of these technologies into the daily lives of older adults (Yang et al., 2021; Hsu, 2020). The successful implementation of new technology largely depends on user acceptance (Davis, 1989).

This study adopts the UTAUT as its primary theoretical framework to examine user acceptance and BI regarding dementia AT. Most existing technology adoption theories, such as the Theory of Planned Behaviour (TPB) (Ajzen, 1991) and the Technology Acceptance Model (TAM) (Davis, 1986), inadequately explain users' actual usage and behavioural intentions (Dai et al., 2020). UTAUT is a prominent framework in information systems, developed to harmonise the fragmented literature on how individuals adopt and use new technologies (Zuiderwijk et al., 2015). It emphasises four core constructs: PE, EE, SI, and FC. These constructs influence an individual's BI to use and actual use of technology (Venkatesh et al., 2003). It provides a robust model for understanding technology adoption in healthcare, particularly among older adults and in dementia care, by identifying key determinants of BI and use (Peek et al., 2014; Meiland et al., 2017; Goodarzi et al., 2025). Its application offers a structured approach to capture the perceptions of users, caregivers, and healthcare professionals, informing design, implementation, and policy to enhance acceptance and sustained use.

The study investigates the adoption of the proposed adaptive AR-based AT system by extending UTAUT to include SS, reflecting concerns about stigma, social judgment, and autonomy, and TA, addressing apprehension and stress associated with using new technologies. Incorporating these factors enables a more comprehensive understanding of the psychosocial barriers and facilitators that influence technology acceptance among older adults and individuals with cognitive impairments, thereby guiding the development of more user-centred and acceptable assistive solutions.

6.3 Research Model and Hypothesis Formulation

Studies suggest that design-related factors such as interactivity, privacy, and aesthetics can directly influence SS and TA, which in turn affects individuals' BI (Bispo and Branco, 2011; Thorpe et al., 2016; Elueze and Quan-Haase, 2018; Olatunji et al., 2021; Lazaro et al., 2022; König et al., 2022; Chang et al., 2022; Wang et al., 2025b). Accordingly, this study hypothesises a direct relationship between SS and BI in the context of AT acceptance among PwD. Hence, an extended UTAUT-based research model to examine BI to use AT among PwD is developed. It incorporates the unique characteristics of older adults by adding a SS construct and its predictors, such as IN, PR, and AE, to better understand the determinants of technology adoption in the target population.

Most technological solutions are not specifically designed to meet the unique needs and preferences of older adults, which differ significantly from those of younger users (Yueh et al., 2010; Moschis et al., 2003). Design choices can unintentionally lead to individual stigmatisation when they make users stand out in negative or unwanted ways (Chang et al., 2022). AT needs to meet users' functional needs without causing social embarrassment (Santos et al. 2020). Hersh (2015) notes that while AT, such as a white cane, serves as a mobility aid, it also publicly signals blindness, leading some users to avoid it to escape stigma and unwanted attention. In contrast, Santos et al. (2020) study showed that the perceptions of smart glasses were mostly neutral or free of negative judgments related to disability.

This study hypothesises that AT design choices, particularly IN, PR, and AE, significantly influence SS and TA among older adults and individuals with cognitive impairments, such as dementia. These psychosocial factors can either hinder or facilitate the adoption and sustained use of AT by shaping users' perceptions of stigma, autonomy, and competence. Prior research indicates that older adults and people with cognitive impairment are especially vulnerable to technology-related anxiety and concerns about social judgment, which contribute to low acceptance and high rates of device abandonment (Peek et al., 2014; Greenhalgh et al., 2013; Czaja et al., 2006). Understanding socially sensitive design choices is therefore crucial for developing AT that are more acceptable, dignified, and desirable, ultimately promoting sustained use and reducing the likelihood of abandonment among individuals with impairments. However, research examining the influence of SS on technology acceptance, particularly BI, remains limited. Table 6.1 presents the constructs incorporated into the extended UTAUT model.

Table 6.1 Constructs of Extended UTAUT for Individual with Cognitive Impairment

Constructs	**Definition**	**Studies**
Performance Expectancy (PE)	The extent to which an individual believes that utilising a particular technology will assist them in improving their task performance.	Venkatesh et al. (2003)
Effort Expectancy (EE)	The degree of ease associated with the use of a particular technology.	Venkatesh et al. (2003)
Facilitating Conditions (FC)	The degree to which an individual believes that adequate technical and organisational infrastructure exists to support the use a particular technology.	Venkatesh et al. (2003)
Social Influence (SI)	The extent to which an individual believes that people who are important to them think they should use a particular technology.	Venkatesh et al., (2003)
Technology Anxiety (TA)	The fear or discomfort an individual feels when contemplating or engaging in the practical application of a particular technology.	Meuter et al., (2003)
Social Sensitivity (SS)	The awareness of social perceptions, potential stigmatisation, and the interpersonal implications of using a particular technology.	Santos et al. (2020); Lamela et al., (2020); Chang et al., (2022)
Behavioural Intention (BI)	An individual's intention or willingness to use a particular technology	Venkatesh et al., (2003)
Interactivity (IN)	Individual ability to engage directly with a particular technology, receive immediate feedback, and influence its behaviour in a meaningful and adaptive manner.	Meiland et al., (2014); Kim and Park, (2012); Orpwood et al., (2005)
Privacy (PR)	Individual concern over the collection, access, use, and potential misuse of their personal information while using a particular technology.	Jokisch et al., (2022); Yusif et al. (2016)
Aesthetics (AE)	The visual appeal and attractiveness of a particular technology interface which can influence user satisfaction and willingness to adopt the technology.	Santos et al., (2020); Shinohara and Wobbrock, (2011)

Based on the constructs defined in Table 6.1, the hypotheses formulated for this study are presented in Figure 6.1.

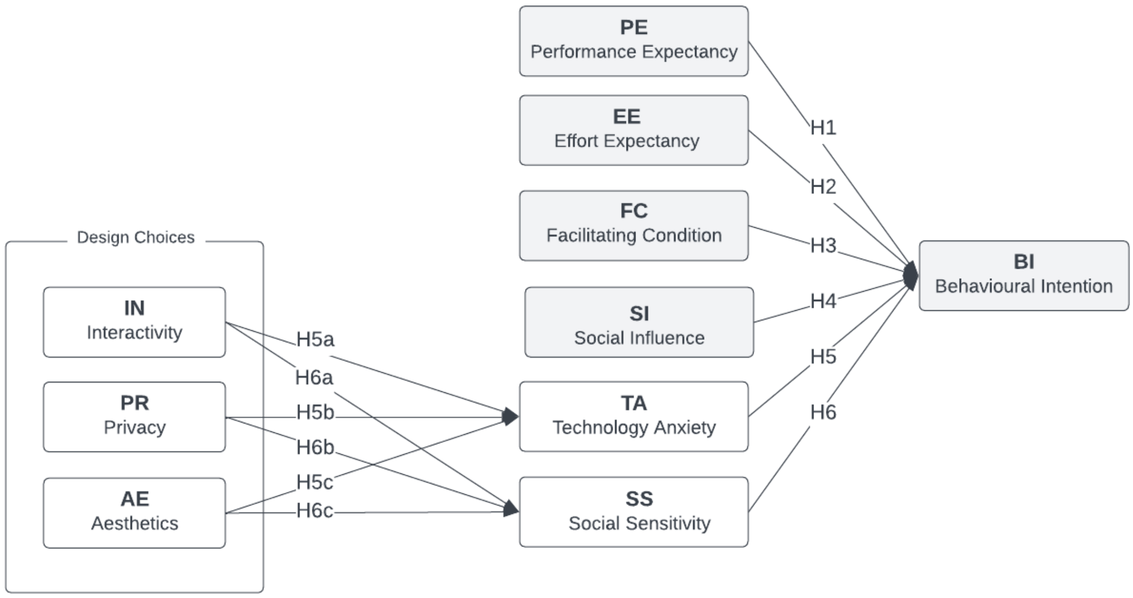


Figure 6.1. Proposed Extended UTAUT with Social Sensitivity and Technology Anxiety

6.3.1. Extended UTAUT Constructs

This study extended the UTAUT framework by adding constructs specific to older adults and individuals with cognitive impairments to better understand the factors influencing acceptance and sustained use of AT. This section discusses each construct in detail.

I. Performance Expectancy (PE)

Recent empirical evidence consistently demonstrates that PE is a strong predictor of BI to use AT, particularly among older adults and individuals experiencing cognitive decline. Studies show that perceived usefulness significantly influences adoption decisions for rehabilitation and AT (Goodarzi et al., 2025), while systematic reviews in dementia care similarly identify PE as one of the most influential determinants of intention to use AT (Felpete et al., 2025). These findings align with UTAUT theory, underscoring the value of PE as a key construct for assessing actual use behaviour of healthcare and wearable AT as considered in this study.

Hypothesis 1 (H1): *Performance expectancy positively influences the behavioural intention to use assistive technologies among people with dementia.*

II. Effort Expectancy (EE)

For any system to be used effectively in meeting users' needs, the perceived difficulty associated with its use is critical, as cognitive impairments related to dementia may hinder learning, memory, and interaction with technology. Consequently, understanding how users perceive the level of difficulty involved in using healthcare wearable devices is imperative, since high perceived effort can negatively influence acceptance and sustained use of such technologies (Peek et al., 2014; Meiland et al., 2017). Therefore, EE is considered in this study to examine its influence on the BI of PwD to use healthcare wearable devices and to inform the design of technologies that are accessible, usable, and supportive of their cognitive abilities.

Hypothesis 2 (H2): *Effort expectancy positively influences the behavioural intention to use assistive technologies among people with dementia.*

III. Facilitating Condition (FC)

According to the UTAUT, FC play a critical role in influencing users' actual technology usage by reducing barriers related to resources, knowledge, and system compatibility (Venkatesh et al., 2003). When users perceive that sufficient support, training, and infrastructure are available, they are more likely to adopt and consistently use a technological system. Therefore, FC is considered in this study to examine how the available support and the type of device used will influence users' acceptance and effective use of the technology under investigation.

Hypothesis 3 (H3): *Facilitating condition positively influences the behavioural intention to use assistive technologies among people with dementia.*

IV. Social Influence (SI)

This factor is especially critical for PwD, as decisions regarding technology adoption are frequently guided or mediated by caregivers, family members, and healthcare professionals, owing to cognitive decline and diminished autonomy in decision-making (Peek et al., 2014; Czaja et al., 2019; Heart and Kalderon, 2013). The perceptions, encouragement, and behaviours of these influential individuals can therefore significantly shape the acceptance and continued use of assistive healthcare technologies by PwD. Therefore, SI is considered in this study to examine how support and expectations from caregivers and healthcare professionals contribute to actual use behaviour of wearable technologies and, consequently, to improvements in the QoL of PwD.

Hypothesis 4 (H4): *Social influence positively influences the behavioural intention to use assistive technologies among people with dementia.*

V. Technology Anxiety (TA)

Extensions of the UTAUT model that incorporate TA alongside constructs such as SI and EE show that caregiver perceptions of TA can significantly affect BI to use wearable health devices for PwD (Dai et al., 2020). Although direct UTAUT research on PwD is limited, qualitative studies indicate that anxiety and discomfort when interacting with digital tools act as barriers to adoption among individuals with early-stage dementia (Bults et al., 2024). Similarly, studies applying extended UTAUT models to older adults consistently demonstrate that higher TA reduces BI, particularly among those with lower experience or education, suggesting that PwD may face even greater challenges in technology acceptance due to cognitive and emotional vulnerabilities (Chen et al., 2024). These findings highlight the importance of addressing TA in interventions aimed at improving the adoption and effective use of AT for PwD. Therefore, TA is considered in this study to better explain variations in BI and to highlight the need for interventions that reduce anxiety and foster greater acceptance and sustained use of AT.

Hypothesis 5 (H5): *Technology anxiety influences the behavioural intention to use assistive technologies among people with dementia.*

VI. Social Sensitivity (SS)

This study introduces SS to extend the UTAUT framework to better capture the concerns of older adults and individuals with cognitive impairments. SS is a crucial factor influencing the acceptance of technology among PwD and individuals with impairment (Greenhalgh et al. 2013; Peek et al. 2014). It is the ability to perceive and respond appropriately to social cues, which is essential for effective interpersonal interactions and decision-making (Magrì 2021; van Hoorn et al. 2018).

While AT can help alleviate various impairments, its visible nature may unintentionally highlight a user's condition, potentially increasing self or social stigma (Parette and Scherer, 2004; Chang et al., 2022). Technologies that are obviously associated with disability may increase users' visibility and reinforce negative stereotypes, leading to discomfort or rejection of otherwise beneficial tools (Gibson et al., 2019; Santos et al., 2020).

Stigmatisation is a well-documented social risk that occurs when the design or visibility of a device inadvertently labels the user as disabled, frail, or other (Santos et al., 2020; Chang et al., 2022). Stigmatised individuals may be less likely to adopt technology, especially if it's associated with a negative social image or perceived as a sign of weakness or deviance (Lamela et al., 2020). Stigma can affect self-perception and lead individuals to feel ashamed or embarrassed about using certain technologies, further reducing adoption (Rodríguez-Rivas et al. 2022). As a result, socially sensitive design, considering aesthetics, discretion, and cultural norms, can help mitigate stigma, promote dignity, and encourage broader acceptance and sustained use among people with disabilities (Newell and Gregor, 2000).

The problem of stigma affects many people, including PwD. Social stigma of PwD is a global problem (Rewerska-Juśko and Rejdak 2020) as a recent global survey found that as many as 84% of PwD report experiencing stigma and discrimination (Alzheimer's Disease International, 2019). Although several interventions have been developed to mitigate public stigma, based on the use of innovative technologies (Rodríguez-Rivas et al. 2022). However, concerns about how others will perceive them using a particular technology remains an issue even if the technology offers real benefits (Santos et al. 2020).

Research in AT and inclusive design emphasises that perceived stigma both internalised (self-stigma) and external (social-stigma) can significantly impact individuals' willingness to adopt and use such technologies (Pullin, 2009; Greenhalgh et al., 2013; Santos et al. 2020; Chang et al., 2022). SS, therefore, includes not only functional and usability aspects but also emotional and social dimensions of user experience. Devices that appear "medical" or conspicuously "assistive" may serve as constant reminders of impairment, potentially affecting self-identity and social inclusion (Pols and Willems, 2011; Story et al., 1998). Pethig et al. (2021) study reflected on how continuing experiences of stigma at the societal level triggers disengagement from digital services at the individual level. Social stigma associated with aging and dependence on technology, along with fears of weakened relationships with the society, have also been seen as key barriers to technology adoption among older adults (König et al. 2022).

SS can shape BI by making users cautious about adopting technologies that might affect their social identity or public image (Pullin 2009). It can increase TA, particularly when individuals fear negative evaluation or judgment in social contexts (Chen and Persson 2022; An et al., 2024). This heightened anxiety serves as a barrier to technology acceptance, as individuals may avoid adopting technologies that they perceive could expose them to social scrutiny or stigma

(Cheng et al. 2023). Understanding this relationship is crucial for designing technologies that are more socially acceptable and for developing interventions that address both SS and TA to enhance adoption rates (Chang et al., 2022).

Drawing from the literature, this study suggests that consideration of the SS of technology is essential for fostering acceptance among individuals with various forms of impairment. Accordingly, the following hypotheses are proposed:

Hypothesis 6 (H6): *Social sensitivity influences the behavioural intention to use assistive technologies among people with dementia.*

VII. Behavioural Intention (BI)

The BI is a key predictor of technology adoption, as stronger intentions increase the likelihood of actual use (Venkatesh et al., 2003). In the context of dementia care, BI has been shown to significantly influence caregivers' intention to use wearable health devices for people with dementia, highlighting the relevance of UTAUT constructs in this setting (Dai et al., 2020). Research with older adults further confirms that BI is shaped by PE, EE, SI, and FC, and is positively associated with actual use of digital health technologies (Venkatesh et al., 2003; Dai et al., 2020). Given the cognitive and emotional challenges faced by PwD, examining BI is crucial for identifying psychological and contextual barriers to technology adoption, as well as for designing interventions that enhance acceptance and sustained use of AT to support wellbeing.

VIII. Interactivity (IN)

A lack of interactive design features could be a barrier to technology adoption (Bertolazzi et al., 2024). Enhanced interactivity in technology can improve the old adult experience and increase perceived usefulness (Sun et al. 2024; Zhou et al. 2021). Improving the interactivity and ease of use of technology can also address anxiety and enhance the overall user experience (Jeng et al., 2022).

A pervasive design approach may further support adoption among people with dementia, as such technologies are less stigmatising and do not highlight the user's impairment (Thorpe et al., 2016). Technologies requiring unusual physical gestures can draw unwanted attention and seem awkward in public. Older adults tend to prefer voice commands for interaction (Kanno et al., 2018). While speech and gesture interfaces support natural engagement, they may appear socially awkward, as users may look like they are talking or gesturing to no one (Lazaro et al., 2022).

Bretschneider et al., (2022) explored how the design of assistive devices, such as prostheses, influences social perceptions. Their study found that users of high-tech prostheses were perceived as more competent compared to those using low-tech versions. However, when these devices were perceived as enhancements beyond normal human capabilities, users were sometimes viewed as less warm or even frightening. This suggests that the technological sophistication of assistive devices can shape societal perceptions of their users.

Poor interactivity in technology increases user TA and SS, especially in social contexts. Lack of responsive or adaptive features can reduce users' sense of control, cause confusion or errors, and make individuals particularly those with cognitive or functional impairments feel exposed or judged. This heightened SS and visible struggle with technology can reinforce stigma and act as a barrier to adoption and continued use (Olatunji et al., 2021; Jeng et al., 2022; Chen and Persson, 2002; Peek et al., 2014).

While study that indicates a relationship between system interactivity with SS and TA is hardly found, based on insights from the literature, interactive system features can shape how users are socially perceived. Therefore, the following is hypothesised:

Hypothesis 5a: *Low interactivity in AT is associated with increased technology anxiety among older adults and individuals with cognitive impairments.*

Hypothesis 6a: *Low interactivity in AT is associated with increased social sensitivity among older adults and individuals with cognitive impairments.*

IX. Privacy (PR)

Privacy concerns have been widely examined in the literature. These concerns stem from issues related to the collection, unauthorised secondary use, misuse, and improper access to personal information, as well as errors in data handling (Jokisch et al., 2022). A number of studies, including a systematic review by Yusif et al. (2016), identify privacy as a key factor influencing older adults' decisions to adopt AT, often acting as a significant barrier that may outweigh perceived benefits. Similarly, Elueze and Quan-Haase (2018) found that privacy concerns among older adults are closely associated with fears of social exposure and the potential misuse of personal information, which can discourage technology adoption. These concerns are frequently linked to fears of social judgment and loss of dignity, underscoring the relationship between privacy concerns and SS in the context of technology acceptance (Courtney et al., 2008).

Lower privacy concerns contributed to a higher intention to use technology among older adults (Jokisch et al. 2022). AlMahadin et al. 2020) posit that AT for older adults should be non-invasive and comfortable to encourage use. Personal data signals vulnerability, making privacy breaches socially significant rather than purely technical (Yusif et al., 2016). Privacy concerns amplify SS by increasing awareness of social exposure, potential stigma, and threats to dignity, autonomy, and social identity. Users may anticipate negative evaluation and feel vulnerable to judgment, especially when personal or health-related information could be accessed, misused, or misinterpreted by others (Yusif et al., 2016; Jokisch et al., 2022). Higher levels of privacy concern tend to increase anxiety and avoidance toward technology. In older adults and other sensitive populations, these concerns can intensify psychological stress and discourage continued or initial technology use (An et al., 2025)

These studies collectively underscore that privacy concerns are intertwined with SS and TA among older adults and individuals with disabilities. Therefore, the following hypothesis is proposed:

Hypothesis 5b: *Privacy concern in AT is associated with increased technology anxiety among older adults and individuals with cognitive impairments.*

Hypothesis 6b: *Privacy concern in AT is associated with increased social sensitivity among older adults and individuals with cognitive impairments.*

X. Aesthetics (AE)

Aesthetic design plays a central role in how technologies align with users' self-concept and social identity. Aesthetic includes elements such as layout, colour scheme, and overall interface design that enhance the user experience (Wang et al., 2025b). Aesthetic design applies sensory and stylistic features to improve visual appeal, foster emotional connection, and increase social acceptability, thereby boosting satisfaction and reducing the risk of device rejection or stigma (Hassenzahl, 2004; Santos et al., 2020; Shinohara and Wobbrock, 2011). Aesthetic design of

AT has a clear effect on reducing or reinforcing social stigma, which influences the adoption of AT among older adults (Bispo and Branco 2011; König et al. 2022; Chang et al. 2022).

Chang et al. (2022) posit that AT can unintentionally reinforce impairment-related stereotypes by increasing the visibility of a user's condition, thereby making their identity more pronounced in social contexts. Several studies, including those by Mitzner et al. (2010), Santos et al. (2020), and Garcia et al. (2023), have found that stigma related to the aesthetic design of assistive technologies is a significant factor contributing to their abandonment.

Santos et al. (2020) argues that addressing the factors behind perceived stigma in assistive technology can reduce both stigma and abandonment. König et al. (2022) observed that older adults tend to appreciate designs that resemble familiar, archetypal objects. Some studies found that older adult often engage in bricolage with technologies partly due to stigma and mismatch with user needs or preferences (Gibson et al., 2019; Pols and Willems, 2011; Greenhalgh et al., 2013).

Designing solutions to be broadly inclusive and usable by people of all abilities helps to mitigate stigmatisation (Newell and Gregor, 2000; Coleman et al., 2003; Pullin, 2009). Research shows that when devices are visually discreet, stylish, or integrated into familiar objects, they are more likely to be accepted and used (Shinohara and Wobbrock, 2011; König et al. 2022). However, Jonge et al. (2016) highlight that AT development often prioritises functionality over aesthetics. Santos et al. (2020) emphasis that while functionality aids adaptation, aesthetics are crucial for fostering positive user perceptions. However. Poor aesthetic design is linked with lower acceptance and engagement which aligns with increased anxiety, stress, or avoidance of technology (Wei, et al., 2025).

Aesthetics influence SS by shaping how technologies is socially interpreted, how users anticipate judgment, and how well their social identity and dignity are preserved. Well-designed, attractive technologies can normalise use, reduce stigma, lower anxiety, and support confident social participation all of which are critical for technology acceptance among PwD and individuals with impairments. Given what we know from the above, we argue that a system development process that is socially sensitive will pay attention to how its users will react to the finished solution and adjust the design choices accordingly. Hence, we formulated the following hypothesis:

Hypothesis 5c: *Aesthetics of AT is associated with increases technology anxiety among older adults and individuals with cognitive impairments.*

Hypothesis 6c: *Aesthetics of AT is associated with increases social sensitivity among older adults and individuals with cognitive impairments.*

6.4 Materials and Methods

In this study, an online survey was administered to 68 caregivers of PwD between the second week of January and the second week of February 2026. Caregivers for PwD were instructed to wear Vuzix smart glasses running the AR application and move through both indoor and outdoor environments. Following this evaluation, caregivers completed a structured questionnaire to provide feedback on their observations and the user experience. The responses were collected, downloaded, and analysed to gain insights into caregivers' perspectives on the acceptance and usability of the proposed assistive tool among PwD. The following sections provide a detailed description of the study procedures.

6.4.1 Ethical Approval

This research received ethics approval from the University of Essex Ethics Sub Committee 2 (Reference numbers: ETH2425-1705). Submission of the online questionnaire was taken as implied consent for all participants in this research.

6.4.2 Proxy Decision-Making by Caregivers of People with Dementia

Recruiting vulnerable adults, particularly PwD, poses significant challenges in empirical research due to cognitive impairment, fluctuating decision-making capacity, communication difficulties, and ethical considerations surrounding informed consent (Hirt et al., 2024). These challenges are especially pronounced in studies involving emerging digital health technologies, where understanding abstract concepts, evaluating hypothetical interactions, and sustaining engagement throughout the research process may be difficult for some participants with cognitive decline (Ko et al., 2025). Consequently, dementia research frequently adopts alternative methodological approaches to maintain both ethical integrity and methodological feasibility. One widely accepted approach is the inclusion of caregivers or family members as proxy respondents or study partners. When PwD are unable to provide informed consent or reliably communicate preferences and experiences, caregivers often support participation and decision-making on their behalf, thereby enabling ethically appropriate inclusion in research activities (Sugarman et al., 2001; Black et al., 2013; Dai et al., 2020).

The use of caregivers as proxies is particularly justified in AT and dementia care research because caregivers are typically deeply involved in the daily routines, safety management, technology adoption decisions, and environmental support of PwD (Alarcao et al., 2022). They frequently observe behavioural changes, mobility difficulties, adherence to safety interventions, and responses to care technologies over extended periods of time. As a result, caregivers are often well positioned to provide ecologically grounded observations regarding usability challenges, behavioural patterns, and contextual factors affecting technology use within real-world home environments (Lariviere et al., 2021). Prior studies have shown that caregivers serve not only as ethical gatekeepers but also as valuable informants for evaluating dementia-related needs, behavioural symptoms, care practices, and technology engagement (Lord et al., 2015; Chandra et al., 2021; Baker et al., 2023). Caregiver-based approaches have therefore become an established methodological strategy in dementia research where direct and sustained participation from PwD may not always be feasible. However, substantial evidence suggests that proxy responses may introduce systematic bias, particularly when subjective constructs such as QoL, emotional experience, usability, and perceived usefulness are assessed. Studies have shown that caregivers may unintentionally project their own stress, burden, expectations, or perceptions onto evaluations of PwD experiences, resulting in discrepancies between patient self-reports and proxy assessments (Arons et al., 2013; Smith et al., 2020).

Caregiver perceptions may not accurately reflect the lived experiences, emotional responses, or preferences of PwD. Caregivers may overestimate or underestimate factors such as usability, anxiety, or acceptance of AT due to caregiving burden or personal expectations, thereby affecting construct validity (Arons et al., 2013; Smith et al., 2020).

Reliance on caregiver perspectives also limits ecological validity because caregivers cannot fully capture the subjective and embodied experiences of PwD when interacting with AR systems. Experiences such as cognitive load, attentional demands, confusion from multimodal feedback, and emotional reassurance are highly individual and may not be directly observable (Buchholz et al., 2024). Consequently, usability assessment through proxy reporting alone may fail to accurately evaluate cognitive effort, fatigue, comfort, and perceptual clarity associated with AR technologies.

In addition, caregiver-based findings may reduce generalisability. Caregivers often prioritise safety and monitoring, whereas PwD may value autonomy, dignity, privacy, and social acceptability. Sampling bias may also occur because caregivers participating in research are often more technologically engaged than the wider caregiving population (Sriram et al., 2019).

Despite these limitations, caregiver involvement remains methodologically valuable and ethically necessary in exploratory dementia research. However, future studies should incorporate more direct participation from PwD through co-design methods, observational usability testing, and longitudinal real-world evaluations to improve construct validity, ecological validity, usability assessment, and the generalisability of findings related to adaptive AR-based assistive technologies.

6.4.3 Questionnaire Design and Data Collection

A structured questionnaire was developed in English using Google Forms for caregivers in the United Kingdom. Data was collected between the first week of January and the second week of February 2026. Caregivers were used as proxy respondents instead of individuals with dementia due to ethical and informed-consent considerations. As discussed in Section 6.4.2, many studies rely on caregivers or family members to respond on behalf of PwD. Consequently, it is expected that the findings of this study would not differ substantially if PwD themselves had completed the survey. To reduce response bias, the questionnaire consisted of closed-ended questions. The survey was distributed via social media platforms and email, accompanied by an introduction that clearly explained the study objectives, eligibility criteria for participation, and a hyperlink to the questionnaire.

The questionnaire was divided into two sections. The first section collected demographic information, including respondents' age, gender, occupation, professional category, experience, where support is provided, and the number of individuals with dementia cared for and the number of hours spent daily in care. The second section included questions related to the constructs of the extended UTAUT model presented in the research framework, using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Participants were informed that no risks were anticipated from participating in the study. A confidentiality statement assured respondents that their data would not be linked to personal identifiers and would remain strictly confidential unless explicit permission to disclose information was provided. Respondents were also reminded that participation was entirely voluntary and that they could withdraw at any time by exiting the survey; any responses submitted up to that point would still be retained. Submission of a completed questionnaire was considered as providing informed consent.

A total of 68 valid responses were collected with no missing data, as the questionnaire required all questions to be completed before submission. The composition of the questionnaire, adapted and formulated from existing literature, is presented in Table 6.2.

Table 6.2. Measurement Instruments

Caregivers Perception	**Number of Questions**	**Notations**	**Literature Sources**
Interactivity (IN)	5	IN1-IN5	Albeedan et al. (2023)
Privacy (PR)	5	PR1-PR5	Dekkal et al., (2023)
Aesthetics (AE)	5	AE1-AE5	Wang et al., (2025b)
Social Sensitivity (SS)	5	SS1-SS5	Chang & Tucker, et al., (2022)
Technology Anxiety (TA)	5	TA1-TA5	Hoque and Sorwar (2017); An et al., (2024)
Performance Expectancy (PE)	5	PE1-PE5	Venkatesh et al., (2003)
Effort Expectancy (EE)	5	EE1-EE5	Venkatesh et al., (2003)
Social Influence (SI)	5	SI1-SI5	Venkatesh et al., (2003)
Facilitating Condition (FC)	5	FC1-FC5	Venkatesh et al., (2003)
Behavioural Intention (BI)	5	BI1-BI5	Venkatesh et al., (2003)

6.4.4 Data Analysis

Questionnaire data were exported from Google Forms to Microsoft Excel, where exploratory and confirmatory analyses were performed to validate the reflective measurement model. Exploratory and descriptive analyses were conducted using Python, which provides robust libraries (e.g., pandas, NumPy, and matplotlib) for data cleaning, summary statistics, and data visualisation.

Due to the small sample size (n = 68), Covariance-Based Structural Equation Modelling (CB-SEM) was not appropriate, as CB-SEM relies on large samples and strict distributional assumptions. In contrast, Partial Least Squares Structural Equation Modelling (PLS-SEM) is appropriate for smaller samples and exploratory research because it requires fewer distributional assumptions and is robust in prediction-oriented contexts (Hair and Alamer, 2022; Ringle et al., 2023; Jhantasana, 2023; Angelelli et al., 2025). PLS-SEM is a suitable alternative to CB-SEM in a number of situations that are common in quantitative research (Hair and Alamer, 2022). Prior research in dementia and related caregiver populations demonstrates that pilot feasibility studies and preliminary intervention research often proceed with sample sizes smaller than 68 (e.g., Han et al., 2023; Kwok et al., 2023; Carrard, 2024; Bozoki et al., 2025), focusing on feasibility, acceptability, and preliminary effect estimation. Such small sample research plays an important role in shaping later large-scale investigations. The most widely used minimum sample size estimation method in PLS-SEM, in the field of information system as well as other fields, is the “10-times rule” method (Hair et al., 2011; Peng and Lai, 2012; Kock and Hadaya, 2018). The 10-times rule is a heuristic commonly used to estimate the minimum sample size required for PLS-SEM. According to this rule, the minimum sample size should be at least ten times the maximum number of structural paths directed at any endogenous construct or alternatively, ten times the largest number of indicators used to measure a single construct, whichever is greater (Hair et al., 2011; Peng and Lai, 2012; Kock and Hadaya, 2018).

Formally, the rule can be expressed as:

Minimum sample size = 10 × max {(number of formative indicators of a construct), (number of structural paths pointing to an endogenous construct)}

In the study, the most complex endogenous construct in the structural model receives six direct paths from exogenous constructs. Applying the 10-times rule therefore yields:

$$\text{Minimum sample size} = 10 \times 6 = 60$$

This implies that a minimum of 60 observations would be required to ensure stable parameter estimation under this heuristic.

6.5 Results and Discussion

This section presents and discusses the results of the study evaluating user acceptance of the proposed adaptive AR-based AT. The findings are organised according to the extended UTAUT framework, highlighting the relationships between key constructs and caregivers’ perceptions of acceptance among PwD. Quantitative results from the survey analysis are interpreted in relation to existing literature to explain their implications for usability, adoption, and sustained use. The discussion also considers how design factors and psychosocial influences inform future improvements to AT in dementia care.

6.5.1 Results

The results of the study, including both descriptive statistics summarising participants' demographic characteristics and PLS-SEM analysis, are presented below in Tables 6.2–6.6.

6.5.1.1 Descriptive Statistics

A total of 68 participants took part in the study. Frequencies and percentages were calculated for the participants' demographic characteristics, as presented in Table 6.3.

Table 6.3. Summary of Participants' Demographic Characteristics

Participants demographic characteristic (N=68)	**N**	**(%)**
Age Range (Years)		
18-29	8	12
30-39	34	50
40-49	17	25
50+	9	13
Gender		
Male	21	31
Female	47	69
Other	0	0
Prefer not to say	0	0
Occupation		
Healthcare Assistant/ Caregiver	62	91
Other	6	9
Category		
Professional	64	94
Family member/Friend	4	6
Experience (Years)		
1-3	12	18
4-7	43	63
8-11	9	13
12+	4	6
Place of care or support		
Residential or Nursing care facility	66	97
Domiciliary care	12	18
Number of PwD cared for or supported		
1-3	9	13
4-6	6	9
7-9	10	15
10+	43	63
Daily hours spent with PwD		
1-8	5	7
9-16	61	90
17-24	2	3

6.5.1.2 Evaluation of Measurement Model

The measurement model was assessed to ensure the reliability and validity of the constructs, which are prerequisites for meaningful interpretation of structural relationships (Hair et al., 2017; Fornell and Larcker, 1981). The evaluation focused on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity as shown in Table 6.4 – 6.5. Indicator reliability was examined using factor loadings, with a recommended threshold of 0.70 or higher for reflective constructs (Hair et al., 2019). In this study, all retained items showed acceptable loadings, ranging from 0.616 to 0. 987. Although a loading of 0.70 is commonly recommended as the ideal threshold, prior methodological literature indicates that factor loadings in the range of 0.60 to 0.69 may be considered acceptable when other measures of construct validity are satisfactory. Specifically, Hair et al. (2017, 2019) argues that indicators with loadings above 0.60 can be retained provided that composite reliability exceeds 0.70, the Average Variance Extracted (AVE) is at least 0.50, and the removal of such indicators does not substantially improve the measurement model. Accordingly, indicators with loadings between 0.60 and 0.69 indicators such as PR4, PR5, PE5 were retained in this study due to their theoretical relevance and the satisfactory reliability and convergent validity of the constructs similar to Yahya et al., (2025) study. Indicators with low or missing loadings, specifically IN1, IN3, IN4, PR3, AE2, EE3, EE4, SI2, SI3, FC3, and FC4, were removed from the measurement model due to insufficient reliability, consistent with established recommendations for reflective constructs (Chin, 1998; Hair et al., 2019). After removal, the remaining indicators demonstrated satisfactory convergent validity, supporting the overall reliability of the measurement model. Figure 6.2 illustrates the constructs along with their respective outer loadings.

Table 6.4. Measurement model

		Convergent Validity		Internal Consistency Reliability	
Construct	**Notations**	**Factor Loadings**	**AVE**	**Cronbach's Alpha (α)**	**CR**
Interactivity (IN)	IN2	0.937	0.844	0.806	0.915
	IN5	0.900			
Privacy (PR)	PR1	0.762	0.579	0.725	0.845
	PR2	0.881			
	PR4	0.616			
	PR5	0.616			
Aesthetics (AE)	AE1	0.925	0.871	0.949	0.964
	AE3	0.928			
	AE4	0.925			
	AE5	0.928			
Social Sensitivity (SS)	SS1	0.875	0.714	0.882	0.926
	SS2	0.875			
	SS3	0.714			

	SS4	0.875			
	SS5	0.921			
Technology Anxiety (TA)	TA1	0.987	0.909	0.972	0.980
	TA2	0.987			
	TA3	0.987			
	TA4	0.900			
	TA5	0.900			
Performance Expectancy (PE)	PE1	0.976	0.825	0.947	0.958
	PE2	0.976			
	PE3	0.976			
	PE4	0.913			
	PE5	0.657			
Effort Expectancy (EE)	EE1	0.776	0.574	0.639	0.812
	EE2	0.918			
	EE5	0.918			
Social Influence (SI)	SI1	0.876	0.863	0.908	0.949
	SI4	0.954			
	SI5	0.954			
Facilitating Condition (FC)	FC1	0.809	0.852	0.912	0.945
	FC2	0.975			
	FC5	0.975			
Behavioural Intention (BI)	BI1	0.899	0.681	0.873	0.913
	BI2	0.773			
	BI3	0.899			
	BI4	0.738			
	BI5	0.660			

Convergent validity was assessed using AVE, with a threshold of 0.50 or higher, indicating that a construct explains at least 50% of the variance in its indicators (Fornell and Larcker, 1981). All constructs exceeded the minimum threshold, confirming that the indicators share sufficient common variance with their underlying latent constructs. Internal consistency reliability was evaluated using Cronbach’s alpha and Composite Reliability (CR). Cronbach’s alpha (α) values above 0.70 indicate acceptable reliability, while CR values above 0.70 reflect strong internal consistency (Hair et al., 2017; Henseler et al., 2015). These results indicate high internal consistency for all constructs, with CR values exceeding Cronbach’s alpha, as expected in reflective measurement models.

Discriminant validity of the measurement model was evaluated using both the Fornell-Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio of correlations. According to the Fornell-Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct should exceed its correlations with all other constructs, indicating that the construct shares more variance with its own indicators than with other constructs (Fornell and Larcker, 1981; Hair et al., 2019). In the current analysis, the diagonal values representing the square root of AVE for IN (0.919), PR (0.761), AE (0.933), and SS (0.845) were greater than their respective inter-construct correlations (e.g., IN–PR = 0.443; IN–AE = 0.782; AE–SS = 0.567).

These results indicate that each construct shares more variance with its own indicators than with other constructs, thereby supporting discriminant validity according to the Fornell–Larcker criterion. However, the relatively high correlation between IN and SI (0.909) suggests a potential overlap that may warrant further examination. Complementary assessment using HTMT showed values of IN–PR = 0.618, IN–AE = 0.835, and PR–AE = 0.920. Based on simulation-based recommendations, HTMT values below 0.85 indicate strong discriminant validity, while values below 0.90 may be acceptable in models with conceptually related constructs (Henseler et a., 2015; Hair et al., 2019). In this study, the HTMT value for PR–AE (0.920) slightly exceeds the liberal threshold (0.90), suggesting potential overlap between privacy and aesthetics constructs. Together, the results indicate that discriminant validity is generally supported, but there may be a modest discriminant validity issue between the privacy and aesthetics constructs that should be addressed or discussed in the limitations.

Table 6.5. Fornell–Larcker Criterion Matrix

	IN	PR	AE	SS	TA	PE	EE	SI	FC	BI
IN	0.919									
PR	0.443	0.761								
AE	0.782	0.544	0.933							
SS	0.756	0.301	0.567	0.845						
TA	0.246	0.058	0.302	-0.232	0.953					
PE	0.407	0.486	0.501	0.391	0.334	0.908				
EE	0.286	0.253	0.128	-0.023	0.298	0.619	0.758			
SI	0.909	0.414	0.779	0.813	0.235	0.460	0.230	0.929		
FC	-0.013	0.141	-0.110	-0.307	0.227	0.430	0.646	-0.085	0.923	
BI	0.814	0.311	0.656	0.788	0.173	0.494	0.103	0.861	-0.193	0.825

6.5.1.3 Evaluation of Structural Model

The structural model was evaluated using multiple assessment criteria, including path coefficients (β), t-statistics, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) obtained through the blindfolding procedure as presented in Table 6.5 – 6.6.

The structural model forms a core component of the Structural Equation Modelling (SEM) approach, representing the relationships among latent constructs specified within the overall model (Hair et al., 2019; Kline, 2016). SEM is a comprehensive multivariate technique that consists of two main elements: the measurement model, which defines the relationships between observed indicators and their underlying latent variables, and the structural model, which specifies the hypothesised relationships among those latent variables (Byrne, 2016; Hair et al., 2019). Within this framework, the structural model is used to test theoretical assumptions by examining the direction and strength of relationships through path coefficients and related statistical measures (Hair et al., 2019; Henseler et al., 2009). Thus, while SEM provides the overarching analytical framework, the structural model serves as the component that evaluates causal relationships and hypothesis testing, making it essential for understanding how constructs interact within the proposed research model (Kline, 2016; Byrne, 2016).

To ensure the robustness and stability of the estimated parameters, a bootstrapping procedure with 5,000 resamples was employed. The results of the PLS-SEM analysis are illustrated in Figure 6.2.

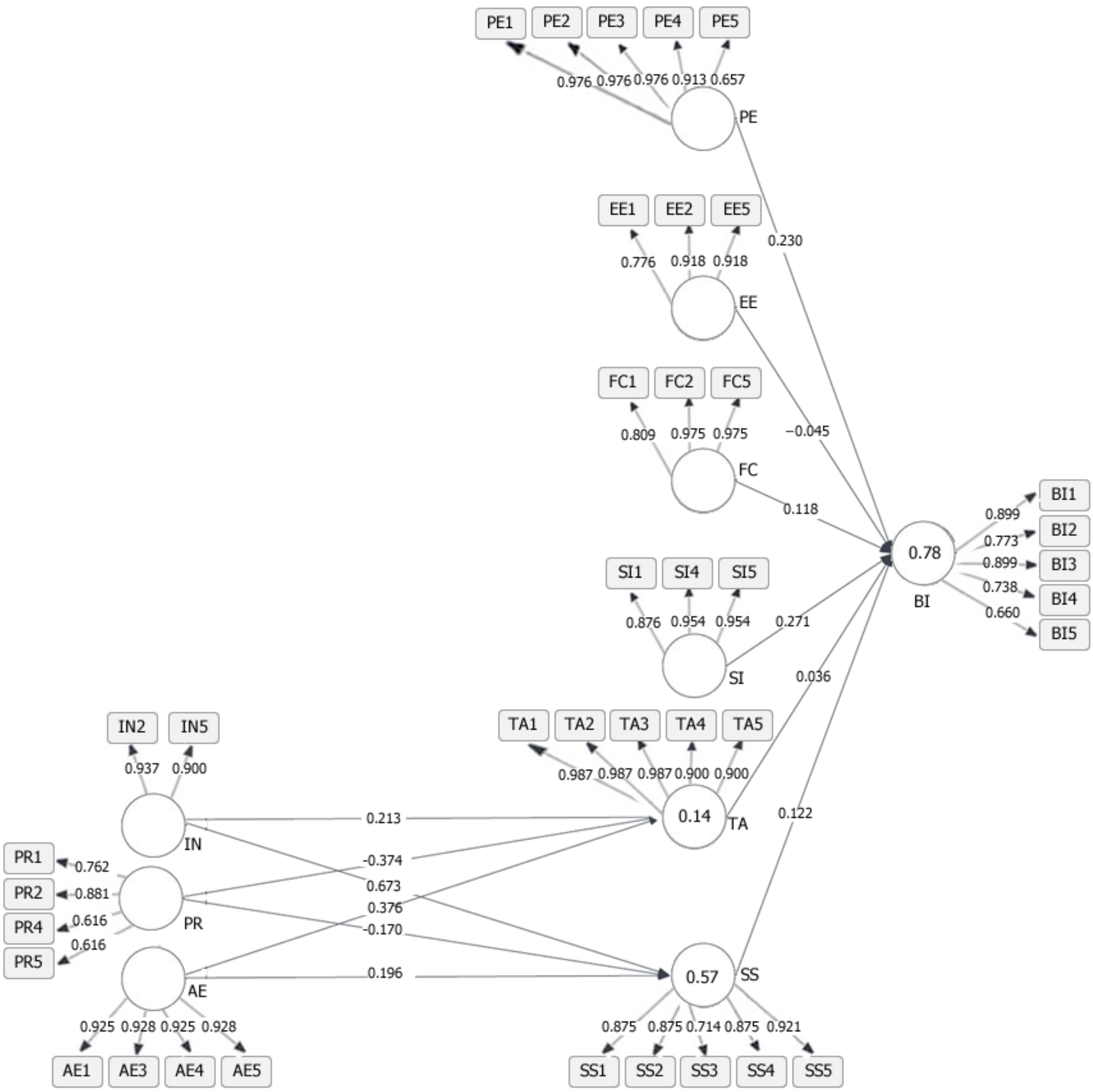


Figure 6.2. The structural model with loading and R^2

Hypotheses Testing

Table 6.6 presents the results of the structural model developed to test the hypothesised relationships among the independent and dependent variables in the research framework, based on the path coefficients (β) and corresponding t-statistics. To evaluate the predictive accuracy and relevance of the model, the coefficients of determination (R^2) and predictive relevance (Q^2) for the endogenous constructs were examined. R^2 values range from 0 to 1, with higher values indicating greater explanatory power, while Q^2 values greater than zero indicate predictive relevance (Hair et al., 2019; Henseler et al., 2009).

The results show that the model explains a substantial proportion of variance in BI, with an R^2 value of 0.78, indicating strong explanatory power (Hair et al., 2017; Chin and Marcoulides, 1998). Furthermore, the Q^2 value for BI ($Q^2 = 0.738$) exceeds the recommended threshold of zero, demonstrating strong predictive relevance.

Table 6.6. Predictive Relevance and Accuracy R^2 and Q^2

Construct	**R^2**	**Q^2**
BI	0.78	0.738
TA	0.14	-0.027
SS	0.57	0.300

For SS, the R^2 value of 0.57 indicates a moderate to substantial level of explained variance, while the Q^2 value of 0.300 confirms adequate predictive relevance. This means, design-related constructs explain a considerable proportion of the variance in SS perceptions. In contrast, TA exhibits a relatively low R^2 value of 0.14, suggesting limited explanatory power. Additionally, the Q^2 value for TA is negative ($Q^2 = –0.027$), indicating a lack of predictive relevance for this construct within the model. These findings suggest that the model demonstrates strong predictive accuracy and relevance for BI and SS, but weaker predictive capability for TA.

Table 6.7. Structural Model Hypothesis Testing Results

Hypothesis	**Path**	**β**	**t**	**p**	**f^2**	**Remark**
H1	PE → BI	0.230	5.963	< .001	0.084	Supported
H2	EE → BI	−0.045	−1.458	.150	−0.046	Not Supported
H3	FC → BI	0.118	3.448	.001	−0.017	Supported
H4	SI → BI	0.271	5.143	< .001	0.045	Supported
H5	TA → BI	0.036	2.797	.007	0.008	Supported
H6	SS → BI	0.122	3.721	< .001	0.102	Supported
H5a	IN → TA	0.213	2.761	0.007	-0.095	Supported
H5b	PR → TA	-0.374	-2.303	0.024	0.062	Supported
H5c	AE → TA	0.376	3.398	0.001	0.094	Supported
H6a	IN → SS	0.673	7.949	< 0.001	0.318	Supported

H6b	PR → SS	-0.170	-2.588	0.012	-0.010	Supported
H6c	AE → SS	0.196	2.458	0.017	-0.010	Supported

β = standardised path coefficient; t = bootstrapped t-statistics; p < 0.05 indicates significance; f^2 represents effect size (Cohen, 1988): 0.02 = small, 0.15 = medium, 0.35 = large

The results in Table 6.7 indicate that most hypothesised relationships are statistically significant. PE has a positive and significant effect on BI ($\beta = 0.230$, $t = 5.963$, $p < .001$; $f^2 = 0.084$), supporting H1. EE however, does not significantly influence BI ($\beta = -0.045$, $t = -1.458$, $p = .150$; $f^2 = -0.046$), leading to the rejection of H2. FC positively affect BI ($\beta = 0.118$, $t = 3.448$, $p = .001$; $f^2 = -0.017$), supporting H3. Similarly, SI demonstrates a significant positive relationship with BI ($\beta = 0.271$, $t = 5.143$, $p < .001$; $f^2 = 0.045$), supporting H4.

Both psychosocial constructs also significantly predict BI. TA shows a positive effect on BI ($\beta = 0.036$, $t = 2.797$, $p = .007$; $f^2 = 0.008$), supporting H5. The relationship is positive and statistically significant. However, the effect size is very small ($f^2 < 0.02$), while SS exerts a positive and comparatively stronger influence ($\beta = 0.122$, $t = 3.721$, $p < .001$; $f^2 = 0.102$), supporting H6. Among all predictors of BI, SS ($f^2 = 0.102$) and PE ($f^2 = 0.084$) demonstrate the largest practical effects, followed by SI ($f^2 = 0.045$), underscoring their critical role in shaping adoption intentions.

Regarding the antecedents of TA, IN positively and significantly affects TA ($\beta = 0.213$, $t = 2.761$, $p = .007$; $f^2 = -0.095$), supporting H5a. PR has a significant negative effect on TA ($\beta = -0.374$, $t = -2.303$, $p = .024$; $f^2 = 0.062$), supporting H5b. AE positively influences TA ($\beta = 0.376$, $t = 3.398$, $p = .001$; $f^2 = 0.094$), supporting H5c.

Similarly, the results show that IN strongly and positively influences SS ($\beta = 0.673$, $t = 7.949$, $p < .001$; $f^2 = 0.318$), supporting H6a, with a substantial effect size. PR negatively affects SS ($\beta = -0.170$, $t = -2.588$, $p = .012$; $f^2 = -0.010$), supporting H6b. In addition, AE has a positive and significant effect on SS ($\beta = 0.196$, $t = 2.458$, $p = .017$; $f^2 = -0.010$), supporting H6c.

The result shows that all hypotheses (H1, H3–H6, H5a–H5c, and H6a–H6c) are supported except for H2. These findings suggest that while core UTAUT constructs such as PE and SI remain important determinants of BI, psychosocial factors, particularly SS, play a pivotal role in shaping the adoption of AT among PwD.

6.6 Discussion

The evaluation of the structural model provides meaningful insights into the factors influencing the adoption of AT among PwD. The model demonstrates strong explanatory power, with BI exhibiting an R^2 of 0.78 and predictive relevance ($Q^2 = 0.738$), indicating that the extended UTAUT framework effectively captures the key determinants of technology acceptance in this context. Consistent with Hypothesis 1 (H1), PE emerged as a significant positive predictor of BI, underscoring that perceived usefulness remains a central driver of adoption, in line with prior findings in healthcare and dementia care (Felpete et al., 2025; Goodarzi et al., 2025). Conversely, EE did not significantly influence BI, leading to the rejection of Hypothesis 2 (H2), which aligns with emerging evidence suggesting that for PwD, cognitive and functional support may outweigh perceived ease of use when considering new technologies (Peek et al., 2014). FC positively affect BI in support of Hypothesis 3 (H3), but with a small effect, suggesting that while support and compatibility help adoption of the system when running on smart glasses, they are less influential than factors like PE, SI, and SS, consistent with previous studies (Meiland et al., 2017; Yang et al., 2021). SI showed a robust positive effect on BI, supporting Hypothesis 4 (H4), and confirming the critical role of caregivers, family members, and healthcare professionals in shaping adoption decisions among PwD. This is consistent with the studies emphasising mediated decision-making in dementia care (Czaja et al., 2019; Heart and Kalderon, 2013). Importantly, the psychosocial constructs added in this study TA and SS demonstrated significant impacts on BI, highlighting the relevance of extending the UTAUT model. SS, in particular, had a moderate effect size, emphasising that concerns about stigma, social judgment, and visibility of assistive devices substantially influence adoption decisions, supporting the assertions of Santos et al. (2020) and Lamela et al. (2020). TA also affected BI, albeit with a smaller effect size, aligning with previous findings that anxiety and discomfort with technology can act as barriers for older adults and cognitively impaired populations (Bults et al., 2024; Chen et al., 2024).

The antecedents of TA and SS further clarify the influence of design-related factors. IN significantly influences both TA and SS. This indicates that highly interactive systems can reduce TA and SS, consistent with Jeng et al., (2022) and Thorpe et al. (2016), who emphasised the role of engaging and responsive designs in older adult adoption. PR also significantly increased both TA and SS, reinforcing the notion that perceived threats to personal information and social exposure are critical barriers to adoption (Yusif et al., 2016; Jokisch et al., 2022).

Finally, AE significantly influenced both TA and SS, highlighting that visually appealing, discreet, and socially considerate designs can foster acceptance by minimising stigma and promoting dignity (Santos et al., 2020; König et al., 2022).

These findings collectively underscore that while core UTAUT constructs such as PE and SI remain influential, psychosocial factors, particularly SS shaped by design attributes play a central role in the adoption of AT among PwD. The results demonstrate the value of extending the UTAUT framework to incorporate social and emotional considerations, offering practical guidance for the development of user-centred, socially sensitive assistive devices for dementia care. From a practical perspective, these insights provide clear guidance for designers and policymakers. Promoting demonstrable functional benefits and leveraging social endorsement are critical strategies to enhance adoption, necessitating the active involvement of caregivers, clinicians, and family members. Reducing TA and SS requires human-centred design that prioritises appropriate interactivity, discreet aesthetics, and transparent privacy safeguards. Rather than focusing solely on ease of use, developers should aim to minimise stigma and emotional discomfort, thereby facilitating adoption among cognitively impaired users and ensuring AT are both effective and socially acceptable.

6.6.1 Research Limitations and Future Research Directions

This study has several methodological and contextual limitations that should be carefully considered when interpreting the findings. First, the relatively small sample size limits statistical power and may reduce the robustness and generalisability of the results. Although PLS-SEM is appropriate for exploratory models with limited samples, its use in this study still constrains the extent to which the proposed relationships can be confidently extrapolated to broader populations. A larger and more heterogeneous sample would improve model stability, reduce estimation bias, and enable stronger external validity.

Second, the study relies exclusively on caregivers as proxy respondents to represent the attitudes and behavioural tendencies of PwD. While caregiver-informed data are widely accepted in dementia research due to ethical and cognitive constraints affecting direct participation (Lord et al., 2015; Sugarman et al., 2001), this approach introduces an inherent perceptual gap between observed behaviour and lived experience. Caregivers may unintentionally overestimate or underestimate PwD’s cognitive capabilities, technology acceptance, or emotional responses, leading to potential proxy bias. This limitation directly affects construct validity, particularly for latent variables related to perceived usefulness, usability, and behavioural intention toward multimodal AR-based assistive technologies.

Third, participant selection constraints may have introduced sampling bias. Caregivers who are more engaged in care routines or more technologically aware may have been more likely to participate, thereby skewing findings toward higher perceived acceptability or usability of assistive technologies. Additionally, the absence of direct participation from PwD represents a significant limitation in terms of ecological validity. Without first-hand input from end users, the study cannot fully capture lived experience factors such as cognitive load, sensory perception of AR cues, emotional responses to alerts, or real-time usability challenges within home environments. This also limits the interpretive depth of behavioural constructs derived from caregiver reporting.

Fourth, the study did not incorporate co-design or participatory design methods involving PwD, which is increasingly recognised as a critical requirement in developing inclusive assistive technologies. Excluding PwD from early-stage design decisions may reduce the extent to which the resulting framework reflects user-centred needs, preferences, and interaction constraints. Co-design with PwD has been shown to improve usability, acceptance, and long-term engagement with digital health technologies (Fox et al., 2022; Wang et al., 2019). The absence of such approaches may therefore limit the practical applicability and adoption potential of the proposed system.

Fifth, a critical limitation of this study is that it does not directly measure actual system effectiveness in terms of fall risk reduction, behavioural change, or long-term real-world impact. The evaluation is primarily based on perceived acceptance and intention-related constructs rather than objective outcome measures such as reduced fall incidence, improved hazard avoidance behaviour, or sustained engagement with assistive interventions over time. As a result, the study cannot establish causal evidence that the proposed AR-based system would lead to measurable reductions in falls or sustained improvements in safety-related behaviour. This also limits the ability to assess long-term usability, adherence, or adaptation effects, which are particularly important in progressive conditions such as dementia where cognitive and functional abilities change over time.

Finally, dataset constraints, including cross-sectional design and reliance on proxy-reported survey data, limit the ability to infer causality or capture longitudinal changes in technology acceptance and usage behaviour over time. Dementia is a progressive condition, and attitudes toward assistive technologies may evolve with disease progression, caregiver burden, and familiarity with digital systems. The lack of longitudinal data restricts the temporal validity of the findings and limits understanding of sustained use and real-world adoption trajectories.

Future research should therefore prioritise larger, more diverse samples and adopt multi-stakeholder data collection strategies that include PwD and individual with MCI wherever ethically and practically feasible. In addition, integrating co-design methodologies, longitudinal study designs, and mixed-methods approaches would significantly strengthen construct validity, ecological validity, and generalisability. Such approaches would also enable a more accurate and holistic understanding of AR-based assistive technology adoption in dementia care contexts, ultimately supporting the development of more inclusive and effective interventions.

6.7 Conclusion

In conclusion, this study provides a comprehensive examination of the factors influencing the adoption of AT among PwD by extending the UTAUT framework. The findings demonstrate that while traditional UTAUT constructs such as PE and SI remain central drivers of BI, EE plays a limited role, reflecting the unique cognitive vulnerabilities of this population and highlighting a shift in adoption decisions from usability considerations toward perceived benefits and social reassurance. By incorporating TA and SS, this study captures affective and stigma-related dimensions that are particularly relevant in dementia care, revealing how emotional and social concerns shape technology acceptance. Furthermore, design-related antecedents, including IN, PR, and AE, were found to influence BI indirectly by shaping users' emotional responses, emphasising the importance of socially sensitive and human-centred design. Practically, these insights underscore the need for AT that deliver clear functional benefits, promote positive social endorsement through caregivers and healthcare professionals, and minimise stigma and emotional discomfort through discreet, engaging, and privacy-conscious design.

It is important to note that the evaluation presented in this chapter primarily focuses on technology acceptance, perceived feasibility, and adoption-related factors associated with the proposed adaptive AR-based assistive technology, rather than direct clinical effectiveness or measurable health outcomes. Specifically, the study examines caregivers' perceptions regarding the usability, acceptability, perceived usefulness, and behavioural intention to use the system through the extended UTAUT framework. While the proposed system is conceptually designed to support fall risk mitigation through adaptive guidance and real-time hazard awareness, the current evaluation does not directly measure objective outcomes such as fall reduction, behavioural change, mobility improvement, or long-term clinical effectiveness in real-world settings. Similarly, the study does not assess whether use of the system leads to sustained improvements in adherence to safety interventions, reduced fall incidence, or measurable changes in cognitive or functional performance among PwD. Instead, the evaluation is intended as an exploratory assessment of the psychosocial, technological, and design-related factors that may influence the feasibility and potential adoption of wearable AR-based assistive technologies in dementia care. As such, the findings provide important insights into user acceptance and implementation readiness, while establishing a foundation for future longitudinal and clinical studies that can evaluate real-world effectiveness, behavioural outcomes, and fall prevention impact.

In all, this study not only advances theoretical understanding of technology acceptance in cognitively vulnerable populations but also provides actionable guidance for the development and implementation of assistive technologies that are both effective and socially acceptable, supporting the independence, dignity, and wellbeing of PwD.

Chapter 7

Conclusion, Limitation and Future Work

This chapter provides a comprehensive summary of the thesis, highlighting its key conclusions, limitations and directions for future work, with a focus on advancing wearable, AR-based AT for enhancing the safety and independence of PwD and individuals with MCI.

Contents

7.1 Conclusion

This thesis demonstrates the potential of adaptive AR-based AT to enhance the safety and independent mobility of PwD and individuals with MCI. Falls in this population arise from a complex interplay of physical, cognitive, and environmental factors, which differ significantly from those affecting cognitively healthy older adults. As such, conventional fall prevention strategies often fail to adequately address these unique and dynamic risk profiles, highlighting the need for more personalised, context-aware interventions.

To address this gap, the system integrates multimodal data from wearable sensors and device cameras with DL and HMM probabilistic modelling to enable real-time, adaptive fall risk assessment. By combining environmental hazard and safety intervention detection with attention inference, the system is capable of recognising risks, estimating users' cognitive engagement, and delivering timely, personalised safety cues. This context-aware approach ensures that guidance is provided when it is most needed, while minimising unnecessary alerts, reducing alert fatigue, and preserving user autonomy. In addition, the system design incorporates privacy-conscious processing and ethical considerations, addressing critical limitations associated with many existing AT.

The findings emphasise the importance of moving beyond static, one-size-fits-all solutions toward intelligent, responsive systems that adapt to users' cognitive states, behavioural patterns, and environmental context. Through initial real-world evaluation, the system demonstrated its capability to support safer navigation, mitigate fall risk, and promote independent living. This thesis contributes to the advancement of next-generation AT by presenting a scalable, adaptive, and human-centred framework for fall risk assessment. It highlights the transformative potential of intelligent wearable multimodal systems in bridging the gap between passive environmental modifications and active, personalised support, ultimately improving safety, autonomy, and QoL for individuals with cognitive impairment.

7.2 Limitation and Future Work

Building on the development and evaluation of the adaptive AR-based AT presented in this thesis, future work will focus on enhancing the technical robustness and real-world applicability of the system. While the current implementation demonstrated the feasibility of integrating object detection and context-aware risk assessment models, these components were partially dependent on external computational resources. Future research will extend this work by implementing fully on-device processing for both the object detection framework and the attention state prediction model. This advancement will enable faster response times, reduce latency, and eliminate reliance on continuous network connectivity. Additionally, optimising the models for low-power wearable devices, such as smart glasses, will ensure energy efficiency, seamless operation, and sustained performance in real-world environments. This will further strengthen the system's ability to deliver real-time hazard detection, fall risk assessment, and adaptive safety cues in everyday settings.

The current research primarily explored caregivers' perspectives to understand the unmet needs of PwD. Subsequent studies will directly involve PwD, particularly those in the early and mild stages, alongside caregivers in the co-design process. This shift will ensure that the system evolves in closer alignment with users' lived experiences, preferences, and cognitive capabilities. Iterative incorporation of user feedback will further enhance usability, accessibility, and ethical considerations, particularly in relation to autonomy, privacy, and trust. In addition, longitudinal studies will be conducted to examine how user interaction, cognitive engagement, and system effectiveness evolve over time, providing deeper insights into long-term adoption and real-world impact.

In terms of evaluation, the current research provides an initial validation of the system's functionality, usability, and acceptance; however, it is limited by a relatively small participant sample. In addition, the assessment of usability and acceptance was conducted primarily through caregivers, serving as proxies for PwD, rather than through direct user interaction. While this approach offers valuable insights into unmet needs and practical considerations, it may not fully capture the lived experiences, preferences, and real-time interactions of PwD themselves. Future work will address these limitations by conducting large-scale studies involving a more diverse and representative cohort of participants, including PwD across different stages of cognitive impairment. Direct involvement of PwD in usability testing and system evaluation will provide more accurate and ecologically valid insights into user experience, engagement, and acceptance. Furthermore, adopting a RCT design will enable rigorous quantitative evaluation of the system's impact on key safety outcomes, such as fall reduction, navigation efficiency, and adherence to safety interventions. Complementary qualitative methods, including interviews and observational studies, will be employed to capture user perceptions, challenges, and contextual factors influencing system use. Additional subgroup analyses will also be undertaken to examine how variables such as age, cognitive severity, and prior experience with technology influence interaction with the system, thereby supporting the development of more inclusive, personalised, and effective AR-based assistive solutions.

Finally, future research will explore the scalability and generalisability of the system beyond fall risk assessment. While this thesis focuses on safety and mobility, the underlying adaptive and context-aware architecture has the potential to be extended to other assistive domains, such as support for individuals with visual impairments. By integrating technical optimisation, comprehensive evaluation, and inclusive design practices, future work aims to advance the development of scalable, human-centred AR-based AT that can effectively respond to the dynamic needs of individuals with cognitive impairment, ultimately promoting greater independence, safety, and QoL.

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Appendices

Appendix I: Mixed Methods Appraisal Tool (MMAT)

References	Qualitative					Quantitative RCT					Quantitative Non-RCT					Quantitative Descriptive					Mixed Methods				
	1.1	1.2	1.3	1.4	1.5	2.1	2.2	2.3	2.4	2.5	3.1	3.2	3.3	3.4	3.5	4.1	4.2	4.3	4.4	4.5	5.1	5.2	5.3	5.4	5.5
Hervas et al. (2014)	Y	Y	Y	Y	CT																				
Lera et al. (2014)	Y	Y	Y	Y	CT																				
Saracchini et al. (2015)	Y	Y	Y	Y	Y																				
Bianco et al. (2016)	Y	Y	Y	Y	Y																				
Połap et al., (2017)	Y	Y	Y	Y	Y																				
Kanno et al. (2018)	Y	Y	Y	CT	CT																				
Ingeson et al., (2018)	Y	Y	Y	Y	CT																				
Liang (2018)	Y	Y	Y	Y	Y											Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Gacem et al. (2019)	Y	Y	Y	Y	CT																				
Younis et al. (2019)	Y	Y	Y	Y	Y																				
Liu et al. (2019)	Y	Y	Y	Y	Y																				
Zhao et al. (2019b)	Y	Y	Y	Y	Y																				
Blusi and Nieves (2019)	Y	Y	Y	Y	Y																				
Ro et al. (2019)	CT	CT	CT	CT	CT																				
Park et al. (2019)	Y	Y	Y	Y	Y																				
Guerrero et al. (2019)	Y	Y	Y	Y	Y																				
Rossi et al. (2020)	CT	CT	Y	Y	CT																				
Yang et al. (2021)	Y	Y	Y	Y	CT																				
Mettouris et al. (2021)	Y	Y	Y	Y	Y																				
Varghese et al. (2021)	Y	Y	Y	CT	CT																				
Ghorbani et al. (2022)						Y	Y	Y	Y	Y															
Htike et al. (2023)																Y	Y	Y	Y	Y					
Taghian et al. (2023)	Y	Y	Y	Y	Y																				
Miura et al. (2023)	Y	Y	Y	Y	CT																				
Ball et al. (2023)											Y	Y	Y	Y	Y										
Franzén (2023)	Y	Y	Y	Y	Y																				
Achilleos et al. (2023)	Y	Y	Y	Y	Y																				
Dylan et al. (2023)						Y	Y	Y	Y	Y															
Ghorbani, et al. (2023)	Y	Y	Y	Y	Y																				
Su et al. (2024)	Y	Y	Y	Y	Y																				
Yadav and Kirit (2024)	CT	CT	CT	Y	CT																				

Appendix II: Questionnaire for Caregivers of People with Dementia

QUESTIONNAIRE

Title of Research: People with Dementia Assistive Technology (PwDAT)
Research Institution: University of Essex, Wivenhoe Park, Colchester CO4 3SQ
Principal Investigator: Ise Anderson Orobor - io22721@essex.ac.uk
Supervisor: Dr Ramy Hammady - r.hammady@essex.ac.uk

People Living with Dementia Attitude Towards Home Hazards and Existing Home Safety Interventions

This study aims to explore caregivers' perspectives on the attitudes of older adults in the early stages of dementia toward home hazards and existing home safety interventions. The exercise will take approximately 10 minutes. If your duties do not involve interacting with people living with dementia, you may have received this questionnaire in error, and there is no obligation for you to complete it.

Participation in this research is anonymous (no need to share identifying information) and voluntary. If you have any questions or concerns, please contact the Principal Investigator using the email above.

Please fill out as much as you can; even partial completion contributes valuable information.

Here are some definitions for your guide.

Early-Stage Dementia: *refers to the initial phase of dementia where a person will start to experience problems that affect their everyday living. The stage is often characterised with forgetfulness, difficulties in making decisions, etc.*

Home safety interventions: *refer to a set of measures and actions taken to enhance safety within the home environment. These interventions are designed to reduce the risk of accidents, injuries, and other hazards within the home, promoting a safe and supportive living space. Examples of home safety interventions to prevent fall are installing handrails, grab bars, marking the edges of steps and non-slip flooring, as well as removing tripping hazards.*

Thank you for taking the time to contribute to this research.

SECTION 1: Demographics

1. What is your age?
   18-29 ☐
   30-39 ☐
   40-49 ☐
   50+ ☐

2. How do you define your gender?
   Male ☐
   Female ☐
   Other ☐
   Prefer not to say ☐

3. What is your ethnicity?
   White/White British ☐
   Black/Black British ☐
   Asian/Asian British ☐
   African ☐
   Other ☐

4. What is your location post code? ________________

5. What is your occupation?
   Healthcare assistant/ Caregiver ☐
   Other ______________________

6. Please select the category that best describes you:
   Professional with experience caring for or supporting person or people living with dementia ☐
   Family member/friend with experience caring for or supporting person or people living with dementia ☐

7. How long have you been providing care or support for person or people living with dementia?
   1-3 years ☐
   4-7 years ☐
   8-11 years ☐
   12+ years ☐

8. Where do you provide the care or support?
   - Residential or Nursing care facility ☐
   - Domiciliary care ☐

9. How many persons or people living with dementia have you cared for?
   - 1-3 ☐
   - 4-6 ☐
   - 7-9 ☐
   - 10+ ☐

10. How many hours do you typically spend with a person or people living with dementia during your care or support?
    - 1-8 hours ☐
    - 9-16 hours ☐
    - 17-24 hours ☐

SECTION 2: Safety and Use of Home Interventions

11. Do the person or people living with dementia you care for or support use glasses?
    - Yes ☐
    - No ☐
    - Sometime ☐

12. If Yes, what are they? ____

13. Do the person or people living with dementia consistently maintain awareness of their surroundings, avoiding collisions with objects or unsafe environment?
    - Yes ☐
    - No ☐
    - Sometime ☐

14. Assuming there is no physical mobility impairment, are people living with dementia able to navigate staircases, uneven surfaces, obstacles, etc., safely without assistance?
    - Yes ☐
    - No ☐
    - Sometime ☐

15. Are there home safety interventions to prevent fall in the places where you provide care for or support to the person or people living with dementia?
    - Yes ☐
    - No ☐
    - Sometime ☐

16. Do the person or people living with dementia able to recognise when to use home safety interventions (e.g., holding handrails, grab bars etc) without being reminded?
    - Yes ☐
    - No ☐
    - Sometime ☐

17. Do the person or people living with dementia always able to utilise home safety interventions without being guided?
    - Yes ☐
    - No ☐
    - Sometime ☐

18. Do the person or people living with dementia use any wearable electronic interventions or devices?
    - Yes ☐
    - No ☐
    - Sometime ☐

19. If yes, what kind of interventions or devices? ___________________________

20. Do you think wearable electronic devices can help improve the safety of people living with dementia?
    - Yes ☐
    - No ☐
    - Maybe ☐

21. Do you think combining wearable electronic devices, alongside the current home safety interventions, would be advantageous for people living with dementia?
    - Yes ☐
    - No ☐
    - Maybe ☐

22. In your opinion, what measures can be taken to improve the safety of people living with dementia, especially those living alone?

    ____

    ____

23. How do you handle some household hazards that pose a risk to the safety of a person or people living with dementia?

____

____

____

24. Would you be happy to take part in the assessment of the proposed system that is been developed once it's completed?

Yes ☐
No ☐
Maybe ☐

25. Is there anything else you would like to add?

____

____

Appendix III: Participants Consent Form

CONSENT FORM

Title of the Project: People with Dementia Assistive Technology (PwDAT)

Research Team: Ise Anderson Orobor - io22721@essex.ac.uk (**Principal Investigator**)
Dr. Ramy Hammady - r.hammady@essex.ac.uk (**Supervisor**)

Please initial box

1. I confirm that I have read and understand the Information Sheet for the above study. I have had an opportunity to consider the information, ask questions and have had these questions answered satisfactorily.

2. I understand that my participation is voluntary and that I am free to withdraw from the project at any time without giving any reason and without penalty. I understand that any data collected up to the point of my withdrawal e.g., will be destroyed; cannot be withdrawn because it cannot be identified.

3. I understand that, due to the nature of the interventions used in this research, those who have had epileptic seizures in the past may not be suitable as participants due to the risk of triggering such a seizure. I confirm that, to the best of my knowledge, I have never had an epileptic seizure.

4. I understand that the identifiable data provided will be securely stored and accessible only to the members of the research team directly involved in the project, and that confidentiality will be maintained.

5. I understand that my fully anonymised data will be used for academic report submitted as a requirement for the partial fulfilment of a Doctor of Philosophy degree in Computer Science at the University of Essex and also in research publications.

6. I understand that the data collected about me will be used to support other research in the future, and may be shared anonymously with other researchers.

7. I give permission for the survey data that I provide to be deposited in UK Data Archive so that they will be available for future research and learning activities by other individuals.

8. I agree to take part in the above study.

Participant Name	Date	Participant Signature
______________________	_________	______________________

Researcher Name	Date	Researcher Signature
______________________	_________	______________________

Appendix IV: Participants Information Sheet

PARTICIPANT INFORMATION SHEET

Project Title: People with Dementia Assistive Technology (PwDAT)

Introduction

My name is Ise Anderson Orobor and I am a doctoral research student in the Department of Computer Science at the University of Essex. I would like to invite you to take part in a research study. Before you decide whether or not to take part, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully.

What is the purpose of the study?

Studies shows that there are currently 120,000 people with dementia (PwD) living alone in the United Kingdom (UK), and this figure is anticipated to double to approximately 240,000 by 2039. In another survey report, 85% of participants expressed a preference to remain at home for as long as possible upon a dementia diagnosis. However, the desire to continue maintaining independence raises safety concerns due to dementia-associated symptoms.

Considering the foregoing, this research seeks to explore how the safety of people with early-stage dementia can be enhanced especially for those living independently using technology-based interventions.

This research is designed to gather insights from caregivers and family members providing care or support to person or people living with dementia. Based on the insights provided, system requirements will be produced to create an intelligent system with the capability of improving the safety of people living with dementia through fall prevention mechanism.

The research is conducted as part of the requirements for obtaining a Doctor of Philosophy (PhD) degree in Computer Science.

Why have I been invited to participate?

I have invited you to take part in this study because you are an adult having at least 1 years experience (formal/informal) providing care or support to people living with dementia. This research aims to recruit 50 participants, and it would be a pleasure to have you as one of the participants.

Do I have to take part?

No, your participation is entirely voluntary. If you decide to participate, you will receive this information sheet for your records and will be asked to sign a consent form. You retain the right to withdraw at any time without giving reason or notice. If you choose to withdraw, any personally identifiable information collected will be destroyed, while non-identifiable data may be retained.

What will happen to me if I take part?

The research involves two activities: an online questionnaire and an interview. Depending on your preference, the Principal Investigator will provide you with a link to the online questionnaire or schedule an interview at a mutually convenient time. The interview can be conducted via phone call or face-to-face, allowing you to share your experiences in providing support for people living with dementia. The questionnaire will take approximately 10 minutes to complete, while the interview will last around 30 minutes. It's important to note that the interview will be audio recorded to ensure accurate capture of the information you provide.

What are the possible disadvantages and risks of taking part?

We do not feel there are any risks associated with this study. If you are asked to wear a head-mounted display device in this study, there is a very minimal chance you might experience dizziness, nervousness, headaches or local discomfort. The Principal Investigator will ask you about any problems or discomfort you are experiencing with the device and the researcher will try to correct these or discontinue the activity.

What are the possible benefits of taking part?

Participating in this research will not provide direct benefits to you personally. However, your involvement may contribute to the development of systems aimed at enhancing the quality of life for people living with dementia in the future. Your insights and experiences could potentially inform the design and implementation of technologies and support mechanisms for individuals with dementia, thereby benefiting the broader community.

What information will be collected?

The study will gather demographic data including age range, ethnicity, gender, postal code, occupation, and years of experience. It's important to note that this information will not be directly linked to you as a participant. Instead, each participant will be assigned a unique identifier, comprised of a combination of letters and numbers, upon their response. This approach ensures anonymity and confidentiality throughout the research process.

Will my information be kept confidential?

All data collected from you throughout the research will be password-protected and stored on the University of Essex secured shared drive. This storage system is password-protected and maintained with strict confidentiality measures in place. Access to the data will be restricted to authorised members of the research board of examiners only. Additionally, your data will be anonymised using unique participant identification numbers to further safeguard your privacy.

If you choose to participate in the interview activity of the research, it will be audio-recorded to ensure an accurate record of the discussion. The recorded conversation will then be transcribed, meaning it will be written down to capture the exact words used by both you and the Principal Investigator. This transcription process will be conducted solely by the Principal Investigator, who will remove any identifiable information such as name if it exists to maintain your anonymity. After the information has been transcribed and analysed, the recordings will be securely destroyed to uphold confidentiality.

The anonymised data will be retained indefinitely in compliance with the University's Research Data Management Policy in the University of Essex secured shared drive.

What is the legal basis for using the data and who is the Data Controller?

This research adheres to the UK General Data Protection Regulation (GDPR) by adhering to the guidance provided by the University of Essex when creating the participant information sheet and consent forms. All participants involved in the research will receive access to the participant information sheet and consent forms prior to engaging in any research activities. This ensures transparency and allows participants to make informed decisions about their involvement in the research.

The University of Essex serves as the Data Controller for the data collected in this research. The designated contact person for inquiries regarding data management is the University Information Assurance Manager (dpo@essex.ac.uk).

What should I do if I want to take part?

Participants will receive a participant information sheet containing comprehensive details about the research to help them decide whether or not to take part in the research study. Upon choosing to participate, both the participant and the Principal Investigator will obtain consent by signing the consent form.

What will happen to the results of the research study?

The results of the research will be used by the Principal Investigator in writing part of the doctoral thesis, which upon completion will be deposited in the University of Essex Research Repository. Additionally, based on the research findings, articles will be written and submitted for publication in scientific journals. These articles will be openly accessible to the public, thereby facilitating broader dissemination of the research findings.

Only anonymised data will be utilised to ensure the protection of participants' privacy while still allowing for the dissemination of research findings.

Who is funding the research?

This research is an academic exercise conducted by the Principal Investigator as a requirement for the partial fulfilment of a Doctor of Philosophy degree in Computer Science at the University of Essex.

Who has reviewed the study?

This study has been reviewed by the University of Essex Ethics Committee, to protect your safety, rights, well-being and dignity. The study has been given a favourable opinion.

Concerns and Complaints

If you have any concerns about any aspect of the study or you have a complaint, in the first instance please contact the principal investigator of the research using the contact details below. If you are still concerned, you think your complaint has not been addressed to your satisfaction or you feel that you cannot approach the principal investigator, please contact the departmental Director of Research in the department responsible for this project. If you are still not satisfied, please contact the University of Essex Research Integrity Manager, Mantalena Sotiriadou (email: ms21994@essex.ac.uk). Please include the ERAMS reference which can be found at the foot of this page.

Name of the Researcher/Research Team Members

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Appendix V: Participants Evaluation Questionnaire

People with Dementia Assistive Technology (PwDAT) Evaluation Questionnaire

Thank you for taking part in the assessment phase of 'PwDAT'. Your feedback is crucial in the design validity of this AR safe mobility tool.

Once you have used PwDAT, kindly complete the questionnaire below by ticking the option that best reflects your opinion.

This questionnaire is divided into 11 sections for you to complete:
1. Background Information
2. Performance Expectancy
3. Effort Expectancy
4. Social Influence
5. Facilitating Condition
6. Interactivity
7. Privacy Concern
8. Aesthetics
9. Social Sensitivity
10. Technology Anxiety
11. Behavioural Intention

The questionnaire will take approximately 20 minutes to complete.

Section 1: Background Information

1. Age: ○18-29 ○30-39 ○ 40-49 ○ 50+

2. Sex: ○ Male ○ Female ○ Prefer not to say

3. Occupation:
   ○Healthcare Assistant/ Caregiver
   ○Other

4. Category:
   ○Professional
   ○Family member/Friend

5. Experience (Years):
   ○1-3
   ○4-7
   ○8-11
   ○12+

Section 2: Performance Expectancy
This section assesses how beneficial or helpful the technology is in helping users achieve their goals or solve problems.

1. PwDAT offers useful real-time visual cues about potential hazards?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. Using PwDAT will enables user navigate safely in their homes?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. Using PwDAT will remind user when to use safety interventions in their homes?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. Using PwDAT will help user avoid fall risk and promote the use of existing safety interventions?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. PwDAT object detection capability is satisfactory?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 3: Effort Expectancy
This section assesses how simple and straightforward it is for users to interact with the technology without needing extensive training or prior experience.

1. PwDAT is ease to use?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. I found the interaction of PwDAT clear and understandable?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. PwDAT user interface is easy to navigate?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. It is easy and comfortable to walk around wearing PwDAT smart glasses?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. Learning to use PwDAT will be easy for users?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 4: Social Influence

This section aims to assesses how your opinions and expectations affect others view of the technology and the extent to which you believe others should use it.

1. Those in my profession would likely recommend using PwDAT if they are aware it existed?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. If the individuals I support are aware of PwDAT, they would likely be interested in giving it a try?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. If the individuals I support for knows about PwDAT, they would likely be inclined to share their experiences with others?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. I believe I can recommend PwDAT to stakeholders, as its discreet wearable glasses appear to reduce social stigma?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. I think I would recommend the use of PwDAT for anyone diagnose with dementia?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 5: Facilitating Condition

This section is intended to evaluate whether the available support and the type of device used will facilitate effective use of the system.

1. The use of PwDAT smart glasses does not contradict the regular use of recommended glasses?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. PwDAT is more preferable on smart glasses compared to other personal items like smart phone, wrist band, belt, necklace etc?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. When using the PwDAT, I am able to get help by asking question on the system?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. I think users will have no difficulty in accessing PwDAT on the smart glasses?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. I think PwDAT smart glasses is bulkier than the regular recommended glasses?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 6: Interactivity

This section assesses the extent to which you believe users can actively engage with the technology and receive immediate feedback.

1. Getting information from PwDAT was very fast?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. I could interact with PwDAT in a natural manner?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. I could interact with PwDAT interface as I expected?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. PwDAT interactivity is intuitive and engaging?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. User could select prefer mode of feedback (visual or auditory)?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 7: Privacy Concern
This section assesses your opinion on sensitivity to potential risks related to data security, unauthorised access, or misuse of their information.

1. The PwDAT does not require personal information to setup?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. I am not bother about privacy since PwDAT do not asks me for personal information?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. I would be concerned if PwDAT ask personal information?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. When any assistive technology asks me for personal information, I sometimes think twice before providing it?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. I thought that giving out personal information to the any assistive technology could threaten my private life?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 8: Aesthetics
This section assesses your perception on the visual appeal and overall look and feel of the technology.

1. Wearing PwDAT look like the regular glasses?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. I think PwDAT is unobtrusive and does not draw unnecessary attention?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. I think PwDAT is modern and social-friendly?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. I think PwDAT does not look like medical or clinical device?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. I think PwDAT will not makes user impairment pronounce?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 9: Social Sensitivity

This section assesses your opinion on the extent to which the technology respects users' social contexts, emotions and cultural values.

1. There is no feeling of being stigmatised when wearing PwDAT?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. I do not feel embarrassed because I am wearing PwDAT?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. I think other people will not make users feel ashamed because of wearing PwDAT?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

4. PwDAT keeps users' cognitive impairments discreet in social interactions.?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

5. I believe individuals will not face discrimination for wearing PwDAT?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

Section 10: Technology Anxiety

This section assesses your opinion on the feelings of fear, nervousness, or discomfort that individuals may experience when using or thinking about using the technology.

1. Using PwDAT will not make users uncomfortable?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

2. Users will not feel worried when using PwDAT?

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
1	2	3	4	5

3. Using PwDAT will not make users nervous?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

4. Using PwDAT will not be disturbing or confusing to users?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

5. Users will feel calm to use PwDAT?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

Section 11: Behavioural Intention

This section evaluates your intention to use or recommend the technology, as well as your belief about whether others are likely to do the same.

1. I intend to use PwDAT if diagnose with dementia?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

2. I predict to use PwDAT if diagnose with dementia?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

3. I will use PwDAT for family member diagnose with dementia?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

4. I predict people with dementia will use PwDAT?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5

5. I predict people with dementia will regularly use PwDAT?

Strongly Disagree	**Disagree**	**Neither**	**Agree**	**Strongly Agree**
1	2	3	4	5