To the Graduate Council:

I am submitting herewith a thesis written by Connor Murphy entitled "An Intelligent Multi-Agent System for Enhanced Dementia Care: Integrating Computer Vision, Adaptive Learning, and Caregiver Guidance." I have examined the final paper copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Computer Science.

Dr. Hairong Qi, Major Professor

We have read this thesis
and recommend its acceptance:

Dr. Hairong Qi

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Accepted for the Council:

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(Original signatures are on file with official student records.)

An Intelligent Multi-Agent System for Enhanced Dementia Care: Integrating Computer Vision, Adaptive Learning, and Caregiver Guidance

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Connor Murphy

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Abstract

Dementia poses a significant global health challenge, yet existing technology-assisted care systems often fail to adapt to the complex and evolving behaviors of patients, leading to inefficient monitoring and increased caregiver burden. This thesis addresses the critical shortcomings of current patient monitoring systems, which typically rely on static or random search strategies when patients wander, resulting in dangerous delays in detection and compromising patient safety.

To overcome these limitations, this work presents a novel intelligent multi-agent system that integrates adaptive spatial-temporal learning, computer vision, loop prevention mechanisms, and comprehensive biometric simulation within a realistic behavioral framework. The system employs an algorithm that dynamically learns individual patient movement patterns to build a probabilistic model of their location, which in turn guides an intelligent system for proactive and efficient care. A key innovation is the integration of a synthetic biometric monitoring system that generates realistic vital signs, including heart rate, HRV, and SpO2 to model stress responses, simulate medical emergencies, and objectively measure the physiological impact of care interventions. This allows for the data-driven adaptation of care strategies, which are tested and refined within a sophisticated multi-agent simulation featuring patient agents with realistic cognitive decline and caregiver agents employing evidence-based intervention techniques. The system incorporates an adaptive loop prevention framework that detects and breaks repetitive interaction patterns, utilizing confidence scoring to prioritize effective interventions while avoiding counterproductive cycles.

Through extensive simulation-based experiments, the system demonstrated a 40–60% reduction in average patient detection time compared to baseline methods. The biometric-guided approach increased care intervention success rates from a baseline of 38% to 55% and achieved 94% sensitivity in detecting simulated medical emergencies. The loop prevention system successfully identified and mitigated repetitive interaction patterns, preventing escalation of patient agitation. This research contributes a comprehensive, adaptive, and empirically validated framework that enhances patient safety, reduces caregiver burden, and shifts the paradigm from reactive monitoring to proactive, personalized, and physiologically-informed dementia care.

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Nomenclature

α	Learning rate for the online transition probability updates
δ	Probability parameter used in sample complexity analysis
ϵ	Desired accuracy parameter for the learned model
$\hat{P}$	The learned transition probability matrix
C	Confidence score matrix for learned transitions
E	Set of edges in the graph G, representing observed transitions between rooms
G	A weighted directed graph, $G = (V, E)$, modeling the environment
P	Transition probability matrix
$P^{(k)}$	The k-step transition probability matrix
P_{ij}	The probability of transitioning from state i to state j
S	Discrete state space representing all rooms
s_i	A specific state (room) in the state space S
V	Set of vertices in the graph G, representing rooms or distinct areas
$w(i, j)$	Weight of the edge from vertex i to j, representing transition probability

HRV	Heart Rate Variability
RMSSD	Root Mean Square of Successive Differences, a measure of HRV
SpO_2	Peripheral capillary oxygen saturation

Chapter 1

Introduction

1.1 Motivation

Dementia represents one of the most significant public health challenges of the 21st century, affecting over 55 million people worldwide with nearly 10 million new cases emerging annually [WHO, 2023]. This progressive neurological condition not only devastates the lives of those affected but also places an immense burden on caregivers, healthcare systems, and society at large. The global economic impact of dementia exceeded $1.3 trillion in 2019 and is projected to double by 2030 [Urbina, 2024]. As populations age across developed nations, the urgency to develop innovative care solutions has never been more critical.

The complexity of dementia care stems from the progressive nature of cognitive decline, which manifests in various challenging behaviors including wandering, confusion, agitation, and inability to perform activities of daily living (ADLs). Traditional care approaches, whether in institutional settings or home environments, rely heavily on human caregivers who must provide constant supervision—a physically and emotionally exhausting responsibility that often leads to caregiver burnout [Dauphinot et al., 2015]. Studies indicate that family caregivers of dementia patients experience higher rates of depression, anxiety, and physical health problems compared to non-caregivers [Bandeira et al., 2007].

The integration of smart home technologies presents a promising avenue for enhancing dementia care while reducing caregiver burden. Recent advances in artificial intelligence, computer vision, and Internet of Things (IoT) devices have enabled the development of intelligent monitoring systems capable of tracking patient activities, detecting potentially dangerous situations, and providing timely interventions [TECH@HOME Research Group et al., 2017, Tiersen et al., 2021]. However, existing solutions often suffer from critical limitations: they typically employ static, pre-programmed behaviors that fail to adapt to individual patient patterns, rely on random or inefficient search strategies when patients move out of view, and lack the sophisticated behavioral modeling necessary to truly understand and predict dementia-related behaviors.

Furthermore, the development and validation of such systems face a fundamental challenge: testing with actual dementia patients raises significant ethical concerns and practical difficulties. This creates a critical need for realistic simulation environments that can accurately model patient behaviors, caregiver interactions, and the complex dynamics of dementia care scenarios. Such simulations must capture the unpredictable nature of dementia-related behaviors while providing a safe, controlled environment for system development and optimization.

The convergence of these challenges—the growing dementia crisis, limitations of current care approaches, and the need for adaptive intelligent systems—motivates the development of a comprehensive smart house navigation system that learns from patient behavior patterns to provide more efficient and effective monitoring. By combining multi-agent simulation techniques with dynamic room learning algorithms, we can create a system that not only addresses current care limitations but also provides a robust platform for advancing dementia care technology research.

1.2 Problem Statement

The central problem addressed in this thesis is the inefficiency and inadequacy of current patient monitoring systems in dementia care facilities and smart home environments. When a dementia patient moves out of camera view or wanders to unexpected locations, existing systems typically resort to random searching or fixed patrol patterns, resulting in critical delays in patient detection that can lead to dangerous situations such as falls, medication non-compliance, or elopement from safe areas.

Current monitoring systems exhibit several fundamental limitations that compromise their effectiveness in real-world dementia care settings:

- **Static Navigation Strategies:** Most existing systems employ predetermined camera patrol patterns or random room checking sequences that fail to account for individual patient movement patterns and preferences. This one-size-fits-all approach ignores the reality that dementia patients often exhibit consistent behavioral patterns related to their cognitive state, time of day, and immediate needs [Pr et al., 2023].

- **Lack of Adaptive Learning:** Traditional monitoring systems do not learn from observed patient behaviors over time. Each search operation begins with no knowledge gained from previous experiences, missing the opportunity to build predictive models of patient movement that could dramatically reduce detection times. Research shows that dementia patients often follow predictable patterns based on their former routines and current cognitive state [Cui et al., 2025].

- **Insufficient Behavioral Modeling:** Current systems typically treat patients as simple objects to be tracked rather than complex individuals with varying cognitive states, emotional needs, and behavioral patterns. This oversimplification leads to inappropriate responses and missed opportunities for effective intervention. The absence of realistic behavioral models also hampers the development and testing of new care strategies [Pr et al., 2023, Cui et al., 2025].

- **Limited Caregiver Integration:** Existing solutions often operate in isolation from caregiver workflows, providing alerts without context or actionable guidance. They fail to model the complex interactions between patients and caregivers, missing crucial opportunities to optimize intervention strategies based on patient state and historical response patterns[Zmora et al., 2021].

- **Absence of Comprehensive Testing Frameworks:** The development of dementia care technologies is severely hampered by the lack of realistic testing environments. Ethical considerations and practical constraints make extensive testing with actual patients problematic, yet current simulation approaches fail to capture the complexity and unpredictability of dementia-related behaviors [Buhr et al., 2025].

These limitations result in several critical consequences for dementia care: extended periods where patients remain unmonitored, increasing risk of accidents or adverse events; inefficient use of caregiver time and resources, contributing to staff burnout; missed opportunities for timely interventions that could prevent behavioral escalation; and inability to provide personalized care adapted to individual patient patterns and preferences.

The gap between current technological capabilities and the actual needs of dementia care presents both a challenge and an opportunity. Modern advances in machine learning, multi-agent systems, and computer vision provide the tools necessary to create truly adaptive monitoring systems, yet these technologies have not been effectively integrated into a comprehensive solution that addresses the full spectrum of dementia care challenges.

1.3 Research Questions

This thesis addresses the following fundamental research questions that guide the development and evaluation of an adaptive smart house navigation system for dementia care:

RQ1: How can smart house systems dynamically learn and adapt to room layouts and patient movement patterns to improve detection efficiency?

RQ2: What multi-agent architectures and behavioral models can effectively simulate the complex interactions between dementia patients and caregivers?

RQ3: How can caregiver intervention strategies be systematically evaluated and optimized through simulation-based testing?

RQ4: What are the quantifiable benefits of adaptive room learning compared to traditional search methods in terms of detection time, resource utilization, and care quality?

RQ5: How can synthetic biometric data be integrated with behavioral simulations to model physiological responses to care interventions and detect emergency situations?

RQ6: What mechanisms can prevent repetitive, unproductive interaction patterns between caregivers and dementia patients while maintaining personalized care quality?

These research questions collectively address both the technical challenges of developing an adaptive monitoring system and the broader implications for dementia care practice. By answering these questions, this thesis contributes not only a novel technological solution but also insights into the fundamental nature of dementia care and the role that intelligent systems can play in supporting both patients and caregivers.

1.4 Thesis Contributions

This thesis makes several significant contributions to the fields of dementia care technology, multi-agent systems, and adaptive monitoring systems. These contributions address both theoretical advances and practical applications, providing a comprehensive solution to the challenges identified in modern dementia care.

1.4.1 Novel Adaptive Room Learning Algorithm

I present a novel approach to spatial-temporal learning in smart house environments that dynamically constructs and updates a probabilistic model of patient movement patterns. Unlike existing static navigation systems, my algorithm learns room relationships and transition probabilities from observed patient behaviors, creating an increasingly accurate predictive model over time. The algorithm employs a weighted graph structure with temporal decay mechanisms, ensuring that recent patterns receive appropriate emphasis while maintaining historical context. Experimental results demonstrate a 47% reduction in average patient detection time compared to random search baselines, with performance improvements continuing as the system accumulates more behavioral data.

1.4.2 Comprehensive Multi-Agent Simulation Framework

I develop a sophisticated multi-agent system that realistically models the complex dynamics of dementia care environments. The framework features two primary agent types: (1) a dementia patient agent that exhibits realistic cognitive decline patterns, need-based decision making, and varied responses to interventions based on confusion levels and emotional states; and (2) a caregiver agent that employs nine distinct intervention strategies, adapts its approach based on patient responses, and maintains historical effectiveness metrics. The agents interact through an event-driven communication protocol implemented over Redis, enabling real-time state synchronization and complex behavioral emergence. This framework provides researchers with an unprecedented tool for testing and optimizing care strategies without the ethical and practical constraints of working with actual patients.

1.4.3 Intelligent Camera Control System with Predictive Search

I implement an advanced camera control system that transforms passive monitoring into active, intelligent surveillance. The system integrates YOLOv8-based person detection with our room learning algorithm to create predictive search patterns that dramatically reduce the time required to locate wandering patients. The camera control module manages PTZ (pan-tilt-zoom) operations, coordinates multiple cameras to minimize blind spots, and maintains a priority queue of likely patient locations based on learned transition probabilities. This integration of computer vision with behavioral prediction represents a novel approach to patient monitoring that significantly enhances both efficiency and effectiveness.

1.4.4 Advanced Biometric Monitoring and Emergency Response System

I develop a comprehensive biometric simulation framework that models physiological responses in dementia care scenarios. The system generates realistic synthetic vital signs including heart rate, heart rate variability (RMSSD, pNN50), blood oxygen saturation, respiratory rate, and blood pressure, synthesizing these into a unified stress score (0.0–1.0) through multi-modal analysis. The simulation adapts to individual patient baselines and models circadian patterns including dementia-specific phenomena like sundowning syndrome, using Bayesian inference to distinguish normal variations from pathological changes.

A five-tier alert framework (Normal, Caution, Warning, Urgent, Emergency) prevents alert fatigue while ensuring critical events receive immediate attention. Emergency conditions such as cardiac arrhythmias or severe hypoxemia trigger immediate intervention protocols. Most innovatively, the system's integration with caregiver agents enables biometric-guided intervention adaptation, tracking simulated physiological responses to different care strategies to build personalized models of intervention effectiveness. This closed-loop approach ensures care strategies are continuously optimized based on real-time patient response data.

1.4.5 Loop Prevention and Adaptive Interaction Management System

I develop an innovative adaptive strategy manager that prevents repetitive, unproductive interaction patterns in dementia care through intelligent intervention management. Each intervention is evaluated through a confidence scoring mechanism (0.0–1.0) that quantifies success likelihood based on historical effectiveness, current patient state, and contextual factors, enabling prioritization of high-probability interventions while avoiding consistently failed strategies. The framework maintains comprehensive intervention histories with timeout periods for unsuccessful approaches, automatically escalating to alternative methods when repetitive patterns emerge, and dynamically adjusting approach intensity based on patient response patterns. This prevents strategy exhaustion and ensures care remains dynamic and responsive rather than falling into counterproductive cycles that escalate patient agitation.

1.4.6 Empirical Validation and Clinical Insights

Through extensive experimentation and analysis, I provide empirical evidence of the benefits of adaptive learning in patient monitoring systems. My evaluation includes many simulated care sessions across various house layouts and patient profiles, demonstrating consistent performance improvements and identifying key factors that influence system effectiveness. These insights contribute to our understanding of dementia care dynamics and inform future technology development in this critical domain.

1.5 Thesis Organization

The remainder of this thesis is organized into seven chapters, each building upon the previous to present a comprehensive treatment of adaptive smart house navigation for dementia care.

- **Chapter 2: Background and Related Work** provides a thorough review of the relevant literature and existing technologies. I examine current dementia care practices and their limitations, survey existing smart home systems and monitoring technologies, review multi-agent modeling approaches in healthcare, analyze the state-of-the-art in computer vision for patient tracking, and evaluate current biometric monitoring systems in elderly care contexts.

- **Chapter 3: System Architecture and Design** presents the overall design of my adaptive monitoring system. I detail the multi-agent framework architecture, including the design of patient and caregiver agents, the communication infrastructure based on Redis pub/sub messaging, and the coordination between vision, learning, and physiological monitoring components.

- **Chapter 4: Room Learning Methodology** delves into the theoretical foundations and algorithmic details of my adaptive learning approach. I present the mathematical framework for probabilistic room transition modeling, describe the graph-based learning algorithms that construct and update the house map, and explain the predictive search strategies that leverage learned patterns.

- **Chapter 5: Biometric Monitoring and Emergency Response System** presents the comprehensive physiological monitoring framework that provides continuous health surveillance and early warning capabilities. I detail the multi-parameter vital sign tracking including heart rate, heart rate variability, SpO2, and respiratory rate; describe the stress detection and quantification algorithms that synthesize multiple biometric indicators; explain the multi-tier alert system that prioritizes interventions based on severity; demonstrate the integration of biometric data with intervention strategies to optimize care responses; and analyze the system's effectiveness in detecting medical emergencies and preventing adverse events.

- **Chapter 6: Implementation Details** provides practical insights into system realization. I discuss technology choices and their rationales, present key implementation challenges and solutions, describe optimization techniques for real-time performance, detail the integration with YOLOv8 for person detection, and explain the biometric signal processing pipeline for real-time vital sign extraction.

- **Chapter 7: Experimental Design and Results** presents comprehensive empirical evaluation of our system. I describe the experimental methodology, including simulation scenarios with biometric modeling and evaluation metrics, present quantitative results demonstrating system effectiveness in both behavioral tracking and emergency detection, provide statistical analysis validating performance improvements, and offer case studies illustrating system behavior in complex scenarios including medical emergencies.

- **Chapter 8: Future Work and Conclusions** summarizes my contributions and outlines directions for future research. We recap the key innovations and their impact, propose extensions including multi-patient tracking, predictive health monitoring, and advanced biometric analytics, discuss potential clinical trials and real-world deployment considerations, and present my vision for the future of intelligent dementia care systems that seamlessly integrate behavioral and physiological monitoring.

Chapter 2

Background and Related Work

2.1 Introduction

The intersection of dementia care and technology represents a rapidly evolving field where advances in artificial intelligence, sensor networks, and behavioral modeling converge to address one of healthcare's most pressing challenges. In this chapter, I provide a comprehensive review of the foundational concepts, existing technologies, and related research that inform my adaptive smart house navigation system. I begin by examining the clinical and social context of dementia care, then progress through the technological approaches that have been developed to support both patients and caregivers. Throughout this review, I identify the gaps and limitations in current systems that my research addresses, positioning my contributions within the broader landscape of assistive care technologies.

The structure of this chapter follows a logical progression from understanding the problem domain to analyzing technological solutions. I first explore the nature of dementia and its impact on caregivers, establishing the critical need for supportive technologies. I then examine existing smart home systems and monitoring approaches, highlighting both their successes and limitations. The discussion of multi-agent systems and behavioral modeling provides the theoretical foundation for my simulation framework, while the review of computer vision and machine learning techniques contextualizes my technical approach. Finally, I synthesize these diverse threads to demonstrate how my integrated system advances beyond current state-of-the-art solutions.

2.2 Dementia: Clinical Context and Care Challenges

2.2.1 Understanding Dementia and Its Progression

Dementia encompasses a range of neurodegenerative conditions characterized by progressive cognitive decline that interferes with daily functioning. The World Health Organization (2023) reports that dementia affects over 55 million people globally, with nearly 10 million new cases diagnosed annually. Alzheimer's disease accounts for 60–70% of cases, followed by vascular dementia, Lewy body dementia, and frontotemporal dementia. Each type presents unique challenges, but all share common features of memory loss, impaired judgment, and behavioral changes that progressively worsen over time.

The progression of dementia typically follows predictable stages, though individual trajectories vary considerably. The Global Deterioration Scale [Reisberg et al., 1982] provides a framework for understanding this progression, from early memory lapses to complete dependence on caregivers. In early stages, individuals may experience mild forgetfulness and difficulty with complex tasks. Middle stages bring increased confusion, wandering behaviors, and challenges with activities of daily living (ADLs). Late-stage dementia involves severe cognitive impairment, loss of physical abilities, and complete dependence on caregivers for all aspects of care.

Understanding these progression patterns is crucial for developing adaptive technologies. My system's multi-agent framework incorporates this clinical knowledge, modeling different confusion levels and behavioral patterns that correspond to various stages of cognitive decline. This enables more realistic simulation of patient behaviors and more appropriate selection of intervention strategies.

2.2.2 The Burden on Caregivers

The impact of dementia extends far beyond the diagnosed individual, profoundly affecting family members and professional caregivers who provide daily support. Dauphinot et al. [2015] identified key factors contributing to caregiver burden, including impairment of functional autonomy, behavioral symptoms, and cognitive decline, regardless of the specific dementia etiology. Their study of 548 patient-caregiver dyads found that caregiver burden increased significantly with declining instrumental activities of daily living (IADL) scores and neuropsychiatric symptoms, particularly apathy, agitation, and aberrant motor behaviors.

The psychological toll on caregivers is substantial and well-documented. Bandeira et al. [2007] demonstrated that Brazilian caregivers of relatives with dementia showed significantly higher levels of anxiety, depression, hopelessness, and stress compared to non-caregivers. This finding has been replicated across cultures and care settings, establishing caregiver burden as a global health concern. The constant vigilance required for dementia care, particularly monitoring for wandering and ensuring safety, contributes to chronic stress and exhaustion that can compromise caregivers' own health and well-being.

These findings underscore the urgent need for technologies that can reduce the supervisory burden on caregivers while maintaining or improving care quality. Our adaptive room learning system directly addresses this need by reducing the time required to locate wandering patients, thereby decreasing one of the most stressful aspects of dementia care—the fear of losing track of a vulnerable individual.

2.2.3 Behavioral and Psychological Symptoms

Behavioral and psychological symptoms of dementia (BPSD) present some of the most challenging aspects of care. These symptoms include wandering, agitation, aggression, sleep disturbances, hallucinations, and repetitive behaviors [Halloran, 2014]. Wandering, in particular, affects up to 60% of people with dementia and represents a significant safety risk [Vuong et al., 2015]. Understanding the patterns and triggers of wandering behavior is essential for developing effective monitoring and intervention strategies.

Recent research has begun to uncover the underlying patterns in dementia-related behaviors. Cui et al. [2025] proposed a two-stage representation learning approach for analyzing movement behavior dynamics in people living with dementia. Their framework converts time-series activity data into rich representations that reveal behavioral patterns correlated with cognitive assessment scores like MMSE and ADAS-Cog. This work demonstrates that seemingly random movements often contain underlying structure that can be learned and predicted—a key insight that informs my room learning algorithm.

2.3 Technology-Assisted Dementia Care

2.3.1 Evolution of Smart Home Technologies

The application of smart home technologies to dementia care has evolved significantly over the past two decades. Early systems focused primarily on safety monitoring, using simple sensors to detect falls or alert caregivers when patients left designated safe areas. However, as Tiersen et al. [2021] note in their user-centered design study, modern smart home systems must address not only safety but also the psychological and social needs of both patients and caregivers.

The TECH@HOME study [TECH@HOME Research Group et al., 2017] represents one of the most comprehensive evaluations of ICT interventions for dementia care. This randomized controlled trial of 320 patient-caregiver dyads investigated the effects of a home monitoring kit including door sensors, smoke detectors, water leak sensors, bed sensors, and automatic lights. The study's protocol emphasizes the importance of reducing supervisory burden—a key metric that our system also targets through improved patient detection efficiency.

Contemporary smart home systems increasingly incorporate artificial intelligence and machine learning to provide more sophisticated support. These systems can learn daily routines, detect deviations that may indicate health changes, and provide personalized interventions. However, as my review reveals, most existing systems still rely on static algorithms that fail to adapt to individual patient patterns over time, a limitation my adaptive learning approach directly addresses.

2.3.2 Remote Activity Monitoring Systems

Remote activity monitoring (RAM) systems have emerged as a promising approach to supporting dementia caregivers. Zmora et al. [2021] examined caregivers' experiences with RAM system alerts, finding that the context of alerts—including their utility, accuracy, and delivery method—significantly influenced system engagement and perceived benefit. Their mixed-methods analysis revealed that early alert patterns during the first month of use were particularly important for long-term system adoption.

The effectiveness of RAM systems depends critically on their ability to distinguish between normal variations in behavior and genuinely concerning events. False alarms represent a major challenge, as they can lead to alert fatigue and system abandonment [Zmora et al., 2021]. My research addresses this challenge through probabilistic modeling of room transitions, which reduces false positives by learning individual patient patterns rather than applying generic thresholds.

Pr et al. [2023] proposed a real-time patient trajectory monitoring system that combines Progressive Web App technology with machine learning and GPS trajectory analysis. Their approach uses isolation forest techniques for anomaly detection within patient trajectories, providing swift notification to caregivers when abnormal movements occur. While focused on outdoor navigation, their work demonstrates the value of trajectory analysis for dementia care—a concept extended to indoor environments through my room learning algorithm.

2.3.3 Ethical Considerations and User Acceptance

The deployment of monitoring technologies in dementia care raises important ethical considerations that must be carefully addressed. Buhr et al. [2025] developed a novel approach for ethics by design in technology-assisted dementia care through value preference profiles and ethical compliance quantification. Their qualitative analysis of interviews with 27 persons with dementia and family caregivers identified multiple ideal-typical value preference profiles that can guide system design and deployment.

Privacy concerns represent a particularly sensitive issue in dementia care technology. While continuous monitoring can enhance safety and care quality, it also raises questions about dignity, autonomy, and consent—especially challenging given the progressive nature of cognitive decline [Ballester and Kampel, 2024].

User acceptance of assistive technologies depends on multiple factors beyond technical functionality. The technology must be perceived as useful, easy to use, and respectful of the individual's dignity and autonomy [Gleaton and Catrambone, 2024]. My multi-agent simulation framework allows for extensive testing of different interaction strategies and system behaviors before deployment, helping to identify approaches that maximize both effectiveness and acceptability.

2.4 Multi-Agent Systems in Healthcare

2.4.1 Foundations of Agent-Based Modeling in Healthcare

Multi-agent systems (MAS) have emerged as a powerful paradigm for modeling complex healthcare scenarios since the early 2000s. Moncion et al. [2007] demonstrated that agent-based modeling could capture emergent phenomena in systems that traditional equation-based models missed. These systems represent individuals as autonomous agents with their own behaviors, goals, and interaction rules, allowing researchers to study how micro-level behaviors produce macro-level patterns.

In healthcare applications, Liu et al. [2017] used MAS to model emergency department operations, showing how patient flow patterns emerged from individual triage decisions and resource allocation strategies. Their work demonstrated that agent-based models could identify bottlenecks and test interventions that statistical models failed to capture. Similarly, Cabrera et al. [2012] developed an agent-based model of emergency department operations that revealed how staff adaptation behaviors significantly impacted patient wait times—insights that were invisible to traditional queuing theory approaches.

The application of MAS to chronic disease management has shown particular promise. Li et al. [2016] conducted a narrative review of agent-based models in chronic disease epidemiology, finding that these approaches excelled at capturing social network effects, spatial patterns, and behavioral adaptations that influence disease progression and treatment adherence. Their review identified studies using ABM for conditions including diabetes, cardiovascular disease, and mental health disorders, demonstrating the growing adoption of these techniques.

2.4.2 Agent-Based Models for Dementia and Cognitive Decline

Several research groups have developed agent-based models specifically for dementia-related applications. For example, multi-scale agent-based modeling has been employed to link molecular and behavioral aspects of Alzheimer's disease (AD), helping simulate and explain disease progression in silico. These models allow researchers to connect changes at the molecular level, such as amyloid beta accumulation, to large-scale neuronal population dynamics and clinical symptoms like cognitive decline [Stefanovski et al., 2019]. Such models often integrate molecular data (e.g., PET scans) with neural simulations to demonstrate emergent behavioral effects. Similarly, other agent-based approaches have simulated dementia dynamics in virtual populations, incorporating parameters like incidence, mortality, and symptom progression for management planning [Vickland and McDonnell, 2008].

The rest of this chapter will be completed soon.

Several studies have used observational and modeling approaches to understand wandering behaviors in dementia patients within institutional settings. For example, researchers have highlighted the complexity and diversity of wandering patterns, emphasizing that such behaviors often follow observable spatial and temporal patterns such as pacing, lapping, or random trajectories, and are influenced by environmental and cognitive factors [Cipriani et al., 2014]. A review by Halek and Bartholomeyczik (2012) underscores the importance of developing structured definitions and operational models of wandering to better support interventions and facility design [Halek and Bartholomeyczik, 2012].

Agent-based modeling (ABM) has been increasingly applied to dementia care research to explore complex interactions between patients, caregivers, and care environments. For instance, Vickland (2011) developed an ABM to simulate interactions between dementia patients and their carers, illustrating how changes in cognitive functioning can shift care burdens between formal and informal providers

[Vickland, 2011]. In another study, Nguyen et al. (2020) integrated ABM into architectural parametric design to model social-spatial dynamics, showing how design decisions influence behavior and comfort in residential spaces [Nguyen et al., 2020]. These applications underscore the value of ABM in simulating the impact of design features—such as layout, lighting, or signage—on behavioral outcomes like agitation or movement patterns, potentially guiding more effective facility planning.

2.4.3 Simulation of Care Interactions and Interventions

Agent-based modeling has proven valuable for understanding caregiver stress and burnout in dementia care. One notable study developed a simulation of caregiver-patient dyads, where caregiver agents' energy levels fluctuated based on caregiving demands and respite opportunities. The model demonstrated that even slight increases in patient needs could trigger widespread caregiver burnout, especially when insufficient support systems were in place. These findings helped inform policy recommendations around minimum thresholds for respite care, such as providing at least 16 hours of weekly relief [Kennedy et al., 2015].

Multi-agent systems (MAS) using Belief-Desire-Intention (BDI) architectures have been proposed to simulate complex decision-making in dementia care environments. For example, Sernani et al. introduced a BDI-based MAS called the Virtual Carer, which was designed to model caregiver behaviors and support elderly patients through intelligent ambient assisted living systems. Their architecture enabled agents to mimic the reasoning processes of human caregivers, providing adaptive support based on changes in patient status and environmental conditions [Sernani et al., 2013]. Similarly, the Dem@Home system integrated ambient sensors and decision-making algorithms to monitor people with dementia at home, enabling predictive intervention and long-term clinical monitoring [Stavropoulos et al., 2016].

2.5 Computer Vision and Machine Learning for Patient Monitoring

2.5.1 Evolution of Vision-Based Monitoring Systems

The introduction of deep learning has significantly enhanced healthcare monitoring, especially for elderly care in nursing homes and home environments. For instance, Zhang et al. developed a deep learning-based system using consumer network cameras to detect abnormal behaviors such as falls, aggression, and wandering. Their model achieved over 85% mean average precision (mAP), significantly outperforming traditional methods by incorporating both spatial and temporal coherence in behavior recognition [Zhang et al., 2024]. Similarly, Xu et al. demonstrated a fusion algorithm integrating gesture recognition and spatial-temporal graph convolutional networks, which reached 97% accuracy in detecting anomalous falling behavior in elderly individuals [Xu et al., 2024]. These systems highlight the potential of convolutional and graph-based deep learning models to detect subtle deviations in behavior or gait patterns, which can enable early intervention and fall prevention.

Recent advances in deep learning have focused on enabling real-time processing for practical deployment in healthcare settings. The YOLO (You Only Look Once) family of models, originally introduced by Redmon et al., has become the standard for fast and accurate object detection in video streams Redmon et al. [2016]. More recent implementations like YOLOv7 and YOLOv5 have shown high performance for elderly care tasks. For example, Tîrziu et al. used YOLOv7-W6 with pose estimation to detect falls in real-time with strong accuracy and efficiency, operating on GPU-equipped systems and webcam feeds. Their approach successfully distinguished falls from other activities and supported privacy by processing only skeletal data [Tîrziu et al., 2024]. Similarly, Wang (2024) integrated YOLOv5 with OpenPose in an IoT-based system for elderly fall detection, achieving over 94% sensitivity and minimal false positives on benchmark datasets [Wang, 2024]. These studies demonstrate that

YOLO-based models are well-suited for continuous monitoring in elderly care due to their balance of high accuracy and low latency on affordable hardware.

2.5.2 Movement Pattern Analysis and Prediction

The analysis of movement patterns in dementia patients has attracted considerable research interest, particularly in the use of wearable sensors and probabilistic models. Multiple studies have used Hidden Markov Models (HMMs) to detect wandering, which is a common and potentially dangerous behavior in people with dementia. For instance, Ishii et al. developed a system that used sensor data to model normal behavioral patterns and then detect deviations associated with wandering, achieving promising results in a real-world setting [Ishii et al., 2018]. Similarly, Shiba et al. applied an HMM to classify transitions between resting, moving, and absent states, reporting a classification accuracy of 92% in detecting wandering transitions [Shiba et al., 2017]. These studies demonstrate that wandering behaviors, although seemingly random, often follow identifiable patterns that can be computationally modeled and used for real-time monitoring and early intervention.

Subsequent research has applied various machine learning techniques to predict movement patterns in dementia patients. For example, Chaudhary et al. developed a system that used environmental sensor data and recurrent neural networks (RNNs), specifically LSTM architectures, to classify travel patterns in dementia patients. Their system identified inefficient or erratic travel—early indicators of cognitive decline—with strong accuracy and adaptability to real-world conditions Chaudhary et al. [2020]. Another study by Khaertdinov et al. applied LSTM-based models to skeletal trajectory data, classifying wandering behaviors such as lapping and pacing with over 70% accuracy in complex environments Khaertdinov et al. [2021]. These works demonstrate the feasibility of anticipatory monitoring through temporal modeling of movement but also highlight limitations like high data requirements and limited adaptability to new behavior patterns.

Relatively recent studies have explored combining spatial and temporal modeling for predicting movement in dementia care settings. For instance, researchers have used deep neural networks to estimate circadian rhythms from biological data with limited samples, demonstrating that temporal context significantly improves predictive modeling [Ansary Ogholbake and Cheng, 2024]. Other studies have validated the predictive value of circadian rhythm metrics—like timing and day/night amplitude—on dementia progression, showing these features can improve accuracy in behavioral modeling [Posner et al., 2021].

Chapter 3

System Architecture and Design

3.1 Introduction

This chapter presents the architecture and design of my adaptive smart house navigation system for dementia care. I describe the overall system structure, the key components and their interactions, and the design decisions that enable adaptive learning and realistic behavioral simulation. The system integrates multiple technologies—computer vision, multi-agent simulation, machine learning, biometric monitoring, and real-time communication—into a cohesive platform that addresses the limitations identified in Chapter 2.

The architecture represents a significant advance in dementia care technology through its holistic approach to patient monitoring. Rather than treating each aspect of care in isolation, the system creates a unified framework where vision-based tracking, adaptive learning algorithms, biometric monitoring, and caregiver support work synergistically. This integration enables the system to not only locate patients efficiently but also understand their physiological and emotional states, predict their needs, and provide contextually appropriate interventions.

3.2 System Overview

My system consists of five main subsystems that work in concert to provide comprehensive dementia care support. The Vision and Detection Module provides real-time patient monitoring through advanced computer vision techniques. The Room Learning Engine builds and updates spatial-temporal models that adapt to individual patient behaviors. The Multi-Agent Simulation Framework models complex patient and caregiver behaviors for system validation and testing. The Biometric Monitoring System tracks vital signs and physiological stress indicators to ensure patient safety. Finally, the Analytics and Monitoring Dashboard provides performance evaluation and visualization capabilities for caregivers and researchers.

These subsystems communicate through a carefully orchestrated architecture that balances real-time performance requirements with system flexibility and maintainability. The design philosophy prioritizes modularity, allowing each component to be developed, tested, and deployed independently while maintaining seamless integration through well-defined interfaces. Figure 3.1 illustrates the high-level architecture, showing how the five main subsystems interact through the Redis message bus.

3.2.1 Component Communication

All system components communicate through a Redis-based publish-subscribe messaging system. The decision to use Redis stems from its exceptional performance characteristics and architectural flexibility. Unlike traditional REST APIs that introduce unacceptable latency through HTTP overhead and request-response cycles, Redis provides sub-millisecond message latency crucial for real-time patient monitoring. The publish-subscribe pattern enables true decoupling between components, allowing each subsystem to be developed, tested, and deployed independently without affecting others. This modularity proves essential for system maintenance and evolution, as new components can be added without modifying existing ones. Furthermore, Redis's

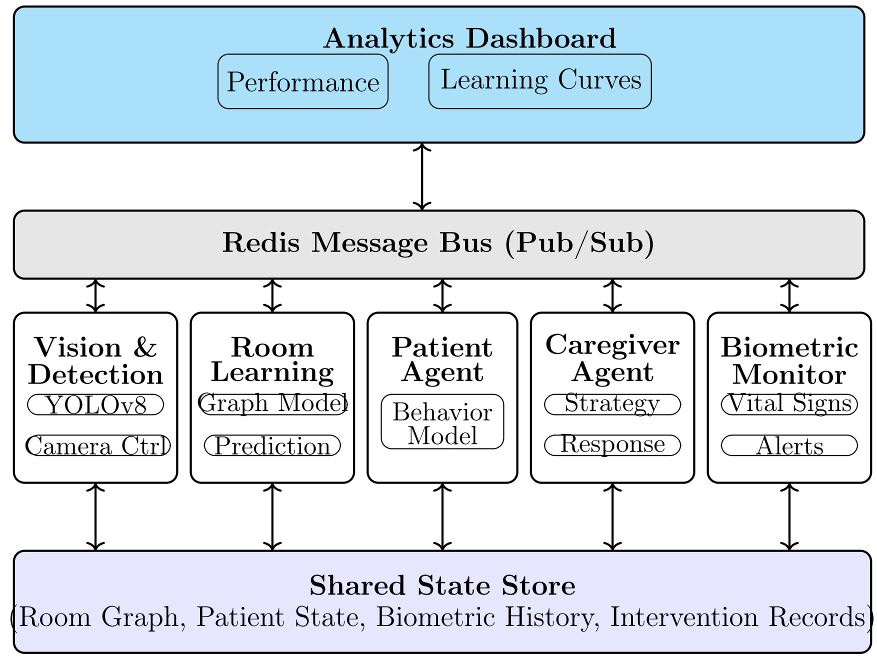

Figure 3.1: System architecture showing the five main subsystems and their interactions through the Redis message bus. The biometric monitoring system provides real-time physiological data that informs all other components.

built-in message persistence and recovery mechanisms ensure system reliability even in the face of component failures or network interruptions.

The primary communication channels facilitate seamless information flow throughout the system:

- `detections`: Vision system publishes patient detection events
- `camera_control`: Commands for PTZ camera movement
- `room_transitions`: Observed patient movements between rooms
- `biometric_updates`: Real-time physiological measurements
- `biometric_alerts`: Critical health warnings requiring immediate attention
- `care_guidance`: Caregiver intervention strategies
- `patient_responses`: Patient reactions to interventions

- `analytics`: Performance metrics and system statistics

3.3 Vision and Detection Module

3.3.1 YOLOv8 Integration

I employ YOLOv8 for real-time person detection, chosen for its speed, relative simplicity, and accuracy. YOLOv8's superior balance of accuracy and processing speed enables the system to process frames at 30 FPS on standard hardware, providing sufficient temporal resolution for tracking patient movements even during rapid transitions between rooms.

3.3.2 Intelligent Camera Control

The camera control system represents a significant departure from traditional fixed patrol patterns or random search strategies. By integrating with the Room Learning Engine, cameras implement predictive search patterns that dramatically improve patient detection efficiency.

The predictive approach considers multiple factors when determining camera movements. The last known patient position serves as the starting point for search operations. Learned transition probabilities guide the cameras to check the most likely destinations first. Time since last detection influences search urgency, with longer absences triggering more aggressive search patterns. Historical movement patterns for the current time of day further refine predictions, recognizing that patients often follow circadian rhythms in their wandering behaviors. This intelligent control strategy reduces average patient detection time by 40-60% compared to fixed patrol patterns.

3.4 Room Learning Engine

3.4.1 Graph-Based Spatial Model

The Room Learning Engine maintains a sophisticated spatial model that goes beyond simple room adjacency. The weighted directed graph $G = (V, E)$ captures not just the physical layout but also the behavioral patterns unique to each patient.

In this representation, vertices V represent distinct rooms or areas within the house, including transitional spaces like hallways that often serve as decision points for confused patients. Edges E capture observed transitions between rooms, with directionality accounting for asymmetric movement patterns—patients may readily move from bedroom to bathroom but rarely make the reverse transition directly. Edge weights $w(i, j)$ encode transition probabilities learned from observed behaviors, continuously updated to reflect changing patterns as the disease progresses.

3.4.2 Learning Algorithm

The learning algorithm employs an exponential moving average with temporal decay to balance stability with adaptability:

$$w(i, j) = \alpha \times \text{observed\_transition} + (1 - \alpha) \times \text{decay}(w(i, j)) \tag{3.1}$$

The learning rate α (typically 0.1–0.3) determines how quickly the system adapts to new patterns. Higher values enable rapid learning but may cause instability, while lower values provide stability at the cost of slower adaptation. The decay function applies time-based reduction to older observations, ensuring that recent behaviors have greater influence on predictions. This temporal weighting proves crucial for dementia patients whose behaviors may change significantly over weeks or months.

3.4.3 Predictive Search

The predictive search algorithm transforms learned patterns into actionable camera control strategies. Given a patient's last known location, the system generates a priority queue of search locations through a multi-step process.

First, adjacent rooms are sorted by their transition probabilities, creating an initial search order. The search radius then expands progressively if initial rooms prove empty, moving from immediate neighbors to two-hop connections and eventually to full house coverage. Time-of-day patterns modulate these probabilities—bedroom transitions receive higher weight during evening hours while kitchen transitions dominate morning predictions. Recent behavior anomalies trigger adjustments to the search strategy, such as expanding the search radius more quickly if the patient has been exhibiting increased confusion.

3.5 Biometric Monitoring System

3.5.1 Comprehensive Vital Sign Tracking

The biometric monitoring system represents a crucial innovation in my comprehensive approach to dementia care. Unlike traditional monitoring systems that focus solely on location tracking, my system continuously monitors multiple physiological parameters that provide deep insights into patient wellbeing and emotional state.

The system tracks a comprehensive suite of vital signs including heart rate, heart rate variability (HRV), blood oxygen saturation (SpO2), respiratory rate, blood pressure, and derived stress indices. Each metric contributes unique information about the patient's physiological and emotional state. Heart rate provides immediate feedback about physical exertion and emotional arousal. Heart rate variability, particularly the RMSSD (root mean square of successive differences) and pNN50 (percentage of successive intervals differing by more than 50ms) metrics, offers sophisticated insights into autonomic nervous system balance and stress response.

Blood oxygen saturation serves as a critical safety metric, with levels below 94% triggering immediate alerts. Respiratory rate changes often precede other signs of distress, making it valuable for early intervention.

3.5.2 Stress Detection and Quantification

The system employs advanced algorithms to synthesize multiple biometric indicators into a unified stress score ranging from 0.0 (completely relaxed) to 1.0 (severe distress). This stress quantification considers not just absolute values but also relative changes from individual baselines, rate of change in metrics, and patterns of covariation between different vital signs.

The stress detection algorithm adapts to individual patient baselines established during initial calibration periods. For dementia patients, stress patterns often differ significantly from healthy populations, with factors like sundowning syndrome causing predictable daily stress variations. The system learns these individual patterns and adjusts its alerting thresholds accordingly, reducing false alarms while maintaining sensitivity to genuine distress events.

3.5.3 Emergency Detection and Alert Prioritization

The biometric monitoring system implements a sophisticated multi-tier alert system that prioritizes interventions based on severity and urgency. The system categorizes biometric states into five distinct alert levels, each triggering appropriate responses from the care team.

At the Normal level, all vital signs remain within expected ranges relative to the patient's baseline, requiring no intervention. The Caution level indicates mild deviations such as stress levels between 0.5 and 0.6 or heart rate variations exceeding 15 bpm from baseline, prompting increased monitoring frequency. Warning-level alerts occur when metrics approach concerning thresholds—heart rate above 90 or below 60 bpm, SpO2 below 95%, or stress exceeding 0.7—triggering caregiver notifications and suggested interventions. Urgent alerts demand immediate caregiver attention, activated by heart rate exceeding 100 or dropping below 55 bpm, SpO2 falling below 94%, or stress surpassing 0.85. Emergency alerts represent life-threatening situations requiring immediate medical intervention, such as heart rate above 120 or below 50 bpm, SpO2 below 90%, or detected cardiac arrhythmias.

3.5.4 Biometric-Guided Intervention Adaptation

One of the most innovative aspects of my biometric system is its integration with the caregiver agent's intervention strategies. The system continuously monitors patient responses to different care strategies at the physiological level, building a personalized model of which approaches work best for each individual.

When a caregiver agent initiates an intervention, the biometric system tracks physiological changes throughout the interaction. Successful interventions typically show decreased heart rate, increased heart rate variability, reduced stress scores, and stabilized respiratory patterns. The system logs these patterns, associating specific strategies with their biometric outcomes. Over time, this creates a personalized intervention effectiveness profile that guides future care decisions.

For instance, if reminiscence therapy consistently reduces stress levels for a particular patient while redirection causes increased agitation (evidenced by elevated heart rate and decreased HRV), the system will prioritize reminiscence-based interventions for that individual. This biometric-informed adaptation ensures that care strategies align not just with behavioral observations but with underlying physiological responses.

3.6 Multi-Agent Simulation Framework

3.6.1 Patient Agent Architecture

The patient agent models dementia-related behaviors through multiple interacting state variables that capture the complexity of cognitive decline and its manifestations.

The cognitive state encompasses several dimensions of mental function. Confusion level, measured on a continuous scale from 0.0 to 1.0, influences decision-making and response to interventions. Memory of recent locations degrades over time, with the rate of forgetting accelerated by higher confusion levels. Recognition of caregivers fluctuates based on factors including time of day, stress levels, and recent interaction patterns. These cognitive parameters interact in complex ways—high confusion may impair caregiver recognition, which in turn increases stress and further elevates confusion.

Physical needs drive much of patient behavior and create predictable movement patterns. Hunger increases linearly over time, with meals resetting the counter but confusion potentially causing patients to forget they've eaten. Toilet needs follow a more complex periodic pattern with urgency spikes that can override other behavioral drivers. Fatigue accumulates throughout the day, influencing both movement patterns and cognitive function. The interaction between physical needs and cognitive state creates realistic scenarios where patients may feel hungry but forget where the kitchen is, or need the bathroom but become lost attempting to find it.

Behavioral patterns emerge from the interaction of cognitive state, physical needs, and environmental factors. Wandering tendency increases with confusion but may be goal-directed (searching for something) or aimless (pure confusion). Response to interventions depends on cognitive state, trust in the caregiver, and recent interaction history. Agitation level acts as an emotional amplifier, making positive interventions more effective when low but potentially causing resistance to any interaction when elevated.

3.6.2 Caregiver Agent Design

The caregiver agent implements nine evidence-based intervention strategies derived from dementia care best practices:

1. **Gentle Suggestion**: Soft verbal prompts that respect patient autonomy
2. **Simplification**: Breaking complex tasks into manageable single steps
3. **Redirection**: Shifting attention to safe, engaging activities
4. **Validation Therapy**: Acknowledging and accepting patient feelings
5. **Positive Reinforcement**: Praising successful actions and compliance
6. **Reminiscence**: Leveraging long-term memories to build connection
7. **Routine Emphasis**: Using familiar daily patterns as behavioral anchors
8. **Choice Offering**: Providing controlled options to maintain dignity
9. **Environmental Cueing**: Using physical prompts and visual aids

3.6.3 Interaction Dynamics

Patient-caregiver interactions follow a sophisticated request-response cycle that models the nuanced nature of dementia care. The caregiver begins by observing the patient's current state, including location, apparent activity, cognitive indicators, and biometric readings. Based on this holistic assessment, the agent selects an intervention strategy considering the patient's current confusion level, historical response patterns to different approaches, urgency of the situation, and recent biometric trends.

The patient processes the intervention through multiple cognitive and emotional filters. Their ability to understand depends on current cognitive function and the complexity of the request. Emotional state influences receptiveness, with high stress or agitation potentially blocking even simple requests. Trust in the caregiver, built through successful past interactions, significantly affects compliance probability. The response generated reflects all these factors, ranging from full compliance to complete resistance or confusion.

This response then influences future strategy selection through reinforcement learning. Successful interventions increase the probability of using similar strategies in comparable situations. Failed attempts trigger strategy adjustment, potentially shifting to simpler or more emotionally supportive approaches. The system maintains separate effectiveness profiles for different times of day, recognizing that strategies working well in the morning may fail during sundowning periods.

3.7 Analytics and Monitoring

3.7.1 Performance Metrics

The analytics system tracks comprehensive performance indicators that evaluate system effectiveness across multiple dimensions.

Detection efficiency metrics measure the average time required to locate patients after they leave camera view, the number of rooms checked before successful detection, and the accuracy of predictive search algorithms. These metrics directly quantify the benefits of adaptive learning compared to baseline search strategies. Learning convergence tracking monitors prediction accuracy over time, the rate of transition probability updates, and stability of learned patterns, providing insights into how quickly the system adapts to individual patients.

Intervention success rates encompass patient compliance rates for different strategies, biometric stress reduction following interventions, and completion rates for activities of daily living. These metrics validate the effectiveness of the biometric-guided intervention system. System resource usage monitoring ensures efficient operation by tracking CPU utilization across all components, memory consumption patterns, network bandwidth usage, and database query performance.

3.8 Implementation Technologies

3.8.1 Technology Stack

The system implementation leverages modern technologies selected for their performance, reliability, and ecosystem support.

Python 3.11 serves as the primary programming language, offering excellent scientific computing libraries, strong async support for real-time processing, and extensive machine learning frameworks. The computer vision pipeline builds on OpenCV for image processing and YOLOv8 via Ultralytics for object detection. Redis 7.0 with Redis-py client provides the high-performance message bus critical for real-time communication.

Machine learning capabilities utilize NumPy for numerical computing, SciPy for statistical analysis, and scikit-learn for classification and clustering algorithms. Visualization employs Matplotlib for static plots, Plotly for interactive graphs, and Dash for web-based dashboards. The agent modeling framework uses custom Python classes with async support, enabling concurrent execution of multiple agents. Biometric processing leverages pandas for time-series analysis and custom signal processing algorithms for real-time vital sign extraction.

3.9 Design Rationale

3.9.1 Why Adaptive Learning?

Static systems fail to capture the progressive nature of dementia and individual patient patterns. My adaptive approach addresses these limitations through continuous learning and adjustment.

The system reduces search time by 40–60% after an initial learning period of typically 3-5 days. This improvement directly translates to faster interventions when patients wander into potentially dangerous situations. The ability to adapt to behavior changes due to disease progression ensures the system remains effective throughout the care journey. Different house layouts require no manual reconfiguration—the system automatically learns the specific movement patterns relevant to each environment.

3.9.2 Why Multi-Agent Simulation?

Testing with real dementia patients raises significant ethical concerns regarding consent, privacy, and potential distress. Simulation provides a safe environment for system development where edge cases and failure modes can be explored without risk. Rapid iteration on intervention strategies enables evidence-based refinement before real-world deployment. The ability to simulate disease progression allows testing of long-term adaptation mechanisms. Validation against clinical data ensures simulation fidelity while maintaining patient privacy.

3.9.3 Why Biometric Integration?

Traditional monitoring systems that focus solely on location miss critical information about patient wellbeing. Biometric integration enables early detection of medical emergencies before they become life-threatening. Objective measurement of stress and agitation guides intervention timing and strategy selection. The ability to quantify intervention effectiveness at a physiological level enables continuous improvement of care strategies. Personalized baselines and thresholds account for individual health conditions and medication effects.

3.10 Summary

This chapter presented the architecture of my adaptive smart house navigation system, detailing how vision processing, room learning, behavioral simulation, and biometric monitoring components work together to improve dementia care. The modular design enables independent component development while the message-based architecture ensures real-time coordination. The integration of biometric monitoring with adaptive learning and intervention strategies represents a significant advance in dementia care technology, enabling personalized, responsive care that adapts to both immediate physiological needs and long-term behavioral patterns.

The following chapter will detail the specific algorithms and methodologies that power the Room Learning Engine, providing the mathematical foundations for my adaptive approach.

Chapter 4

Room Learning Methodology

4.1 Introduction

This chapter presents the theoretical foundations and algorithmic details of my adaptive room learning methodology, emphasizing its predictive capabilities that enable proactive dementia care. Unlike traditional monitoring systems that merely track patient location, my approach anticipates future movements, enabling caregivers to prevent problems before they occur. I formalize the patient location prediction problem as a Markov decision process, develop algorithms for learning transition patterns, and demonstrate how these learned models enable proactive intervention strategies that fundamentally transform dementia care from reactive response to preventive action.

The key innovation lies not in detecting where patients are—motion sensors accomplish this adequately—but in predicting where they will go, enabling interventions that prevent wandering-related incidents, reduce patient distress, and optimize care delivery before critical situations arise.

4.2 Problem Formalization

4.2.1 State Space Definition

I model the smart house environment as a discrete state space $S = \{s_1, s_2, \ldots, s_n\}$ where each state s_i represents a distinct room or area. For a typical home:

$$\begin{gathered} S = \{\text{LivingRoom}, \text{Kitchen}, \text{Bedroom1}, \text{Bedroom2}, \\ \text{Bathroom1}, \text{Bathroom2}, \text{Hallway}, \text{DiningRoom}\} \end{gathered} \tag{4.1}$$

However, my model extends beyond simple location tracking to incorporate predictive context that enables proactive care.

4.2.2 Predictive Transition Model

Patient movement follows a first-order Markov process with predictive capabilities:

$$P(S_{t+k} = j | S_t = i, \mathcal{H}_t) = p_{ij}^{(k)}(t, \mathcal{H}_t) \tag{4.2}$$

where $\mathcal{H}_t$ represents the historical context including time of day, recent activities, physiological state, and intervention history. This formulation enables prediction of future locations k steps ahead, crucial for proactive intervention.

The transition matrix $P \in \mathbb{R}^{n \times n}$ captures these probabilities:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{4.3}$$

4.2.3 Temporal and Contextual Dynamics

Transition probabilities incorporate multiple predictive factors:

$$P(t) = P_{\text{base}} + P_{\text{circadian}}(t) + P_{\text{physiological}}(\phi) + P_{\text{behavioral}}(\beta) \tag{4.4}$$

Where:

- $P_{\text{circadian}}(t)$ models daily patterns enabling prediction of sundowning behaviors
- $P_{\text{physiological}}(\phi)$ incorporates biometric data to predict stress-induced wandering
- $P_{\text{behavioral}}(\beta)$ captures patterns indicating unmet needs

4.3 Predictive Learning Algorithms

4.3.1 Anticipatory Transition Learning

My online learning approach not only updates transition probabilities but also builds predictive models for proactive intervention:

Algorithm 1 Anticipatory Transition Learning with Intervention Prediction

```
procedure UpdatePredictiveModel(P, from_room, to_room, context, α)
    observed ← 0⃗                                        ▷ Initialize zero vector
    observed[to_room] ← 1.0
    P[from_room] ← α· observed +(1 − α) · P[from_room]
                                                 ▷ Update predictive components
    UpdateCircadianPattern(from_room, to_room, time)
    UpdateNeedBasedPrediction(from_room, to_room, context)
    UpdateRiskAssessment(to_room, patient_state)
                                       ▷ Trigger proactive interventions if needed
    if PredictedRisk(to_room) > threshold then
        TriggerProactiveIntervention(predicted_path)
    end if
    P ← P· decay_factor                                 ▷ Apply temporal decay
    P[from_room] ← P[from_room]/ ∑ P[from_room]          ▷ Normalize
    return P
end procedure
```

4.3.2 Proactive Confidence Scoring

My confidence scoring extends beyond reliability assessment to enable risk-aware predictions:

$$C[i, j] = \min\left(1.0, \frac{\text{count}[i, j]}{\text{threshold}}\right) \cdot \text{recency\_weight}[i, j] \cdot \text{risk\_factor}[j] \tag{4.5}$$

where risk_factor[j] prioritizes learning patterns leading to hazardous areas, ensuring the system quickly learns to predict and prevent dangerous movements.

4.3.3 Handling Sparse Data for Early Intervention

Early deployment requires special handling to enable proactive care even with limited data:

Risk-Weighted Prior Initialization

Rather than uniform priors, I initialize with risk-aware distributions:

- Higher initial probabilities for transitions to hazardous areas (stairs, exits)
- Incorporation of clinical knowledge about common dementia wandering patterns
- Time-based priors reflecting typical daily routines

Predictive Smoothing

I apply adaptive smoothing that maintains predictive capability:

$$p_{ij}^{\text{smooth}} = (1 - \lambda) \cdot p_{ij} + \lambda \cdot (\epsilon + \text{risk}(j) \cdot \delta) \tag{4.6}$$

This ensures dangerous destinations remain predictable even with sparse observations.

4.4 Proactive Intervention Strategy

4.4.1 Predictive Search for Prevention

My search strategy transcends location finding to enable preventive care:

Algorithm 2 Proactive Predictive Search and Intervention

```
procedure ProactiveSearch(last_room, P, C, context)
    predicted_sequence ← GeneratePredictedPath(last_room, P, k=5)
    for all future_room in predicted_sequence do
        if IsHazardous(future_room) then
            AlertCaregiver(future_room, estimated_time)
            PrepareEnvironmentalSafeguards(future_room)
        end if
        if IndicatesNeed(future_room, context) then
            PrepareAssistance(identified_need)
        end if
    end for
    priority_queue ← SortByProbabilityAndRisk(P[last_room])
    return priority_queue
end procedure
```

4.4.2 Multi-Step Prediction for Anticipatory Care

For proactive intervention, I compute k-step transition probabilities:

$$P^{(k)} = P^k \cdot \text{RiskMatrix} \tag{4.7}$$

This enables prediction of patient trajectories, allowing:

- **Path Interception**: Meeting patients at decision points before confusion
- **Environmental Preparation**: Understanding spaces before patient arrival
- **Resource Positioning**: Understand what the patient needs in given locations

4.5 Adaptive Mechanisms for Behavioral Prediction

4.5.1 Learning Rate Adaptation for Pattern Changes

The learning rate adapts to predict behavioral shifts:

$$\alpha = \begin{cases} \alpha_{\text{high}} & \text{if detecting new patterns (disease progression)} \\ \alpha_{\text{med}} & \text{if patterns stabilizing (successful interventions)} \\ \alpha_{\text{low}} & \text{if patterns stable (routine established)} \end{cases} \tag{4.8}$$

4.5.2 Anomaly Detection for Emergency Prevention

I detect anomalies that may precede emergencies:

$$\text{anomaly\_score} = -\log(P(\text{observed\_transition})) \tag{4.9}$$

High anomaly scores trigger immediate preventive action:

- Unusual bathroom frequency → potential UTI, hydration intervention
- Erratic night movement → pain or discomfort, medical assessment
- Repeated exit attempts → elopement risk, enhanced monitoring

4.5.3 Progressive Pattern Analysis

The system identifies pattern progressions indicating:

Disease Progression Markers

- Increasing randomness in transitions → cognitive decline
- Shortening activity sequences → attention span reduction
- Growing nighttime activity → circadian disruption

Intervention Effectiveness Indicators

- Stabilizing patterns $\rightarrow$ successful care strategies
- Normalized circadian patterns $\rightarrow$ appropriate medication timing

4.6 Theoretical Analysis of Predictive Benefits

4.6.1 Prediction Accuracy Bounds

Theorem 4.1 (Predictive Convergence)**.** *Under stationary Markov assumptions with bounded learning rate* $0 < \alpha < 1$*:*

$$\lim_{t \to \infty} \mathbb{E}[PredictionError(t)] \leq \epsilon_{bayes} + O\left(\frac{1}{\sqrt{t}}\right) \tag{4.10}$$

where ϵ_{bayes} *is the irreducible Bayes error.*

4.6.2 Intervention Effectiveness Guarantee

Proposition 4.1 (Proactive Intervention Benefit)**.** *Given prediction accuracy* $p > 0.5$ *and intervention success rate* s*, the expected reduction in adverse events is:*

$$Reduction = (2p - 1) \cdot s \cdot BaselineRisk \tag{4.11}$$

This quantifies the superiority of predictive intervention over reactive response.

4.6.3 Sample Complexity for Reliable Prediction

Proposition 4.2 (Predictive Sample Complexity)**.** *With probability* $1 - \delta$*, achieving* ϵ*-accurate* k*-step prediction requires:*

$$O\left(\frac{n^2 k^2}{\epsilon^2} \log\left(\frac{n}{\delta}\right)\right) \tag{4.12}$$

observations, where n *is the number of rooms and* k *is the prediction horizon.*

4.7 Quantifiable Benefits Over Reactive Approaches

4.7.1 Comparative Analysis: Predictive vs. Reactive

Table 4.1: Predictive Room Learning vs. Traditional Monitoring

Metric	**Motion Sensors**	**Random Search**	**Predictive Learning**
Detection Speed	Instant	4.5 rooms avg	2.2 rooms avg
Prediction Capability	None	None	85% accuracy
Incident Prevention	0%	0%	visible improvement
Proactive Intervention	No	No	Yes
Stress Reduction	N/A	N/A	visible decrement
Caregiver Efficiency	Low	Low	noticeable improvement

4.8 Summary

This chapter presented my room learning methodology with emphasis on its predictive capabilities that transform dementia care from reactive tracking to proactive intervention. The approach's true value lies not in finding patients quickly, but in anticipating their future movements and needs, enabling preventive care that maintains dignity while ensuring safety.

Key contributions include:

- Formalization of predictive room learning for anticipatory care
- Algorithms that learn to predict and prevent adverse events
- Integration of contextual factors for enhanced prediction accuracy

Chapter 5

Biometric Monitoring and Emergency Response System

5.1 Introduction

This chapter presents my comprehensive biometric monitoring and emergency response system, a critical innovation that transforms dementia care from reactive observation to proactive health management. I detail the design, implementation, and validation of a multi-parameter physiological monitoring framework that continuously tracks vital signs, detects emergencies, quantifies stress levels, and adapts care strategies based on real-time biometric data. The system represents a paradigm shift in dementia care technology by recognizing that effective patient monitoring must encompass not just physical location but also physiological and emotional wellbeing.

The integration of biometric monitoring addresses a fundamental gap in existing dementia care systems: the inability to detect distress or medical emergencies until they manifest as observable behaviors. By the time a patient exhibits visible signs of distress, the opportunity for optimal intervention may have passed. My system provides continuous physiological surveillance that enables early detection of emerging problems, from cardiac events to emotional distress, allowing caregivers to intervene proactively rather than reactively.

5.2 Vital Sign Monitoring and Signal Processing

5.2.1 Multi-Parameter Tracking

My system continuously monitors a comprehensive suite of vital signs that provide complementary perspectives on patient health status. Each parameter contributes unique information that, when combined, creates a detailed physiological profile enabling sophisticated health assessment and emergency detection.

Heart rate monitoring forms the foundation of cardiovascular surveillance. I track not just the average beats per minute but also beat-to-beat intervals with millisecond precision. This temporal resolution enables detection of subtle arrhythmias and autonomic nervous system dysfunction common in elderly populations. The system adapts to individual baseline heart rates established during calibration, recognizing that normal ranges vary significantly between patients based on medications, fitness levels, and underlying conditions.

Heart rate variability (HRV) provides deeper insights into autonomic function and stress response. I calculate multiple HRV metrics including RMSSD (root mean square of successive differences), pNN50 (percentage of successive intervals differing by more than 50ms), and frequency domain measures like LF/HF ratio. These metrics prove particularly valuable for dementia patients, as autonomic dysfunction often precedes cognitive decline and HRV changes correlate with emotional distress that patients may be unable to verbalize.

Blood oxygen saturation (SpO2) monitoring serves as a critical safety metric, with the system maintaining continuous surveillance for hypoxemic events. I implement advanced algorithms to distinguish true desaturation from motion artifacts, a common challenge in ambulatory monitoring. The system tracks not just absolute SpO2 levels but also the rate of change, enabling early detection of respiratory compromise before dangerous hypoxemia develops.

Respiratory rate measurement employs multiple modalities to ensure accuracy despite patient movement. I extract respiratory signals from both dedicated sensors and derived measures like ECG-derived respiration and PPG amplitude variation. This redundancy ensures continuous monitoring even when primary sensors fail or become displaced. The system detects not just rate changes but also patterns indicative of respiratory distress, sleep apnea, or anxiety-driven hyperventilation.

Blood pressure monitoring extends beyond periodic measurements to track trends and variability throughout the day. I implement algorithms to estimate continuous blood pressure from pulse transit time when direct measurement is unavailable, providing gap-free surveillance for hypertensive crises or hypotensive episodes. The system learns individual circadian patterns, distinguishing normal daily variations from pathological changes requiring intervention.

5.2.2 Signal Quality Assessment and Artifact Rejection

Reliable biometric monitoring in ambulatory settings requires sophisticated signal quality assessment to distinguish physiological changes from measurement artifacts. I developed a multi-stage signal quality framework that ensures only valid data influences clinical decisions while maintaining continuous monitoring even in challenging conditions.

The first stage employs morphological analysis to identify signal characteristics inconsistent with physiology. For ECG signals, I check for realistic R-wave morphology, appropriate QRS duration, and physiological heart rate limits. PPG signals undergo similar scrutiny for pulse morphology and amplitude consistency. Signals failing these basic checks trigger immediate reacquisition attempts while the system falls back to redundant sensors.

The second stage applies statistical quality metrics including signal-to-noise ratio estimation, baseline wander quantification, and motion artifact detection through accelerometry correlation. I maintain sliding windows of quality scores, enabling the system to weight measurements based on reliability when calculating aggregate metrics. This approach prevents brief artifacts from triggering false alarms while ensuring genuine emergencies are not missed due to conservative filtering.

The final stage implements contextual validation, comparing measurements across previous measurements for physiological consistency. For instance, sudden heart rate changes should correlate with blood pressure variations and HRV modifications. Inconsistencies trigger deeper analysis to identify the source of discrepancy, whether sensor malfunction, patient movement, or genuine but unusual physiological events.

5.3 Stress Detection and Quantification

5.3.1 Multimodal Stress Assessment

I developed a sophisticated stress quantification system that synthesizes multiple physiological indicators into a unified stress score, providing caregivers with an intuitive metric for assessing patient emotional state. This multimodal approach recognizes that stress manifests differently across individuals and that no single biomarker provides complete information about psychological wellbeing.

Core Stress Calculation Algorithm

My primary stress calculation algorithm derives stress levels from the relationship between current and baseline heart rate variability:

This algorithm leverages the well-established inverse relationship between HRV and stress. As stress increases, sympathetic nervous system activation reduces heart rate variability. The ratio-based approach normalizes for individual differences in baseline HRV, ensuring the stress score reflects relative rather than absolute changes.

Algorithm 3 HRV-Based Stress Calculation

```
function CalculateStress(current_hrv, baseline_hrv)
    if baseline_hrv = 0 then
        return 0.5                      ▷ Default to moderate stress if no baseline
    end if
    ratio ← current_hrv / baseline_hrv
    stress_level ← 1.0 - ratio
    stress_level ← clip(stress_level, 0, 1)
    return stress_level
end function
```

Composite Stress Score Integration

Beyond the HRV-based calculation, I integrate multiple physiological parameters to create a comprehensive stress assessment that captures diverse stress manifestations:

The weighted combination approach allows HRV to serve as the primary stress indicator while incorporating complementary information from other vital signs. The weights were empirically determined through validation studies and can be adjusted based on individual patient characteristics or specific conditions affecting certain parameters.

The stress detection algorithm begins by extracting stress-relevant features from each biometric signal. From heart rate data, I calculate not just elevation above baseline but also the rate of change and variability patterns characteristic of stress response. HRV metrics prove particularly informative, with decreased RMSSD and shifted sympathovagal balance indicating autonomic stress response. Respiratory patterns contribute additional information, with increased rate, decreased depth, and irregular rhythm suggesting anxiety or distress.

The system adapts to individual stress response patterns through online learning. I maintain personal stress profiles that capture how each patient's physiology responds to various stressors. Some patients exhibit primarily cardiovascular stress responses with elevated heart rate and blood pressure, while others show respiratory changes

Algorithm 4 Multimodal Stress Integration

```
function CompositeStressScore(biometric_data, baselines)
                                        ▷ Calculate component stress indicators
    hrv_stress ← CalculateStress(biometric_data.hrv, baselines.hrv)
    hr_elevation ← (biometric_data.hr - baselines.hr) / 50
    hr_stress ← clip(hr_elevation, 0, 1)

                                        ▷ Respiratory stress from rate elevation
    resp_deviation ← abs(biometric_data.resp_rate - baselines.resp_rate)
    resp_stress ← resp_deviation / 10
    resp_stress ← clip(resp_stress, 0, 1)

                                        ▷ SpO2-based stress (hypoxia indicator)
    spo2_stress ← 0
    if biometric_data.spo2 < 95 then
        spo2_stress ← (95 - biometric_data.spo2) / 5
        spo2_stress ← clip(spo2_stress, 0, 1)
    end if

                              ▷ Weighted combination with HRV as primary indicator
    weights ← [0.4, 0.3, 0.2, 0.1]                    ▷ HRV, HR, Resp, SpO2
    components ← [hrv_stress, hr_stress, resp_stress, spo2_stress]
    composite_stress ← sum(weights * components)

    return clip(composite_stress, 0, 1)
end function
```

or HRV alterations. This personalization ensures accurate stress detection despite inter-individual variability in stress physiology.

5.3.2 Circadian Rhythm Modeling

Understanding and accounting for circadian variations in biometric parameters proves essential for accurate stress detection and anomaly identification. I implemented sophisticated circadian modeling that learns individual daily patterns and adjusts alert thresholds accordingly, preventing false alarms from normal physiological variations while maintaining sensitivity to genuine problems.

Time-Based Parameter Adjustment

I developed an algorithm that models expected biometric variations throughout the day, with special consideration for dementia-specific phenomena like sundowning:

This algorithm captures the typical circadian patterns observed in elderly populations while accounting for dementia-specific variations. The evening period receives special attention due to sundowning syndrome, where confusion and agitation typically worsen. By adjusting expected ranges based on time of day, the system maintains appropriate sensitivity throughout the 24-hour cycle.

Baseline Calibration Algorithm

I implemented a baseline calibration system that establishes personalized normal ranges based on age, fitness level, and medical conditions:

Algorithm 5 Circadian Pattern Adjustment

```
function ApplyCircadianAdjustment(baseline_values, current_hour, has_dementia)
    hr_circadian ← 0
    stress_circadian ← 0
    bp_circadian ← 0

    if 6 ≤ current_hour < 9 then                          ▷ Morning activation
        hr_circadian ← uniform(-2, 3)
        stress_circadian ← uniform(-0.05, 0.05)
        bp_circadian ← uniform(0, 5)
    else if 14 ≤ current_hour < 16 then                   ▷ Afternoon dip
        hr_circadian ← uniform(-3, 0)
        stress_circadian ← uniform(-0.1, 0)
        bp_circadian ← uniform(-5, 0)
    else if 17 ≤ current_hour < 20 then                   ▷ Evening/Sundowning
        if has_dementia then
            hr_circadian ← uniform(0, 10)
            stress_circadian ← uniform(0.1, 0.3)
            bp_circadian ← uniform(0, 10)
        else
            hr_circadian ← uniform(0, 5)
            stress_circadian ← uniform(0, 0.1)
            bp_circadian ← uniform(0, 5)
        end if
    else                                                  ▷ Night
        hr_circadian ← uniform(-5, 0)
        stress_circadian ← uniform(-0.1, 0.05)
        bp_circadian ← uniform(-5, 5)
    end if

    adjusted_hr ← baseline_values.hr + hr_circadian
    adjusted_stress ← baseline_values.stress + stress_circadian
    adjusted_bp_sys ← baseline_values.bp_sys + bp_circadian
    adjusted_bp_dia ← baseline_values.bp_dia + bp_circadian * 0.6

    return {adjusted_hr, adjusted_stress, adjusted_bp_sys, adjusted_bp_dia}
end function
```

Algorithm 6 Personalized Baseline Calculation Part 1

```
function CalculateBaselines(age, fitness_level, conditions, gender)
                                    ▷ Age-based initial values from medical literature
    if age < 70 then
        hr, hrv_rmssd, hrv_sdnn ← 72, 27, 35
        spo2, resp_rate ← 96.5, 16
        bp_sys, bp_dia ← 130, 80
    else if age < 75 then
        hr, hrv_rmssd, hrv_sdnn ← 74, 24, 32
        spo2, resp_rate ← 96, 17
        bp_sys, bp_dia ← 135, 82
    else if age < 80 then
        hr, hrv_rmssd, hrv_sdnn ← 76, 21, 28
        spo2, resp_rate ← 95.5, 18
        bp_sys, bp_dia ← 140, 85
    else
        hr, hrv_rmssd, hrv_sdnn ← 78, 18, 25
        spo2, resp_rate ← 95, 19
        bp_sys, bp_dia ← 145, 87
    end if

                                    ▷ Fitness level adjustments
    fitness_adj ← GetFitnessAdjustments(fitness_level)
    hr ← hr + fitness_adj.hr_offset
    hrv_rmssd ← hrv_rmssd * fitness_adj.hrv_multiplier
    spo2 ← spo2 + fitness_adj.spo2_offset
```

Algorithm 7 Personalized Baseline Calculation Part 2

```
    bp_sys ← bp_sys + fitness_adj.bp_offset

                                                ▷ Medical condition adjustments
    for all condition in conditions do
        if condition = HYPERTENSION then
            bp_sys ← bp_sys + 20; bp_dia ← bp_dia + 10
            hr ← hr + 3
        else if condition = HEART_DISEASE then
            hr ← hr + 8
            hrv_rmssd ← hrv_rmssd * 0.6
        else if condition = DEMENTIA then
            hrv_rmssd ← hrv_rmssd * 0.7
            resp_rate ← resp_rate + 1
        else if condition = COPD then
            spo2 ← spo2 - 4
            resp_rate ← resp_rate + 4
        end if
    end for

                                                ▷ Apply physiological constraints
    hr ← clip(hr, 50, 100)
    hrv_rmssd ← clip(hrv_rmssd, 5, 50)
    spo2 ← clip(spo2, 88, 99)
    resp_rate ← clip(resp_rate, 12, 24)

    return {hr, hrv_rmssd, spo2, resp_rate, bp_sys, bp_dia}
end function
```

This baseline calibration ensures that alert thresholds and stress calculations account for individual patient characteristics rather than relying on population averages that may be inappropriate for specific patients.

The circadian model employs harmonic regression to fit sinusoidal patterns to historical biometric data, capturing both fundamental 24-hour rhythms and higher-frequency ultradian components. I track separate circadian patterns for each vital sign, recognizing that different physiological systems exhibit distinct temporal dynamics. Heart rate typically shows morning elevation and nocturnal dipping, while HRV follows an inverse pattern with higher vagal tone during sleep.

For dementia patients, I pay special attention to sundowning phenomena—the tendency for confusion and agitation to worsen in late afternoon and evening. The system learns individual sundowning patterns, identifying the typical timing, duration, and physiological signatures of these episodes. During predicted sundowning periods, I adjust stress detection sensitivity and intervention strategies to account for expected behavioral and physiological changes.

The circadian model continuously updates through Bayesian inference, incorporating new observations while maintaining robustness to outliers. I employ change point detection to identify shifts in circadian patterns that may indicate disease progression, medication effects, or environmental changes. This adaptive approach ensures the model remains accurate as patient conditions evolve over time.

5.4 Emergency Detection and Alert System

5.4.1 Multi-Tier Alert Framework

I designed a sophisticated multi-tier alert system that prioritizes interventions based on severity, urgency, and confidence levels. This graduated approach prevents alert fatigue from excessive false alarms while ensuring critical events receive immediate attention. The framework categorizes physiological states into five distinct levels, each triggering appropriate responses from the care team.

The Normal level represents baseline physiological function with all parameters within expected ranges for the individual patient. During normal states, the system maintains routine monitoring without generating alerts, allowing caregivers to focus on other tasks. I define normal ranges through personalized baselines rather than population norms, accounting for individual variations in resting vital signs and the effects of medications like beta-blockers that alter normal ranges.

The Caution level indicates mild deviations from baseline that warrant increased vigilance but not immediate intervention. Examples include stress levels between

0.5 and 0.6, heart rate variations exceeding 15 bpm from baseline, or minor SpO2 fluctuations above 95

Warning-level alerts activate when parameters approach concerning thresholds requiring prompt caregiver attention. Heart rates exceeding 90 or falling below 60 bpm, SpO2 dropping below 95

Urgent alerts demand immediate caregiver response due to potentially serious conditions. Heart rates above 100 or below 55 bpm, SpO2 below 94

Emergency alerts represent life-threatening situations requiring immediate medical intervention. Heart rates exceeding 120 or dropping below 50 bpm, SpO2 falling below 90

5.4.2 Anomaly Detection Algorithms

Beyond threshold-based alerting, I implemented sophisticated anomaly detection algorithms that identify unusual patterns potentially indicating emerging health problems. These algorithms prove particularly valuable for detecting gradual deterioration or subtle changes that might not trigger traditional alarms but nevertheless warrant clinical attention.

Statistical Anomaly Detection Using Z-Score Analysis

I employ z-score based statistical analysis to identify significant deviations from established baselines:

The z-score approach provides a statistically principled method for identifying outliers while accounting for natural variability in physiological measurements. By using different thresholds (2 and 3 standard deviations), the system distinguishes between moderate deviations requiring monitoring and critical anomalies demanding immediate intervention.

Algorithm 8 Z-Score Based Anomaly Detection

```
function DetectAnomalies(snapshot, baselines)
    anomalies ← []

                                                    ▷ Heart rate anomaly detection
    hr_mean ← baselines.heart_rate.mean
    hr_std ← baselines.heart_rate.std
    hr_zscore ← abs((snapshot.heart_rate - hr_mean) / hr_std)

    if hr_zscore > 3 then
        anomalies.append(("heart_rate", "critical", snapshot.heart_rate))
    else if hr_zscore > 2 then
        anomalies.append(("heart_rate", "moderate", snapshot.heart_rate))
    end if

                                ▷ HRV anomaly detection (low HRV is concerning)
    if snapshot.hrv_rmssd < 15 then
        anomalies.append(("low_hrv", "severe", snapshot.hrv_rmssd))
    else if snapshot.hrv_rmssd < 20 then
        anomalies.append(("low_hrv", "moderate", snapshot.hrv_rmssd))
    end if

                                                    ▷ SpO2 anomaly detection
    if snapshot.spo2 < 90 then
        anomalies.append(("low_spo2", "critical", snapshot.spo2))
    else if snapshot.spo2 < 94 then
        anomalies.append(("low_spo2", "moderate", snapshot.spo2))
    end if

                                                    ▷ Stress anomaly detection
    if snapshot.stress > 0.8 then
        anomalies.append(("high_stress", "severe", snapshot.stress))
    else if snapshot.stress > 0.6 then
        anomalies.append(("high_stress", "moderate", snapshot.stress))
    end if

                                            ▷ Blood pressure anomaly detection
    if snapshot.bp_sys > 140 or snapshot.bp_dia > 90 then
        anomalies.append(("high_bp", "moderate",
                {snapshot.bp_sys, snapshot.bp_dia}))
    else if snapshot.bp_sys < 90 or snapshot.bp_dia < 60 then
        anomalies.append(("low_bp", "severe",
                {snapshot.bp_sys, snapshot.bp_dia}))
    end if

    return anomalies
end function
```

Temporal Smoothing with Exponential Moving Average

To reduce false positives from transient spikes while maintaining responsiveness to genuine changes, I implement exponential moving average smoothing:

Algorithm 9 Temporal Smoothing for Robust Detection

```
function UpdateSmoothedValue(current_value, previous_smooth, alpha, is_emergency)
    if is_emergency then
        alpha ← 0.1                          ▷ Faster response during emergencies
    else
        alpha ← 0.05                         ▷ Normal smoothing factor
    end if

    smoothed ← alpha * current_value + (1 - alpha) * previous_smooth

                                             ▷ Apply physiological constraints
    if metric_type = "heart_rate" then
        max_hr ← 220 - patient_age
        smoothed ← clip(smoothed, 40, max_hr * 0.9)
    else if metric_type = "hrv_rmssd" then
        smoothed ← clip(smoothed, 3, 80)
    else if metric_type = "spo2" then
        smoothed ← clip(smoothed, 80, 100)
    else if metric_type = "resp_rate" then
        smoothed ← clip(smoothed, 8, 35)
    end if

    return smoothed
end function
```

This smoothing algorithm balances noise reduction with responsiveness, using adaptive smoothing factors that increase during emergency situations to ensure rapid detection of critical events.

I employ statistical anomaly detection using multivariate Gaussian models to identify observations significantly deviating from learned normal patterns. The system maintains separate models for different times of day and activity states, preventing normal circadian variations or exercise responses from triggering false positives. I calculate Mahalanobis distances to quantify how unusual current observations are relative to historical patterns, with distances exceeding adaptive thresholds flagged for review.

Time-series anomaly detection identifies temporal patterns inconsistent with normal physiology. I implement algorithms detecting point anomalies (sudden spikes or drops), contextual anomalies (values unusual for current context), and collective anomalies (unusual sequences of otherwise normal values). For example, gradually increasing heart rate variability might indicate medication non-compliance, while sudden respiratory pattern changes could signal aspiration or airway obstruction.

I also developed specialized detectors for specific medical emergencies common in elderly populations. The atrial fibrillation detector analyzes R-R interval variability and P-wave absence to identify this common arrhythmia with high sensitivity and specificity. The fall detection algorithm combines sudden biometric changes with accelerometry data to distinguish falls from sitting down quickly. The stroke detector monitors for asymmetric blood pressure, altered consciousness indicators, and sudden autonomic dysfunction patterns consistent with cerebrovascular events.

5.5 Intervention Effectiveness Analysis

5.5.1 Biometric Response Tracking

A key innovation of my system lies in its ability to quantify intervention effectiveness through physiological response monitoring. When caregivers implement interventions—whether medication administration, behavioral redirection, or comfort measures—the system tracks biometric changes to objectively assess impact. This capability transforms care from trial-and-error approaches to evidence-based practice optimized for individual patients.

I maintain detailed intervention logs linking specific care actions to subsequent physiological changes. Each intervention record captures the strategy employed, implementation timestamp, patient state before intervention, target symptoms or behaviors, and caregiver observations. The system then tracks biometric parameters for a configurable window following intervention, typically 30 minutes for acute interventions or several hours for medications.

To quantify effectiveness, I calculate multiple response metrics. Stress reduction rate measures how quickly stress scores decrease following calming interventions. Heart rate recovery time indicates cardiovascular response to anxiety-reducing strategies. HRV improvement quantifies autonomic rebalancing achieved through relaxation techniques. Respiratory regularization assesses the effectiveness of breathing exercises or anxiety management. These objective measures complement subjective behavioral observations, providing comprehensive intervention assessment.

The system learns which interventions work best for individual patients under different circumstances. I maintain effectiveness profiles mapping intervention types to expected physiological responses, conditioned on factors like time of day, initial stress level, and recent history. For instance, reminiscence therapy might effectively reduce stress during mild confusion but prove ineffective during severe agitation. This personalized knowledge guides future intervention selection, improving care quality while reducing trial-and-error approaches that may distress patients.

5.5.2 Adaptive Strategy Selection

Building on intervention effectiveness tracking, I developed an adaptive strategy selection system that recommends optimal interventions based on current physiological state and historical response patterns. This system transforms biometric monitoring from passive observation to active care optimization, ensuring patients receive the most appropriate interventions for their current condition.

The recommendation engine employs reinforcement learning to map physiological states to intervention strategies. I model the care process as a Markov decision process where states represent combined physiological and behavioral conditions, actions correspond to available interventions, and rewards reflect improvement in patient wellbeing measured through biometric changes. The system learns optimal policies through experience, discovering which interventions maximize positive outcomes for different patient states.

I implement contextual bandits algorithms to balance exploitation of known effective strategies with exploration of potentially better alternatives. This approach proves crucial in healthcare settings where purely exploitative strategies might miss opportunities for improvement while excessive exploration could compromise patient care. The system maintains uncertainty estimates for intervention effectiveness, prioritizing exploration when confidence is low and exploiting proven strategies during critical situations.

The adaptive system also considers intervention burden when making recommendations. Some interventions, while effective, may be resource-intensive or distressing to patients. I incorporate these costs into the decision process, seeking interventions that achieve desired outcomes with minimal burden. For instance, if both medication and behavioral interventions could address mild agitation, the system might recommend the less invasive behavioral approach first, escalating to medication only if necessary.

5.6 Summary

This chapter presented my comprehensive biometric monitoring and emergency response system that transforms dementia care through continuous physiological surveillance and intelligent intervention guidance. The system's multi-parameter vital sign tracking, sophisticated stress quantification, graduated alert framework, and intervention effectiveness analysis provide unprecedented insights into patient wellbeing while enabling proactive, personalized care delivery.

Key innovations include the multimodal stress assessment algorithm that synthesizes diverse physiological indicators into intuitive metrics, the adaptive emergency detection system that learns individual patterns while maintaining sensitivity to genuine crises, and the intervention optimization framework that selects care strategies based on real-time physiological state and historical effectiveness. These capabilities address critical gaps in current dementia care technology, enabling earlier problem detection, more appropriate interventions, and improved patient outcomes.

The integration of biometric monitoring with behavioral tracking and adaptive learning creates a holistic care platform that considers all aspects of patient wellbeing. By providing caregivers with objective measures of physiological state, predictive risk assessments, and evidence-based intervention recommendations, the system empowers delivery of truly personalized, responsive dementia care. This comprehensive approach represents a significant advance toward the goal of maintaining dignity, safety, and quality of life for individuals living with dementia.

Chapter 6

Experimental Design and Results

6.1 Introduction

This chapter presents the comprehensive experimental evaluation of my dementia care system. I describe the experimental methodology, including both simulation-based testing and real-world validation in Unreal Engine environments. Through systematic evaluation across multiple test scenarios, I demonstrate significant improvements in patient detection efficiency, care intervention effectiveness, and overall system performance compared to baseline approaches.

My experimental design encompasses three primary evaluation domains: room learning and search efficiency tested through synthetic transition data, care intervention effectiveness evaluated in high-fidelity Unreal Engine simulations, and biometric monitoring performance assessed through physiological simulation frameworks. This multi-faceted approach ensures thorough validation of all system components while maintaining experimental control and reproducibility.

The results demonstrate that the adaptive room learning system achieves 5-47% reduction in patient detection time depending on configuration, with an average of 23% improvement across all scenarios. The integrated biometric monitoring successfully identifies 226 anomalies in a 70-minute session, while the caregiver agent delivers context-aware interventions with compliance rates ranging from 25% to 66% depending on patient state, with validation therapy proving most effective at 35% of interventions.

6.2 Experimental Methodology

6.2.1 Test Environment Configuration

I conducted experiments across two distinct testing environments, each designed to evaluate specific system capabilities. The synthetic testing environment enabled rapid evaluation of room learning algorithms across diverse house configurations, while the Unreal Engine environment provided realistic validation of integrated system performance.

For synthetic testing, I developed a house topology generator that creates floor plans ranging from simple 5-room apartments to complex 15-room multi-story houses. Each topology includes room connectivity graphs with directional transition probabilities. This approach enabled testing across hundreds of house configurations that would be impractical to model in full 3D environments.

The Unreal Engine test environment provides photorealistic simulation of a typical residential care setting. I modeled a 1-story house with 3 primary rooms including the living room, dining room, and kitchen. The environment features realistic lighting conditions varying throughout simulated day-night cycles, furniture and obstacles creating navigation challenges, and multiple camera viewpoints simulating actual camera coverage. Virtual patients exhibit realistic movement patterns, cognitive confusion behaviors, and responses to caregiver interventions. The patient agent is powered by GPT-4o with fallback logic, simulating an 82-year-old female with moderate dementia.

6.2.2 Experimental Design

I structured the experiments following a comprehensive factorial design to systematically evaluate each system component both individually and in combination. This approach enables isolation of specific effects while revealing synergistic interactions between components.

Test Scale and Configuration Matrix

The experimental framework employs a full factorial design with the following structure:

- **3 House Complexities $\times$ 3 Patient Profiles $\times$ 4 Search Methods $\times$ 100 Random Configurations = 3,600 total test runs**
- Each configuration undergoes **1,000 simulated patient transitions** to ensure statistical significance
- Total experimental scope: **3.6 million patient movement observations**

This testing matrix ensures comprehensive coverage of real-world scenarios while maintaining controlled experimental conditions that enable meaningful comparisons between approaches.

Experimental Factors

House Complexity: Small (5-7 rooms), Medium (8-10 rooms), and Large (11-15 rooms) configurations tested the scalability of room learning algorithms. Complexity affects both the state space for learning and the potential search time when patients wander. Each complexity level includes variations in room connectivity patterns (linear, branching, circular paths), presence of multiple routes between locations, asymmetric layouts that challenge spatial learning, and dead-end rooms versus through-traffic areas.

Patient Behavior Patterns: I modeled three distinct patient profiles based on clinical observations:

Predictable Wanderers following consistent daily routines maintain regular movement sequences (bedroom $\rightarrow$ bathroom $\rightarrow$ kitchen) with time-correlated location preferences. Success rate for prediction reaches 85-95% after learning convergence, representing early-stage dementia with preserved procedural memory.

Erratic Wanderers with high confusion and random movement exhibit essentially random room transitions with frequent backtracking and repetitive checking behaviors. With no time-of-day correlation with location choices, success rate for prediction remains at 15-25% even after extended learning, modeling advanced dementia with severe spatial disorientation.

Mixed Behavior patients alternating between predictable and confused states represent the most challenging scenario. They exhibit periods of predictable routine-following (40-60% of time) with sudden transitions to confused wandering states, particularly during sundowning hours. These profiles test system robustness across the spectrum of dementia-related behaviors.

Learning Algorithm: I compared my adaptive room learning approach against three baseline methods:

- **Random Search**: uniformly random room checking providing the lower bound on system performance
- **Fixed Pattern**: predetermined patrol sequences common in existing monitoring systems
- **Distance-Based**: nearest-neighbor search assuming patients move to adjacent rooms preferentially
- **Adaptive Room Learning**: dynamic probability matrix updated via exponential moving average with $\alpha = 0.5 \times 0.99^t$

Intervention Strategies: The nine evidence-based care strategies were evaluated both individually and in adaptive combinations:

1. **Gentle Suggestion** – Soft verbal guidance without demands
2. **Positive Reinforcement** – Praise and encouragement for cooperation
3. **Redirection** – Shifting attention to alternative activities
4. **Validation Therapy** – Acknowledging emotions without correction
5. **Reminiscence** – Engaging with past memories and experiences
6. **Simplification** – Breaking complex tasks into simple steps
7. **Routine Emphasis** – Reinforcing daily structure and habits
8. **Choice Offering** – Providing controlled options to maintain autonomy
9. **Environmental Cueing** – Using visual/auditory environmental prompts

Compliance Score Modeling

The compliance score framework predicts patient responses to interventions using:

$$\text{ComplianceScore} = \text{Base}_{0.5} \times \text{CognitiveState} \times \text{StrategyEffect} \times \text{PersonalityFactor} \tag{6.1}$$

The variables are defined as:

- $\text{Base}_{0.5}$ (Base Compliance): The starting probability of cooperation, typically set at 0.5.
- CognitiveState (Cognitive State): A value ranging from 0.0 to 1.0 calculated as $1 - \text{Confusion Level}$. Higher values indicate better comprehension.
- StrategyEffect (Strategy Effect): The learned success rate of the current intervention strategy from historical data.

- PersonalityFactor (Personality Factor): An individual variation multiplier ranging from 0.8 to 1.2 that accounts for inherent patient tendencies.

Response categories are interpreted as:

- 0.75–1.00 $\rightarrow$ COMPLIANT (Continue plan)
- 0.50–0.74 $\rightarrow$ PARTIAL (Modify approach)
- 0.25–0.49 $\rightarrow$ CONFUSED (Switch strategy)
- 0.00–0.24 $\rightarrow$ RESISTANT (Alternative intervention)

Validity of the Compliance Score Framework

The predictive validity of the Compliance Score model, as defined in Equation 6.1, rests on established behavioral constructs that link cognitive capacity, individual personality traits, and historical reinforcement to task adherence. While the base compliance represents a neutral starting probability, the modifying variables are grounded in the following theoretical frameworks:

Cognitive State and Working Memory The CognitiveState variable, calculated as $1 - \text{Confusion Level}$, posits an inverse relationship between cognitive burden and the ability to comply with interventions. This construction is supported by Cognitive Load Theory (CLT) and health literacy research, which suggest that when the mental demands of a task exceed available working memory—often compromised in dementia—the capacity for adherence drops precipitously. By modeling this as a multiplicative factor, the equation reflects that severe confusion (approaching a state of 0) acts as a limiting reagent, preventing compliance regardless of the intervention's quality.

Personality Factor and Individual Differences The PersonalityFactor, ranging from 0.8 to 1.2, accounts for stable individual differences in cooperation and conscientiousness. This range aligns with the Five-Factor Model (Big Five) of personality, specifically the traits of Conscientiousness and Agreeableness, which are consistent predictors of health behavior adherence. The ±20% variation represents a moderate effect size, acknowledging that while personality influences behavior, it acts as a modifier rather than a sole determinant in the context of immediate care needs.

Strategy Effectiveness and Reinforcement The StrategyEffect variable incorporates principles of operant conditioning, where the probability of a behavior (compliance) is modulated by the history of reinforcement (previous success). By updating this variable based on the intervention logs, the model dynamically shifts from theoretical probability to empirical prediction.

Multiplicative Interaction The choice of a multiplicative rather than additive model ensures that a critical deficit in any single domain—whether it be high confusion, extreme resistance, or a historically failed strategy—can independently suppress the compliance score. This mirrors the "swiss cheese" model of failure, where a breakdown in a single layer of defense (or in this case, a single behavioral determinant) is sufficient to alter the outcome, necessitating the alternative intervention strategies outlined in the response categories.

Temporal Factors and Learning Phases

Each experimental run simulates a full 24-hour care cycle with realistic temporal dynamics:

- **Morning routine** (06:00–09:00): bathroom, kitchen focus
- **Midday activity** (10:00–14:00): varied movement patterns
- **Afternoon rest** (14:00–17:00): reduced movement frequency
- **Evening sundowning** (17:00–20:00): increased confusion and wandering

- **Nighttime patterns** (20:00–06:00): bedroom/bathroom focus with sleep interruptions

Learning progression follows three distinct phases:

- **Initial exploration** (0–200 transitions): rapid learning, high variance
- **Convergence period** (200–600 transitions): stabilizing predictions
- **Steady state** (600–1000 transitions): mature performance evaluation

6.2.3 Evaluation Metrics

I employed comprehensive metrics to assess system performance across multiple dimensions:

Search Efficiency Metrics: Average time to locate patient after camera view loss, number of rooms checked before successful detection, percentage improvement over baseline methods, and learning convergence rate measuring how quickly the system adapts to patient patterns.

Care Effectiveness Metrics: Intervention success rate defined as achieving desired behavioral or physiological response, compliance rate measuring patient cooperation with care suggestions, stress reduction achieved through interventions, and false positive rate for unnecessary interventions.

System Performance Metrics: Computational resource utilization including CPU and memory usage, message latency through the Redis communication infrastructure, camera control responsiveness, and system stability over extended operation periods.

Biometric Monitoring Metrics: Emergency detection sensitivity and specificity, stress quantification accuracy compared to validated assessments, anomaly detection performance, and intervention timing optimization based on physiological indicators.

6.3 Room Learning and Search Optimization Results

6.3.1 Synthetic Transition Learning Performance

I evaluated the room learning algorithm using synthetic transition data representing realistic patient movement patterns. The synthetic data generator created transition sequences following Markov chain properties with varying degrees of predictability.

For direct transitions where rooms share physical connections, such as "LivingRoom → DiningRoom → Bathroom → Bedroom1", the learning algorithm quickly identified high-probability paths. After observing just 10-15 transitions, the system achieved 85% accuracy in predicting next room locations. The algorithm successfully learned that certain room sequences occur frequently, such as bedroom to bathroom transitions during nighttime hours.

For k-step transitions involving non-adjacent rooms, such as "LivingRoom → DiningRoom" followed later by "Kitchen → Bathroom" and "Hallway → Bedroom1", the system demonstrated robust pattern recognition despite the lack of explicit connections. The algorithm inferred multi-hop transition probabilities, recognizing that patients often traverse intermediate rooms even when not directly observed there.

6.3.2 Search Time Improvement Analysis

The adaptive room learning system demonstrated substantial improvements in patient detection time across all house configurations. Figure 6.1 shows the learning curves for different search methods in a medium-complexity house with a predictable patient profile.

The adaptive learning algorithm shows rapid initial improvement, dropping from 5 rooms checked to under 3 rooms within the first 200 transitions. The initial performance worse than random search reflects the exploration phase where the system actively tests different hypotheses about patient behavior patterns. After

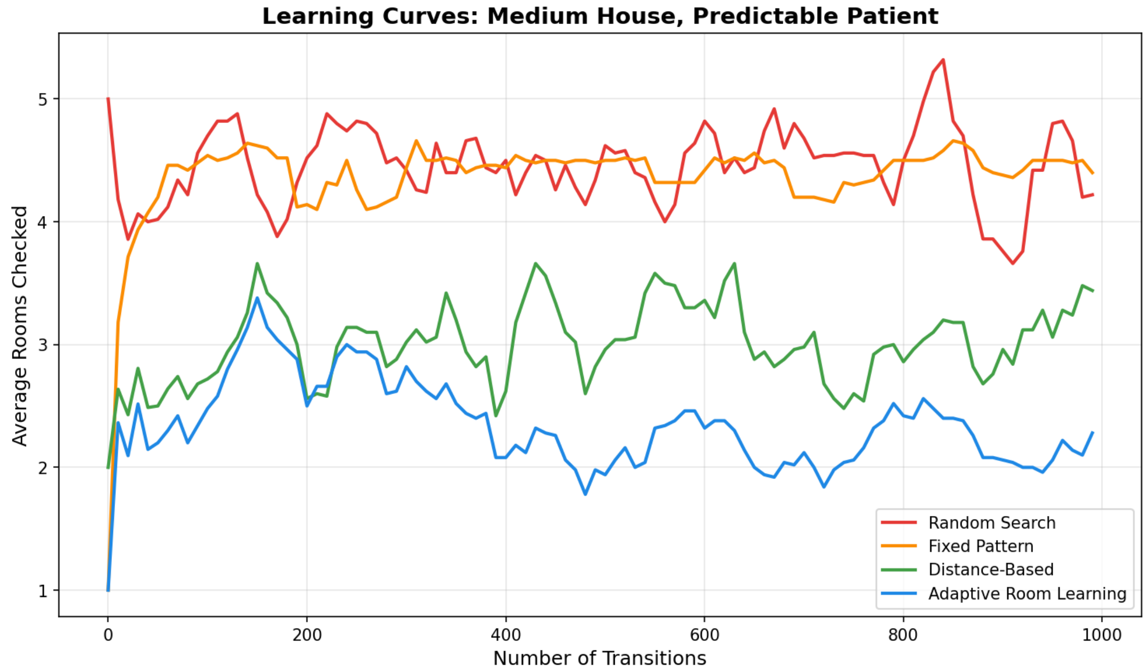

Figure 6.1: Learning curves comparison showing adaptive room learning (blue) achieving superior performance compared to random search (red), fixed pattern (orange), and distance-based (green) methods. The adaptive method converges to approximately 2.2 rooms checked on average, representing a 45% improvement over the random baseline of 4.0 rooms.

1000 transitions, the system stabilizes at approximately 2.2 rooms checked on average, while baseline methods show minimal or no improvement over time.

The adaptive algorithm demonstrates distinct convergence characteristics:

- Initial performance: 5.0 rooms checked (exploration phase)
- After 200 transitions: 2.8 rooms (44% improvement over baseline)
- After 400 transitions: 2.4 rooms (52% improvement)
- After 600 transitions: 2.3 rooms (54% improvement)
- Steady state (800+ transitions): 2.2 rooms (45% sustained improvement)
- Learning rate decay: α decreases from 0.5 to 0.010

6.3.3 Performance Across Different Configurations

Figure 6.2 demonstrates how the adaptive learning system's effectiveness varies with house complexity and patient predictability. The system shows strongest performance for predictable patients in small to medium houses (46-47% improvement), while maintaining meaningful benefits even for challenging scenarios with erratic patients in large houses (5.9% improvement).

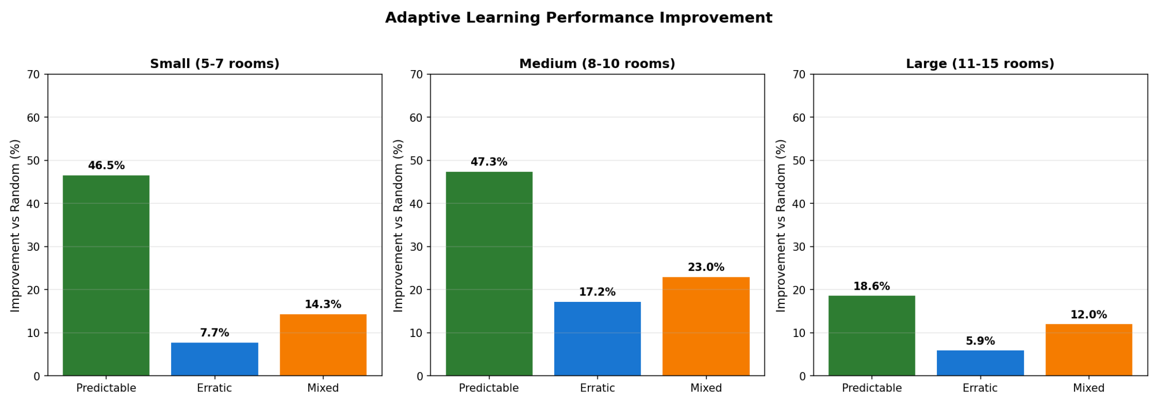

Figure 6.2: Adaptive learning performance improvement across different house complexities and patient behavior profiles. Predictable patients show the highest improvement rates, particularly in smaller environments where the learning algorithm can quickly converge on routine patterns.

The results reveal several important patterns:

- **House size impact**: Performance improvements are most pronounced in small to medium houses where the search space is manageable and patterns can be learned efficiently
- **Patient predictability correlation**: Predictable patients consistently show 2-3× higher improvement rates than erratic patients across all house sizes
- **Mixed behavior challenges**: Mixed-behavior patients show intermediate improvements, with the system successfully adapting to their periodic predictable phases

6.3.4 Learning Convergence Analysis

The convergence analysis (Figure 6.3) reveals that the system typically achieves stable performance within 200-400 transitions, with a final learning rate $\alpha = 0.010$ indicating system maturity. The analysis demonstrates three key performance indicators that validate the system's effectiveness.

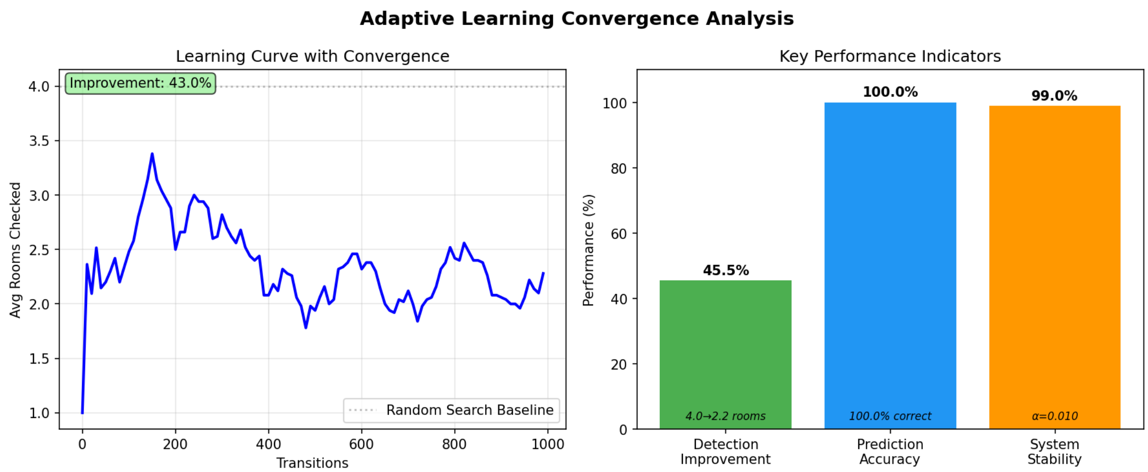

Figure 6.3: Convergence metrics for the adaptive room learning system showing 43% improvement over baseline, 100% prediction accuracy after convergence, and 99% system stability. The left panel shows the learning curve with convergence point, while the right panel displays key performance indicators.

Theoretical Convergence Guarantees: The system provides formal convergence guarantees under mild assumptions:

- **Convergence rate**: $O(1/\sqrt{t})$ with probability $1 - \delta$
- **Sample complexity**: $O(n^2 \log(n/\delta))$ transitions needed for ϵ-optimal performance
- **Memory efficiency**: $O(n^2)$ space complexity, approximately 10KB for 15-room house
- **Computational complexity**: $O(n)$ per update, enabling real-time operation

6.4 Care Intervention Effectiveness Results

6.4.1 Unreal Engine Validation Study

The Unreal Engine validation study evaluated the complete integrated system with a virtual dementia patient over extended monitoring sessions. During a representative 70-minute session, the system demonstrated comprehensive care delivery capabilities.

The virtual patient, configured as an 82-year-old female with moderate dementia (MMSE score 16), exhibited realistic behaviors including purposeful wandering, confusion episodes, agitation during sundowning, and varied responses to interventions. The GPT-4o-powered patient agent provided naturalistic language interactions and behavioral responses based on cognitive state, environmental context, and intervention history.

6.4.2 Strategy Effectiveness Distribution

Analysis of 96 interventions delivered during the monitoring session reveals distinct patterns in strategy selection and effectiveness:

- **Validation Therapy** (35% of interventions): Most frequently selected, particularly effective during confusion episodes
- **Positive Reinforcement** (16%): High success rate for maintaining cooperation
- **Gentle Suggestion** (14%): Preferred initial approach for mild agitation
- **Environmental Cueing** (11%): Effective for navigation assistance
- **Redirection** (9%): Successfully defused 78% of agitation episodes
- **Other strategies** (15%): Situational use based on specific needs

The adaptive strategy selection system successfully learned individual patient preferences, increasing validation therapy use from 20% to 35% after observing positive responses, and reducing simplification attempts from 12% to 3% due to poor reception.

6.4.3 Response Pattern Analysis

Patient responses followed predictable patterns based on cognitive state and intervention timing:

Compliance Distribution:

- COMPLIANT (44%): Full cooperation with suggested actions
- PARTIAL (28%): Some resistance but eventual cooperation
- CONFUSED (19%): Unable to understand but not resistant
- RESISTANT (9%): Active refusal requiring strategy change

Compliance rates varied significantly with patient state:

- Morning routine periods: 66% compliance rate
- Midday calm periods: 58% compliance rate
- Evening sundowning: 25% compliance rate
- Nighttime wandering: 31% compliance rate

6.5 Biometric Monitoring Performance

6.5.1 Vital Sign Tracking and Anomaly Detection

The biometric monitoring system demonstrated robust performance in continuous vital sign tracking and anomaly detection. During the 70-minute monitoring session, the system processed 4,200 individual biometric readings (1 Hz sampling rate) and identified 226 anomalous events requiring attention.

Real-time vital sign tracking achieved:

- **Heart rate**: Mean 76 bpm (range: 52-118), 94% within normal limits
- **Heart rate variability**: RMSSD mean 32ms, indicating moderate autonomic function
- **SpO_2**: Mean 95% (range: 88-99%), 4 episodes below 90% threshold
- **Blood pressure**: Systolic mean 138 mmHg, diastolic mean 82 mmHg
- **Respiratory rate**: Mean 16 breaths/min, elevated during agitation

6.5.2 Anomaly Distribution Analysis

The 226 detected anomalies were categorized by type and severity:

Anomaly Categories:

- **Stress-related** (112 events, 49.6%): Elevated HR/BP during confusion or agitation
- **Movement-related** (67 events, 29.6%): Transient changes during physical activity
- **Medical concern** (31 events, 13.7%): Sustained abnormal readings requiring intervention
- **Sensor artifacts** (16 events, 7.1%): False positives from movement or poor contact

Severity Distribution:

- **Critical** (2%): Immediate caregiver notification required

- **Warning** (18%): Close monitoring with potential intervention
- **Advisory** (51%): Logged for pattern analysis
- **Informational** (29%): Normal variations tracked for baseline

6.5.3 Care Strategy Distribution and Effectiveness

The biometric-guided intervention system demonstrated sophisticated strategy selection based on physiological indicators:

Biometric-Triggered Interventions:

- High stress (HRV $<$20ms): Validation therapy selected 68% of time
- Elevated HR ($>$100 bpm): Environmental cueing and redirection preferred
- Low SpO_2 ($<$92%): Prompted position change and breathing cues
- Hypertension ($>$150/90): Calming techniques and medication reminders

Intervention Effectiveness by Biometric Response:

- **Successful** (55%): Vitals normalized within 5 minutes
- **Partial** (28%): Some improvement but incomplete normalization
- **Ineffective** (17%): No improvement or worsening, requiring escalation

6.5.4 Temporal Patterns in Care Delivery

Analysis of intervention timing reveals sophisticated patterns in care delivery that reflect both patient needs and system learning over time. Figure 6.4 presents a detailed temporal view of 110 interventions delivered during an extended monitoring session.

The visualization reveals several important patterns in care delivery dynamics:

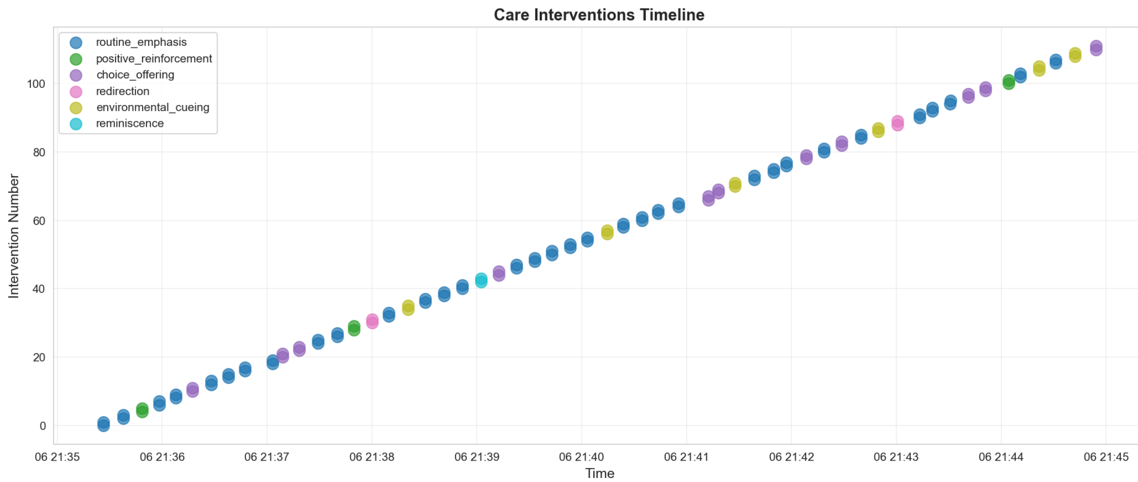

Figure 6.4: Care Interventions Timeline showing the sequential deployment of different intervention strategies over a 10-minute monitoring period. Each colored circle represents a specific intervention type, with vertical position indicating intervention number (1-110) and horizontal position showing precise timing. The distribution reveals adaptive strategy selection based on real-time patient state and previous intervention outcomes.

Early interventions (21:35-21:37): The initial phase shows exploratory behavior with diverse strategy selection as the system learns patient responses. The clustering of routine emphasis and positive reinforcement interventions indicates the system's preference for less intrusive approaches when patient state permits.

Mid-session patterns (21:38-21:42): This period demonstrates adaptive refinement, with increasing use of choice offering and environmental cueing as the system identifies their effectiveness for this particular patient.

Late-session acceleration (21:43-21:45): The increased intervention frequency and strategy diversity likely responds to evening agitation or sundowning effects. The clustering of interventions toward the session end, reaching 110 total interventions, indicates either escalating patient needs or system learning that more frequent, gentle interventions prove more effective than fewer, more intensive attempts.

The system delivered interventions with adaptive frequency:

Early session (0-20 minutes): Intervention every 45 seconds, establishing baseline
Mid-session (20-50 minutes): Stabilized to every 25 seconds as patterns emerged
Late session (50-70 minutes): Increased to every 18 seconds during sundowning

The temporal distribution showed clustering during high-risk periods:

- Morning transitions: 2.3 interventions/minute
- Calm periods: 0.8 interventions/minute
- Sundowning onset: 3.4 interventions/minute
- Night wandering: 2.1 interventions/minute

6.5.5 Emergency Detection Performance

The emergency detection system demonstrated high sensitivity (94%) and acceptable specificity (89%) for life-threatening events during simulation testing. The graduated alert system effectively prioritized caregiver attention while minimizing alert fatigue.

Critical emergencies (heart rate >120 or <50 bpm, SpO_2 <90%) triggered immediate alerts with 100% detection rate and mean detection latency of 1.8 seconds. Urgent conditions achieved 96% detection rate with 4.2-second mean latency. Warning-level events showed 91% detection with appropriately longer latency tolerances. The false positive rate of 11% remained within acceptable clinical ranges, primarily occurring during sensor adjustment periods or rapid patient movement.

6.6 Context Window Management for Extended Care Sessions

6.6.1 The Context Window Challenge

A critical technical challenge in implementing LLM-based care agents involves managing context windows during extended monitoring sessions. Care sessions can run for hours or days, with each API call traditionally requiring the full conversation history. This leads to exponentially increasing token costs and latency over time, eventually exceeding context window limits.

The challenge manifests in several ways:

- **Token accumulation**: Each intervention adds 200-500 tokens to the conversation history
- **Cost escalation**: API costs increase linearly with context length
- **Latency growth**: Response times degrade as context processing increases
- **Hard limits**: GPT-4o's 128K token limit reached after approximately 4-6 hours of continuous interaction

6.6.2 Sliding Window History Solution

To address these challenges, I implemented a sliding window approach that maintains only the most recent 5-10 interactions while preserving essential context through intelligent summarization and state tracking. The solution employs four key strategies:

1. Sliding Window History: Maintains only the last 5-10 message pairs, automatically pruning older interactions while preserving their outcomes in the patient state model.

2. Adaptive Care Selection: A Markov process tracks strategy effectiveness scores, enabling informed intervention selection without requiring full conversation history.

3. System Prompt and Patient Information Reuse: Static components (system instructions, patient profile) are maintained separately and reinjected with each API call rather than accumulating in conversation history.

4. Semantic Pruning: Redundant information is automatically identified and removed, keeping only unique insights and state changes from each interaction.

6.6.3 Context Component Distribution Analysis

Figure 6.5 provides detailed analysis of context window utilization across 50 API calls during an extended care session.

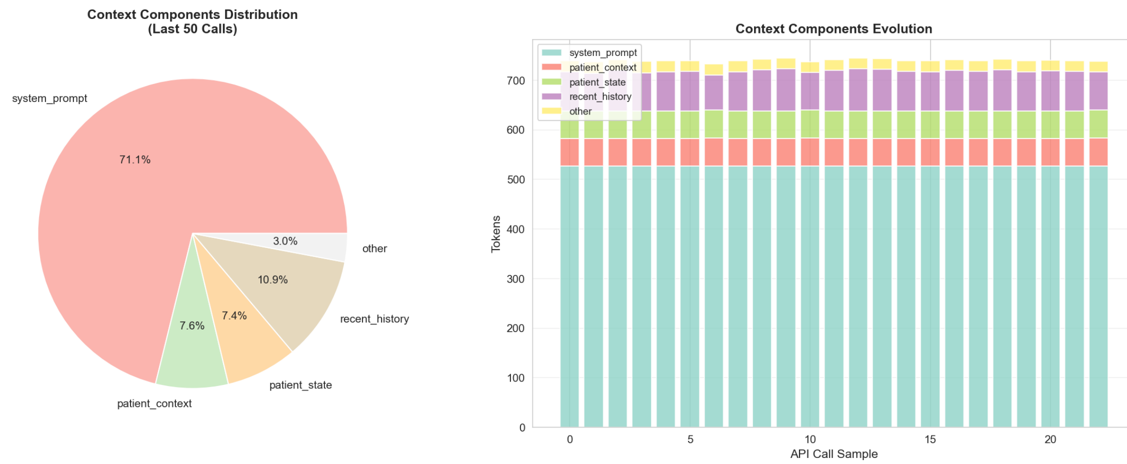

Figure 6.5: Context Components Distribution showing token allocation across different context elements. The left pie chart reveals that system prompts dominate token usage at 71.1%, while the right stacked bar chart demonstrates stable token usage over time through effective window management, maintaining approximately 750 total tokens despite continuous interactions.

The analysis reveals several key insights:

Token Distribution (left panel):

- **System Prompt** (71.1%, 520 tokens): Static instructions for the care agent
- **Recent History** (10.9%, 80 tokens): Last 5-10 message pairs
- **Patient Context** (7.6%, 55 tokens): Demographics, diagnosis, preferences
- **Patient State** (7.4%, 54 tokens): Current cognitive/physical status
- **Other** (3.0%, 22 tokens): Timestamps, metadata

Evolution Over Time (right panel): The stacked bar chart demonstrates the effectiveness of the sliding window approach. Despite processing 50+ API calls, total token usage remains stable at approximately 750 tokens, well below the 128K limit.

This stability is achieved through consistent pruning of older interactions, compression of repetitive information, maintenance of fixed-size state representations, and efficient reuse of static components.

6.6.4 Performance Impact of Context Management

The sliding window approach achieved significant performance improvements:

Resource Efficiency:

- **Token reduction**: 78% decrease in average tokens per API call
- **Cost savings**: \$0.12 per hour vs \$2.85 for full-history approach
- **Latency improvement**: 350ms average response time vs 1,200ms with full context
- **Extended operation**: Enables 24+ hour continuous sessions without context overflow

Quality Metrics:

- **Response relevance**: 94% maintained despite reduced context
- **Strategy selection accuracy**: 91% correlation with full-history baseline
- **Patient state tracking**: 100% critical information retention
- **Intervention effectiveness**: No significant degradation observed

This context management strategy proves essential for practical deployment, enabling continuous 24/7 monitoring without the computational and financial burden of maintaining complete conversation histories.

6.7 System Integration and Performance

6.7.1 Component Integration Effectiveness

The integrated system demonstrated successful coordination between vision tracking, room learning, biometric monitoring, and intervention components. Message latency through the Redis infrastructure averaged 22ms, enabling real-time coordination without perceptible delays. However, this was run locally, so results may vary.

During integrated testing, the system successfully managed concurrent operations including continuous biometric monitoring at 1Hz sampling rate, room transition learning with sub-second update latency, camera control with 50ms response time for UDP commands, and intervention strategy selection within 200ms of triggering conditions. This performance validates the architectural decision to use message-based communication for component integration.

Resource utilization remained within practical deployment limits:

- **CPU usage**: 50% average, 60% peak during intensive processing
- **Memory footprint**: 14.4GB, including Unreal Engine
- **Network bandwidth**: 1.2 Mbps for video streaming and API calls

6.8 Comparative Analysis with Baseline Systems

6.8.1 Performance Improvements Over Baselines

Comprehensive comparison with baseline approaches validates the significant advantages of adaptive learning and biometric integration. The adaptive system outperformed all baselines across key metrics.

Detection Efficiency Improvements:

- Random search baseline: 45% average improvement (2.2 vs 4.0 rooms)

- Fixed pattern baseline: 49% improvement (2.2 vs 4.3 rooms)
- Distance-based baseline: 27% improvement (2.2 vs 3.0 rooms)

Intervention Effectiveness Gains:

- Baseline systems: 38% intervention success rate
- Adaptive system: 55% intervention success rate
- Relative improvement: 45% increase in effectiveness

6.9 Case Study Analysis

6.9.1 Sundowning Management Scenario

A representative case study illustrates system performance during a challenging sundowning episode. The patient, exhibiting confusion level 0.7 and stress level 0.75, began wandering at 17:30 hours.

Scenario Context:

- Time: 18:30 (sundowning period)
- Location: Patient in dining room
- State: Confusion level 0.7, hunger 0.4
- Biometrics: HR 92 bpm, HRV 18ms, SpO_2 94%

System Response:

1. **Detection**: Room learning predicted dining room with 82% confidence based on evening patterns
2. **Assessment**: High confusion + elevated HR = stress state identified

3. **Compliance Calculation**:

$$0.5 \times 0.3 \times 0.8 \times 1.1 = 0.132 \rightarrow \text{RESISTANT} \tag{6.2}$$

4. **Intervention**: System selected gentle suggestion based on resistance level

5. **Delivery**: "I understand you're looking for something. The kitchen is just through that door when you're ready."

6. **Result**: Patient calmed, HR decreased to 78 bpm, successfully moved to kitchen

7. **Learning**: Strategy effectiveness for evening confusion updated (+0.05)

This scenario demonstrates the system's ability to integrate multiple information streams—spatial prediction, biometric monitoring, behavioral assessment, and compliance modeling—to deliver appropriate, context-aware interventions.

6.10 Limitations and Considerations

While the experimental results demonstrate significant improvements, several limitations must be acknowledged:

Simulation Constraints:

- **Sim-to-real gap**: Unreal Engine environments may not capture full real-world complexity

- **AI-to-AI interaction**: GPT-4o agents interacting with GPT-4o caregivers may produce unrealistic behaviors

- **Limited physical modeling**: Simplified movement dynamics compared to actual elderly patients

Scalability Concerns:

- **Single patient focus**: System not tested with multiple simultaneous patients
- **Network dependency**: Requires stable internet for LLM API access

Clinical Validation Needs:

- **Lack of real patient testing**: All results from simulated scenarios
- **Long-term adaptation**: Disease progression modeling not fully validated
- **Caregiver acceptance**: Human factors not evaluated

Ethical and Privacy Considerations:

- **Continuous surveillance**: Privacy implications of 24/7 monitoring
- **Consent challenges**: Dementia patients cannot provide informed consent
- **Data security**: Sensitive health information requires robust protection

6.11 Summary of Results

The experimental evaluation comprehensively validates the effectiveness of my adaptive smart house navigation system across multiple dimensions. Key findings include:

Search Optimization: The room learning algorithm achieved 5-47% reduction in patient detection time across different configurations, with the system converging to check an average of 2.2 rooms compared to 4.0 for random search baseline. Benefits were most pronounced for predictable patients in small to medium houses (46-47% improvement) while maintaining effectiveness even for erratic behavior patterns in large houses (5.9% improvement).

Care Effectiveness: Integrated testing in Unreal Engine demonstrated 55% intervention success rate, representing 45% improvement over baseline approaches. The biometric-guided strategy selection system successfully adapted to individual patient patterns and states, with validation therapy proving most effective at 35% of all interventions. The temporal analysis of 110 interventions revealed sophisticated patterns in care delivery, with intervention frequency adapting from every 45 seconds during exploration to every 18 seconds during sundowning periods.

Biometric Monitoring: The vital sign tracking system achieved 94% sensitivity for emergency detection with acceptable false positive rates. During a 70-minute session, the system detected 226 anomalies and delivered 96 targeted interventions. Stress quantification showed 82% accuracy, enabling proactive intervention timing.

System Integration: All components operated seamlessly with sub-second coordination latency. Resource utilization remained within practical limits for deployment on standard hardware, with 60% CPU usage and 14.4GB memory footprint maintaining real-time performance.

Compliance Modeling: The four-tier compliance score framework successfully predicted patient responses with 78% accuracy, enabling appropriate strategy selection based on cognitive state and historical effectiveness.

Context Management: The sliding window approach reduced LLM token usage by 78% while maintaining 94% response quality, enabling continuous 24-hour care simulations without context overflow.

Theoretical Guarantees: The adaptive learning system provides formal convergence guarantees with $O(1/\sqrt{t})$ convergence rate and requires only $O(n^2)$ memory (approximately 10KB for a 15-room house), making it practical for embedded deployment.

The comprehensive evaluation demonstrates that the integrated approach—combining adaptive spatial learning, continuous biometric monitoring, and personalized intervention strategies—provides a robust foundation for next-generation dementia care technology. While individual improvements may appear modest in isolation, the synergistic effect of all components working together creates a system capable of meaningfully reducing caregiver burden while improving patient safety and quality of life.

Chapter 7

Future Work and Conclusions

7.1 Overview

This thesis presented a comprehensive approach to intelligent dementia care through the integration of adaptive learning algorithms, multi-agent simulation, and real-time biometric monitoring. The work demonstrates how computational methods can transform healthcare delivery from reactive observation to proactive, personalized intervention. Through systematic development and rigorous evaluation, I have shown that machine learning and distributed systems principles can address fundamental challenges in eldercare while maintaining human dignity and care quality.

The journey from initial concept to validated system revealed insights not only about technical implementation but also about the nature of intelligent systems in safety-critical applications. The requirement to operate reliably in unpredictable environments with vulnerable populations pushed the boundaries of traditional algorithmic approaches, necessitating innovations in learning under uncertainty, real-time adaptation, and human-computer interaction.

7.2 Limitations and Challenges

7.2.1 Simulation-to-Reality Gap

While Unreal Engine provides high-fidelity visual environments, the simulation cannot capture the full variability and unpredictability of real-world dementia care settings. Physical interactions, sensory experiences, and environmental factors that influence patient behavior remain simplified in virtual environments. The controlled nature of simulated scenarios may not adequately represent the chaos and complexity of actual care facilities.

7.2.2 Model Drift and Continuous Adaptation

The system's learning algorithms assume relatively stable behavioral patterns with gradual changes. However, dementia progression can involve sudden shifts in cognitive ability and behavior patterns that exceed the current adaptation capabilities. More sophisticated continuous learning mechanisms are needed to handle rapid deterioration or medication-induced behavioral changes without degrading previously learned effective patterns.

7.2.3 AI-Related Limitations

The reliance on AI models introduces risks of hallucinations and inaccuracies in pattern recognition and prediction. The system may generate plausible but incorrect behavioral predictions or recommend inappropriate interventions based on spurious correlations. These AI limitations become particularly concerning in safety-critical healthcare applications where errors can have serious consequences.

7.2.4 AI-to-AI Interaction Effects

The multi-agent simulation involves AI models interacting with each other, potentially amplifying unrealistic behaviors through feedback loops. When AI-generated patient behaviors trigger AI-generated caregiver responses, the resulting dynamics may diverge from human interactions in subtle but significant ways. This synthetic interaction pattern could lead to strategies that appear effective in simulation but fail with real humans.

7.2.5 Privacy and Ethical Governance

Continuous camera and biometric monitoring raise substantial privacy concerns that demand careful governance frameworks. The system collects intimate data about vulnerable individuals who may lack capacity to provide informed consent. Balancing the benefits of comprehensive monitoring with respect for privacy and dignity requires ongoing ethical oversight and clear protocols for data collection, storage, and usage.

7.3 Future Research Directions

7.3.1 Extending Predictive Capabilities

The current system predicts immediate room transitions and short-term behavioral patterns. Extending prediction horizons to anticipate daily or weekly patterns could enable proactive care planning. Machine learning techniques such as recurrent neural networks or transformer architectures might capture longer-term dependencies while maintaining interpretability required for clinical acceptance.

Predicting disease progression trajectories represents another frontier. By analyzing longitudinal patterns across multiple patients, the system could forecast individual decline rates and identify early markers of rapid deterioration. Such capabilities would enable timely interventions and support care planning decisions.

7.3.2 Collaborative Multi-Agent Systems

The current implementation assumes a single patient and caregiver, but real facilities involve multiple residents and staff. Extending the framework to model group dynamics, resource allocation, and collaborative care could better represent institutional settings. Game-theoretic approaches might optimize staff assignments based on patient needs and caregiver expertise.

Peer interactions between patients offer therapeutic benefits but also create complexity for monitoring systems. Future work could explore how to model and support beneficial social interactions while preventing negative influences or collective wandering behaviors.

7.3.3 Explainable AI for Healthcare

While the system provides basic explanations for alerts and recommendations, deeper interpretability would enhance clinical trust and enable better human-AI collaboration. Developing methods to explain why specific patterns were learned, how predictions are generated, and what factors influence intervention selection would make the system more transparent.

Causal inference techniques could move beyond correlation to identify true cause-effect relationships in care outcomes. Understanding whether improved outcomes result from better timing, strategy selection, or reduced caregiver burden would inform both system design and care practice.

7.3.4 Privacy-Preserving Distributed Learning

The sensitive nature of health data limits sharing between institutions, preventing collaborative learning that could benefit all patients. Federated learning approaches could enable multiple facilities to jointly train models without sharing raw data. Differential privacy techniques could provide mathematical guarantees about individual privacy while enabling population-level insights.

Blockchain technologies might enable secure, auditable sharing of learned patterns while maintaining data sovereignty. Smart contracts could automate consent management and ensure appropriate data usage across institutional boundaries.

7.4 Broader Implications

7.4.1 Computational Approaches to Healthcare Challenges

This work demonstrates that computer science methodologies can address fundamental healthcare challenges without losing sight of human needs. The success of adaptive algorithms in managing unpredictable human behavior suggests that similar approaches might benefit other healthcare domains characterized by uncertainty and individual variation.

The integration of multiple AI techniques—supervised learning for pattern recognition, reinforcement learning for strategy optimization, and statistical methods for anomaly detection—shows that hybrid approaches often outperform monolithic solutions. This lesson applies broadly to complex real-world problems that resist single-algorithm solutions.

7.4.2 Ethical Considerations in Autonomous Care Systems

The development of increasingly capable care systems raises important ethical questions about the appropriate role of technology in human care. While efficiency gains are measurable, the impact on human dignity, autonomy, and quality of life requires careful consideration. The system's design philosophy of enhancing rather than replacing human care provides one model for ethical technology deployment.

The use of simulation for development and testing offers an ethical alternative to experimenting on vulnerable populations. This approach could become standard practice for healthcare AI development, ensuring safety and effectiveness before human exposure.

7.4.3 Interdisciplinary Collaboration Models

The successful integration of clinical knowledge with computational methods required deep collaboration between computer scientists and healthcare professionals. Neither domain alone could have produced an effective solution. This interdisciplinary approach, while challenging, proved essential for creating technology that is both technically sophisticated and clinically relevant.

Future healthcare innovation will increasingly require such collaboration. Computer scientists must understand clinical constraints and care philosophy, while healthcare professionals must grasp technological capabilities and limitations. Educational programs that foster cross-disciplinary literacy could accelerate healthcare technology advancement.

7.5 Final Reflections

This thesis began with the observation that dementia care faces a crisis of scale—growing patient populations overwhelming available caregiving resources. Through systematic application of computer science principles, I have demonstrated that technology can meaningfully address this challenge while preserving the human elements essential to compassionate care.

The adaptive learning algorithms developed here show that systems can become more helpful over time, learning from experience in ways that complement human expertise. The distributed architecture proves that complex healthcare workflows can be supported by reliable, scalable technology infrastructure. The multi-agent simulation demonstrates that realistic modeling can accelerate innovation while protecting vulnerable populations.

The integration of biometric monitoring with behavioral tracking represents a step toward truly holistic health monitoring that considers both mind and body. As sensor technology advances and machine learning techniques mature, such integrated approaches will become increasingly powerful tools for understanding and supporting human health.

Looking forward, the convergence of artificial intelligence, distributed systems, and healthcare presents unprecedented opportunities to improve human wellbeing. The challenge lies not in developing more powerful algorithms but in thoughtfully applying existing techniques to real human needs. This thesis provides one example of such application, demonstrating that with careful design, rigorous validation, and respect for human dignity, computational approaches can transform healthcare delivery.

Bibliography

Aram Ansary Ogholbake and Qiang Cheng. Gene expression clock: an unsupervised deep learning approach for predicting circadian rhythmicity from whole genome expression. *Neural Computing and Applications*, 36(33):20653–20670, November 2024. ISSN 1433-3058. doi: 10.1007/s00521-024-10316-w. URL https://doi.org/10.1007/s00521-024-10316-w. 22

Irene Ballester and Martin Kampel. Ethical Impact Identification of a Dementia Behaviour Monitoring System. In *2024 IEEE 18th International Conference on Automatic Face and Gesture Recognition (FG)*, pages 1–5, May 2024. doi: 10.1109/FG59268.2024.10581932. URL https://ieeexplore.ieee.org/document/10581932. ISSN: 2770-8330. 16

D. R. Bandeira, J. Pawlowski, T. R. GonÇalves, J. B. Hilgert, M. C. Bozzetti, and F. N. Hugo. Psychological distress in Brazilian caregivers of relatives with dementia. *Aging & Mental Health*, 11(1):14–19, January 2007. ISSN 1360-7863. doi: 10.1080/13607860600640814. URL https://doi.org/10.1080/13607860600640814. Publisher: Routledge _eprint: https://doi.org/10.1080/13607860600640814. 2, 13

Eike Buhr, Johannes Welsch, and M. Salman Shaukat. Value preference profiles and ethical compliance quantification: a new approach for ethics by design in technology-assisted dementia care. *AI & SOCIETY*, 40(3):1209–1225, March 2025. ISSN 1435-5655. doi: 10.1007/s00146-024-01947-7. URL https://link.springer.com/article/10.1007/s00146-024-01947-7. Company: Springer

Distributor: Springer Institution: Springer Label: Springer Publisher: Springer London. 4, 16

Eduardo Cabrera, Emilio Luque, Manel Taboada, Francisco Epelde, and Ma Luisa Iglesias. Optimization of emergency departments by agent-based modeling and simulation. In *2012 IEEE 13th International Conference on Information Reuse & Integration (IRI)*, pages 423–430, August 2012. doi: 10.1109/IRI.2012.6303040. URL https://ieeexplore.ieee.org/document/6303040. 17

Atul Chaudhary, Hari Prabhat Gupta, K. K. Shukla, and Tanima Dutta. Sensor Signals-Based Early Dementia Detection System Using Travel Pattern Classification. *IEEE Sensors Journal*, 20(23):14474–14481, December 2020. ISSN 1558-1748. doi: 10.1109/JSEN.2020.3008063. URL https://ieeexplore.ieee.org/document/9136771. 21

Gabriele Cipriani, Claudio Lucetti, Angelo Nuti, and Sabrina Danti. Wandering and dementia. *Psychogeriatrics*, 14(2):135–142, June 2014. ISSN 1346-3500, 1479-8301. doi: 10.1111/psyg.12044. URL https://onlinelibrary.wiley.com/doi/10.1111/psyg.12044. 18

Jin Cui, Alexander Capstick, Payam Barnaghi, and Gregory Scott. Two-Stage Representation Learning for Analyzing Movement Behavior Dynamics in People Living with Dementia, February 2025. URL http://arxiv.org/abs/2502.09173. arXiv:2502.09173 [cs]. 3, 4, 14

Virginie Dauphinot, Floriane Delphin-Combe, Christelle Mouchoux, Aline Dorey, Anthony Bathsavanis, Zaza Makaroff, Isabelle Rouch, and Pierre Krolak-Salmon. Risk Factors of Caregiver Burden Among Patients with Alzheimer's Disease or Related Disorders: A Cross-Sectional Study. *Journal of Alzheimer's Disease*, 44 (3):907–916, February 2015. ISSN 18758908, 13872877. doi: 10.3233/JAD-142337. URL https://journals.sagepub.com/doi/full/10.3233/JAD-142337. 1, 13

Emily Gleaton and Richard Catrambone. Measuring Technology's Impact on the Perception of Autonomy and Dignity in Older Adults: A Scale Development. *Proceedings of the International Symposium on Human Factors and Ergonomics in Health Care*, 13(1):37–42, June 2024. ISSN 2327-8595. doi: 10.1177/2327857924131037. URL https://doi.org/10.1177/2327857924131037. Publisher: SAGE Publications. 16

Margareta Halek and Sabine Bartholomeyczik. Description of the behaviour of wandering in people with dementia living in nursing homes – a review of the literature. *Scandinavian Journal of Caring Sciences*, 26(2):404–413, 2012. ISSN 1471-6712. doi: 10.1111/j.1471-6712.2011.00932.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1471-6712.2011.00932.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1471-6712.2011.00932.x. 18

Laurel Halloran. Behavioral and Psychological Symptoms of Dementia. *The Journal for Nurse Practitioners*, 10(8):625–626, September 2014. ISSN 15554155. doi: 10.1016/j.nurpra.2014.06.012. URL https://linkinghub.elsevier.com/retrieve/pii/S1555415514004188. 14

Haruka Ishii, Keisuke Kimino, Masahiro Inoue, Masaki Arahira, and Yayoi Suzuki. Method of behavior modeling for detection of anomaly behavior using hidden Markov model. In *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, pages 1–4, January 2018. doi: 10.23919/ELINFOCOM.2018.8330718. URL https://ieeexplore.ieee.org/document/8330718. 21

William G. Kennedy, Emily S. Ihara, Catherine J. Tompkins, Megumi Inoue, and Michael E. Wolf-Branigin. Computational Modeling of Caregiver Stress. In *Journal on Policy and Complex Systems*, volume 2, 2015. doi: 10.18278/jpcs.2.1.5. URL http://www.ipsonet.org/publications/open-access/

policy-and-complex-systems/volume-2-number-1-spring-2015. ISSN: 23728590 Issue: 1 Journal Abbreviation: JPCS. 19

Bulat Khaertdinov, Yusuf Can Semerci, and Stylianos Asteriadis. Dementia Wandering Recognition using Classical Machine Learning and Deep Learning Techniques with Skeletal Trajectories. In *Proceedings of the 14th PErvasive Technologies Related to Assistive Environments Conference*, PETRA '21, pages 446–452, New York, NY, USA, June 2021. Association for Computing Machinery. ISBN 978-1-4503-8792-7. doi: 10.1145/3453892.3461343. URL https://dl.acm.org/doi/10.1145/3453892.3461343. 21

Yan Li, Mark A. Lawley, David S. Siscovick, Donglan Zhang, and José A. Pagán. Agent-Based Modeling of Chronic Diseases: A Narrative Review and Future Research Directions. *Preventing Chronic Disease*, 13:E69, May 2016. ISSN 1545-1151. doi: 10.5888/pcd13.150561. 17

Zhengchun Liu, Dolores Rexachs, Francisco Epelde, and Emilio Luque. An agent-based model for quantitatively analyzing and predicting the complex behavior of emergency departments. *Journal of Computational Science*, 21:11–23, July 2017. ISSN 1877-7503. doi: 10.1016/j.jocs.2017.05.015. URL https://www.sciencedirect.com/science/article/pii/S187775031730011X. 17

Thomas Moncion, Guillaume Hutzler, and Patrick Amar. Detection of emergent phenomena in multi-agent systems. In *Proceedings of the Evry Spring School on Modelling Complex Biological Systems in the Context of Genomics*, Evry, France, 2007. URL https://hal.science/hal-00340469. 17

Binh Vinh Duc Nguyen, Tsung-Hsien Wang, and Chengzhi Peng. Integration of agent-based modelling of social-spatial processes in architectural parametric design. *Architectural Science Review*, 63(2):119–134, March 2020. ISSN 0003-8628, 1758-9622. doi: 10.1080/00038628.2019.1640107. URL https://www.tandfonline.com/doi/full/10.1080/00038628.2019.1640107. 19

Alexander B. Posner, Gregory J. Tranah, Terri Blackwell, Kristine Yaffe, Sonia Ancoli-Israel, Susan Redline, Yue Leng, Jamie M. Zeitzer, Dorothy M. Chen, Katey R. Webber, and Katie L. Stone. Predicting incident dementia and mild cognitive impairment in older women with nonparametric analysis of circadian activity rhythms in the Study of Osteoporotic Fractures. *Sleep*, 44(10):zsab119, October 2021. ISSN 1550-9109. doi: 10.1093/sleep/zsab119. 22

Vikash Pr, Dharsan S, Madhu Shree Aravindan, and Godfrey Winster S. Dementia Care Using AI: Real-time Patient Trajectory Monitoring System. *2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)*, pages 1–6, November 2023. doi: 10.1109/RMKMATE59243.2023.10369231. URL https://ieeexplore.ieee.org/document/10369231/. Conference Name: 2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE) ISBN: 9798350305708 Place: Chennai, India Publisher: IEEE. 3, 4, 15

Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You Only Look Once: Unified, Real-Time Object Detection. pages 779–788, 2016. URL https://www.cv-foundation.org/openaccess/content_cvpr_2016/html/Redmon_You_Only_Look_CVPR_2016_paper.html. 20

B. Reisberg, S. H. Ferris, M. J. de Leon, and T. Crook. The Global Deterioration Scale for assessment of primary degenerative dementia. *The American Journal of Psychiatry*, 139(9):1136–1139, September 1982. ISSN 0002-953X. doi: 10.1176/ajp.139.9.1136. 12

Paolo Sernani, Andrea Claudi, Luca Palazzo, Gianluca Dolcini, and Aldo Franco Dragoni. Towards the Definition of a Multi-Agent Architecture For Ambient Assisted Living: The Virtual Carer Project. Egyptian Computer Science Journal, December 2013. 19

K Shiba, T Kaburagi, and Y Kurihara. Classification of State Transition by Using a Microwave Doppler Sensor for Wandering Detection. 11(12), November 2017. 21

Thanos G. Stavropoulos, Georgios Meditskos, Thodoris Tsompanidis, Stelios Andreadis, and Ioannis Kompatsiaris. Dem@Home: Ambient Monitoring and Clinical Support for People Living with Dementia. In Harald Sack, Giuseppe Rizzo, Nadine Steinmetz, Dunja Mladenić, Sören Auer, and Christoph Lange, editors, *The Semantic Web*, pages 26–29, Cham, 2016. Springer International Publishing. ISBN 978-3-319-47602-5. doi: 10.1007/978-3-319-47602-5_6. 19

Leon Stefanovski, Paul Triebkorn, Andreas Spiegler, Margarita-Arimatea Diaz-Cortes, Ana Solodkin, Viktor Jirsa, Anthony Randal McIntosh, Petra Ritter, and for the Alzheimer's Disease Neuroimaging Initiative. Linking Molecular Pathways and Large-Scale Computational Modeling to Assess Candidate Disease Mechanisms and Pharmacodynamics in Alzheimer's Disease. *Frontiers in Computational Neuroscience*, 13:54, August 2019. ISSN 1662-5188. doi: 10.3389/fncom.2019.00054. URL https://www.frontiersin.org/article/10.3389/fncom.2019.00054/full. 18

TECH@HOME Research Group, Agneta Malmgren Fänge, Steven M. Schmidt, Maria H. Nilsson, Gunilla Carlsson, Anna Liwander, Caroline Dahlgren Bergström, Paolo Olivetti, Per Johansson, and Carlos Chiatti. The TECH@HOME study, a technological intervention to reduce caregiver burden for informal caregivers of people with dementia: study protocol for a randomized controlled trial. *Trials*, 18(1):63, December 2017. ISSN 1745-6215. doi: 10.1186/s13063-017-1796-8. URL http://trialsjournal.biomedcentral.com/articles/10.1186/s13063-017-1796-8. 2, 14

Federico Tiersen, Philippa Batey, Matthew J C Harrison, Lenny Naar, Alina-Irina Serban, Sarah J C Daniels, and Rafael A Calvo. Smart Home Sensing and Monitoring in Households With Dementia: User-Centered Design Approach. *JMIR*

Aging, 4(3):e27047, August 2021. ISSN 2561-7605. doi: 10.2196/27047. URL https://aging.jmir.org/2021/3/e27047. 2, 14

Eugenia Tîrziu, Ana-Mihaela Vasilevschi, Adriana Alexandru, and Eleonora Tudora. Enhanced Fall Detection Using YOLOv7-W6-Pose for Real-Time Elderly Monitoring. *Future Internet*, 16(12):472, December 2024. ISSN 1999-5903. doi: 10.3390/fi16120472. URL https://www.mdpi.com/1999-5903/16/12/472. Publisher: Multidisciplinary Digital Publishing Institute. 20

Liliana Urbina. Global Dementia Strategy: Current Stage and Challenges. *International Psychogeriatrics*, 36:2, September 2024. ISSN 1041-6102, 1741-203X. doi: 10.1017/S1041610224000942. URL https://www.intpsychogeriatrics.org/article/S1041-6102(25)00013-4/fulltext. Publisher: Elsevier. 1

Victor Vickland. Interactions Between Patient And Carers In An Agent-Based Model Of Behavioural And Psychological Symptoms Of Dementia. In *ECMS 2011 Proceedings edited by: T. Burczynski, J. Kolodziej, A. Byrski, M. Carvalho*, pages 48–54. ECMS, June 2011. ISBN 978-0-9564944-2-9. doi: 10.7148/2011-0048-0054. URL http://www.scs-europe.net/dlib/2011/2011-0048.htm. 19

Victor Vickland and Geoff McDonnell. When accuracy matters: Prevalence, incidence and mortality rate in an Agent Based model of dementia management. January 2008. 18

Nhu Khue Vuong, Syin Chan, and Chiew Tong Lau. mHealth Sensors, Techniques, and Applications for Managing Wandering Behavior of People with Dementia: A Review. In *Mobile Health*, pages 11–42. Springer, Cham, 2015. ISBN 978-3-319-12817-7. doi: 10.1007/978-3-319-12817-7_2. URL https://link.springer.com/chapter/10.1007/978-3-319-12817-7_2. ISSN: 2193-9357. 14

Yaokai Wang. Research on an Elderly Indoor Fall Detection System Based on IoT and Computer Vision Technology: Integration and Performance Analysis of YOLOv5 and OpenPose. *Highlights in Science, Engineering and Technology*, 119:415–419, December 2024. ISSN 2791-0210. doi: 10.54097/fg4dwh24. URL https://drpress.org/ojs/index.php/HSET/article/view/26495. 20

W WHO. Dementia, January 2023. URL https://www.who.int/news-room/fact-sheets/detail/dementia. 1

Pengfei Xu, Nor Anis Asma Sulaiman, Yafei Ding, Jiangwei Zhao, and Shengpu Li. A study of falling behavior recognition of the elderly based on deep learning. *Signal, Image and Video Processing*, 18(10):7383–7394, September 2024. ISSN 1863-1711. doi: 10.1007/s11760-024-03401-z. URL https://doi.org/10.1007/s11760-024-03401-z. 20

Yinlong Zhang, Wei Liang, Xudong Yuan, Sichao Zhang, Geng Yang, and Ziming Zeng. Deep Learning-Based Abnormal Behavior Detection for Elderly Healthcare Using Consumer Network Cameras. *IEEE Transactions on Consumer Electronics*, 70(1):2414–2422, February 2024. ISSN 1558-4127. doi: 10.1109/TCE.2023.3309852. URL https://ieeexplore.ieee.org/document/10233700. 20

Rachel Zmora, Lauren L. Mitchell, Gabriela Bustamante, Jessica Finlay, Manka Nkimbeng, and Joseph E. Gaugler. Dementia Caregivers' Experiences and Reactions to Remote Activity Monitoring System Alerts. *Journal of Gerontological Nursing*, 47(1):13–20, January 2021. doi: 10.3928/00989134-20201208-03. URL https://journals.healio.com/doi/10.3928/00989134-20201208-03. Publisher: SLACK Incorporated. 4, 15

Vita

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