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Title	Simulation and Detection of Abnormal Behaviors for the Elderly Living Alone in a Smart Home
Author(s)	田中, 海
Degree Grantor	北海道大学
Degree Name	博士(情報科学)
Dissertation Number	甲第16501号
Issue Date	2025-03-25
DOI	https://doi.org/10.14943/doctoral.k16501
Doc URL	https://hdl.handle.net/2115/94932
Type	doctoral thesis
File Information	Kai_Tanaka.pdf



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DOCTORAL THESIS

Simulation and Detection of Abnormal Behaviors for the Elderly Living Alone in a Smart Home

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A thesis submitted in fulfillment of the requirements for the degree of Doctor of information science and technology

January 18, 2025



Declaration of Authorship

I, Kai Tanaka, declare that this thesis titled, "Simulation and Detection of Abnormal Behaviors for the Elderly Living Alone in a Smart Home" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: Kai Tanaka

Date: 2024-12-04

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Abstract

Graduate School of Information Science and Technology

Doctor of information science and technology

Simulation and Detection of Abnormal Behaviors for the Elderly Living Alone in a Smart Home

by Kai Tanaka

This study presents a simulator-based approach to detect anomalies among elderly individuals living alone in smart homes. The proposed simulator generates six typical anomalies: being semi-bedridden, being housebound, wandering, forgetting to turn off appliances, falls while walking, and falls while standing. These anomalies, categorized into state, activity, and moving types, are statistically modeled based on the mini-mental state examination score, which governs their frequency and duration as a proxy for dementia progression. Unlike previous simulators, this framework can generate both short-term and long-term anomalies, ranging from seconds to years, and simulate outputs from ambient sensors such as passive infrared motion sensors and pressure sensors.

Experimental evaluations on simulation data demonstrate the realism of activity sequences and the practicality of the proposed anomaly detection methods. The generated activity sequences closely mimic real-world activity patterns, exhibiting variances and similarities, measured by edit distance, greater than random data. Detection classifiers trained on simulated data achieved a sensitivity of over 0.9 with fewer than one false alarm every 50 days for most anomalies. Sensitivity for falls while walking, initially 0.75, can be improved to 0.96 through oversampling. Newly proposed detection methods for being housebound, being semi-bedridden, and forgetting achieved high precision and recall. By leveraging simulated data, the framework avoids the high costs and challenges associated with collecting long-term real-world data while maintaining a high degree of similarity to real activity sequences.

This work highlights the potential of privacy-preserving ambient sensors, such as infrared motion sensors, pressure sensors, door sensors, and cost sensors, to detect long-term behavioral changes in elderly individuals. The simulator-based framework offers a cost-effective solution for enhancing care in smart homes, emphasizing its scalability and adaptability. Future research will focus on refining the simulation models, incorporating richer sensor data, and bridging the gap between simulated training and real-world deployment to further support early intervention and improved elderly care.

Acknowledgements

I would like to express my deepest gratitude to my supervisors, Professor Mineichi Kudo and Professor Atsuyoshi Nakamura, for their invaluable guidance and support throughout my doctoral studies. Their mentorship extended beyond the research itself, teaching me the essential mindset and attitude required to grow as a researcher. My sincere thanks go to Assistant Professor Keigo Kimura for his assistance and helpful discussions. I am also grateful to my sub-supervisors, Professor Akira Tanaka, Professor Masanori Sugimoto, and Professor Takashi Matsubara, for their insightful advice and encouragement.

I am thankful to all the members of our laboratory for their collaboration and friendship. I am indebted to the Hokkaido University for providing an excellent learning environment. I also extend my appreciation to the Inoue Scholarship Foundation and the Ambitious Doctoral Fellowship for financial support and opportunities of camaraderie with fellow scholarship students. I would also like to extend my sincere gratitude to the long-term caregiving staff at Sun Ju Sou Co. for sharing their valuable insights during interviews. Although the content of these interviews was not directly used in this thesis, their perspectives greatly deepened my understanding and provided essential context for my research.

This work was supported by Hokkaido Gas Co., Ltd., Japan, JSPS KAKENHI Grant Number 19H04128, and JST SPRING, Grant Number JPMJSP2119.

Finally, I would like to express my heartfelt gratitude to my parents for their unwavering support and constant encouragement.

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Chapter 1

Introduction

1.1 Background and motivation

This research aims to prevent in advance the deterioration of health among elderly individuals living alone. This is an urgent issue in aging society.

1.1.1 Aging Society

The global population is experiencing a significant increase in the proportion of elderly individuals. The aging rate, which represents the share of the elderly aged 65 years or older within the total population, is 8.5% in 2015 [1] and 9.3% (727 million persons) in 2020 [2] of the world's total population. This proportion is led by many countries in Europe and East Asia, and expected to increase to be more than 16.0% (1.5 billion persons) by 2050 [1, 2].

In particular, Japan is the highest aging society in 2015 among major countries (whose total population is more than one million in 2015) [1], and the aging rate of Japan in 2020 is 28.8% [3]. This rate has steadily risen from 4.9% in 1950 and is expected to reach 32.8% by 2035 and 38.4% by 2065. The primary factors contributing to this trend are explained by declining age-adjusted mortality rates and decreasing birth rates.

Alongside the growing elderly population, there is a notable rise in the number of elderly individuals living alone. As of 2015 in Japan, 13.3% of males and 21.1% of females aged 65 and over were living independently. These percentages have risen from 4.3% for males and 11.2% for females in 1980 and are projected to reach 20.8% for males and 24.5% for females by 2040 [3]. Similar trends are observed internationally; a study analyzing data from 61 countries in 2011 revealed that approximately 30 countries, including France and the United States, have higher proportions of elderly individuals living alone than Japan [4]. Some nations, such as Switzerland and Denmark, report that over 20% of elderly men and over 40% of elderly women live alone.

1.1.2 Anomalies of the Elderly Persons

As individuals age, they often experience a decline in physical and cognitive abilities, leading to various anomalies that require attention. In 2019, 43.6% of people aged 65 and older in the United States reported some form of disability. Specifically, 27.7% had mobility disabilities, and 6.1% faced self-care difficulties [5]. Cognitive function also diminishes with age; the Mini-Mental State Examination (MMSE), a common measure of cognitive ability, shows a median decrease of four points when comparing the 18–24 age group to those aged 80 and older [6]. These MMSE is related to hazardous situations such as dementia [7], falls [8] and wandering [9, 10].

In the worst case, the increasing rate of elderly individuals found incapacitated or deceased in their homes happen more with age, as demonstrated in a 1993 study from San Francisco, where 3 out of 1000 people aged 60 to 64 were found in such conditions, rising to 27 per 1000 for those aged 85 or older [11]. In Tokyo, the capital of Japan, the number of solitary elderly individuals found deceased in their homes nearly doubled from 2,194 in 2009 to 3,936 in 2019 [3]. This growing issue has led to significant anxiety among elderly people living alone, with 50.8% expressing concerns about dying in isolation [3]. These statistics highlight the increasing importance of monitoring the health of elderly individuals living alone to help alleviate these concerns.

Furthermore, Japanese government is under pressure to treat the social benefits related to the aging population. In 2018, 6.453 million elderly individuals in Japan were certified as needing long-term care, an increase from 4.696 million in 2009. This contributed to elderly-related social security benefits (that is the aggregate cost for pension benefits, medical care, welfare services, and subsidies for elderly employees) totaling 80.8268 trillion yen in 2018, accounting for 66.5% of all social benefits [3]. The primary reasons for requiring nursing care include dementia (18.1%), stroke (15.0%), age-related frailty (13.3%), and fractures or falls (13.0%) [3]. By promptly detecting anomalies that may occur in the elderly including falls, we can aim to extend healthy life expectancy and potentially reduce the financial strain on social security.

1.1.3 Lack of Care Workers

Long-term care (LTC) workers are paid professionals, typically nurses and personal caregivers, who assist individuals with limited ability to perform daily activities, either at home or in care facilities, excluding hospitals. The demand for LTC workers is projected to increase significantly due to the aging global population. In 2020, in 13 developed countries, including Japan and the United States, the proportion of people requiring daily care ranged from 6.8% to 8.2%. When divided by the working-age population (aged 15–59), this ratio was between 11.4% and 15.0% [12]. However, the supply of these workers is not keeping pace with the growing need. Data from 23 OECD countries show that the number of LTC workers per 100 people aged 65 and over slightly decreased from 5.9 in 2011 to 5.7 in 2021 [13]. This indicates that despite an absolute increase in the number of workers, it's insufficient relative to the rapidly increasing elderly population. Countries such as Japan and the United States not only face insufficient numbers of care workers but also contend with high turnover rates in the profession [14, 15]. In Japan, the job openings-to-applicants ratio for care workers is increasing. The ratio was 3.65 in 2021, about three times higher than the average ratio of 1.03 across all occupations [16]. This significant shortage highlights the challenges in providing consistent and stable care solely through human resources.

1.1.4 Age in Place

Many elderly individuals wish to continue living in their own communities or homes. According to a 2019 survey in Japan [16], 78% of people aged 65 and over prefer to stay in their current municipalities or nearby areas. Additionally, the another survey [3] reports that about half (51%) of those aged 60 and over would choose to spend their final days at home if faced with an incurable illness. This demonstrates a strong desire among the elderly to receive care in their home.

This needs align with the Aging in Place model [17], which enables older adults to age in their preferred unrestrictive environment. The model allows individuals to control the timing and intensity of services delivered at home to prevent the mental and physical decline often called as relocation stress syndrome [18]. Furthermore, the Sustainable Development Goal (SDG) No. 3 aims to ensure healthy lives and promote well-being for people of all ages. From this viewpoint, it is desirable to monitor the health of elderly persons living alone and to maximize their healthy life expectancy. Addressing the labor shortage is crucial to provide the necessary services that allow elderly people to continue living independently in their homes.

1.1.5 Smart Home

By leveraging smart home technology, it is possible to continuously monitor the health and behavior of elderly people living alone without the need for constant human visit. Sensor-based health monitoring systems need only the initial setup and running costs of the equipment. This approach addresses both the shortage of care workers and the need for cost-effective caregiving services. Implementing non-invasive sensors in smart homes offers a practical and sustainable solution to meet the growing demand for home medical care.

Many studies has been exploring information and communication technology (ICT) and internet of things (IoT) technologies to monitor the physical and mental well-being of elderly individuals [19, 20]. This approach is known as Ambient Assisted Living (AAL) [21] that involves placing sensors in living environments to collect data mainly for monitoring daily activities to support independent living. AAL is part of Gerontechnology [22] that is a field focused on solving health issues of the elderly through technology. AAL is also the one application of the concept of ambient intelligence [23] that aims to provide assistive and predictive support for residents via invisible devices embedded in the surrounding environment.

In particular, smart homes are residences equipped with multiple unobtrusive sensors, such as infrared motion sensors, to monitor the behavior and health of the residents [24]. In these smart homes, data collected by the sensors about the residents and their environment are analyzed to achieve health monitoring and other goals [24]. Health monitoring using smart homes remains an active area of research since the 2010s including assessing the long-term health score [25, 26, 27], detecting deviating behaviors [28, 29, 30, 31, 32, 33], detecting concrete anomalies such as falls [34, 35, 36] and wanderings [37, 38, 39], gait speed estimation [27], activity recognition [40], and large testbeds [27, 41, 26, 42].

Smart homes use various types of sensors to monitor the health and behavior of elderly residents, including wearable sensors, camera sensors, and ambient (environmental) sensors [36]. To continuously and long-term assess residents' health while minimizing physical burden and preserving privacy, smart homes often prefer sensors that are ubiquitous and non-intrusive [43, 27]. In this viewpoint, ambient sensors such as motion infrared sensors and pressure sensors are especially beneficial because they are unobtrusive and help protect the privacy of residents [36, 44]. These sensors are also robust against changes in light conditions and can operate for years without needing a battery change. In this regard, ambient sensors are more advantageous than camera or wearable sensors.

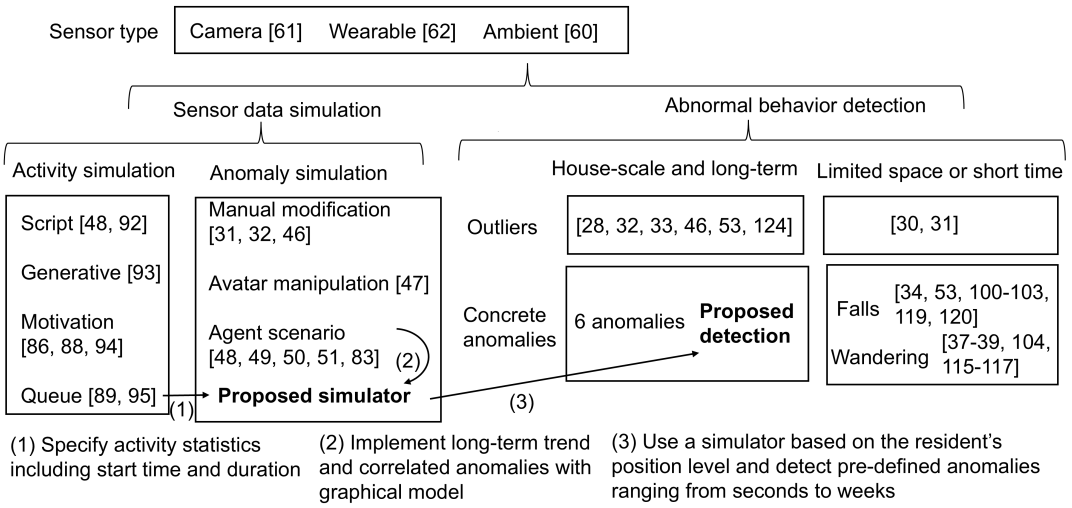


FIGURE 1.1: The development routes within related works. Our work uses ambient sensors. To collect data, we developed an activity simulator and an anomaly simulator to generate long-term correlated anomalies. Using these simulators, we detect six concrete anomalies at a house scale and over long-term periods.

1.2 Objectives

In this study, we propose an anomaly detection method that, with privacy considerations, simultaneously detects multiple anomalies of different durations from sensor data such as infrared and pressure sensors. Furthermore, since the anomaly detection model requires learning from data, we introduce a simulator capable of providing a large amount of sensor data incorporating abnormal patterns. We introduce two problems in this field. For more details, please refer to the 'Related Works' section. The development routes is summarized in Fig. 1.1.

1.2.1 Modeling and Simulation of Anomalies

Developing anomaly detection algorithms requires large sensor data that includes labels of anomalous behaviors. However, gathering such data as desired over long-term is challenging due to the difficulties to change settings including floor plan and resident's activity patterns. Additionally, labeling behaviors in collected data is time-consuming and often impractical for anomaly behaviors.

To overcome these obstacles, sensor data simulators are proposed [45] including anomalous labels [32, 46, 31, 47, 48, 49, 50, 51]. However, existing methods have certain limitations:

Increasing frequency of anomalies: They do not consider that anomalies may become more frequent or severe over time.

Correlation between anomalies: They do not account for the correlations between different anomalies.

Limited incorporation of typical anomalies: While existing research targets anomalies such as falls and wandering, they often represent anomalies as mere outliers and do not aim to simulate anomalies with specific, concrete characteristics.

For the first point, we need to include mechanisms that allow the frequency of some anomalies to increase as time goes on. Regarding the second point, for example, dementia is known to cause various anomalies in behavior [52].

To address these limitations, we propose the development of a sensor data simulator capable of generating large volumes of sensor data that incorporate predefined anomaly models of six typical abnormal patterns such as being semi-bedridden, being housebound, forgetting to turn off home appliances, wanderings, falls while walking, falls while standing. The simulator allows for the inclusion of different room layouts, resident routines, and anomalies, providing a diverse dataset necessary for training effective anomaly detection algorithms. This simulator also allows for operating correlation of frequencies or durations between anomalies in timely manner by introducing the anomaly simulator component in the existing simulation framework.

1.2.2 Detection of Anomalies

Under the environment embedded ambient sensors, some studies detect anomalous behavioral deviation [31, 53, 28, 54]. However, existing anomaly detection methods using binary motion sensors have the following problems.

Limited detection across different time scales: Existing methods cannot detect anomalies across various time scales (seconds to weeks) simultaneously and lack standardized sensor data processing.

Not explicitly defined multiple anomalies: Many methods do not explicitly define the anomalies they aim to detect, requiring manual verification after detection. Even if the famous anomaly is targeted, it only detects the anomaly, not multiple anomalies.

Lack of methods handling specific anomalies: Specific anomalies like being semi-bedridden, housebound, or forgetting are often overlooked in existing research.

To address these problems, we propose detection methods for six types of anomalies including novel detection methods for being semi-bedridden, being housebound, and forgetting to turn off appliances. Our method is customizable to various environments by adjusting simulator parameters, allowing us to incorporate different floor plans, sensor arrangements, resident activity patterns, and anomaly patterns without relying on real smart home data. We utilize a unified approach to preprocess data from unobtrusive ambient sensors to simultaneously detect anomalies occurring over different durations, from seconds to weeks.

1.3 Contributions

The contributions of this study for sensor data simulator are as follows [55, 56].

- **C1.** We develop a simulator that covers six typical anomalies characterized by the physical movements of the resident, detectable by binary sensors like infrared motion or pressure sensors. These anomalies are categorized into three types: *state anomalies* (being semi-bedridden, being housebound) occurring over many days; *activity anomalies* (forgetting to turn off home appliances, wanderings) happening occasionally; and *moving anomalies* (falls while walking, falls while standing) that occur during movements.

- **C2.** The simulator generates anomalies ranging from seconds to years, unlike previous simulators that handle only short-term or long-term anomalies. To achieve this wide range, we employ a graphical model that represents hierarchical causal relationships among anomalies, especially from long-term activities down to short-term actions like walking steps.

- **C3.** We statistically model the correlation among anomalies using a latent variable based on the Mini-Mental State Examination (MMSE). This means the frequency or duration of anomalies increases in line with the progression of dementia symptoms as the resident ages.

- **C4.** We compare simulated activity sequences with real-world activity sequences using edit distance. The results show that the daily variance and closeness of activities in the simulation closely match the real-world data. Furthermore, the similarity is higher than that of random data, which considers only the duration of activities.

The contributions of this study for anomaly detection methods are as follows [57, 58].

- **C5.** We extend our detection methods to simultaneously detect six types of abnormal behaviors using a unified sensor preprocessing framework with unobtrusive ambient sensors—such as infrared motion sensors, pressure sensors, door sensors, power sensors, and flow sensors. This approach is cost-effective and capable of handling anomalies with various occurrence durations, from seconds (e.g., falls) to weeks (e.g., being housebound). The proposed methods demonstrate practical performance with high sensitivity and low false alarm rates across all anomalies.

- **C6.** The detection methods achieved practically usable performance on simulated sensor test data generated by predefined anomaly models over nine years. For example, considering an anomaly as correctly detected if the detected period overlaps even slightly with the true abnormal period, the sensitivity (the proportion of true anomalies correctly detected; e.g., 0.9 means 90% of anomalies were detected) and false alarm rate per day are as follows:

  - Being semi-bedridden: sensitivity 1.0, false alarm rate 0.
  - Being housebound: sensitivity 1.0, false alarm rate 0.004.
  - Forgetting: sensitivity 1.0, false alarm rate 0.01.
  - Wanderings: sensitivity 1.0, false alarm rate 0.017.
  - Falls while walking: sensitivity 0.75, false alarm rate 0.02.
  - Falls while standing: sensitivity 0.92, false alarm rate 0.

  These results achieves a sensitivity of over 0.9 with fewer than one false alarm every 50 days, except for falls while walking. For falls, oversampling in the simulated data can improve sensitivity to 0.92.

The simulator code and data is in public at
https://github.com/tanakai0/SensorDataSimulator.

1.4 Thesis Structure

The remainder of this thesis consists of five chapters:

- **Chapter 2: Related Works.** This chapter reviews existing studies on smart homes, including the types of sensors used, notable smart home projects, sensor data simulation methods, activity simulation approaches, and anomaly behavior detection techniques.
- **Chapter 3: Simulation.** This chapter presents the proposed simulation framework, including the floor plan and sensor arrangement, activity simulation, walking trajectory generation, and modeling of anomalous behaviors. Qualitative and quantitative evaluations of the simulator are also discussed.
- **Chapter 4: Detection.** This chapter describes the proposed methods for detecting anomalies using the simulation data. It covers the preprocessing steps, detection methods for each type of anomaly, and experimental evaluations.
- **Chapter 5: Discussion.** This chapter discusses the realism and validity of the proposed simulator, its limitations, and potential areas for improvement.
- **Chapter 6: Conclusion and Future Work.** This chapter summarizes the contributions of the thesis and outlines directions for future research.

The thesis concludes with references.

Chapter 2

Related Works

We list related works below in three parts: smart home projects, studies on sensor data simulation and detection methods of anomaly behaviors from sensor data.

2.1 Sensors Used in Smart Homes

To assess the health of residents continuously over long periods in smart homes, many types of sensors are used in monitoring systems [36, 59, 44, 43]. These include:

- Ubiquitous sensors attached to the room enclosure, including motion sensors [60] and cameras [61].
- Wearable devices such as wearable sensors (wristbands and badges), smart phones, and interactive devices [62].
- Machines such as robots [63] and drones [64].

In particular, sensors that are ubiquitous in the surrounding environment and do not impose a physical burden are often referred to as *ambient sensors*. In this study, we exclude cameras from ambient sensors as defined in [20] because cameras tend to be obtrusive and have a negative impact on privacy. Examples of ambient sensors include infrared motion sensors, pressure sensors, contact sensors, light sensors, power sensors, and flow sensors [24]. Because these ambient sensors minimize physical burden and preserve privacy, smart homes often use ambient sensors due to their ubiquity and unobtrusiveness as shown in Tab. 2.1. Advantages of ambient sensors over cameras and wearable sensors are less intrusive to the privacy of residents [44, 36], robust against changes in light conditions, not requiring battery changes [36], and low cost and low power consumption [44, 26], while they tend to have lower accuracy [44] and be influenced by residents' and environmental temperatures [65].

In the viewpoint of privacy, some smart home projects reported that ambient sensors are preferred than camera. According to residents' impressions in ORCATECH smart home project [66], cameras are unpopular among participants, highlighting privacy concerns. In the Tiger Place project [41], 15 older adults aged 65 and above in a continuing care retirement community in Columbia, Missouri, stated that usage of cameras to detect falls or abnormal behaviors was an obtrusive violation of privacy [67]. This project also reported that almost all 14 participants stated motion sensors and pressure mats were accepted [68], while 10 persons stated they would not want to install cameras in their homes. Other studies [69] using self-administered questionnaires with 18 participants reported a privacy concern scale of 4 for video monitoring (1 being no concern and 5 being very concern). The primary concern were privacy invasion and fear of abuse. These studies indicate a preference for non-intrusive monitoring. Therefore, we focus on the ambient sensors in this study.

2.2 Smart Home Projects

To produce real datasets, many smart home projects have been planned and executed, as shown in Table 2.1.

The ORCATECH (Oregon Center for Aging and Technology) Life Lab smart home system project [27] started in 2004 at Oregon Health & Science University. This large-scale testbed uses ambient sensor-equipped smart homes with over 300 elderly participants living in the community. Projects such as gait speed estimation have been conducted [27]. Tiger Place [41] is part of the Aging in Place project [17] and conducted at the University of Missouri. This research aims to develop classifiers to evaluate changes in the activity patterns from sensor data collected on 21 seniors over nine months with a ground truth by clinicians. CASAS [26] is a testbed located at Washington State University. It often uses ambient motion sensors including infrared motion sensors, door sensors and light sensors. It has released 89 datasets [1], leading to various related studies ranging from activity recognition[70, 71, 70] to anomaly detection [72, 73]. The Centre for Effective Solutions for Ambient Living Awareness (CASALA) at Dundalk Institute of Technology proposed 16 smart homes, where residents have been living since June 2010. This project proposed an integrated approach to use various residents' behaviors, including movement's level, go out patterns, and sleeping patterns. From those information, feedback applications reported their wellbeing, home's security and energy usage. There are many other testbeds before 2010s. The Elite Care [74] is a testbed equipped with infrared sensors, RFID tags, bed weight sensors, and screen interfaces. The Aware Home [75] at the Georgia Institute of Technology uses motion sensors and wearable pendants to record daily activities in a residential setting. This project focuses on capturing daily living patterns of residents. The GATOR Tech Smart House [76], developed by the University of Florida, is equipped with sensors like RFID tags and cameras installed in mailboxes, entrances, blinds, beds, washing machines, mirrors, bathrooms, and refrigerators. It focuses on elderly care. The Managing an Adaptive Versatile Home (MavHome) [77] is a smart home test environment located at the University of Texas at Arlington. It is designed to collect data for multi-objective optimization tasks such as reducing manual labor, improving operational efficiency, and ensuring the health and safety of residents. The dataset is open [2]. The Adaptive Home [78], developed by the University of Colorado, is a smart home aimed at reducing electricity costs. It controls lighting, air conditioning, and water temperature using neural networks and reinforcement learning. The iDorm [79] is a testbed that learns user-specific fuzzy rules through active learning to optimize air conditioning and lighting for individuals. It focuses on creating a comfortable living environment based on resident preferences.

[1] https://casas.wsu.edu/datasets/

[2] https://ailab.wsu.edu/mavhome/research.html

TABLE 2.1: Smart home testbeds aimed at supporting elderly independence reported since 2010s.

Year & Ref.	Organization & project name	Data collection scale	Available labels	Types of sensors	Data usage
2011 [27]	Oregon Health & Science University, Oregon Center for Aging and Technology (ORCATECH) Life Lab smart home system	30 people over 33 months	Health-related questionnaires and physical examinations, neuropsychological tests conducted semi-annually or annually depending on the item	Studio apartments equipped with passive infrared sensors, contact sensors, and door sensors	Gait speed estimation [80], detection of mild cognitive impairment [81]
2012 [41]	University of Missouri, Tiger Place	21 people over 9 months	Clinicians evaluate the relevance of sensor event warning patterns to anomalies each time	Motion sensors, pneumatic bed (chair) sensors, temperature sensors in elderly housing facilities	Anomaly detection classifying normal and abnormal days
2013 [26]	Washington State University, Center of Advanced Studies In Adaptive Systems (CASAS), CASAS Smart Home Project	Various datasets ranging from several months to 2 years, involving 1 to several dozen people	In some datasets, activity labels are manually added through sensor data visualization methods	Passive infrared sensors, door sensors, thermometers, light sensors in three-bedroom apartments	Activity recognition [71], anomaly detection [73], activity discovery [70]
2014 [42]	Centre for Effective Solutions for Ambient Living Awareness (CASALA) at Dundalk Institute of Technology, Great Northern Haven Smart Home	15 people over 3 years	Daily self-reported health status; quarterly assessments including depression scales, cognitive evaluations, detailed health surveys, quality of life questionnaires, social loneliness scales, instrumental activities of daily living evaluations, sleep quality indices	Passive infrared sensors, window sensors, door sensors, temperature sensors, light sensors, power sensors, appliance sensors for heating in a layout with two bedrooms, a living room, and a kitchen	Reporting health status, forgotten appliance turn-offs, doors left open, and power consumption to residents via devices

Creation of effective anomaly detection algorithms requires a large amount of sensor data, including instances of anomalous behaviors. However, even if there are many smart home testbeds, collecting such data in the real world presents significant challenges:

Long-term monitoring: Gathering sufficient sensor data necessitates extended monitoring periods over months or years.

Fixed patterns: There is a limited number of residents' activity patterns, floor plans and sensor arrangements. These types are difficult to be changed during observation periods.

Unpredictable anomalies: Anomalous events occur unpredictably and cannot be controlled or induced for data collection purposes.

Complex data labeling: Labeling behaviors and anomalies in the collected data is time-consuming and often impractical.

These challenges make data preparation for various patterns impractical and fixed only particular types.

2.3 Sensor Data Simulation

To solve the problem on lack of data, many studies have utilized sensor data simulations [45, 82]. Some studies includes not also normal daily patterns but also anomalous behaviors [32, 46, 31, 47, 48, 49, 50, 83, 51] as summarized in Tab. 2.3 and Tab. 2.4. These methods are divided into three types according to their data type as shown in Tab. 2.2:

- *Manual modification* [32, 46, 31]:
- *Avatar manipulation* [47]:
- *Agent scenario generation* [48, 49, 50, 83, 51]:

We explained each type by below.

2.3.1 Manual Modification

In manual modification approaches, anomaly patterns are artificially inserted into real smart home sensor data. For example, studies have added data for repetitive behaviors, sleep disruptions, and anomalies involving frequency, temporal, transitional, and spatial deviations, such as moving after a fall or watching TV at night [32, 46]. However, these methods require long-term handcraft and lack diversity in room layouts, sensor arrangements, and anomaly types.

2.3.2 Avatar Manipulation

In avatar manipulation approaches, a virtual avatar is controlled by subjects to simulate elderly behavior, interacting with household objects, such as doors and TVs. For example, Alshammari *et al.* [47] had seven subjects use a simulator [84] to reproduce anomalies, such as leaving a fridge door open for a long time. While this method avoids risks to real residents, it still requires long-term interaction and real-time behavior simulation.

TABLE 2.2: Comparison among sensor data simulators with anomalous patterns. This table is a slightly modified version of the one in [56].

Type	Method	Speed	Adjustability			Parameters for reproducing statistical data properties
			EI	HA	AB	
Manual modification	[32, 46, 31]	slow	×	×	◎	real data and inserted anomaly patterns
Avatar manipulation	[47]	very slow	◯	◎	◎	manipulator's habit
Agent scenario generation	[48, 49, 50, 83, 51], proposed method [55, 56]	fast	◯	◯	◯	scripts of models or hyperparameters of models

Abbreviations are; environment information such as the room layout and the sensor arrangement (EI), human activity on how a resident behaves a day and informations about walking trajectories (HA), and anomalous behavior (AB). Evaluations are; ◎: Exact, ◯: Approximate, and ×: Not available.

2.3.3 Agent Scenario Generation

This approach uses intermediate data to control an agent's autonomous behavior in a virtual smart home, specifying schedules, walking models, and sensor rules. The agent scenario approach includes four main components:

- **Floor plan simulator**: Partitions rooms and places furniture in a virtual house,
- **Behavioral (activity) simulator**: Determines the schedule of a virtual resident within the floor plan,
- **Walking trajectory simulator**: Simulates a virtual resident moving through rooms according to the schedule, and
- **Sensor data simulator**: Generates sensor data based on the virtual resident's behavior.

This method generates sensor data quickly but requires careful control logic. Studies like Bouchard *et al.* [48] use scripts to simulate behaviors, including dementia symptoms. However, the variety depends on the script writer. Francillette *et al.* [49] used a sensor data simulator [85] to introduce diverse anomalies seen in mild cognitive impairment patients such as omission of activities, substitution of activities, wrong order between activities, perseveration of activities, and addition of irrelevant sub-actions in activities. However, they only focused on short-term anomalies but not long-term anomalies of activities like being housebound. In addition, generated frequency of anomalies are sometimes unrealistically high or low. Veronese *et al.* [50] used a sensor data generator [86] to model dementia patients acting transitional anomalies such as interrupted sleep, increased duration time of complex behaviors,

and a reduced frequency of dinner. Casaccia *et al.* [87] simulated indoor wandering. However, they only focused on trajectory patterns of wandering, but not frequency or duration over days. Jiang and Mita [51] used a sensor data simulator [88] to model wandering over long-term, albeit with almost fixed frequencies and durations. This cannot simulate an increase trend and unpredictable occurrences of wandering as the elderly get old. Kristiansen, Plagemann and Goebel *et al.* [83] used an activity simulator [89] to simulate long-term sensor data with hypothetical anomalous behaviors, such as gradual sleep disorder and self-medication improvements, but their simulations lacked realism as virtual sensors captured designed behaviors without modeling physical movements or room layouts.

TABLE 2.3: Summary of simulated anomalies (1/2). This table is a slightly modified version of the one in [56].

Type	Ref.	Floor plan *	Activity *	Sensor *, **	Simulated anomalies (the number)	Viewpoint ***	
						LT	CR
Manual modification	[32]	RD ([26, 90])	mRD	mRD	**repetitive behaviors**, sleep disruption, confusion (3)	×	×
	[46]	RD ([26])	mRD	mRD	frequency anomaly, temporal anomaly, transitional anomaly (3)	×	×
	[31]	RD ([91])	mRD	mRD	spatial anomaly, temporal anomaly, transitional anomaly (3)	×	×
Avatar Manipulation	[47]	3D layout made with GUI	determined by a user	DOOR, PIR, SWITCH	anomalous control patterns of home appliances (1)	×	×
Agent scenario generation	[48]	3D layout	scripts	virtual sensor represented by scripts of objects	(unclear)	×	×
	[49]	3D layout made with GUI	generated by behavior trees	COST, PIR, PR, RFID and contact sensor	**omission of activities**, **substitution of activities**, **wrong order between activities**, **perseveration of activities**, **addition of irrelevant sub-actions in activities** (5)	×	×

Abbreviations are follows.
* RD: real data, mRD: modified real data, 2(3) D layout: 2(3) dimensional artificially designed layout.
** COST: cost (power or flow) sensor, DOOR: door sensor, PIR: passive infrared motion sensor, PR: pressure sensor, RFID: radio-frequency identification based sensor, and SWITCH: switch of home appliances.
*** LT: whether the method controls long-term trends of statistical properties of anomalous behaviors, CR: whether or not the method considers the causal relationships among multiple anomalous behaviors (◯: equipped, and ×: not equipped).

TABLE 2.4: Summary of simulated anomalies (2/2). This table is a slightly modified version of the one in [56].

Type	Ref.	Floor plan *	Activity *	Sensor *, **	Simulated anomalies (the number)	Viewpoint ***	
						LT	CR
Agent scenario generation	[50]	2D layout made by a text	motivation based planning with habitual activities	DOOR, COST, PIR, SWITCH and motion sensor	interrupted sleep, **increased duration time of complex behaviors**, **a reduced frequency of dinner and going out** (3)	◯	×
	[83]	(unclear)	determined by a distribution with priority rules	time, position and logical sensors	immobility caused by falling, sleep disorder (2)	◯	×
	[51]	automatic generation of 2D layout and height data of studio apartment	probability motivation based planning	PIR	wandering (1)	×	×
	Proposed [55, 56]	2D layout borrowed from [51] with some modifications	determined by a distribution with hierarchical order	COST, PIR, PR	falling while walking, **falling while standing**, wandering, forgetting, **being housebound**, **being semi-bedridden** (6)	◯	◯

Abbreviations are follows.
* RD: real data, mRD: modified real data, 2(3) D layout: 2(3) dimensional artificially designed layout.
** COST: cost (power or flow) sensor, DOOR: door sensor, PIR: passive infrared motion sensor, PR: pressure sensor, RFID: radio-frequency identification based sensor, and SWITCH: switch of home appliances.
*** LT: whether the method controls long-term trends of statistical properties of anomalous behaviors, CR: whether or not the method considers the causal relationships among multiple anomalous behaviors (◯: equipped, and ×: not equipped).

Previous simulators face the following issues.

S1 Long-term trends in anomalies, such as age-related worsening, are not handled as seen in dementia [6].

S2 Correlations among anomalies, which often occur together with age, are ignored

S3 Sensor data do not always reflect activation by physical movements of the agent

None of them consider both a gradually changing frequency/duration of anomalies and the correlation among anomalies. To address S1 and S2, we introduce a latent variable representing dementia progression over time and use a statistical graphical model to link this variable to anomaly frequency and duration. For S3, we ensure sensor responses are tied to the resident's physical indoor movements.

2.4 Activity simulation

As the one component of the sensor data simulator based on agent scenario generation, activity sequences are generated. Activity simulators are classified into the four types: script-based model, generative model, motivation-based model, and queue-based model. Each type is explained below.

Script-based model

Script-based method configures resident's activities by scripts. Bouchard *et al.* [48] and Francillette *et al.* [92] proposed methods that construct scripts by hand. The latter method can also learn scripts from data using a behavior tree that represents activities hierarchically.

Such script-based design of activities has high interpretability and can be used repeatedly, but lacks flexibility. It requires longer and more scripts to describe other types of activities, including day-long or week-long anomalies. Indeed, the authors made scripts only for short activities, such as cooking and washing.

Generative model

Generative method used a generative model to imitate human activity statistics learned from real data. Noury and Hadidi [93] used the urns of Pólya and hidden Markov models.

This enables us to generate behavior automatically, but we need to share real data for reproducibility. Furthermore, interpretability is insufficient because the interpretation of hidden states in the HMM is rarely given directly.

Motivation-based model

Motivation-based methods are based on the motivation that induces activities. Lee *et al.* [94] used motivation value for each activity, for example, dining from hunger, and sleep from sleepiness. As the motivation values increase with time at their own rates, an activity is induced when the value exceeds a threshold. When multiple activities become candidates, rules resolve to decide what activity should be done. Once an activity is done, the motivation value resets, while others still increase. Veronese *et al.* also used a similar approach [86], where multiple combinations of activities

are allowed to model. Routine behaviors such as sleep acted at specific intervals are scheduled on formulas. Jiang and Mita [88] also proposed a motivation-driven method that adds a probability to select activities.

The reproducibility is sufficiently high because it requires only numerical parameters to share this simulator. This method is applicable to realize routine behavior that has almost the same start time. However, it is difficult to deal with irregular behavior that occurs accidentally, such as wandering.

Queue-based model

Queue-based methods selected activities in chronological order from stacked activities that are ready to act. Next activity is chosen as the most preferential activity in the queue. Kamara-Esteban *et al.* [95] determined next activity with priority rules that are determined by priority value of each activity. This rules are configured by desirable start time of activities, and desirable activities done already before the activity. Selected activity and its relevant activities are newly added to the queue. Kristiansen, Plagemann and Goebel [89] also used rules to select activities queued according to the probability distributions on the start (or interval) time and duration.

The reproducibility is sufficiently high because it suffices to share the values of the parameters and the priority. It can also be incorporated with anomaly behavior because the priority can resolve overlap with anomaly behavior that occurs randomly. The drawback is the hardness of the parameter setting, because the number of rules reaches the square order with respect to the number of activities.

Tab. 2.5 compares the proposed simulator with existing ones. Most existing simulators do not incorporate randomly occurring anomalies, such as wandering. Because these methods determine activity sequence in chronological order, they lack the ability to precisely determine the frequency of activities as statistical features of long-term behavioral changes. Our proposed simulator aims to build on the advantages of queue-based methods, offering high controllability of behavior through statistical parameters and simple rules.

TABLE 2.5: Comparison between activity simulators. This table is modified version in [55].

Type	Method	Reproducibility		Reproducible activity			Controllability		
		DTS	NNP	ARB	AMB	IRA	S	D	Freq.
Script-based	[48]	script	N.A.	×	×	×	×	◎	×
	[92]	script	N.A.	×	×	◎	×	◎	×
Generative model	[93]	IL	N.A.	×	×	×	×	×	×
Motivation-based	[94]	NP	$O(n)$	◯	◎	×	◯	◎	◯
	[86]	NP	$O(mn)$	◎	◎	×	◎	◎	◯
	[88]	NP	$O(n)$	◯	◎	×	◯	◎	◯
Queue-based	[95]	NP	$O(n)$	◎	◯	×	◎	◎	◯
	[89]	NP	$O(n^2)$	◎	◎	×	◎	◎	◯

Abbreviations are; description type for share (DTS), number of numerical parameters (NNP), adaptability of routine behavior (ARB), adaptability of motivation-based behavior (AMB), insertion of random anomaly (IRA), start time of routine behavior (S), duration time (D), frequency (Freq.), ingredients for learning (IL), and numerical parameters (NP). In big-oh notation, n is the number of activities and m is the number of motivations related with activities. Evaluations are; ◎: Available/Exact, ◯: Possibly available/Approximate, and ×: Not available.

2.5 Anomaly Behavior Detection

Using only ambient sensors, many studies detect various kinds of anomalous behaviors. Target anomalous behaviors are unusual or abnormal activities acted by human [44]. Anomaly detection detects changes of usual behavior. Once any anomaly is detected, these systems can record anomaly status and alert monitors of the elderly individuals [96].

2.5.1 Types of anomalies

Detected anomalies are divided into two types: concrete anomalies, detected via supervised learning (discriminating in [97]) and outliers, detected via unsupervised learning (profiling in [97]). Concrete pre-defined anomalies are common and well-known symptoms in elderly individuals including falls, wandering, and memory lapses. Outliers are deviations from normal behaviors based on statistical spatio-temporal patterns. A study [96] exemplified six types of use cases of abnormal behavior detection: temporal duration, timing of occurrences, spatial patterns, action patterns, environmental changes, and context switching. While many studies focus on detecting outliers [31, 53, 28, 54] due to the lack of true anomaly labels [44], mere statistical outliers are often difficult to interpret and understand for monitors such as family members, care workers, or the individuals themselves. In contrast, concrete anomalies are easy to interpret to provide monitors with feedbacks. Therefore, we prioritize specific anomalies which can be simulated for data generation.

In this study, we focus on six concrete anomalies mainly depended on cognitive status,

- being semi-bedridden,
- being housebound,
- forgetting to turn off home appliances,
- indoor wandering,
- fall while walking,
- fall while standing.

These anomalies are commonly associated with symptoms observed in elderly individuals. Indoor health risks for the elderly include falls, self-medication errors, and kitchen accidents such as fires, burns, or gas leaks (linked to forgetting), as well as reduced mobility and activity levels (linked to being semi-bedridden or housebound) [98]. Many demands for fall detection are reported by participants [67, 69]. Indoor wandering is also the famous abnormal behaviors [9, 10]. Causes of each anomalies are summarized in Tab. 3.6.

From the perspective of anomaly simulations, several studies have utilized pre-defined hypotheses of anomalies when actual data is difficult to obtain. For wandering detection, two studies [38, 39] assigned labels based on decision tree models of movement trajectories [99]. For fall detection, numerous studies [100, 101, 34, 102, 103] collected fall data by simulating falls performed by actors. Additionally, other research [53, 104] employed computer simulations to generate data. These simulation-based approaches offer the advantage of flexibility in adjusting the floor

plan, sensor placements, and abnormal behavior patterns. An early epidemic detection method [105] employed a discrete event simulator to evaluate abnormal events within activities.

Our proposed framework [56] also detects pre-defined anomalies, but the spatio-temporal variations in anomaly occurrences are extensive. For example, anomalies range from a few instances of being housebound to over a thousand instances of wandering, occurring throughout the home during nine years of continuously generated sensor data.

2.5.2 Detection methods

We summarized existing studies that aim to detect such kinds of anomalies: forgetting in Tab. 2.8, indoor wandering in Tab. 2.7, fall detections in Tab. 2.6, and other functions in Tab. 2.9).

While no existing research directly addresses detecting being semi-bedridden or housebound, related methods provide insights into these anomalies. J. Williams and D. Cook [106] modeled wake and sleep patterns by predicting univariate scores, while T. Hayes *et al.* [107] modeled sleep using parameters such as start time, end time, latency, and total duration. Some studies detect sleep anomalies through pattern modeling. Z. Shahid, S. Saguna, and C. Åhlund [108] used features like start time, duration, and frequency to identify long-term sleep behavior changes via clustering. A. Forkan *et al.* [28] modeled sleep start time as a normal distribution, flagging deviations beyond $\delta_1\sigma$ as outliers in daily activity statistics. For going-out behavior, S. Tominaga *et al.* [109] proposed a generative model based on positional trajectories captured by a laser range finder. Similar housebound state, J. Kim *et al.* proposed the depression detection using ambient sensors. They classified health condition into three level (normal, mild depression and sever depression) with more than 94% of AUC using hierarchical activity features with dimensionality reduction by PCA.

In relation to forgetting anomalies, memory impairments can disrupt daily activities for elderly individuals, such as cooking, and may lead to hazards like forgetting to turn off appliances [98]. To prevent fires caused by such forgetfulness, sensor systems integrating gas, flame, and temperature detection have been proposed [110, 111, 112, 42]. M. Logeshwaran and J. Sheela [110] developed an alarm system combining flame, gas, temperature, and PIR sensors, while W. Hsu *et al.* [111] proposed a similar system with notifications via buzzers and LEDs. A. Wa *et al.* [112] introduced a system for monitoring kitchen usage and heating times. Beyond fire prevention, J. Doyle *et al.* [42] explored detecting open windows, doors, and active appliances using window, door, and power sensors, with confirmation interfaces for residents. However, these methods lack sufficient quantitative evaluations for detecting forgetfulness over long-term scenarios.

Indoor wandering is a common anomaly, particularly among dementia patients [113]. Various methods have been proposed to detect non-routine walking patterns, such as pacing (repeated back-and-forth movement), wrapping (moving to a goal point via multiple intermediate locations), and random transitions described by the Martino-Saltzman model [114]. K. Ota *et al.* [115] classified elderly activities, including wandering, using ultra-wideband impulse radio monitoring sensors to estimate movements. W. Zhao *et al.* [116] utilized active infrared sensors to detect frequent reactivations within two minutes, indicating wandering. Q. Lin *et al.* [37] employed rule-based methods based on walking trajectory length and frequency. Neural network-based approaches have also been explored, such as convolutional

neural networks (CNNs) treating indoor trajectories as images [38, 104] and recurrent neural networks learning from sensor time series data [39]. E. Khodabandehloo and D. Riboni [117] used random forests to classify walking patterns (e.g., normal, abnormal, and partially abnormal) based on loop locations, center coordinates, and loop durations. Their approach also categorized the resident's condition as healthy, mild dementia, or dementia. These methods leverage position estimation from infrared motion sensors, simulated ultrasonic sensors, or other sensor systems to detect wandering effectively.

Falls are a common anomaly among the elderly, with a 1988 study reporting that 35% of individuals aged 65 and older fell at least once a year [118]. Due to their significant risks in indoor activities [98], numerous studies have focused on detecting falls while walking [102, 100, 34, 119] and both falls while walking and standing [103, 101, 120, 53]. Infrared sensors have been widely used for detecting human movement. M. Popescu *et al.* [100] applied hidden Markov models to classify falls using infrared sensor signals. A. Yazar *et al.* [102] combined vibration sensors and infrared sensors, detecting falls with support vector machines. S. Tao *et al.* [34] utilized randomized power martingale to identify falls from discretized infrared sensor data. J. H. Shin *et al.* [53] used infrared motion sensors in rooms to detect falls among nine anomalies via support vector data description. Other studies have leveraged floor and pressure sensors. M. Alwan *et al.* [120] applied pattern matching to floor vibrations, while H. Rimminen *et al.* [101] used Markov chains with electric near-field floor sensors to distinguish falls. K. Chaccour *et al.* [103] analyzed pressure sensor thresholds to detect falls effectively. K. Wu *et al.* [119] detected falling mode (trip and slip) from floor vibration pattern with geophone sensors.

Beyond typical anomalies, mobility, cognitive function, and mental health are evaluated as predictors for assessment scores. A. Akl, B. Taati, and A. Mihailidis [81] used walking speed features from motion sensors to classify individuals with mild cognitive impairment (MCI), achieving an AUC of 0.97. T. Hayes *et al.* [121] analyzed long-term data from MCI patients and healthy individuals, finding that MCI patients exhibit greater fluctuations in median walking speed and daily activities. C. Galambos *et al.* [122] visually examined activity levels and going-out patterns to assess cognitive functions and psychological state. A. Alberdi *et al.* [25] evaluated motor abilities through tests like timed up and go (TUG) and arm curl, cognitive functions using RBANS, PRMQ, and digit cancellation tests, and emotional state with the geriatric depression scale (GDS-15). These metrics were inferred from behavioral data to detect change points, demonstrating prediction methods on weekly [81, 121] and monthly scales [25].

TABLE 2.6: Related works of fall detections by ambient sensors. This table is a slightly modified version of the one in [58].

Anomaly	Reference	Sensors	Methods	Performance
Fall while walking	M. Popescu *et al.*, 2012 [100]	Vertical PIR sensors array (8 units, 1000 Hz)	Classified higher likelihood using two hidden Markov models with Gaussian output distributions for fall and non-fall	Area under the ROC curve 0.93 for 2-second data, 15% precision for 26-minute data
	S. Tao, M. Kudo and H. Nonaka, 2012 [34]	Horizontal PIR sensors array (20 units, 20 Hz)	Treated 20 sensors as pixel values and used randomized power martingale on strangeness, which is the Euclidean distance from the past average	Precision 92.5%, recall 98.0%, F-score 95.14%
	A. Yazar *et al.*, 2013 [102]	PIR sensors (256-level output, 100 Hz) and vibration sensors (one per room, range 25 m, 256-level output, 900 Hz)	After detecting human presence when variance of infrared sensor signal exceeds a threshold, it uses Mahalanobis distance, SVM classifies, and single-tree complex wavelet transform	Correctly identified all 60 falls out of 994 data points
	K. Wu *et al.*, 2023 [119]	geophone sensors (3 sensors for a room, 1190 Hz)	The method trains HMM with features of floor vibration events using discrete wavelet transform. EoA positioning detects movements after falls to reduce false alarms.	When trained from seven individuals, the method achieved a recall of 95.74% with a false alarm rate 4.76% caused by confusing events such as object falls, marked time heavily, and walking heavily. The false alarm rate was nearly 0% when using EoA positioning was used.
Fall while walking and fall while standing	M. Alwan *et al.*, 2006 [120]	Floor vibration using piezoelectric sensor	Vibration pattern matching using frequency, amplitude, duration, and succession	Correctly detected all 70 falls and 53 object drops. Fisher's exact test shows a true recall range between 94.87% and 100%, and true specificity range between 93.28% and 100% with a 95% confidence interval ($p < 0.0001$).
	H. Rimminen *et al.*, 2010 [101]	Floor sensor of electric near field (9×16 units/$19m^2$, 4.5 Hz)	Two-state (fall, non-fall) Markov chain using number of activated sensors, maximum distance, and total pressure as features	Sensitivity 91%, specificity 91%
	J. H. Shin, B. Lee and K. Park, 2014 [53]	5 PIR sensors (10Hz) for 5 rooms and simulated sensor data	Support vector data description with the features such as activity level, mobility level and nonresponse duration.	The average performance for the nine anomalies including falls, is a sensitivity of 86%, a precision of 95.8% and a specificity of 85.5%.
	K. Chaccour *et al.*, 2015 [103]	Differential piezoresistive pressure sensors (4 units / $1m^2$, 21 kHz)	If the values of three or more pressure sensors exceed the threshold, it is considered a fall.	Sensitivity 88.8%, specificity 94.9%

Abbreviations are passive infrared (PIR), hidden Markov model (HMM), support vector machine (SVM), and energy of arrival (EoA).

TABLE 2.7: Related works of indoor wandering by ambient sensors. This table is a slightly modified version of the one in [58].

Anomaly	Reference	Sensors	Methods	Performance
Indoor wandering	K. Ota *et al.*, 2011 [115]	Ultra-wideband impulse-radio sensor	Estimated actions by linking distance from the antenna with behavior	Classification accuracy including wandering is 95%
	W. Zhao *et al.*, 2014 [37]	PIR sensors	Rule-based classification using trajectory position and duration time of stay	Accuracy 90.03%
	M. Gochoo *et al.*, 2017, [38]	PIR sensors	Convolutional neural network using binary images converted from binary sensor activation sequences	Accuracy 97.84%, precision 97.9%, recall 97.8%
	Q. Lin, W. Zhao, and W. Wang, 2018 [116]	Active infrared sensors	Classified as wandering when sensor activation interval is less than 2 minutes and the same sensor reactivates	Accuracy 98%, precision 98%
	A. Chaudhary *et al.*, 2020,[39]	PIR sensors	Recurrent neural network Learned by binary sensor activation sequences	Accuracy 98.63%
	R. Oliveira *et al.*, 2022 [104]	Simulated ultrasonic sensors for human position and microphone recording for 5 seconds after proximity detection	Convolutional neural network using images of hourly movements	Precision 100%, recall 60%, F-score 75%
Indoor wandering and dementia	E. Khodabandehloo and D. Riboni, 2020 [117]	PIR sensors (51 units) and door sensors (16 units) in a two-story house	Firstly, it estimated loop-like trajectories from sensor data where start and end points of walking match. Then, it classified walking into three categories (normal, abnormal, partially abnormal) using random forest based on features of loop location, center coordinates, and duration. It also classified dementia status (healthy, dementia, mild dementia) from walking classifications using random forest.	Average recall for wandering is 60.5%, average precision is 60.2%. Classification accuracy for dementia is 80.7%.

Abbreviations are passive infrared (PIR).

TABLE 2.8: Related works of forgetting by ambient sensors. This table is a slightly modified version of the one in [58].

Anomaly	Reference	Sensors	Methods	Performance
Forgetting to turn off	A. Wai *et al.*, 2011 [112]	Motion sensor, current sensor, temperature sensor	Detects absence of people with motion sensor, alerts with power and high temperature	No quantitative evaluation
	J. Doyle *et al.*, 2014 [42]	Window sensor, door sensor, power sensor	Notifies residents of open windows or lights left on through devices	No quantitative evaluation
	W. Hsu *et al.*, 2019, [111]	Flame sensor, gas sensor, temperature sensor	Alerts when flame, gas leak, or high temperature is detected by sensors	No quantitative evaluation
	M. Logeshwaran and J. Sheela, 2022 [110]	Flame sensor, gas sensor, temperature sensor, passive infrared sensor	Alerts when flame, gas leak, or high temperature is detected by sensors	No quantitative evaluation

TABLE 2.9: Related works of cognitive, motor and psychological functions by ambient sensors. This table is a slightly modified version of the one in [58].

Anomaly	Reference	Sensors	Methods	Performance
Cognitive function	T. Hayes *et al.*, 2008 [121]	PIR sensor (1/6Hz), magnetic contact sensor	Estimates features related to walking speed and activity level and analyzes the correlation with mild cognitive impairment	For mild cognitive impairment group, the coefficient of variation of median walking speed is twice as high compared to healthy group ($p < 0.03$), 24-hour wavelet variance is larger (greater variation in daily activity patterns) ($p < 0.008$)
	A. Akl, B. Taati, and A. Mihailidis, 2015, [81]	PIR sensor	Estimates features related to walking speed and activity level and trains a binary classifier (for healthy and mild cognitive impairment) using SVM and random forest	For binary classification of mild cognitive impairment, area under ROC curve is 0.97, area under precision-recall curve is 0.93
Cognitive function and psychological state	C. Galambos *et al.*, 2013 [122]	PIR sensor (1/7Hz)	Visualizes activity level by showing values proportional to the number of sensor activations in each room on a 2D coordinate system of day and time, visually checks for abnormalities	Qualitatively evaluates the visualization of activity level and going out, comparing with unhealthiness in each case
Motor and cognitive functions, psychological state	A. Alberdi *et al.*, 2018 [25]	PIR sensor, door (cupboard) sensor, e.g., 23 PIR sensors and 6 door sensors in a layout with bedroom, kitchen, dining room, living room, and bathroom	Firstly, it assigns behavior labels using activity recognition method [71]. Then, it regresses test item values from features of behavior, movement, and habitual behavior using kNN, and detects score differences with the previous day using Reliable Change Index [123]	Statistically significant detection of change points in Arm Curl, TUG, and delayed memory impairment items in RBANS, under p-value adjusted by McNemar test compared to random algorithm (< 0.005)

Abbreviations are; passive infrared (PIR), repeatable battery for the assessment of neuropsychological status (RBANS), short-form health survey (SF-12), and timed up and go (TUG).

Detection methods for anomalies across various durations have been explored in prior research. T. Mori *et al.* [124] used a Gaussian Mixture Model to analyze the start time and duration of activities, identifying anomalies ranging from minutes to days, and detecting behavioral shifts over months based on distribution changes. However, this approach focused on outliers and shifts rather than meaningful, typical anomalies. Existing methods typically address specific time scales, such as seconds for falls or weeks for going-out patterns, but they cannot handle multiple anomalies with varying time scales. Furthermore, even though being housebound, being semi-bedridden, and forgetting are well-known anomalies, there are no studies explicitly detecting these anomalies using ambient sensors.

To address these issues, we propose an unified framework to detect six types of anomalies, including novel approaches for being semi-bedridden, housebound, and forgetting to turn off appliances. Our customizable simulator adapts to various environments, enabling unified detection of anomalies over durations ranging from seconds to weeks using data from ambient sensors. Detecting multiple anomalies by sharing a common sensor arrangement can reduce management costs.

Chapter 3

Simulation

We explained a sensor data simulator to generate six typical anomalies.

3.1 Data Format

Table 3.1 presents the final data format produced by the simulator. The sensor data is represented as a sequence of tuples in the format: (Sensor ID, Timestamp, Reading). This format is common in sensor data [26].

TABLE 3.1: Example of ambient sensor data.

Sensor ID	Timestamp	Reading
Motion sensor 1	0 days 8:12:34.5	ON
Motion sensor 2	0 days 8:12:34.6	ON
Motion sensor 1	0 days 8:12:34.7	OFF
Pressure sensor 3	0 days 8:12:34.7	ON
Motion sensor 2	0 days 8:12:34.9	OFF
...	...	...

3.2 Simulation Framework

The proposed simulator extends the agent scenario generation method presented in [51]. It consists of three primary component simulators: (1) a floor plan (and sensor arrangement) [125], (2) an activity simulator [88], (3) a walking trajectory simulator [126], and (4) sensor data simulator [51]. In addition, we introduce a fifth component, (5) an anomalous behavior simulator. The relationships among these component simulators are illustrated in Fig. 3.1. A virtual floor plan of a studio apartment is created with sensors arranged to cover the resident's main flow. Activities are scheduled over several years, each tied to specific locations (e.g., cooking in the kitchen). The virtual agent moves between activities according to the schedule, activating sensors based on activities or walking, with all sensor data recorded. Each component simulator is described in detail below.

3.2.1 Floor Plan and Sensor Arrangement

The floor plan simulator determines the layout of rooms, furniture, and sensor placements where the virtual agent lives (e.g., Fig. 3.2 and Fig. 3.3). We used the studio apartment floor plan simulator from [51], which arranges rooms and furniture based on elderly-friendly guidelines, such as keeping furniture at least 0.6 m apart. Sensors can be positioned manually or randomly by specifying their coordinates.

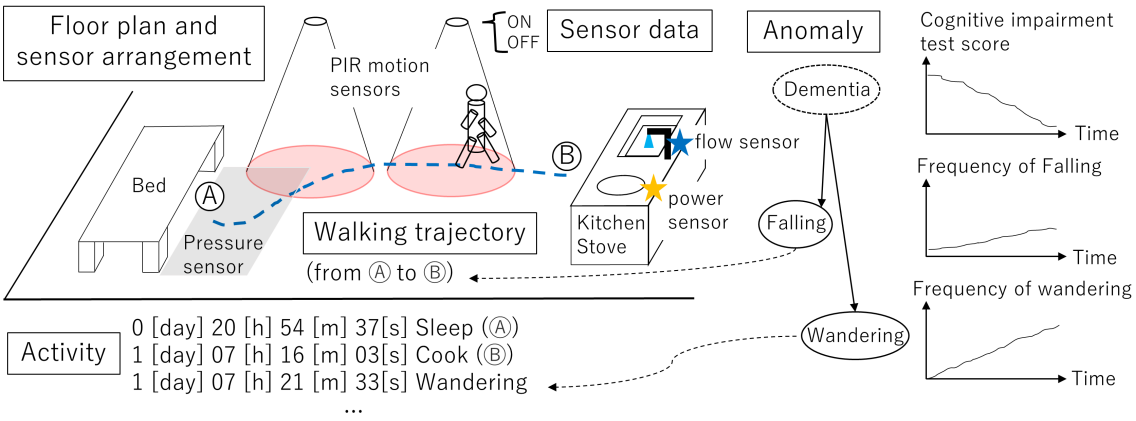


FIGURE 3.1: The proposed simulator consisting of four component simulators and a sensor data collector (each surrounded by lines).

TABLE 3.2: List of ambient sensors with binary outputs used in this study. This table is modified version in [58].

Sensor	Sampling rate	Place	Detected target
Infrared motion sensor	10Hz	Open area with a detection range of 50 cm radius	Resident motion
Pressure sensor	10Hz	Floor near the bed with a detection range of 0.75m^2 and 1m^2	Resident presence
Door sensor	10Hz	Entrance door	Door openings and closings
Flow sensor	1Hz	Faucets in bathroom and kitchen	Captures water usage, similar to a utility meter
Power sensor	1Hz	TV and kitchen stove	Captures power consumption, similar to a utility meter

This study focuses on four types of ambient binary sensors: (1) passive infrared (PIR) motion sensors activated by movement at 10Hz, (2) pressure sensors triggered by presence at 10Hz, (3) door sensors activated when a door is opened at 10Hz, and (4) cost (power and liquid flow) sensors triggered by home appliance use at 10Hz. PIR sensors were manually placed to cover the resident's main walking flow. Pressure sensors were positioned at the foot of the bed, door sensors at the entrance door, and cost sensors on appliances such as the TV, stove, and faucets (Tab. 3.2). In this study, we use the floor plan in Fig. 3.2 and Fig. 3.3.

3.2.2 Activity

Activity simulators generate daily schedules of the virtual agent (e.g., Fig. 3.4).
Previous simulators have at least one of the following problems.

S1 Existing methods lack the precision to directly determine activity frequency as a statistical feature, making it challenging to model daily activities easily.

S2 Sensor responses are not always linked to the agent's physical movements, such as walking near or using objects, reducing realism

S3 Randomly occurring anomalies, like wandering, are often excluded.

S4 Long-term trends in anomalies and correlations among them, such as co-occurrences increasing with age, are overlooked [6].

These challenges are addressed by the proposed simulator [55, 56].

S1& S4 : We introduce a latent variable representing the degree of dementia, which varies over time to model age-related anomaly progression [6]. Using

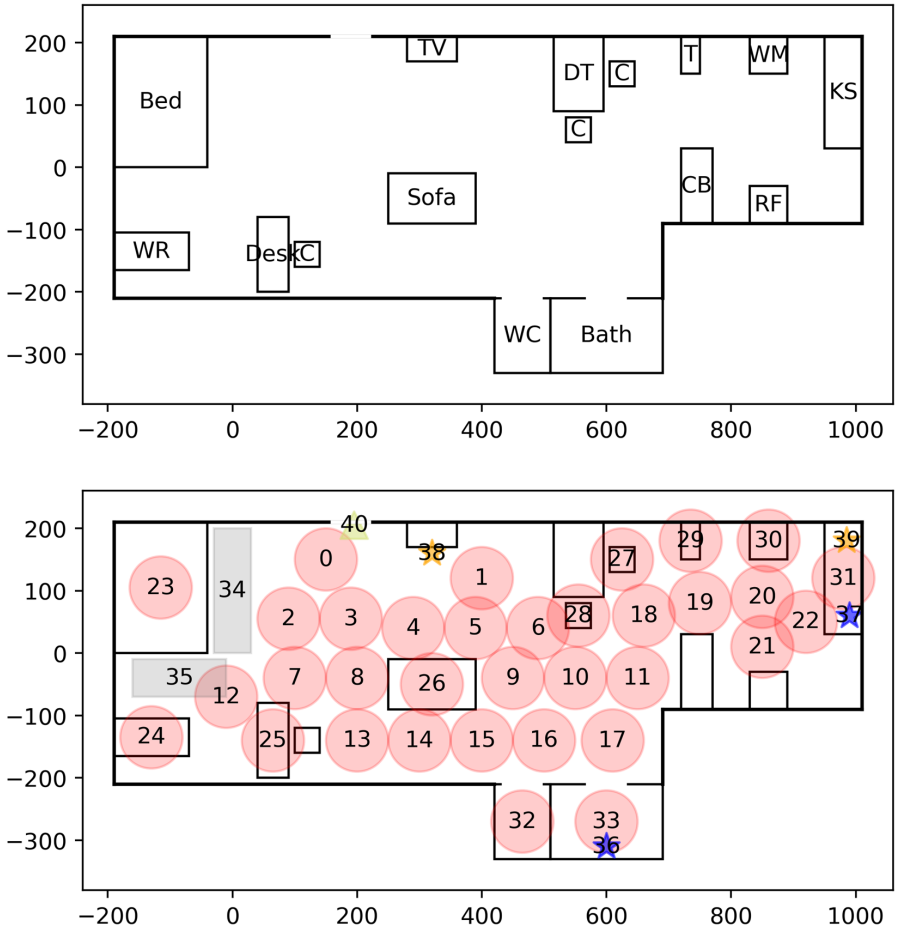


FIGURE 3.2: The example of floor plan (above) and sensor arrangement (below) are shown with lengths in meters. Furniture includes chairs (C), a cupboard (CB), a dining table (DT), a kitchen stove (KS), a refrigerator (RF), a trash box (T), a wardrobe (WR), a washing machine (WM), and a water closet (WC). Sensor types are distinguished by colors and symbols: red (PIR sensors, #0 to #33), gray (pressure sensors, #34 and #35), green (door sensor, #40), blue (flow sensors, #36 and #37), and yellow (power sensors, #38 and #39). This layout is used in anomaly detection.

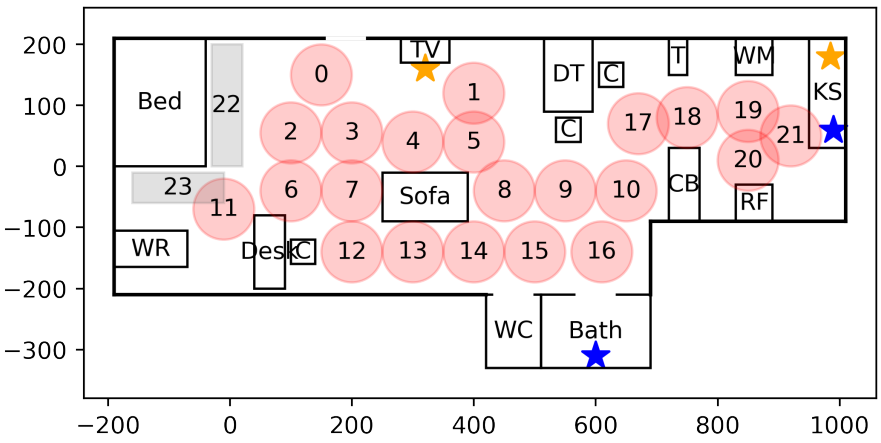


FIGURE 3.3: Another example of sensor arrangement. The symbols are same with Fig. 3.2.

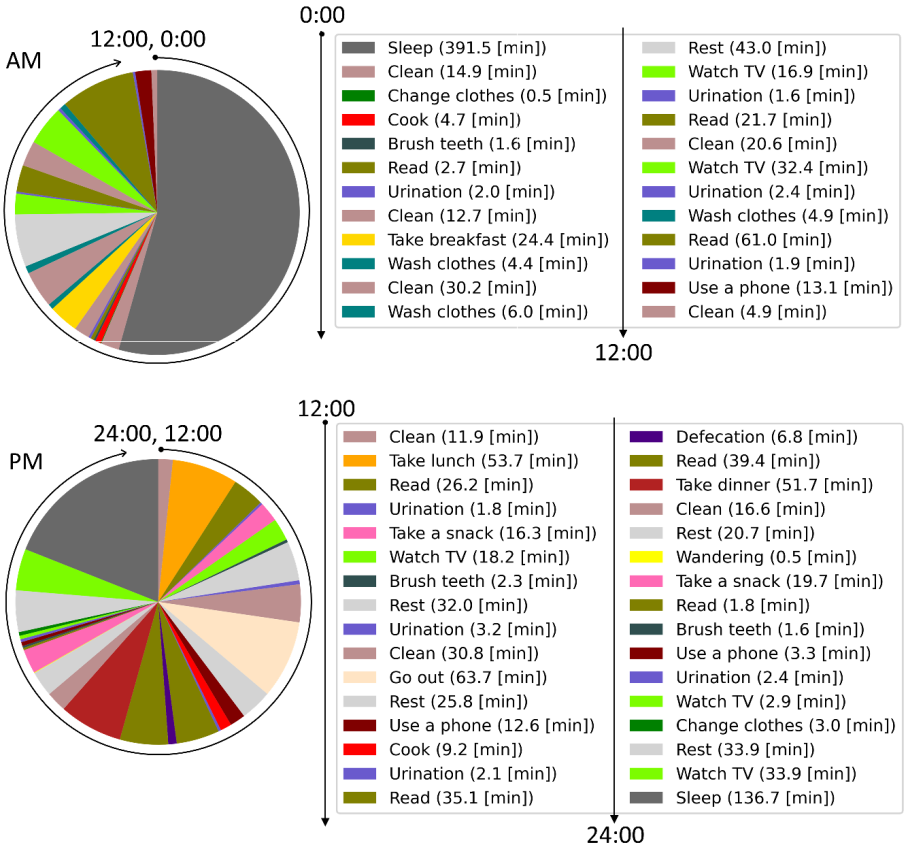


FIGURE 3.4: An example of activity schedule that the proposed simulator generated. The right side shows the names and duration of the activities.

a statistical graphical model, each anomaly's frequency and duration, or time are governed using reproducible parameters.

S2 : Sensor responses are activated directly by the agent's walking trajectory or activity, ensuring realistic data collection.

S3 : Randomly occurring anomalies are integrated into the simulation.

To develop activity simulators that ensure the accurate reflection of essential daily activity statistics, we categorized activities into three types based on the classification of activities of daily living (ADL) [127] that is often used in elderly care field. The classifications are as follows:

Fundamental activity : These activities almost always occur daily and have two core parameters: start time and duration. They constitute a minimal set of self-care activities, sometimes referred to as *basic activities of daily living* (BADL) [127]. Their sequence is typically fixed. We identified four fundamental activities: Take breakfast, Take lunch, Take dinner, and Sleep, performed in the following order: Take breakfast, Take lunch, Take dinner, and Sleep.

Necessary activity : These activities can occur multiple times per day and have a single core parameter representing their frequency. They are another subset of self-care activities included in BADL. The occurrence frequency is modeled using a Poisson distribution. We identified five necessary activities: Brush teeth, Change clothes, Defecation, Take a bath, and Urination.

Random activity : These activities may occur multiple times a day but are not strictly essential. They are necessary for independent living and refer to *instrumental ADL* (IADL) [128]. We identified nine random activities: Clean, Cook, Go out, Read, Rest, Take a snack, Use a phone, Wash clothes, and Watch TV.

By these activities, we construct activity sequences as follows (See Fig. 3.5 and algorithm 1).

First, we define the symbols. The activity simulator generates a time series of activities representing the resident's daily behavior. An activity sequence is defined as $A = (\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots, \boldsymbol{a}_{N_A})$, where each activity $\boldsymbol{a}_k = (a_{k,n}, a_{k,s}, a_{k,d}, a_{k,l})$ consists of:

- $a_{k,n} \in S_A$: Activity name,
- $a_{k,s} \in \mathbb{R}$: Start time,
- $a_{k,d} \in \mathbb{R}$: Duration,
- $a_{k,l} \in U \subseteq \mathbb{R}^2$: Start location.

The location $a_{k,l}$ is randomly chosen from $f_z(a_{k,n})$, which maps activities to possible starting locations, ensuring activities are performed in relevant places (e.g., read a book at a desk). The sequence A covers an entire day without gaps.

Each activity is modeled and scheduled based on its type. Let S_F be fundamental activities, S_N necessary activities, and S_R random activities, so that $S_A = S_F \cup S_N \cup S_R$. Let T be the daily time range to be filled with activities, initialized as [0:00-24:00) (a half-open interval). Once an activity a is scheduled, T is updated as $T \setminus [a.s, a.s + a.d)$, segmenting T by this interval.

Each day is filled by activities as follows.

1. Fundamental activities (S_F): For each fundamental activity ($a \in S_F$), the start time and duration are sampled from normal distributions $\mathcal{N}(\mu_{a,s}, \sigma^2_{a,s})$ and $\mathcal{N}(\mu_{a,d}, \sigma^2_{a,d})$, where $\mu_{a,s}$ and $\mu_{a,d}$ are the mean start time and duration, and $\sigma_{a,s}$ and $\sigma_{a,d}$ are the standard deviations. If the order of fundamental activities is violated, the values are resampled.

2. Necessary activities (S_N): For each necessary activity ($a \in S_N$), the daily frequency λ_a is sampled from a Poisson distribution $\mathrm{Poi}(\mu_a)$, where μ_a is the mean daily frequency. The start time is sampled from an uniform distribution $\mathrm{Uni}(T)$. The duration is sampled from $\mathcal{N}(\mu_{a,d}, \sigma^2_{a,d})$. If overlaps with existing activities occur, or a sub-interval of T is too short (e.g., less than 30 seconds), the values are resampled.

3. Random activities (S_R): Remaining time T is filled with random activities. An activity $a \in S_R$ is chosen with probability p_a, where $\sum_{a \in S_R} p_a = 1$. The start time is set to $\min(T)$, and the duration time is sampled from $\mathcal{N}(\mu_{a,d}, \sigma^2_{a,d})$. As with necessary activities, overlaps or sub-intervals shorter than 30 seconds are resampled.

For now, we use probability distributions with parameters derived from statistical surveys in Japan [129]. Examples of parameters are shown in Table 3.3. In future work, alternative probability distributions or parameters learned from data may be applied. Note that durations of activities are truncated to ensure a minimum activity duration (30 seconds) or to align with the start time of subsequent activities. As a result, the durations do not strictly follow normal distributions or truncated normal distributions.

3.2.3 Walking trajectory

The walking trajectory simulator generates the agent's 2-dimensional movement within the home. The agent moves between activity areas to start the next activity after completing the previous one. We adopted the walking trajectory simulator proposed in [51, 126], which generates a movement path (Fig. 3.6). We explained this simulator below.

Trajectories are determined as follows. Let $W_{\boldsymbol{a},\boldsymbol{b}} \in (\mathbb{R} \times U)^+$ be a sequence of time-location pairs for the movement between the current activity $\boldsymbol{a}$ and the next activity $\boldsymbol{b}$, where $+$ denotes the Kleene closure. Each location represents the center of the resident's body. For instance, when transitioning from $\boldsymbol{a}_k = (a_{k,n}, a_{k,s}, a_{k,d}, a_{k,l})$ to $\boldsymbol{a}_{k+1} = (a_{k+1,n}, a_{k+1,s}, a_{k+1,d}, a_{k+1,l})$, the trajectory with duration T_W is represented as:

$$W_{\boldsymbol{a}_k,\boldsymbol{a}_{k+1}} = ((t_1, l_1), (t_2, l_2), \ldots, (t_N, l_N)),$$

where $l_1 = a_{k,l}$, $l_N = a_{k+1,l}$, $t_1 = a_{k+1,s} - T_W$, and $t_N = a_{k+1,s}$.

The trajectory is generated by considering the following factors:

1. The straight distance between the start and end positions,

2. A discomfort value for walking near furniture or walls,

3. A discomfort value for abrupt body turns,

4. The difference between step length and the preferred stride length

After determining the trajectory, T_W is calculated based on a walking speed. In our experiments, we assumed a fixed walking speed of 68.75 [cm/s].

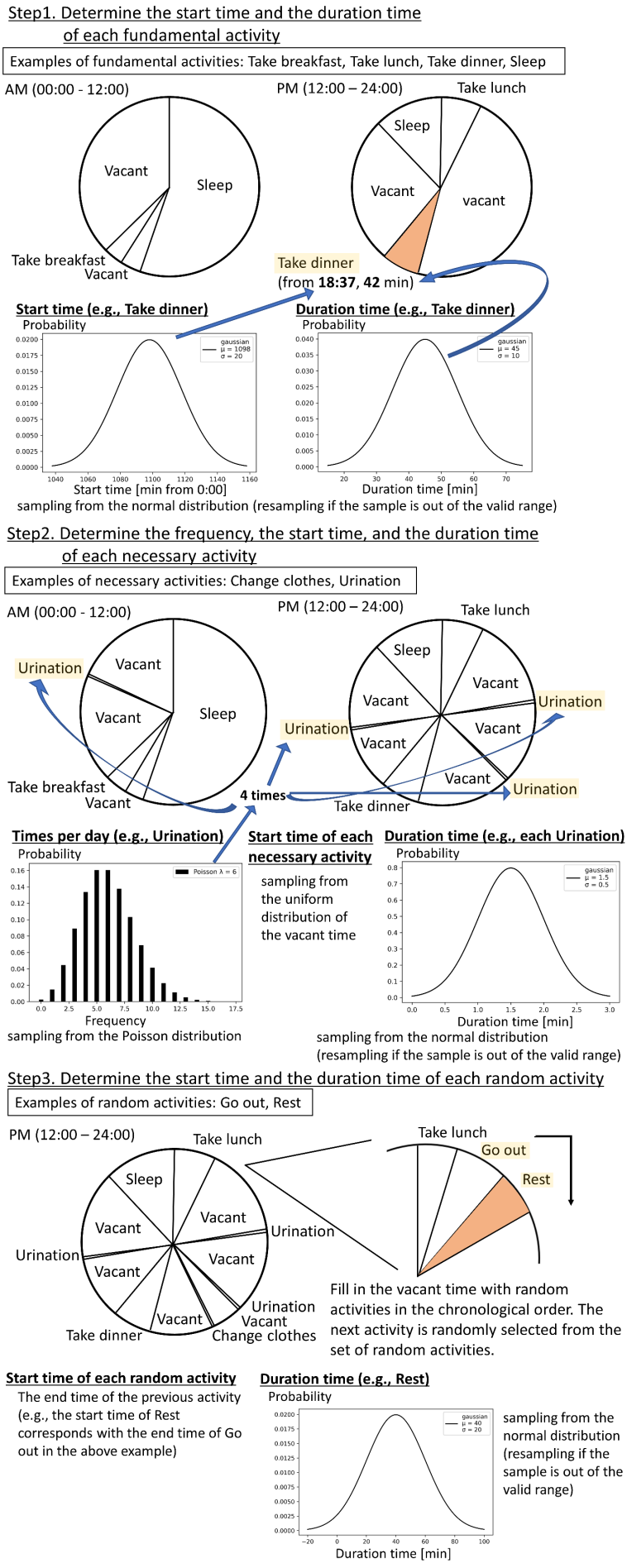


FIGURE 3.5: Overview of the proposed behavioral simulator.

TABLE 3.3: Classification of 20 activities into categories (F: Fundamental, N: Necessary, R: Random) along with their statistics. Here, $\mu_{a,s}$ and $\sigma_{a,s}$ represent the mean and standard deviation of start time, $\mu_{a,d}$ and $\sigma_{a,d}$ represent those of duration, and λ_a is the mean daily frequency. Units are in minutes, and values are based on statistical surveys in Japan [129]. This table is modified version in [56].

Type	Activity	Start time [m]		Freq. [times/day]	Duration [m]		Place	Appliances
		$\mu_{a,s}$	$\sigma_{a,s}$	λ_a	$\mu_{a,d}$	$\sigma_{a,d}$		
F	have breakfast	437 (7:17)	30	—	34	10	Table	—
	have lunch	720 (12:00)	30	—	42	10	Table	—
	have dinner	1098 (18:18)	30	—	45	10	Table	—
	sleep	1289 (21:29)	40	—	482	30	Bed	—
N	brush teeth	—	—	2	1.5	0.5	Bathroom	Faucet
	change clothes	—	—	2	5	1	Wardrobe	—
	defecation	—	—	1	10	3	Toilet	—
	take a bath	—	—	1	30	10	Bathroom	Shower
	urination	—	—	5	3	0.5	Toilet	—
	wandering^{*w}	—	—	λ_w	μ_w	$\mu_w/5$	Walking	—
	go out^{*h}	—	—	1/14	20	4	Entrance	—
	use the phone^{*h}	—	—	1/3	10	2	Desk	—
	go out^{*s}	—	—	1/7	20	4	Entrance	—
R	clean	—	—	—	30	10	Trash box	—
	cooking	—	—	—	30	10	Kitchen	Stove and faucet
	go out	—	—	—	40	20	Entrance	—
	read a book	—	—	—	40	20	Desk	—
	rest	—	—	—	30	10	Sofa	—
	take a snack	—	—	—	10	3	Table	—
	use the phone	—	—	—	10	3	Desk	—
	wash clothes	—	—	—	5	1	Washer	—
	watch TV	—	—	—	40	20	Sofa	TV
	nap^{*s}	—	—	—	40	8	Sofa	—
	rest^{*s}	—	—	—	60	10	Sofa	—

*w: The frequency λ_w and duration μ_w of wandering are determined by the anomaly simulators.
*h: During housebound periods, go out and use the phone are switched from random to necessary activities.
*s: During semi-bedridden periods, go out is switched from random to necessary activities, the duration of rest increases, and nap is added to random activities.
**hs: When housebound and semi-bedridden states occur simultaneously, the go out^{*s} is prioritized.

Sensor Activation

Sensor data are obtained from sensors attached to rooms (Tab. 3.2). These sensors are activated by the resident's movements or activities, with different activation rules depending on the type of sensor:

- **PIR sensors**: Activated when the resident enters their detection area and deactivated upon leaving. For this study, the resident's body radius is set to 10 [cm], and the sensor's detection radius is 0.5 [m]. Since PIR sensors detect motion, they are also deactivated if the resident remains stationary without movement.
- **Pressure sensors**: Activated when the resident's body is standing on the sensor.
- **Door sensors**: Activated when the resident starts or finishes go out. The sensor remains ON for a duration sampled from a normal distribution with a mean of 7 seconds and a standard deviation of 1 second, after which it switches OFF.
- **Flow sensors**: Constantly activated during activities such as cooking, taking a shower, and brushing teeth.
- **Power sensors**: Constantly activated during activities such as cooking and watching TV.

All sensors are synchronized to start sampling at 0 day 0:00:00.

Motion sensors detect motions beyond walking. While an activity is performed, motion sensors near the corresponding activity location are activated but are not always continuously active. To reflect realistic sensor reactions, we calculated the statistics of ON and OFF states using the CASAS Aruba dataset [26]. The results are shown in Tab. 3.4. For example, work at desk often causes sensors to remain inactive for an average of 30 seconds with staying active for an average of 4.8 seconds during this activity, while sleeping results in an average inactivity of around 10 minutes. And these real sensor activations can be modeled by log normal distribution and exponential distribution in Fig. 3.7.

In the simulation, sensor activations during activities are implemented as follows (Tab. 3.5):

- The closest sensor to the activity location is assigned as the *representative sensor*.
- The *active duration* is sampled from a log-normal distribution with a mean of 5 seconds and a standard deviation of 5 seconds, common to all activities.
- The *inactive interval* (the duration between two active states) is sampled from an exponential distribution specific to the activity:
  - Mean of 600 seconds for sleep and nap,
  - Mean of 60 seconds for rest,
  - Mean of 20 seconds for all other activities.
- During these activities, all sensors within a radius of 30 cm from the activity location are activated.

TABLE 3.4: Statistics [sec.] of activation of a motion sensor according to activation in the dataset [26]. This is modified version in [57].

Activity	Location	Active duration (mean ± 2SD)	Inactive interval (mean ± 2SD)
Sleeping	Bed	5.5 ± 115.0	591.8 ± 4119.2
Eating	Dining table	3.7 ± 6.0	22.2 ± 117.0
Work	Desk	4.8 ± 12.4	30.6 ± 139.4
Meal Preparation	Kitchen	5.4 ± 9.6	9.5 ± 52.4
Relax	Sofa	3.2 ± 5.6	49.7 ± 366.2

TABLE 3.5: Statistics [sec.] of a motion sensors in this study. Active duration is 5 ± 10 [sec.] (mean ± 2SD) for all activities. This is modified version in [57].

Activity	Location (sensor #)	Inactive interval (mean ± 2SD)
1) Sleep or nap	Bed (# 23)	600 ± 1200
2) Change clothes	Wardrobe (# 24)	20 ± 40
3) Work, use the phone, or read a book	Chair at the desk (# 25)	20 ± 40
4) Rest or watch a TV	Sofa (#26)	60 ± 120
5) Watch a TV	Sofa (#26)	20 ± 40
6) Take food	Chair at the dining table (#6, #27, #28)	20 ± 40
7) Clean	Trash bin (# 29)	20 ± 40
8) Wash clothes	Washing machine (# 30)	20 ± 40
9) Cooking	Kitchen (#31)	20 ± 40
10) Urination or defecation	WC (#32)	20 ± 40
11) Take a bath or blush teeth	Bathroom (# 33)	20 ± 40

3.2.4 Anomalous Behavior

Anomalous behavior simulator reflects anomalous behaviors into activity, walking trajectory, or sensor data.

We selected six anomalies: *being semi-bedridden*, *being housebound*, *forgetting*, *indoor wandering*, *falls while walking*, and *falls while standing*. Tab. 3.6 and Tab. 3.7 summarizes these anomalies, including their symptoms, causes, and the corresponding implemented models in our simulator.

Algorithm 1 Generation of a daily schedule. This algorithm is modified version in [130].

Input: S_F, S_N and S_R that are the sets of fundamental activities, necessary activities and random activities.
Output: A that is a sequence of activities of the day.
Let $\mathcal{N}$, Poi, Uni and P_R be a normal distribution, a Poisson distribution, a uniform distribution, and a discrete distribution of random activities.
Let ϵ be an allowable minimum duration time, e.g., 30 seconds.

procedure BEHAVIORAL_SIMULATION(S_F, S_N, S_R)
    $T \leftarrow [0:00, 24:00)$ // Time range of a day.
    $A \leftarrow \emptyset$
    for $a \in S_F$ **do** // Set up S_F.
        repeat
            $s \sim \mathcal{N}(\mu_{a,s}, \sigma^2_{a,s})$
            $d \sim \mathcal{N}(\mu_{a,d}, \sigma^2_{a,d})$
        until UPDATE(T, A, a, s, d) == Success
    end for
    for all $a \in S_N$ **do** // Set up S_N.
        $b \sim \text{Poi}(\lambda_a)$
        for all $i \in \{1, 2, \ldots, b\}$ **do**
            repeat
                $s \sim \text{Uni}(T)$
                $d \sim \mathcal{N}(\mu_{a,d}, \sigma^2_{a,d})$
            until UPDATE(T, A, a, s, d) == Success
        end for
    end for
    while $T \neq \emptyset$ **do** // Set up S_R.
        repeat
            $a \sim P_R(S_R)$
            $s \leftarrow \min(T)$
            $d \sim \mathcal{N}(\mu_{a,d}, \sigma^2_{a,d})$
        until UPDATE(T, A, a, s, d) == Success
    end while
    Return A
end procedure

procedure UPDATE(T, A, a, s, d)
    // d^* is the maximum duration between s and the previous activity
    $d^* \leftarrow \min(d, \max(\{e \mid [s-e, s) \subseteq T\}))$
    // d' is the maximum duration between s and the previous activity
    $d' \leftarrow \min(d, \max(\{e \mid [s, s+e) \subseteq T\}))$
    if $d < \epsilon \vee (d^* < \epsilon) \vee (d' < \epsilon) \vee$ (the order of F in A is invalid) **then**
        return Failure
    else// When activities have enough duration.
        $T \leftarrow T \setminus [s, s+d')$
        $A \leftarrow A \cup (a, s, d')$ // a is done for d' [m] from s.
        return Success
    end if
end procedure

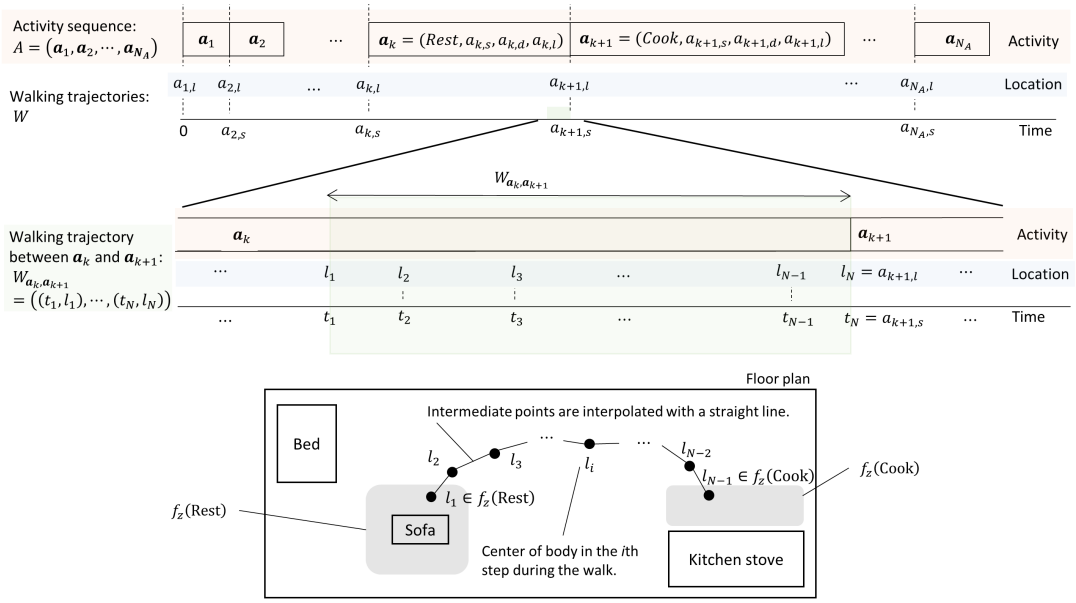


FIGURE 3.6: Generation of a walking trajectory from an activity sequence. A walking trajectory between $\boldsymbol{a}_k$ and $\boldsymbol{a}_{k+1}$ is $W_{\boldsymbol{a}_k,\boldsymbol{a}_{k+1}} = ((t_1,l_1),(t_2,l_2),\ldots,(t_N,l_N))$, where $l_1 = a_{k,l}$ and $l_N = a_{k+1,l}$. The trajectory is obtained by connecting body centers in nearly straight movements while avoiding furniture. Body centers are determined in short and smooth with a specified stride length.

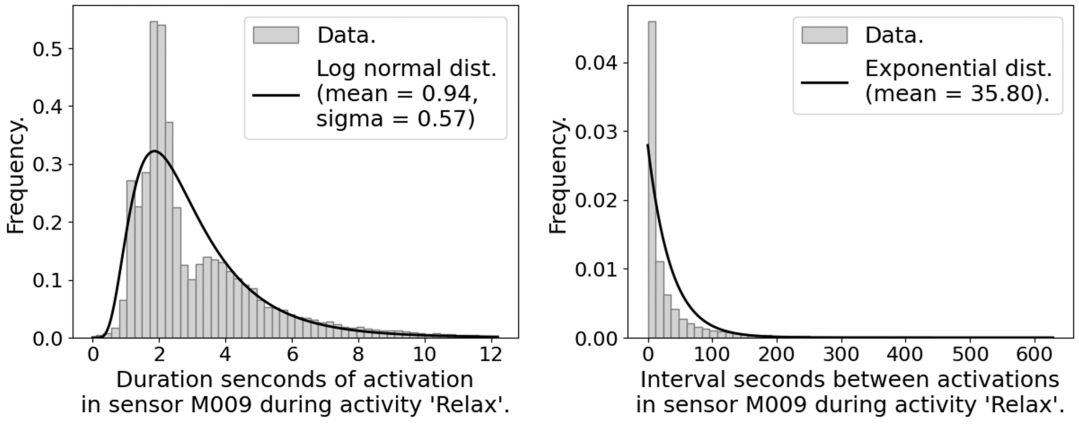


FIGURE 3.7: Duration time (left) and interval time (right) of sensor activations in CASAS Aruba dataset [26]. Histogram, log norm distribution (left) and exponential distribution (right) estimated from data are drawn. Data with an absolute z-score of 3 or above were removed as outliers

TABLE 3.6: Symptoms and causes of six anomalies. This table is modified version in [58].

Anomaly	Symptom	Causes
Being semi-bedridden	The resident often sleeps and avoids movement, indicating a status of grade 2 or 3 in an Eastern Cooperative Oncology Group (ECOG) performance [131].	Bedridden is preceded by various kinds of disabilities due to health problem such as stroke, weakened body by aging and injuries caused by falls [132]. In addition, housebound is considered as a risk of becoming bedridden [133].
Being housebound	The resident is confined to their home more than one week [134].	There is a correlation between the occurrence of being housebound and dementia, but causal relationship is unknown [135].
Forgetting	The resident forgets to turn off home appliances and faucets.	Age and frequency of forgetfulness are significantly correlated [136].
Indoor wandering	The resident walks around with anomalous travel patterns including randomly roundabout by the Martino-Saltzman model [114].	Mini-mental state examination (MMSE) score [137] is known to be effective to connect the patient to the degree of wandering [9]. Especially, the duration time is reported to be significantly associated with the MMSE score [10].
Fall while walking	The resident suddenly falls down while he or she is walking [138].	The longitudinal associations between MMSE and the falling risk are significantly strong at the individual level for predicting, and cognitive degeneration are predictive of falling risk [8].
Fall while standing	The resident loses their balance when he or she starts standing up from sitting, or vice versa [139].	Same with fall while walking.

TABLE 3.7: Implemented six anomalies. This table is modified version in [58].

Anomaly	Implemented modeling
Being semi-bedridden	The average monthly frequency is 1/20, with an average duration of 30 days. During this period, the resident's daily activities change statistically, including an increase in the average duration of nap and rest activities and a decrease in both the average frequency and duration of going-out activities.
Being house-bound	The average monthly frequency is 1/10, with an average duration of 14 days. During this period, the resident's daily activities statistically change, including a decrease in both the average frequency and duration of going-out and phone-calling activities.
Forgetting	*The average monthly frequency is $-M+30$. Forgetting occurs randomly after the resident uses a home appliance, and the appliance is safely turned off when the resident returns near to the area. As a result, the duration varies over time.
Indoor wandering	*The average monthly frequency is $-1.86M+56$ and average duration $-0.31M+9.8$ minutes. Wandering is defined as continuous walking by the resident without any specific intention, with random staging points selected from activity areas.
Fall while walking	*The average monthly frequency is $-M/15+2$. The resident falls at a random middle point during a walk and remains lying down without moving for an average of 30 seconds, with an increased body range. Afterwards, the resident resumes walking. We define the fall as the period from the fall to the restart of walking.
Fall while standing	The model is almost the same as fall while walking, but the fall location is limited to where the resident starts moving or reaches the bed.

*: M is the MMSE simulated by the simple autoregressive model [56].

We classify these anomalies into three types:

- **State anomalies:** Periodic changes observed in statistical properties. For example, the duration of sleep may gradually increase for a resident suffering from *being semi-bedridden*, while the frequency of outings decreases for a resident who is *being housebound*.
- **Activity anomalies:** Changes linked to specific activities, typically observed as alterations in frequency or duration. Examples include *forgetting* (e.g., failing to turn off the stove) and *wandering*.
- **Moving anomalies:** Abnormalities in walking patterns. Examples include *falls*, where the walking speed drops to zero for several seconds or longer.

The activity simulator are statistically interconnected with other component simulators as illustrated in the graphical model (Fig. 3.8). We explain each anomalies below.

Mini-Mental State Examination Score

Many anomalies, including falls and wandering, are associated with Mini-Mental State Examination (MMSE) scores [137] in terms of frequency or duration [9, 10, 8]. As reported in [9], the MMSE score is effective in separating patients into groups based on the degree of wandering. Additionally, the duration of wandering has been found to be significantly associated with MMSE scores [10].

An MMSE score is calculated from responses to simple questions related to cognitive status (e.g., "What is the date today?"). The maximum score is 30, with lower scores indicating more severe dementia.

In this study, anomalies are assumed to be correlated and governed by a single latent variable associated with the degree of dementia. To ensure realism, we focus on individuals with mild cognitive impairment or early-stage Alzheimer's disease (MMSE scores of 19–27) [7], who are capable of living alone. The MMSE score is used as a governing latent variable to quantify cognitive degeneration with a linear decline. Let M_m represent the MMSE score as a random variable in the mth [month]. The sequence $\{M_m\}$ decreases at a constant rate c, with random noise σ_m according to the following formula:

$$M_{m+1} = M_m - c + \sigma_m, \quad c > 0, \quad \sigma_m \sim \mathcal{N}(0,\, \sigma_e^2). \tag{3.1}$$

In this paper, we used $c = (29 - 19.5)/9/12$, corresponding to a reduction from 29 to 19.5 over nine years, based on average cognitive degeneration in the early stages of dementia [7]. Lower values of M_m typically increase the frequency and/or duration of anomalies.

Frequency and duration of each anomaly

Based on the MMSE state M_m, we consider a state-space model where the outputs are the mean frequency $F_{a,m}$ and mean duration $D_{a,m}$ of each anomaly a in the mth month (Tab. 3.8). The unit for duration varies depending on the anomaly, ranging from seconds to days. In particular, the frequency and duration of anomalies such as *wandering*, *forgetting*, and *falls* vary with the MMSE score.

According to [140], the predicted number of falls is approximately once every three years as a baseline, and it can increase several to dozens of times depending on factors such as dementia, walking ability, and attention impairments. Another

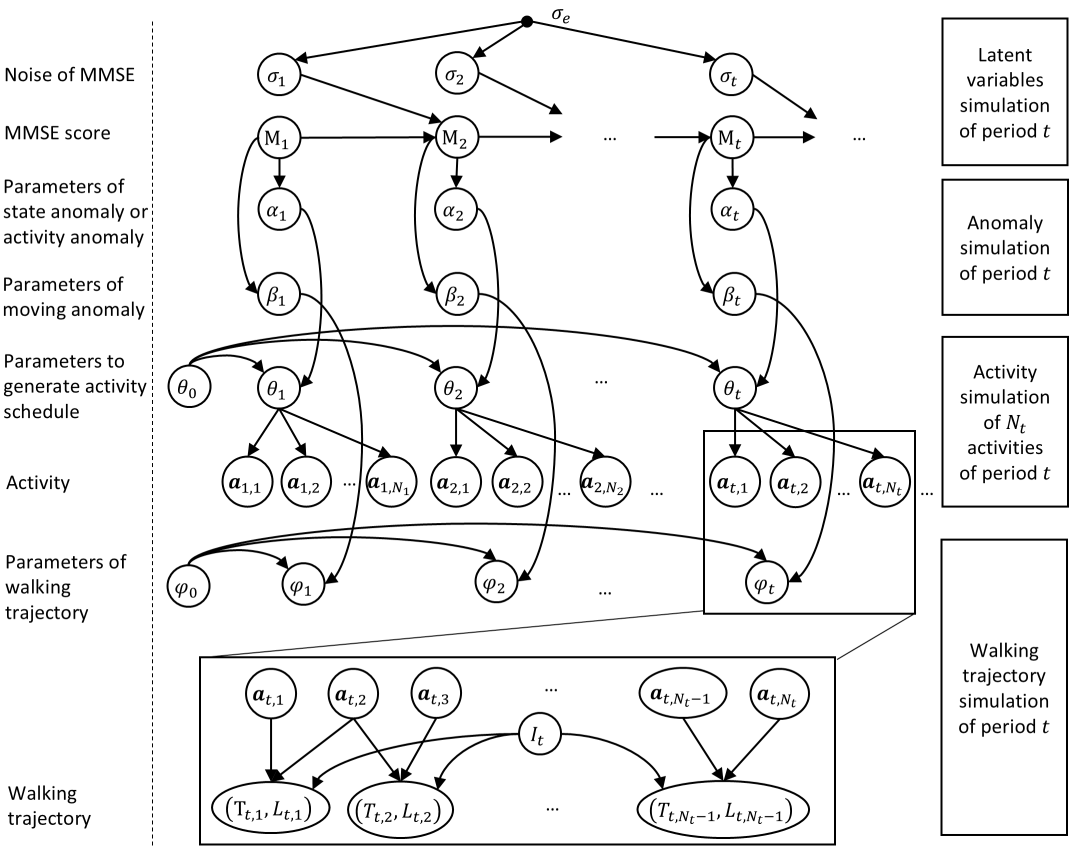


FIGURE 3.8: A graphical model of anomalies. For example, the MMSE score at the tth month, M_t, is generated based on the previous value, M_{t-1}, and noise, σ_t. Random variables α_t and β_t represent the parameters of state and activity anomalies. These are conditioned on M_t and influence the parameters (θ_t and ϕ_t) of activities and walking trajectories, respectively.

TABLE 3.8: Mean frequency and duration of six anomalies. For the mth month, $F_{a,m}$ represents the mean frequency, and $D_{a,m}$ represents the mean duration. Except for the first two anomalies, both values are functions of the MMSE score M_m.

Type	Anomaly	Frequency F_m	Duration D_m
State	*Being semi-bedridden*	$1/20$	30 [day]
	Being housebound	$1/10$	14 [day]
Activity	*Forgetting*	$-M_m + 30$	Until the resident returns to the activity area
	Indoor wandering	$-1.86M_m + 56$	$-0.31M_m + 9.8$ [min.]
Moving	*Fall while walking*	$-M_m/15 + 2$	30 [sec.]
	Fall while standing	$-M_m/15 + 2$	30 [sec.]

study [8] showed that many elderly persons did not fall or fall a few times over half-year. For simplicity, this study assumes that falls occur several times per year depending the MMSE value.

Being semi-bedridden

Being semi-bedridden is characterized by decreased activity levels and prolonged rest durations.

The starting time of *being semi-bedridden* is sampled according to a Poisson distribution with mean frequency $F_{\text{semi-bedridden},m}$, and the duration is sampled from a normal distribution with mean $D_{\text{semi-bedridden},m}$ and standard deviation $D_{\text{semi-bedridden},m}/5$, independent of M_m.

When the resident becomes *semi-bedridden*, certain activities are statistically adjusted (Tab. 3.3):

- nap: The average duration increases to $\mu_{\text{nap},d} = 40$ [min.].
- rest: The average duration increases to $\mu_{\text{rest},d} = 60$ [min.].
- go out: The frequency decreases to $\lambda_{\text{go out}} = 1/7$ [times/day], and the average duration decreases to $\mu_{\text{go out},d} = 20$ [min.].

Being housebound

Being housebound is often associated with a decrease in outings and related activities.

The starting time of *being housebound* is sampled according to a Poisson distribution with mean frequency $F_{\text{housebound},m}$, and the duration is sampled from a normal distribution with mean $D_{\text{housebound},m}$ and standard deviation $D_{\text{housebound},m}/5$, independent of M_m.

When the resident becomes *housebound*, the following statistical changes occur in activities (Table 3.3):

- go out: The frequency decreases to $\lambda_{\text{go out}} = 1/14$ [times/day], and the average duration decreases to $\mu_{\text{go out},d} = 20$ [min.].
- use the phone: The frequency decreases to $\lambda_{\text{use the phone}} = 1/3$ [times/day], and the average duration decreases to $\mu_{\text{use the phone},d} = 10$ [min.].

Forgetting

Forgetting refers to instances where the resident fails to complete a task, such as leaving a kitchen stove.

The frequency of *forgetting* is sampled from a Poisson distribution with mean $F_{forgetting,m}/30$. The target of *forgetting* is randomly selected from activities that involve the use of home appliances.

If *forgetting* occurs, the resident *forgets to turn off* the associated home appliance. The appliance is safely turned off when the resident next returns near its sensor location. For activities involving multiple home appliances, such as Cook (which uses both the faucet and the kitchen stove), one appliance is randomly selected to remain turned on.

Indoor wandering

Indoor wandering involves the resident moving aimlessly within the home, often without a clear purpose.

Wandering belongs to S_N and is characterized by a mean duration $D_{wandering,m}$, a mean daily frequency $F_{wandering,m}/30$, and a standard deviation $F_{wandering,m}/150$. These values are determined by the MMSE score M_m, as shown in Table 3.8.

A resident experiencing *wandering* exhibits anomalous travel patterns by walking around rooms. We implemented *wandering* as a situation where the resident continues walking to a goal point via several staging points randomly selected from activity areas.

The walking trajectory for a transition from a *wandering* activity $\boldsymbol{w}$ to another activity $\boldsymbol{a}$ is represented as:

$$W_{\boldsymbol{w},\boldsymbol{a}} = \left((w_{k,s}, w_{k,l}), \ldots, (t_x, l_1), \ldots, (t_y, l_n), \ldots, (a_{k+1,s}, a_{k+1,l})\right),$$

where:

$$\begin{aligned}\boldsymbol{w} &= (wandering, w_{k,s}, w_{k,d}, w_{k,l}),\\ \boldsymbol{a} &= (a_{k+1,n}, a_{k+1,s}, a_{k+1,d}, a_{k+1,l}),\end{aligned}$$

and $l_1, l_2, \ldots, l_n$ are the randomly selected staging points.

Falls while walking

The daily frequencies of *falling while walking* is sampled using Poisson distributions with means $F_{fall\ while\ walking,m}/30$ converted from 1 month to 1 day. A fall is as follows (Fig. 3.9):

1. A fall occurs during the transition between two successive activities, such as on the walking path from the kitchen (after cooking) to the sofa (for resting). The probability of a fall is governed by the MMSE value, representing the progression of cognitive impairment. The timing of falls during the day is uniformly determined by selecting one walking trajectory from all walking trajectories within the day.

2. Once the walking trajectory $W_{\boldsymbol{a}_k,\boldsymbol{a}_{k+1}}$ is chosen, falling location is randomly and uniformly sampled along the walking path $\{l_2, \ldots, l_{N-1}\}$.

3. During a fall, the agent collapses and remains still for 20–40 seconds. The duration follows a normal distribution with a mean of 30 seconds and a standard

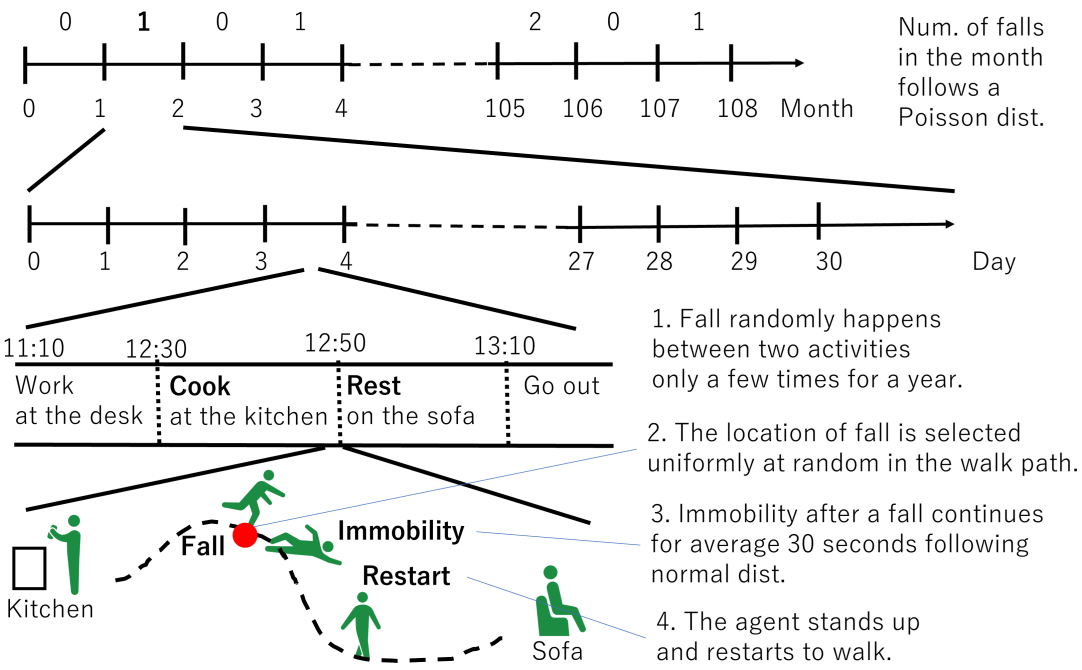


FIGURE 3.9: Simulation flow of falls.

deviation of 6 seconds. During a fall, the body radius of the resident increases from 10 [cm] to 40 [cm], representing the posture change during the fall event. While the agent is lying still during a fall, no motion sensors are activated.

4. After the fall, the agent stands up and resumes walking toward the intended location, activating sensors as expected.

Falls while standing

For *falling while standing*, the falling location is the starting point of the trajectory. If the resident falls on a trajectory $\{(t_1, l_1), \ldots, (t_N, l_N)\}$, they stop suddenly at l_1, remain still for 30 seconds, and then resume walking. Other features are similar with *fall while walking*.

3.3 Qualitative Analysis and Results

We validate the data generated by each component simulator. An example of the floor plan used in this study is shown in Fig. 3.2 and Fig. 3.3. Examples of activity sequences are presented in Fig. 3.4 and Fig. 3.10. Examples of walking trajectories are illustrated in Fig. 3.11. An example of transitional anomaly parameters over long periods is shown in Fig. 3.12, and the sampling occurrences of anomalies based on these parameters are shown in Fig. 3.13. From these figures, no obvious contradictions are observed at first glance.

3.4 Quantitative Analysis and Results

To measure the quantitative performance in the proposed simulator, we compare the real activity sequence with the simulated activity sequence parameterized with the real data. Because sensor data simply follows the walking trajectories and activities

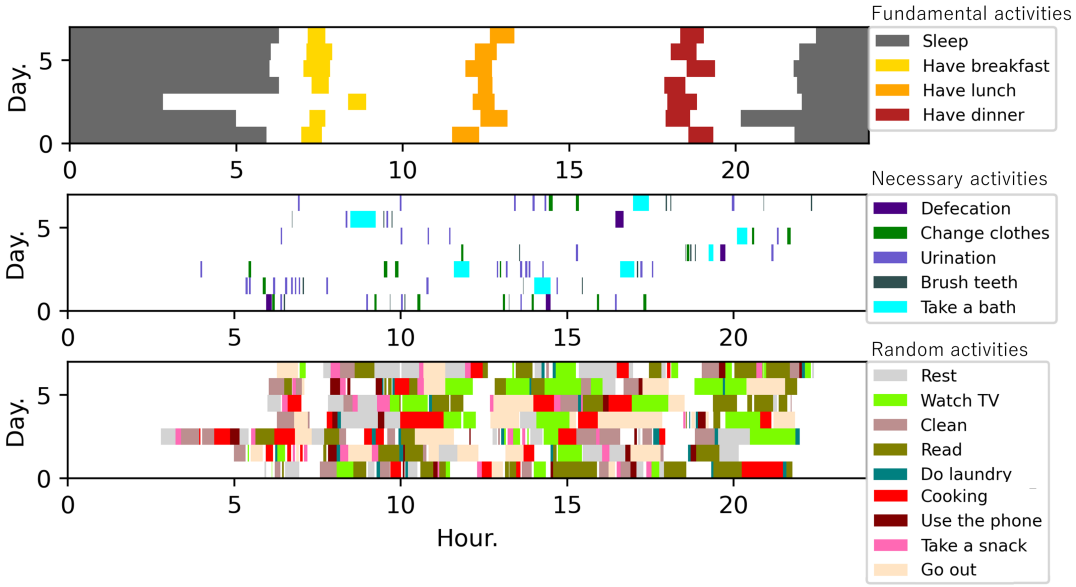


FIGURE 3.10: Simulated activity sequence over 7 days (seven rows in each subfigure). The activities are categorized into three types: fundamental, necessary, and random activities. A total of 18 normal activities are included.

generated from an activity sequence, the reality of the activity sequence is important. Anomalies are difficult to be evaluated because they are rarely observed in real data.

3.4.1 Reality Metrics of Activity Sequences

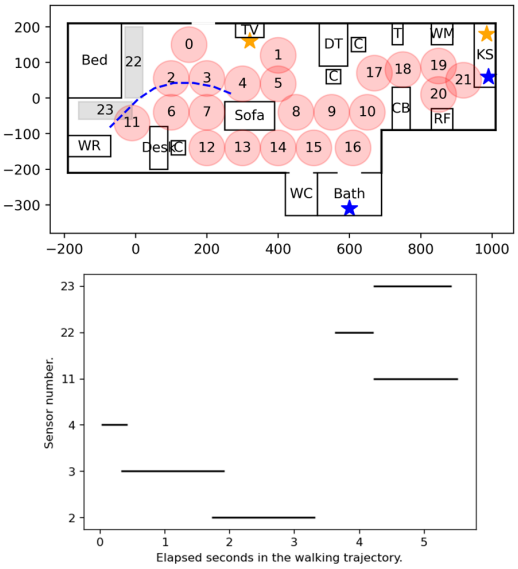
We compared the generated activities with real activity sequences [141, 26]. To compare these activities, we discretized them at intervals of l seconds and represented them as character sequences of constant length. For example, with $l = 30$ seconds, a 20-minute have lunch (L) followed by a 30-minute nap (N) is transformed into LL$\cdots$LNN$\cdots$N (40 occurrences of L and 60 occurrences of N).

Given two daily activity (character) sequences, $\boldsymbol{A}$ and $\boldsymbol{B}$, we measure the similarity $\mathrm{sim}(\boldsymbol{A}, \boldsymbol{B})$ using the Levenshtein distance [142], used in the existing study [89]. Here, A represents a list of daily activity sequences over m days, where each element A_i corresponds to the activity sequence of the ith day. The sequence A_i is discretized into a character string at 30-second intervals, where the kth character in A_i represents the activity at time $k/2$ minutes in the day. Since one day consists of $24 \times 60 \times 2 = 2880$ intervals of 30 seconds, each A_i has a length of 2880 characters. Similarly, B represents the same type of data over n days. Two sequences over different days, $\boldsymbol{A} = (A_1, A_2, \ldots, A_m)$ and $\boldsymbol{B} = (B_1, B_2, \ldots, B_n)$, are compared as follows:

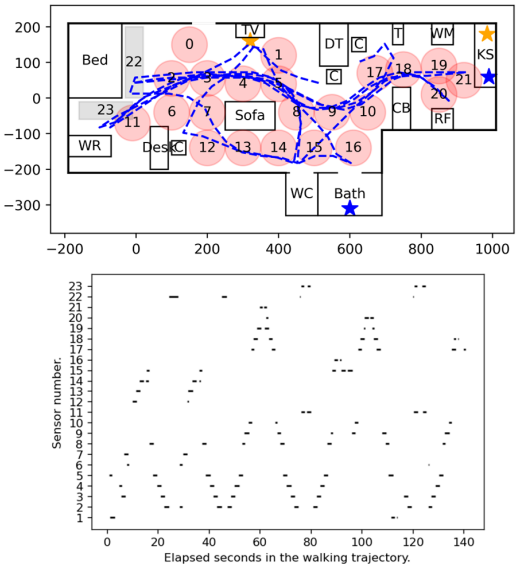
$$\rho(\boldsymbol{A}, \boldsymbol{B}) = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \mathrm{sim}(A_i, B_j)}{mn}, \tag{3.2}$$

$$\rho(\boldsymbol{A}, \boldsymbol{A}) = \frac{\sum_{i=1}^{m} \sum_{j>i}^{m} \mathrm{sim}(A_i, A_j)}{\binom{m}{2}}, \tag{3.3}$$

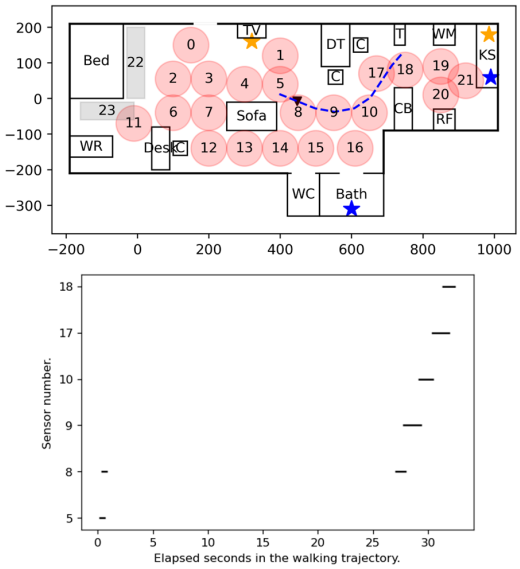
$$\delta_{\mathrm{intra}}(\boldsymbol{A}, \boldsymbol{A}^*) = \left| \rho(\boldsymbol{A}, \boldsymbol{A}) - \rho(\boldsymbol{A}^*, \boldsymbol{A}^*) \right|, \tag{3.4}$$



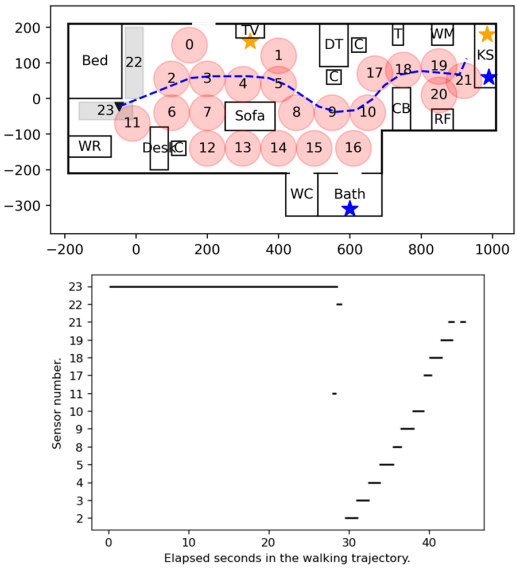
(a) Normal walks (moving for Sofa to WR)



(b) Wandering around two minutes



(c) Fall while walking (starting at Sofa)



(d) Fall while standing at Bed

FIGURE 3.11: Comparison of walking routes and sensor responses between a normal walk (a) and three anomalous walks (b), (c), and (d). Sensor numbers 1–21 represent PIR sensors, while 22 and 23 represent pressure sensors. In (c) and (d), the resident experiences a fall at a specific position (indicated by a black triangle) and subsequently restarts walking.

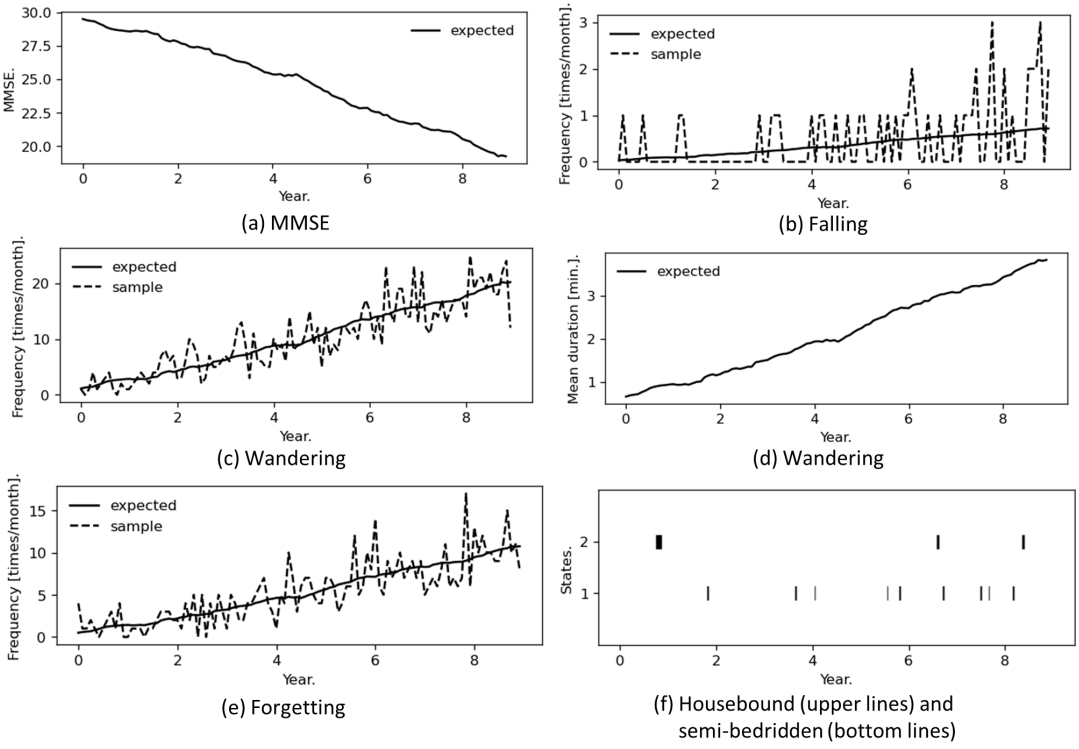


FIGURE 3.12: An example of parameter transitions of six anomalies.

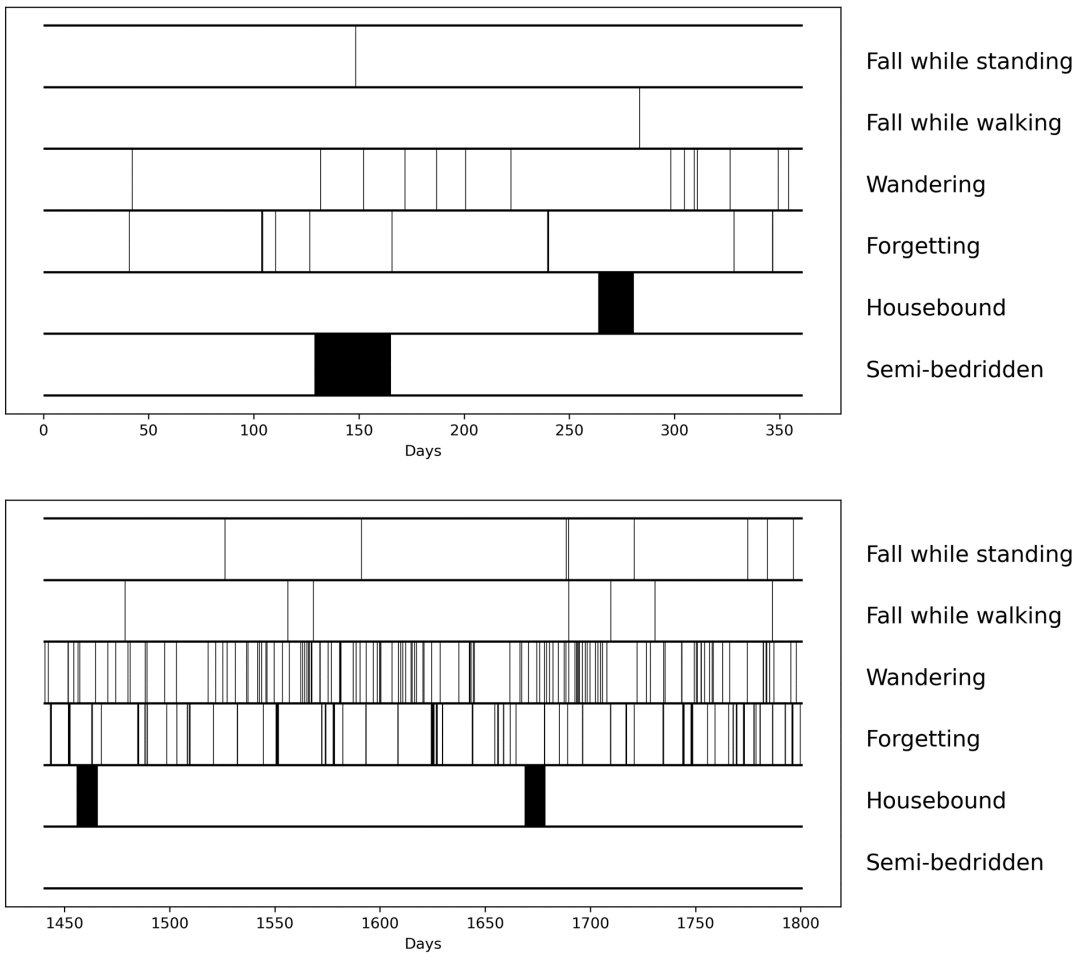


FIGURE 3.13: Spike plot of occurrence of six anomalies.

$$\delta_{\text{inter}}(\boldsymbol{A}, \boldsymbol{A}^*) = \left| \rho(\boldsymbol{A}, \boldsymbol{A}^*) - \rho(\boldsymbol{A}^*, \boldsymbol{A}^*) \right|, \tag{3.5}$$

where $\boldsymbol{A}^*$ represents a real activity sequence.

From $\rho(\boldsymbol{A}, \boldsymbol{A})$, we can determine the variety (or inversely, the self-similarity) of daily schedules within m days of $\boldsymbol{A}$. A large value of $\rho(\boldsymbol{A}, \boldsymbol{A})$ implies a high variety across days. Meanwhile, $\rho(\boldsymbol{A}, \boldsymbol{B})$ indicates the similarity between m days of $\boldsymbol{A}$ and n days of $\boldsymbol{B}$.

The metric $\delta_{\text{intra}}(\boldsymbol{A}, \boldsymbol{A}^*)$ reflects how $\boldsymbol{A}$ differs from $\boldsymbol{A}^*$ in terms of variety. Similarly, $\delta_{\text{inter}}(\boldsymbol{A}, \boldsymbol{A}^*)$ captures the relative difference in similarity between $\boldsymbol{A}$ and $\boldsymbol{A}^*$. A small value of $\delta_{\text{intra}}(\boldsymbol{A}, \boldsymbol{A}^*)$ indicates that $\boldsymbol{A}$ retains a variety comparable to $\boldsymbol{A}^*$. Conversely, a small value of $\delta_{\text{inter}}(\boldsymbol{A}, \boldsymbol{A}^*)$ suggests that $\boldsymbol{A}$ and $\boldsymbol{A}^*$ are similar in content.

3.4.2 Dataset

We used two real activity sequences extracted from two datasets ([141] and [26]).

Kasteren Dataset [141]

First dataset is Kasteren dataset [141], that single male student lives in a smart home. This dataset length is about one month and we use all data for parameter fitting.

We prepare the following five dataset (one from real data, three from the proposed simulator, and one from the existing study) with same time length.

$A_{Kasteren}$ **(24 days)** The real activity sequence over 24 days of a 26-year-old resident living alone [141]. The original data consists of seven activities: prepare breakfast, take shower, prepare dinner, go to bed, use toilet, leave house, and get drink. Some preprocessing and outlier removal were applied.

- The data of 24 days from 0:00 on February 26, 2008 to 24:00 on March 20, 2008 were extracted.
- The following data was regarded as outliers and removed (1) leave house longer than 23 hours (3 cases) (2) go to bed less than 6 hours (4 cases), and (3) get drink before 12 a.m. (4 cases).
- Activity labels in the original data is discontinuous. We filled the unknown time as other.

Finally the activities are eight types, adding other in original labels.

$A_{Proposed}$ **(24 days)** An activity sequence generated for 24 days using our proposed activity simulator. The parameter values were learned from $A_{Kasteren}$ as described in Tab. 3.9. We categorized four activities (take breakfast, take shower, take dinner, and go to bed) as fundamental activities, one activity (use toilet) as a necessary activity, and three activities (go out, get drink, and other) as random activities. The average start time was calculated using the circular mean as in [89] to handle the wrap-around effect at midnight. For example, the average of 23:00 and 1:00 is correctly calculated as 0:00, rather than 12:00. To avoid overlap of fundamental activities, the standard deviations of the start time and duration time of go to bed were reduced to one-third.

A_{RanD} **(24 days)** An activity sequence generated for 24 days with random durations based on normal distributions learned from $A_{Kasteren}$. Activities were

generated chronologically, and the next activity was randomly and uniformly selected from the seven activities above. This data serves as baseline data.

A_{RanS} **(24 days)** An activity sequence generated similarly to A_{RanD}, but with controlled sleep starting times based on $A_{Kasteren}$. The sleep activity was determined first, followed by other activities. This modification was introduced because sleep time occupies a large portion of the day. This data serves as another baseline.

A_{ADLSim} **(24 days)** Explicit activity sequences are not provided, but metric values are available as Sim2 in [89]. The authors used probability distributions to select subsequent activities, applying rules that prioritize certain activities.

TABLE 3.9: Parameters of Kasteren dataset in three types of activities (F: Fundamental, N: Necessary, R: Random). Here, $\mu_{a,s}$ and $\sigma_{a,s}$ denote the mean and the standard deviation of start time, $\mu_{a,d}$ and $\sigma_{a,d}$ denote those of duration time, and λ_a is the mean frequency in a day, p_a is an occurrence probability among random activities. The unit is a minute.

Type	Activity	Start time [min. from 0:00]		Daily freq.	Duration [min.]		occurrence prob.
		$\mu_{a,s}$	$\sigma_{a,s}$	λ_a	$\mu_{a,d}$	$\sigma_{a,d}$	p_a
F	prepare breakfast	562.74 (09:23)	38.43	-	3.34	2.55	-
	take shower	619.02 (10:19)	123.10	-	9.65	2.64	-
	prepare dinner	1159.78 (19:20)	51.46	-	33.31	19.54	-
	go to bed	1416.14 (23:36)	73.63	-	556.07	77.86	-
N	use toilet	-	-	4.33	1.80	1.74	-
R	get drink	-	-	-	0.95	1.32	0.06
	leave house	-	-	-	436.60	213.00	0.13
	other	-	-	-	22.20	35.23	0.82

CASAS Aruba Dataset [26]

We also used another dataset called CASAS Aruba [26], that the elderly woman living alone in smart home with visitors sometime. We compared six activity sequences generated using the following methods. This dataset is approximately nine times longer than the Kasteren dataset, so that we divided the data into training and testing sequences with a 2:1 ratio.

We prepare the following six dataset (three from real data and three from the proposed simulator).

A_{Aruba} **(220 days)** The real activity sequence over 220 days of an elderly woman living alone, whose children and grandchildren visit regularly [26]. The original data consists of eleven activities: meal preparation, relax, eating, work, sleeping, wash dishes, bed to toilet, enter home, leave home, housekeeping, and respirate. Some preprocessing and outlier removal were applied.

- The data for 220 days from November 4, 2010 to June 12, 2011 were used.
- Overlapping between activities was removed such that one activity follows another just in time.
- One of the duplicate data from '2011-05-23 02:43:44.902903 M003 OFF Sleeping end' to '2011-05-23 21:44:59.759837 M003 ON Sleeping begin' was removed.
- A new activity other was assigned to the vacancy in activities. In case that the duration is less than five minutes, then preceding activity was extended.
- leave home and enter home labeled in a few seconds near going out were removed. Instead, go out is assigned to the time.
- eating was separated into three of them, such as take breakfast from 4:00 to 11:00, take lunch from 11:00 to 16:00, take dinner from 0:00 to 1:00, or 16:00 to 24:00.
- sleeping in a day time from 6 to 17 o'clock was replaced with a new label nap.
- bed to toilet and respirate were replaced with the preceding activity.
- Activity labels in the original data is discontinuous. We filled the unknown time as other.

Finally, the activities are eleven types: meal preparation, relax, work, sleeping, wash dishes, housekeeping, take breakfast, take lunch, take dinner, go out, nap, and other.

$A_{ArubaTrain}$ **(146 days)** The first 146 days of A_{Aruba}, used as training data for fitting simulator models.

$A_{ArubaTest}$ **(74 days)** The last 74 days of A_{Aruba}, used as test data for measuring test error.

$A_{Proposed}$ **(74 days)** An activity sequence for 74 days generated by the proposed activity simulator. The parameter values were learned from $A_{ArubaTrain}$ as explained in Tab. 3.10. We categorized four activities (take breakfast, take lunch, take dinner, and sleeping) as fundamental activities, four activities (nap, wash dishes, meal preparation, and housekeeping) as necessary activities, and the remaining activities as random activities. The average start time was

calculated using circular mean as similar in the Kasteren dataset. The standard deviations of the start time and duration time of sleeping were reduced by half to avoid overlapping fundamental activities.

A_{RanD} **(74 days)** Data generated using $A_{ArubaTrain}$ in a manner similar to A_{RanD} in the Kasteren dataset.

A_{RanS} **(74 days)** Data generated using $A_{ArubaTrain}$ in a manner similar to A_{RanS} in the Kasteren dataset.

TABLE 3.10: Parameters of CASAS Aruba dataset in three types of activities (F: Fundamental, N: Necessary, R: Random). Here, $\mu_{a,s}$ and $\sigma_{a,s}$ denote the mean and the standard deviation of start time, $\mu_{a,d}$ and $\sigma_{a,d}$ denote those of duration time, and λ_a is the mean frequency in a day, p_a is an occurrence probability among random activities. The unit is a minute.

Type	Activity	Start time [min. from 0:00]		Daily freq.	Duration [min.]		occurrence prob.
		$\mu_{a,s}$	$\sigma_{a,s}$	λ_a	$\mu_{a,d}$	$\sigma_{a,d}$	p_a
F	take breakfast	582.11 (09:42)	58.27	-	10.04	9.56	-
	take lunch	805.98 (13:25)	86.38	-	14.47	12.00	-
	take dinner	1119.39 (18:39)	92.23	-	14.40	11.71	-
	sleeping	4.83 (00:04)	66.65	-	427.16	110.77	-
N	housekeeping	-	-	0.23	24.67	22.57	-
	meal preparation	-	-	4.86	13.40	11.96	-
	nap	-	-	0.14	85.75	68.87	-
	wash dishes	-	-	0.39	8.52	8.50	-
R	go out	-	-	-	144.13	93.04	0.08
	other	-	-	-	32.55	35.88	0.42
	relax	-	-	-	66.15	74.55	0.46
	work	-	-	-	26.53	29.31	0.04

3.4.3 Result

The results on the Kasteren dataset are presented in Table 3.11. As shown in the table, both $A_{Proposed}$ and A_{ADLSim} exhibit almost the same degree of variety as $A_{Kasteren}$ based on the values of δ_{intra}. Additionally, A_{RanS} demonstrates the highest similarity to the real data in terms of δ_{inter}, followed by $A_{Proposed}$. This result can be attributed to A_{RanS} incorporating the sleeping schedule directly from the real data.

The results on the CASAS Aruba dataset are presented in Table 3.12. From the table, it is evident that $A_{Proposed}$ closely follows $A_{ArubaTrain}$ in both δ_{intra} and δ_{inter}. Furthermore, $A_{Proposed}$ outperforms the two baseline models in terms of δ_{intra}. This indicates that $A_{Proposed}$ achieves a similar degree of daily activity variety as the real activities and is more comparable to the actual data than the random baselines. While the scheduling of sleeping remains a critical factor, it alone is insufficient to fully replicate realistic activities. It is also worth noting that this evaluation measure tends to overlook anomalies and short-duration activities, as these are largely excluded from consideration.

TABLE 3.11: Similarity between activity sequences of Kasteren dataset and simulation. All values are the mean for 10 trials (the standard deviation). For reference, $\rho(A_{ADLSim}, A_{ADLSim})$ is taken from [89], while $\rho(A_{ADLSim}, A_{Kasteren})$ was not mentioned. This is modified version in [56].

data (A)	$\rho(A,A)^{(a)}$	$\rho(A,A_{Kasteren})^{(b)}$	$\delta_{intra}(A,A_{Kasteren})^{(c)}$	$\delta_{inter}(A,A_{Kasteren})^{(d)}$
$A_{Kasteren}$	1027.82	-	0	-
$A_{Proposed}$	923.12 ($\pm$31.30)	1262.27 ($\pm$ 35.36)	104.70 ($\pm$31.30)	234.46 ($\pm$ 35.36)
A_{RanD}	1568.00 ($\pm$45.86)	1676.81 ($\pm$106.81)	540.18 ($\pm$45.86)	649.00 ($\pm$106.81)
A_{RanS}	799.95 ($\pm$76.83)	1004.51 ($\pm$ 46.80)	227.86 ($\pm$76.83)	23.31 ($\pm$ 46.80)
A_{ADLSim}	1130.96 ($\pm$90.47)	N.A.	103.14 ($\pm$90.47)	N.A.

(a) $\rho(A,A)$: intra-difference in the activity sequence in A. (b) $\rho(A_1,A_2)$: inter-difference between A_1 and A_2.
(c) $\delta_{intra}(A,A_{Kasteren}) = |\rho(A,A) - \rho(A_{Kasteren},A_{Kasteren})|$. Lower value means that A is closer to $A_{Kasteren}$ in variety.
(d) $\delta_{inter}(A,A_{Kasteren}) = |\rho(A,A_{Kasteren}) - \rho(A_{Kasteren},A_{Kasteren})|$. Lower value means the closeness in similarity.

TABLE 3.12: Similarity between activity sequences of CASAS Aruba dataset and simulation. All values are the mean for 10 trials (the standard deviation). This is modified version in [56].

data (A)	$\rho(A, A)^{(a)}$	$\rho(A, A_{ArubaTest})^{(b)}$	$\delta_{intra}(A, A_{ArubaTest})^{(c)}$	$\delta_{inter}(A, A_{ArubaTest})^{(d)}$
$A_{ArubaTest}$	1281.85	-	0	-
$A_{ArubaTrain}$	1264.08	1329.98	17.78	48.13
$A_{Proposed}$	1309.92 ($\pm$19.63)	1484.99 ($\pm$10.46)	28.07 ($\pm$19.63)	203.14 ($\pm$10.46)
A_{RanD}	1961.20 ($\pm$58.69)	2243.97 ($\pm$36.90)	679.34 ($\pm$58.69)	962.11 ($\pm$36.90)
A_{RanS}	1801.87 ($\pm$24.45)	1878.31 ($\pm$19.78)	520.02 ($\pm$24.45)	596.46 ($\pm$19.78)

(a)-(d) see the footnote of TABLE 3.11.

Chapter 4

Detection

We proposed an unified framework to detect six types of anomalies from sensor data, including approaches for *wandering*, *falls while walking*, and *falls while standing*, and novel approaches for *being semi-bedridden*, *being housebound*, and *forgetting* to turn off appliances.

4.1 Use Case

First, we show an example of use case in anomaly detection in real scenario. An elderly individual living alone may be healthy or in the early stages of mild cognitive impairment but still capable of living independently. The individual, family members, or caregivers who visit regularly may wish to monitor long-term abnormal behaviors over several years to detect early signs of health deterioration. This system records anomaly predictions and provides alerts to the individual, family members, caregivers, or a service manager.

For abnormal behaviors requiring immediate attention, such as falls or forgetting to turn off appliances, the system could trigger alerts, such as a buzzer for the individual or phone calls to relatives. For behaviors that do not require an urgent response, such as *being housebound* or *being semi-bedridden*, the system records health data, which can be shared during visits or accessed online for detailed health evaluations. This approach helps to prevent further deterioration of the individual's health.

4.2 Simulator-based Anomaly Detection

We propose a simulator-based anomaly detection system to address the issue of data insufficiency in smart homes by utilizing predefined anomaly models and a sensor data simulator. An overview of the system is shown in Fig. 4.1.

The system operates as follows:

1. **Customization of the simulator:** The simulator is tailored to the operational environment by configuring parameters for:
    - **Layout and sensors:** Room size, furniture placement, sensor models, quantity, and arrangement.
    - **Resident's information:** Activity statistics, including start times, durations, frequencies, and walking speed.
    - **Model of anomalies:** Degree of dementia, types of anomalies, observed phenomena, and frequencies.

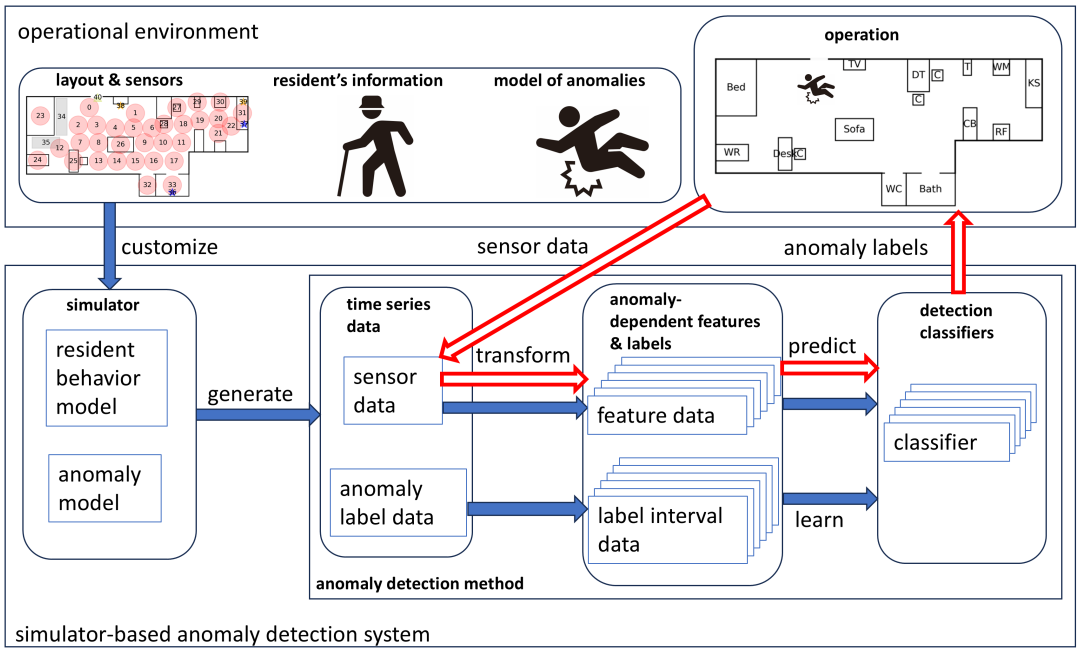


FIGURE 4.1: Overview of the system. Anomaly detection classifiers are trained using simulation data generated by simulators customized based on the operational environment. The simulated time series data are transformed into anomaly-dependent features and label interval data, enabling the detection of anomalies with varying types and durations.

2. **Data generation:** Using the configured simulator, time series data of sensor outputs and corresponding anomaly labels are generated based on resident behavior models and anomaly models.

3. **Data transformation:** The generated time series data are transformed into feature vector sequences and label interval sequences tailored to each anomaly.

4. **Training the classifier:** Detection classifiers are trained for each anomaly using the transformed feature vector and label interval data.

5. **Operation:** In practice, real sensor time series data are processed to extract feature vectors, and the trained classifier predicts the labels of detected anomalies.

For this research, we simulated behavioral and movement patterns using average behavioral statistics of elderly individuals, making the system applicable to a broad target population. However, if personalized data, such as activity statistics (e.g., sleep schedules or frequency of outings) or walking speed, can be collected, the simulator's generation model can incorporate this information. This allows the system to be customized for individual residents, enhancing its effectiveness and relevance.

4.3 Detection Method for Each Anomaly

4.3.1 Preprocessing

We define symbols for sensor data as follows. Binary-output sensors are indexed by the set $\{1, 2, \ldots, S\}$. All sensors share a common sampling period T_s, and the

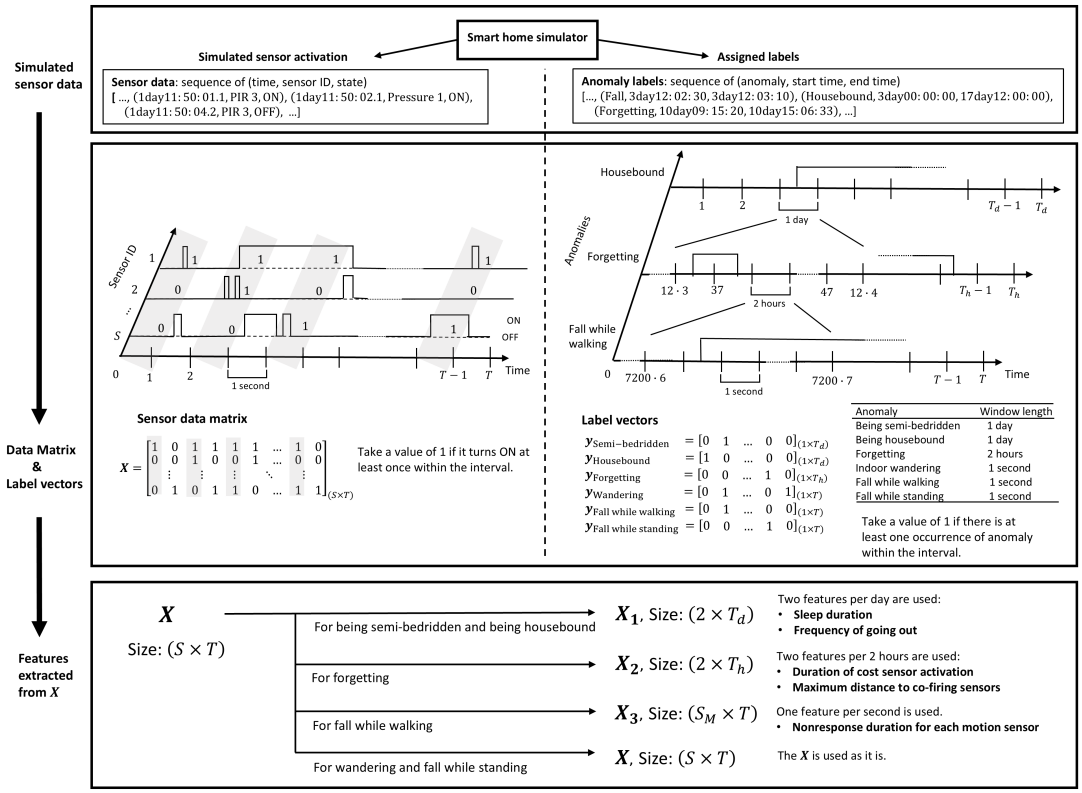


FIGURE 4.2: Illustration of the training data construction process using a simulator. The smart home simulator first generates time-series data of sensor activations along with anomaly labels. The sensor data is then summarized into a binary-value vector sequence (data matrix) with one-second intervals. Each anomaly label sequence is transformed into a binary-value sequence with anomaly-specific intervals. To train a classifier for each of the six anomalies, a sequence of feature vectors tailored to each anomaly is extracted from the sensor data matrix. This figure is modified version in [58].

sampling times are indexed by the set $\{1, 2, \ldots, T\}$. The jth sampling time is given by $T_s \cdot j$. For now, we set $T_s = 1$ seconds.

Sensor data is defined as follows. Let $x_{i,j} \in \{0, 1\}$ represent the state of binary sensor i at sampling point j, that becomes 1 if the sensor was activated at least once during the interval from the $(j-1)$th to the jth sampling times; otherwise, it is 0. The complete data is represented as a data matrix $\mathbf{X} = (x_{i,j})_{1 \le i \le T, 1 \le j \le S}$. This data representation has been used in existing studies as raw data representation [143].

Similarly, label data for each anomaly is also summarized, but the interval length varies depending on the anomaly. For example, the interval is one second for *falls* and *wandering*, two hours for *forgetting*, and one day for *being housebound* and *being semi-bedridden*, as shown in the right part of the middle box in Fig. 4.2. Consequently, the lengths of the label vectors $\boldsymbol{y} \in \{0, 1\}^L$ also differ. Specifically:

- One second as $L = T$ for *wandering*, *falls while walking*, and *falls while standing*,
- Two hours as $L = T_h (= T/7200)$ for *forgetting*,
- One day as $L = T_d (= T_h/12)$ for *being semi-bedridden* and *being housebound*.

This preprocessing procedure is illustrated in Fig. 4.2.

4.3.2 Detection of begin semi-bedridden and housebound

We propose a method to determine *being semi-bedridden* or *being housebound* based on a statistical test approach. Both *semi-bedridden* and *housebound* involve a reduction in the frequency of going out. To distinguish the *semi-bedridden* state from the *housebound* state, we first classify the *semi-bedridden* state using sleep duration and then classify periods with low frequencies of going out as the *housebound* state. The classification interval is set to one day.

The classification method is explained step by step below:

1. **Rule-based estimation of daily sleep duration:** If motion sensors near the bed (#23, #34, and #35 in Fig. 3.2) are activated and the interval until these sensors are next activated exceeds one minute, this interval is considered as sleeping time. However, if any other motion sensors outside the bed are activated during this interval, it is not considered as sleep.

2. **Modeling the sleep duration:** The daily sleep duration is modeled by a normal distribution with mean μ_s and standard deviation σ_s, estimated as the sample mean and sample standard deviation of all the estimated daily sleep durations.

3. **Learning the semi-bedridden classification:** Periods where the sleep duration exceeds the threshold $\theta_s = \mu_s + c_s\sigma_s$ for more than seven consecutive days are classified as *semi-bedridden*. The parameter c_s is selected from the closed interval $[-1, 3]$ to maximize the F1 score on the training data.

4. **Rule-based estimation of daily frequency of going out:** If the door sensor is activated and the interval until the sensor is next activated exceeds one minute, it is counted as one instance of going out. However, if any other motion sensors are activated during this interval, it is not counted.

5. **Modeling the going-out frequency:** The daily frequency of going out is modeled by a normal distribution with mean μ_h and standard deviation σ_h, estimated as the sample mean and sample standard deviation of all the estimated daily going-out frequencies.

6. **Learning the housebound classification:** Periods where the frequency of going out falls below the threshold $\theta_h = \mu_h - c_h\sigma_h$ for more than seven consecutive days and are not classified as *semi-bedridden* are classified as *being housebound*. The parameter c_h is selected from the closed interval $[-1, 3]$ to maximize the F1 score on the training data.

Note that this method assumes that the bed is used exclusively for sleeping and not for other activities such as reading.

4.3.3 Detection of forgetting

To detect instances of *forgetting to turn off appliances and faucets*, we use the following two types of features calculated for every 2-hour interval:

- **Duration of cost sensor activation:** The total time during which the appliance sensor remains activated.

- **Maximum distance to sensors activated during cost sensor activation:** The maximum Euclidean distance from the cost sensor to any other sensor activated during the same time period.

A decision tree [144] is trained with the two-dimensional feature vector to classify the binary label. The splitting criterion is Gini impurity, and the stopping criterion requires each leaf node to contain fewer than five data points.

4.3.4 Detection of wandering

To detect *wandering*, we use the data matrix and label vector without additional preprocessing. These data are modeled using standard time series classifiers [143], such as dynamic naive Bayes [145] and hidden Markov models [146]. To suppress noisy predictions, continuous labels with durations shorter than a specified denoising threshold are removed as a post-processing step.

4.3.5 Detection of falls while walking

To detect *falls while walking*, we use the nonresponse duration (NRD) as a feature. The NRD represents the elapsed time since the last activation of a sensor and means as an approximation of the duration of resident immobility.

The NRD is calculated for all S_M motion sensors, including infrared motion sensors, pressure sensors, and door sensors. For the ith sensor at time j, $\mathbf{NRD}_{i,j}$ represents the nonresponse duration, capturing the time elapsed since the sensor was last activated among all motion sensors until any other motion sensor is activated.

The calculation varies by sensor type:

- Infrared motion sensors and door sensors: These sensors capture instantaneous movements, and the NRD is reset when the same sensor is activated again.
- Pressure sensors: These detect continuous presence, so the NRD is not reset when the same sensor is activated.

For the ith sensor at time j, let $j'(< j)$ be the last time when all sensors were inactive, and $S(j')$ be the set of sensors that fired just before j'. The NRD is defined as:

$$\mathbf{NRD}_{i,j} = \begin{cases} j - j' + 1 & \text{if } i \in S(j'), \\ 0 & \text{otherwise.} \end{cases}$$

All sensors in $S(j')$ share the same NRD value. Collecting $\mathbf{NRD}_{i,j}$ for all sensors $i \in \{1, 2, \ldots, S_M\}$ forms the NRD vector for each time step.

The random forest [147] is trained using NRD vectors to classify each second as either a fall or a non-fall instance. The splitting criterion is based on Gini impurity, and the stopping criterion ensures each leaf node contains fewer than five data points. Decision rule based methods are chosen for their explainability and reliability, making them suitable for detecting *falls while walking*. Classifiers trained directly on a raw binary sensor matrix showed poor performance, so we omit these result.

4.3.6 Detection of falls while walking

To detect *falls while standing*, we used the similar way with detecting *wandering*, detected by typical time series classifiers learned from the data matrix and label vector without additional preprocessing.

4.4 Experiment

We evaluated the detection performance using simulation data. Due to the difficulty of collecting real data that includes anomalies, this study used simulation for both the training and test stages. If the simulator can accurately mimic real-world models, this evaluation framework is expected to work effectively. Based on the aforementioned experiment, we hypothesize that the simulator captures the statistical features of activities realistically.

4.4.1 Metrics

Let $\boldsymbol{y}$ and $\hat{\boldsymbol{y}}$ represent the sequences of true (model-generated) and predicted anomaly labels. We use five evaluation metrics for alarms of anomaly behaviors. Two of these metrics are the typical precision and recall calculated between $\boldsymbol{y}$ and $\hat{\boldsymbol{y}}$.

The other three metrics are defined using the *label interval* sequence of $\boldsymbol{y}$, which is expressed as $I = \{I_1, I_2, \ldots, I_N\}$, where I_i represents the ith maximal time interval of consecutive 1s in $\boldsymbol{y}$. For example, the label interval sequence of $\boldsymbol{y} = [0, 1, 1, 1, 0, 0, 1, 1, 0, \ldots]$ consists of $I_1 = [1, 3], I_2 = [6, 7], \ldots$. Similarly, let $I = \{I_1, I_2, \ldots, I_N\}$ and $\hat{I} = \{\hat{I}_1, \hat{I}_2, \ldots, \hat{I}_{\hat{N}}\}$ be the label interval sequences of $\boldsymbol{y}$ and $\hat{\boldsymbol{y}}$, respectively, where I and $\hat{I}$ are composed of disjoint intervals.

- **Sensitivity:** The proportion of correctly detected anomalies, defined as:

$$\text{Sensitivity} = \frac{|\{I_a \mid I_a \cap \hat{I}_b \neq \emptyset, {}^{\exists}b\}|}{N}.$$

  This is an interval-based version of recall. High sensitivity indicates that a high proportion of anomalies are detected.

- **False Alarm Rate (FAR):** The proportion of wrongly detected anomalies, defined as:

$$\text{FAR} = \frac{|\{\hat{I}_b \mid I_a \cap \hat{I}_b = \emptyset, {}^{\forall}a\}|}{\text{number of days}}.$$

  FAR reflects the number of false alarms per day. A low FAR indicates fewer unnecessary warnings.

- **Mean Alarm Length (MAL):** The average length of predicted label intervals, regardless of correctness, defined as:

$$\text{MAL} = \frac{\sum_{b=1}^{\hat{N}} |\hat{I}_b|}{\hat{N}},$$

  where $|\hat{I}_b|$ represents the length of $\hat{I}_b = [s, e]$, i.e., $|\hat{I}_b| = e - s$. MAL should be minimized to reduce redundant alarms. Note that extending predicted label intervals can improve sensitivity and FAR but worsens MAL.

For wandering and falls, denoising thresholds are applied to remove noisy labels shorter than the threshold. For example, a 5-second threshold removes label intervals shorter than 5 seconds.

Similar evaluation metrics have been used in existing studies on long-term fall detection in real-world scenarios [148]. One such study, which experimented with more than three years of wearable sensor data for fall detection, achieved a sensitivity of 80% with one false alarm per 40 usage hours.

4.4.2 Dataset

We prepare simulation data under the following settings. The floor plan and sensor arrangement are predefined as shown in Fig. 3.2. A total of 41 sensors are placed to cover the main flow lines in the floor plan. The resident follows the activity model (Tab. 3.3) in the house and occur anomalous behavior modeled as in Tab. 3.7. The simulation spans 9 years ($9 \cdot 360$ days) for both training and test datasets. The training dataset contains a total of 7,555,956 sensor activations.

The number of anomaly labels in the training and test datasets are as follows:

- *Being semi-bedridden:* 4 (training), 8 (test),
- *Being housebound:* 11 (training), 17 (test),
- *Forgetting:* 452 (training), 575 (test),
- *Wandering:* 952 (training), 955 (test),
- *Falls while walking:* 26 (training), 40 (test),
- *Falls while standing:* 32 (training), 38 (test).

4.4.3 Parameter setting

For detecting *being semi-bedridden* and *housebound*, the accuracies of estimated daily sleep duration and going-out frequency are evaluated using the mean absolute errors (MAE) between the estimated values from the simulated sensor data and the true values from the activity labels generated by the resident behavior model in the simulation. The MAE values are 6.8 minutes and 0.046 occurrences for the training data, and 6.9 minutes and 0.042 occurrences for the test data.

The models for estimated sleep duration and going-out frequency are $N(8.02, 1.15)$ and $N(3.95, 2.12)$, respectively, where the learned parameters are $c_s = 0.10$ and $c_h = 1.80$. Consequently, the thresholds are calculated as $\theta_s = 8.13$ and $\theta_h = 0.14$.

For detecting *falls while walking*, a random forest classifier with 100 decision trees is trained. To focus the training on relevant data, feature vectors corresponding to non-anomalous labels are reduced by selecting data from the three days before and after each fall occurrence time.

4.4.4 Result

The results are shown in Table 4.1. Note that the evaluation metrics differ from those used in existing works (Table 2.6 and Table 2.7), making direct comparisons between methods difficult.

As a simple numeric comparison, the performance in detecting falls and wandering is comparable to existing works. The three newly implemented methods for detecting *being semi-bedridden*, *being housebound*, and *forgetting* achieve a sensitivity of over 0.9, with false alarms occurring less than once every 100 days.

For detecting *wandering* and *falls while standing*, hidden Markov models outperform dynamic naive Bayes models due to their ability to utilize time context. However, detecting *falls while walking* remains the most challenging, achieving a sensitivity of 0.7. This difficulty arises from distinguishing whether the resident has fallen or simply stopped walking near activity areas. Oversampling labels shows promise for improving performance. In this study, the training data included 26 instances over 9 years, whereas previous research [57] achieved a sensitivity of 0.96 by oversampling the number of falls approximately 200 times.

TABLE 4.1: Test results of detections for six types of anomalies from nine years of a simulation data. The evaluation metrics are calculated by the true labels on the simulation data. This is modified version in [58].

Anomaly	Unit length	#Anoms.	Methods	Raw precision	Raw sensitivity	Denoise threshold	Precision	Sensitivity	FAR [#alarms/day]	Mean alarm length
Semi-bedridden	1 day	8	ST	0.97	0.80	-	1.0	1.0	0.0	14.9 days
Housebound	1 day	17	ST	0.82	1.0	-	0.54	1.0	0.004	9.2 days
Forgetting	2 hours	575	DT	0.98	0.93	-	0.74	1.0	0.01	23.4 hours
Wandering	1 second	955	DNB	0.10	0.53	-	0.10	1.0	68.2	2.78 seconds
						5 seconds	0.10	0.97	13.1	5.97 seconds
			HMM	0.10	1.0	-	0.006	1.0	45.9	8.85 seconds
						28 seconds	0.94	1.0	0.017	144 seconds
Fall while walking	1 second	40	RF	0.20	0.64	-	0.092	0.75	0.09	12.2 seconds
						16 seconds	0.32	0.75	0.02	29.6 seconds
Fall while standing	1 second	38	DNB	0.83	0.20	-	0.13	0.18	0.015	5.13 seconds
			HMM	0.66	0.92	-	0.17	0.92	0.053	7.7 seconds
						6 seconds	0.97	0.92	0.0	30 seconds

Abbreviations are; number of anomalies in test data (#Anoms.), statistical test (ST), decision tree (DT), random forest (RF), dynamic naive Bayes (DNB), and hidden Markov model (HMM). Five evaluation metrics are raw precision, raw recall, sensitivity, false alarm rate (FAR) and mean alarm length. Raw precision and raw recall are calculated using labels for data segments of unit time length. Precision, sensitivity, FAR and mean alarm length are calculated based on the label intervals, which correspond to consecutive anomaly data segments. For the latter metrics, label intervals shorter than the denoising threshold are treated as noise and excluded.

Chapter 5

Discussion

5.0.1 Validation of Reality in Simulated Activities

The validity of the proposed simulator depends on the realism of the simulated behaviors, including both normal and anomalous activities, and the generated sensor data. However, direct comparison with real-world data is challenging due to the difficulty of collecting extensive and varied real data, especially for rare or potentially hazardous anomalies like falls or prolonged housebound states. Conducting long-term experiments with elderly participants in smart homes is ethically and practically difficult.

In this study, we used statistical parameters derived from existing datasets to ensure realism. Our hierarchical probabilistic model (Fig. 3.8) exploits the relationships among these parameters, to simulate activity patterns. Simulated activity sequences have been shown to resemble real data by experiments. Additionally, our simple walking and sensor models according to the activities approximate real activations for binary sensors. However, certain aspects, particularly anomalies such as *falls*, may not fully replicate real-world characteristics. For example, the response to a fall, such as crawling or attempts to stand, is not captured in the current model. While the performance metrics achieved using simulation test data are high, further evaluation using real-world datasets is necessary to confirm this assumption, particularly for *fall detection*.

5.0.2 Expandability of the Model

Our simulation-based method provides a cost-effective way to evaluate anomaly detection systems without requiring real-world data. The proposed simulator serves as a prototype, with several avenues for enhancement:

- **Activity and Anomaly Models:** Current models rely on simple statistical distributions such as Poisson or normal distributions for activity start times, durations, and frequencies. More complex models, such as those in [109, 106, 107], could improve the realism of simulated behaviors. For *falls*, prior data and knowledge of falls incorporating factors like location-specific risks (e.g., stairs or narrow spaces) and resident responses (e.g., crawling after a fall) could improve the similarity. Even there is the argument that simulation cannot replicate all various patterns in real-life [149], our pre-defined falls can enhance its detection range.

- **Personalization:** For personalized applications, statistical parameters can be tailored to an individual by collecting data on their daily routines and behavior patterns including their specific routines, such as sleep schedules or walking speeds. This makes the system more applicable to a broad range of users, including those with unique behavioral patterns.

- **Robustness for Real-World Data:** Real-life scenarios include unexpected events such as sensor malfunctions, irregular resident behaviors (e.g., sleeping on the floor), or seasonal variations in activity patterns. Addressing these challenges may involve integrating federated learning techniques for sensor malfunction detection [150] or concept drift detection methods for activity patterns [151].
- **Feedback from Real-World Data:** Verification and feedback using real-world data would enhance the simulator. While collecting labeled real-world data is costly, partial labeling methods, such as diary-based reports, could provide valuable insights. Unlabeled real data also have possibility to refine activity pools, calibrate behavior statistics, and analyze walking patterns visually.
- **Others:** There are other directions to refine models, and expand their applicability to more complex scenarios. This includes incorporating more flexible floor plans, such as multi-floor layouts and yards, introducing habitual behaviors of the resident to enhance realism, implementing richer sensors with 3D information, and implementing physical models of a body.

Chapter 6

Conclusion and Future Works

6.1 Conclusion

In this paper, we have extended a state-of-the-art sensor data simulator [51], which originally focused on *wandering*, to produce anomalous patterns corresponding to six typical anomalies that can occur among elderly individuals living alone: *being semi-bedridden*, *being housebound*, *forgetting*, *wandering*, *fall while walking*, and *fall while standing*. These anomalies are statistically controlled primarily by frequency and duration and are governed by a single latent variable, the MMSE score, an indicator of dementia severity.

The proposed simulator is superior to previous methods in two key aspects: (1) it naturally simulates the worsening of conditions over time, and (2) it captures the correlations among anomalies through the MMSE score. By utilizing simulated sensor data, we avoided the high costs associated with collecting long-term real-world data while demonstrating the potential to achieve a high degree of similarity with real activity sequences in existing datasets. Experimental results show that our anomaly detection methods that are trained and tested on the simulation data achieve a sensitivity of over 0.9 with fewer than one false alarm every 50 days for most anomalies over nine years, except for *fall while walking*, where the sensitivity is 0.75. Data oversampling improves fall detection as the sensitivity 0.92 with one false alarm per about nine days. Even the experiment settings and evaluation metrics are not shared, these results are competitive performance compared to existing studies, particularly for detecting *wandering* and *falls*. Additionally, the methods for detecting *being semi-bedridden*, *being housebound*, and *forgetting* were newly proposed and evaluated, achieving high precision and recall.

This work demonstrates that privacy-preserving ambient sensors, such as infrared motion sensors, pressure sensors, door sensors, and cost sensors, combined with simulated data, can enable effective anomaly detection without relying on real-world datasets. This approach highlights the potential of simulator-based frameworks to enhance long-term elderly care in smart homes.

6.2 Future Works

We aim to develop cost-effective solutions for detecting long-term behavioral changes and health deterioration in elderly individuals living alone. Future research will focus on refining the simulator and expanding its applicability to real-world scenarios as discussed in the aforementioned discussion section. By bridging the gap between simulation-based training and real-world deployment, these frameworks could further help early intervention and improved care in smart home environments.

Bibliography

[1] Wan He, Daniel Goodkind, and Paul Kowal. *An Aging World: 2015*. International Population Report P95-16-1. United States Census Bureau, Mar. 2016.

[2] United Nations. *World Population Ageing 2020 Highlights: Living arrangements of older persons*. Highlights ST/ESA/SER.A/451. United Nations Department of Economic and Social Affairs, Population Division, Nov. 2020.

[3] Cabinet Office Japan. *Annual Report on the Ageing Society FY2021*. Annual Report. Note: The full report is available in Japanese at: https://www8.cao.go.jp/kourei/whitepaper/index-w.html, while the English version provides a summary at https://www8.cao.go.jp/kourei/english/annualreport/index-wh.html. Cabinet Office, Government of Japan, July 2021.

[4] David Reher and Miguel Requena. "Living alone in later life: a global perspective". In: *Population and Development Review* (2018), pp. 427–454.

[5] Centers for Disease Control and Prevention, National Center on Birth Defects and Developmental Disabilities, Division of Human Development and Disability. *Disability and Health Data System (DHDS) Data [online] [accessed May 6, 2022]*. demographic data. 2019. URL: https://dhds.cdc.gov.

[6] Rosa M Crum, James C Anthony, Susan S Bassett, and Marshal F Folstein. "Population-based norms for the Mini-Mental State Examination by age and educational level". In: *Jama* 269.18 (1993), pp. 2386–2391.

[7] Barry Reisberg, Imran A. Jamil, Sharjeel Khan, Isabel Monteiro, Carol Torossian, Steven Ferris, Marwan Sabbagh, Serge Gauthier, Stefanie Auer, Melanie B. Shulman, Alan Kluger, Emile Franssen, and Jerzy Wegiel. "Staging Dementia". In: *Principles and Practice of Geriatric Psychiatry*. John Wiley & Sons, Ltd, 2010. Chap. 31, pp. 162–169. ISBN: 9780470669600. DOI: https://doi.org/10.1002/9780470669600.ch31. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/9780470669600.ch31. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470669600.ch31.

[8] Kaarin J Anstey, Chwee Von Sanden, and Mary A Luszcz. "An 8-year prospective study of the relationship between cognitive performance and falling in very old adults". In: *Journal of the American Geriatrics Society* 54.8 (2006), pp. 1169–1176.

[9] Donna L. Algase, Cathy L. Antonakos, Elizabeth Beattie, Cynthia A. Beel-Bates, and Lan Yao. "Empirical Derivation and Validation of a Wandering Typology". In: *Journal of the American Geriatrics Society* 57 (2009).

[10] D. Algase, C. Antonakos, E. Beattie, C. Beel-Bates, and L. Yao. "New parameters for daytime wandering". In: *Research in gerontological nursing* 2.1 (2009), pp. 58–68.

[11] R Jan Gurley, Nancy Lum, Merle Sande, Bernard Lo, and Mitchell H Katz. "Persons found in their homes helpless or dead". In: *New England Journal of Medicine* 334.26 (1996), pp. 1710–1716.

[12] Shereen Hussein and Jill Manthorpe. "An International Review of Long-Term Care Workforce: Policies and Shortages". In: *Journal of aging & social policy* 17.4 (2005), pp. 75–94.

[13] OECD. *Health at a Glance 2023*. INDICATORS. OECD, 2023.

[14] Shoki Okubo, Keisuke Kawata, Ting Yin, and Zhaoyuan Xu. *Wage Stratification between Care Workers and Non-care Workers in Japan: Evidence from 2001-2017*. RIETI, 2019.

[15] Robyn I Stone. "The direct care worker: The third rail of home care policy". In: *Annu. Rev. Public Health* 25 (2004), pp. 521–537.

[16] Ministry of health, labour and welfare of Japan. *Annual Health, Labour and Welfare Report 2023*. Annual Report. Note: The full report is available in Japanese at: https://www.mhlw.go.jp/stf/wp/hakusyo/kousei/21/index.html, while the English version provides a summary in old reports at https://www.mhlw.go.jp/english/wp/index.html. Ministry of health, labour and welfare of Japan, 2023.

[17] Karen Dorman Marek and Marilyn J Rantz. "Aging in place: a new model for long-term care". In: *Nursing administration quarterly* 24.3 (2000), pp. 1–11.

[18] Pamela S Manion and Marilyn J Rantz. "Relocation stress syndrome: a comprehensive plan for long-term care admissions: the relocation stress syndrome diagnosis helps nurses identify patients at risk". In: *Geriatric nursing* 16.3 (1995), pp. 108–112.

[19] Xinguo Yu. "Approaches and principles of fall detection for elderly and patient". In: *HealthCom 2008 - 10th International Conference on e-health Networking, Applications and Services*. 2008, pp. 42–47. DOI: 10.1109/HEALTH.2008.4600107.

[20] Nian Chi Tay, Tee Connie, Thian Song Ong, Andrew Beng Jin Teoh, and Pin Shen Teh. "A review of abnormal behavior detection in activities of daily living". In: *IEEE Access* (2023).

[21] Parisa Rashidi and Alex Mihailidis. "A survey on ambient-assisted living tools for older adults". In: *IEEE journal of biomedical and health informatics* 17.3 (2012), pp. 579–590.

[22] Silvestro Micera, Paolo Bonato, and Toshiyo Tamura. "Gerontechnology". In: *IEEE Engineering in Medicine and Biology Magazine* 27.4 (2008), pp. 10–14.

[23] Fariba Sadri. "Ambient intelligence: A survey". In: *ACM Computing Surveys (CSUR)* 43.4 (2011), pp. 1–66.

[24] Diane Joyce Cook. "How Smart Is Your Home?" In: *Science* 335 (2012), pp. 1579–1581.

[25] Ane Alberdi, Alyssa Weakley, Maureen Schmitter-Edgecombe, Diane J. Cook, Asier Aztiria, Adrian Basarab, and Maitane Barrenechea. "Smart Home-Based Prediction of Multidomain Symptoms Related to Alzheimer's Disease". In: *IEEE Journal of Biomedical and Health Informatics* 22.6 (2018), pp. 1720–1731. DOI: 10.1109/JBHI.2018.2798062.

[26] Diane J. Cook, Aaron S. Crandall, Brian L. Thomas, and Narayanan C. Krishnan. "CASAS: A Smart Home in a Box". In: *Computer* 46.7 (2013), pp. 62–69. DOI: 10.1109/MC.2012.328.

[27] Jeffrey A Kaye, Shoshana A Maxwell, Nora Mattek, Tamara L Hayes, Hiroko Dodge, Misha Pavel, Holly B Jimison, Katherine Wild, Linda Boise, and Tracy A Zitzelberger. "Intelligent systems for assessing aging changes: home-based, unobtrusive, and continuous assessment of aging". In: *Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 66.suppl_1 (2011), pp. i180–i190.

[28] Abdur Rahim Mohammad Forkan, Ibrahim Khalil, Zahir Tari, Sebti Foufou, and Abdelaziz Bouras. "A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living". In: *Pattern Recognition* 48.3 (2015), pp. 628–641.

[29] Salisu Wada Yahaya, Ahmad Lotfi, and Mufti Mahmud. "A Consensus Novelty Detection Ensemble Approach for Anomaly Detection in Activities of Daily Living". In: *Applied Soft Computing* 83 (2019), p. 105613. ISSN: 1568-4946. DOI: https://doi.org/10.1016/j.asoc.2019.105613. URL: https://www.sciencedirect.com/science/article/pii/S156849461930393X.

[30] Labiba Gillani Fahad and Syed Fahad Tahir. "Activity recognition and anomaly detection in smart homes". In: *Neurocomputing* 423 (2021), pp. 362–372.

[31] Jens Lundström, Eric Järpe, and Antanas Verikas. "Detecting and exploring deviating behaviour of smart home residents". In: *Expert Systems with Applications* 55 (2016), pp. 429–440. ISSN: 0957-4174. DOI: https://doi.org/10.1016/j.eswa.2016.02.030. URL: https://www.sciencedirect.com/science/article/pii/S0957417416300616.

[32] Damla Arifoglu and A. Bouchachia. "Detection of abnormal behaviour for dementia sufferers using Convolutional Neural Networks". In: *Artificial intelligence in medicine* 94 (2019), pp. 88–95.

[33] Kevin Wong, Tongda Zhang, and Hamid Aghajan. "Data Fusion with a Dense Sensor Network for Anomaly Detection in Smart Homes". In: Springer, Nov. 2014, pp. 211–237. ISBN: 978-3-319-10806-3. DOI: https://doi.org/10.1007/978-3-319-10807-0_10.

[34] Shuai Tao, Mineichi Kudo, and Hidetoshi Nonaka. "Privacy-preserved behavior analysis and fall detection by an infrared ceiling sensor network". In: *Sensors* 12.12 (2012), pp. 16920–16936.

[35] Anuradha Singh, Saeed Ur Rehman, Sira Yongchareon, and Peter Han Joo Chong. "Sensor technologies for fall detection systems: A review". In: *IEEE Sensors Journal* 20.13 (2020), pp. 6889–6919.

[36] Pranesh Vallabh and Reza Malekian. "Fall detection monitoring systems: a comprehensive review". In: *Journal of Ambient Intelligence and Humanized Computing* 9 (2018), pp. 1809–1833.

[37] Weichao Zhao, Xingshe Zhou, Hongbo Ni, and Qiang Lin. "A light-weight system for detecting indoor wandering of demented elders living alone". In: *2014 International Conference on Orange Technologies*. IEEE. 2014, pp. 53–56.

[38] Munkhjargal Gochoo, Tan-Hsu Tan, Vijayalakshmi Velusamy, Shing-Hong Liu, Damdinsuren Bayanduuren, and Shih-Chia Huang. "Device-free non-privacy invasive classification of elderly travel patterns in a smart house using PIR sensors and DCNN". In: *IEEE Sensors Journal* 18.1 (2017), pp. 390–400.

[39] Atul Chaudhary, Hari Prabhat Gupta, KK Shukla, and Tanima Dutta. "Sensor signals-based early dementia detection system using travel pattern classification". In: *IEEE Sensors Journal* 20.23 (2020), pp. 14474–14481.

[40] Liming Chen, Jesse Hoey, Chris D Nugent, Diane J Cook, and Zhiwen Yu. "Sensor-based activity recognition". In: *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 42.6 (2012), pp. 790–808.

[41] Marjorie Skubic, Rainer Dane Guevara, and Marilyn Rantz. "Testing classifiers for embedded health assessment". In: *Impact Analysis of Solutions for Chronic Disease Prevention and Management: 10th International Conference on Smart Homes and Health Telematics, ICOST 2012, Artiminio, Italy, June 12-15, 2012. Proceedings 10*. Springer. 2012, pp. 198–205.

[42] Julie Doyle, Andrea Kealy, John Loane, Lorcan Walsh, Brian O'Mullane, Carl Flynn, Andrew Macfarlane, Brennon Bortz, R Benjamin Knapp, and Rodd Bond. "An integrated home-based self-management system to support the wellbeing of older adults". In: *Journal of ambient intelligence and smart environments* 6.4 (2014), pp. 359–383.

[43] Parisa Rashidi and Alex Mihailidis. "A Survey on Ambient-Assisted Living Tools for Older Adults". In: *IEEE Journal of Biomedical and Health Informatics* 17.3 (2013), pp. 579–590. DOI: 10.1109/JBHI.2012.2234129.

[44] Samundra Deep, Xi Zheng, Chandan Karmakar, Dongjin Yu, Leonard GC Hamey, and Jiong Jin. "A survey on anomalous behavior detection for elderly care using dense-sensing networks". In: *IEEE Communications Surveys & Tutorials* 22.1 (2019), pp. 352–370.

[45] Jonathan Synnott, Chris Nugent, and Paul Jeffers. "Simulation of Smart Home Activity Datasets". In: *Sensors* 15.6 (2015), pp. 14162–14179. ISSN: 1424-8220. DOI: 10.3390/s150614162. URL: https://www.mdpi.com/1424-8220/15/6/14162.

[46] M. Moallem, H. Hassanpour, and A. A. Pouyan. "Anomaly Detection in Smart Homes Using Deep Learning". In: *Iranian (Iranica) Journal of Energy & Environment* 10.2 (2019), pp. 126–135. ISSN: 2079-2115. DOI: 10.5829/ijee.2019.10.02.10.

[47] Talal Alshammari, Nasser Alshammari, Mohamed Sedky, and Chris Howard. "SIMADL: Simulated Activities of Daily Living Dataset". In: *Data* 3.2 (2018). ISSN: 2306-5729. DOI: 10.3390/data3020011. URL: https://www.mdpi.com/2306-5729/3/2/11.

[48] Kevin Bouchard, Amir Ajroud, Bruno Bouchard, and Abdenour Bouzouane. "SIMACT: A 3D Open Source Smart Home Simulator for Activity Recognition". In: *Advances in Computer Science and Information Technology*. Ed. by Taihoon Kim and Hojjat Adeli. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 524–533. ISBN: 978-3-642-13577-4.

[49] Yannick Francillette, Eric Boucher, Nathalie Bier, Maxime Lussier, Kévin Bouchard, Patrícia Belchior, and Sébastien Gaboury. "Modeling the behavior of persons with mild cognitive impairment or Alzheimer's for intelligent environment simulation". In: *User Modeling and User-Adapted Interaction* (2020), pp. 1–53.

[50] Andrea Masciadri, Fabio Veronese, Sara Comai, Ilaria Carlini, and Fabio Salice. "Disseminating Synthetic Smart Home Data for Advanced Applications". In: *Proceedings of the CIKM 2018 Workshops co-located with 27th ACM International Conference on Information and Knowledge Management (CIKM 2018), Torino, Italy, October 22, 2018*. Ed. by Alfredo Cuzzocrea, Francesco Bonchi, and Dimitrios Gunopulos. Vol. 2482. CEUR Workshop Proceedings. CEUR-WS.org, 2018.

[51] C. Jiang and A. Mita. "SISG4HEI_Alpha: Alpha version of simulated indoor scenario generator for houses with elderly individuals". In: *Journal of Building Engineering* 35 (2021), p. 101963. DOI: 10.1016/j.jobe.2020.101963.

[52] Franz Müller-Spahn. "Behavioral disturbances in dementia". In: *Dialogues in clinical neuroscience* (2022).

[53] Jae Hyuk Shin, Boreom Lee, and Kwang Suk Park. "Detection of abnormal living patterns for elderly living alone using support vector data description". In: *IEEE Transactions on Information Technology in Biomedicine* 15.3 (2011), pp. 438–448.

[54] Jérémie Saives, Clément Pianon, and Gregory Faraut. "Activity discovery and detection of behavioral deviations of an inhabitant from binary sensors". In: *IEEE Transactions on Automation Science and Engineering* 12.4 (2015), pp. 1211–1224.

[55] Kai Tanaka, Mineichi Kudo, and Keigo Kimura. "Sensor Data Simulation with Wandering Behavior for the Elderly Living Alone". In: *Proceedings of the 26th International Conference on Pattern Recognition (ICPR 2022)*. Montréal, Québec, Canada, Aug. 2022, pp. 885–891.

[56] Kai Tanaka, Mineichi Kudo, and Keigo Kimura. "Sensor Data Simulation for Anomaly Detection of the Elderly Living Alone". In: *IEEE Internet of Things Journal* 11.19 (2024), pp. 31675–31686. DOI: 10.1109/JIOT.2024.3421548.

[57] Kai Tanaka, Mineichi Kudo, and Keigo Kimura. "Fall Detection by Ambient Sensors on Years-Long Simulation Data". In: *Proceedings of the 6th International Conference on Activity and Behavior Computing (ABC2024)*. Nakatsu and Kitakyushu, Kyushu, Japan, May 2024.

[58] Kai Tanaka, Mineichi Kudo, Keigo Kimura, and Atsuyoshi Nakamura. "Long-term Detection System for Six Kinds of Abnormal Behavior of the Elderly Living Alone". In: *arXiv preprint arXiv:2411.13153* (2024).

[59] Giovanni Acampora, Diane J Cook, Parisa Rashidi, and Athanasios V Vasilakos. "A survey on ambient intelligence in healthcare". In: *Proceedings of the IEEE* 101.12 (2013), pp. 2470–2494.

[60] Misha Pavel, Holly Brugge Jimison, Howard D Wactlar, Tamara L Hayes, Will Barkis, Julia Skapik, and Jeffrey Kaye. "The role of technology and engineering models in transforming healthcare". In: *IEEE reviews in biomedical engineering* 6 (2013), pp. 156–177.

[61] Geetanjali Bhola and Dinesh Kumar Vishwakarma. "A review of vision-based indoor HAR: state-of-the-art, challenges, and future prospects". In: *Multimedia Tools and Applications* 83.1 (2024), pp. 1965–2005.

[62] Ruijiao Li, Bowen Lu, and Klaus D McDonald-Maier. "Cognitive assisted living ambient system: A survey". In: *Digital Communications and Networks* 1.4 (2015), pp. 229–252.

[63] Ha Manh Do, Minh Pham, Weihua Sheng, Dan Yang, and Meiqin Liu. "RiSH: A robot-integrated smart home for elderly care". In: *Robotics and Autonomous Systems* 101 (2018), pp. 74–92.

[64] Radosveta Sokullu, Abdullah Balcı, and Eren Demir. "The role of drones in ambient assisted living systems for the elderly". In: *Enhanced Living Environments: Algorithms, Architectures, Platforms, and Systems*. Springer, 2019, pp. 295–321.

[65] Shota Mashiyama, Jihoon Hong, and Tomoaki Ohtsuki. "A fall detection system using low resolution infrared array sensor". In: *2014 IEEE 25th annual international symposium on personal, indoor, and mobile radio communication (PIMRC)*. IEEE. 2014, pp. 2109–2113.

[66] Linda Boise, Katherine Wild, Nora Mattek, Mary Ruhl, Hiroko H Dodge, and Jeffrey Kaye. "Willingness of older adults to share data and privacy concerns after exposure to unobtrusive in-home monitoring". In: *Gerontechnology: international journal on the fundamental aspects of technology to serve the ageing society* 11.3 (2013), p. 428.

[67] George Demiris, Marilyn J Rantz, Myra A Aud, Karen D Marek, Harry W Tyrer, Marjorie Skubic, and Ali A Hussam. "Older adults' attitudes towards and perceptions of 'smart home'technologies: a pilot study". In: *Medical informatics and the Internet in medicine* 29.2 (2004), pp. 87–94.

[68] George Demiris, Brian K Hensel, Marjorie Skubic, and Marilyn Rantz. "Senior residents' perceived need of and preferences for "smart home" sensor technologies". In: *International journal of technology assessment in health care* 24.1 (2008), pp. 120–124.

[69] Chernbumroong Saisakul, SA Anthony, and Y Hongnian. "Perception of Smart Home Technologies to Assist Elderly People". In: *Proceedings of the 4th International Conference on Software, Knowledge Information Management and Applications (SKIMA2010), Paro, Bhutan*. Vol. 25. 2010.

[70] Diane J Cook, Narayanan C Krishnan, and Parisa Rashidi. "Activity discovery and activity recognition: A new partnership". In: *IEEE transactions on cybernetics* 43.3 (2013), pp. 820–828.

[71] Narayanan C Krishnan and Diane J Cook. "Activity recognition on streaming sensor data". In: *Pervasive and mobile computing* 10 (2014), pp. 138–154.

[72] Diane J Cook, Juan C Augusto, and Vikramaditya R Jakkula. "Ambient intelligence: Technologies, applications, and opportunities". In: *Pervasive and mobile computing* 5.4 (2009), pp. 277–298.

[73] Andrew A Cook, Göksel Mısırlı, and Zhong Fan. "Anomaly detection for IoT time-series data: A survey". In: *IEEE Internet of Things Journal* 7.7 (2019), pp. 6481–6494.

[74] Vince Stanford. "Using pervasive computing to deliver elder care". In: *IEEE Pervasive computing* 1.1 (2002), pp. 10–13.

[75] Elizabeth D Mynatt, A-S Melenhorst, A-D Fisk, and Wendy A Rogers. "Aware technologies for aging in place: understanding user needs and attitudes". In: *IEEE Pervasive Computing* 3.2 (2004), pp. 36–41.

[76] Sumi Helal, William Mann, Hicham El-Zabadani, Jeffrey King, Youssef Kaddoura, and Erwin Jansen. "The gator tech smart house: A programmable pervasive space". In: *Computer* 38.3 (2005), pp. 50–60.

[77] Diane J Cook. "Health monitoring and assistance to support aging in place." In: *J. Univers. Comput. Sci.* 12.1 (2006), pp. 15–29.

[78] MICHAEL C MOZER. *lessons from an adaptive home*. 2005.

[79] Hani Hagras, Victor Callaghan, Martin Colley, Graham Clarke, Anthony Pounds-Cornish, and Hakan Duman. "Creating an ambient-intelligence environment using embedded agents". In: *IEEE Intelligent Systems* 19.6 (2004), pp. 12–20.

[80] Stuart Hagler, Daniel Austin, Tamara L Hayes, Jeffrey Kaye, and Misha Pavel. "Unobtrusive and ubiquitous in-home monitoring: A methodology for continuous assessment of gait velocity in elders". In: *IEEE transactions on biomedical engineering* 57.4 (2009), pp. 813–820.

[81] Ahmad Akl, Babak Taati, and Alex Mihailidis. "Autonomous unobtrusive detection of mild cognitive impairment in older adults". In: *IEEE transactions on biomedical engineering* 62.5 (2015), pp. 1383–1394.

[82] Shadan Golestan, Eleni Stroulia, and Ioanis Nikolaidis. "Smart Indoor Space Simulation Methodologies: A Review". In: *IEEE Sensors Journal* 22.9 (2022), pp. 8337–8359. DOI: 10.1109/JSEN.2022.3159205.

[83] Stein Kristiansen, T. Plagemann, and Vera Goebel. "Smooth and crispy: integrating continuous event proximity calculation and discrete event detection". In: DEBS '16. Irvine, California, 2016, pp. 153–160.

[84] Nasser Alshammari, Talal Alshammari, Mohamed Sedky, Justin Champion, and Carolin Bauer. "OpenSHS: Open smart home simulator". In: *Sensors* 17 (May 2017), p. 1003. DOI: 10.3390/s17051003.

[85] Yannick Francillette, Eric Boucher, Abdenour Bouzouane, and Sébastien Gaboury. "The Virtual Environment for Rapid Prototyping of the Intelligent Environment". In: *Sensors* 17.11 (2017). ISSN: 1424-8220. DOI: 10.3390/s17112562. URL: https://www.mdpi.com/1424-8220/17/11/2562.

[86] Fabio Veronese, Andrea Masciadri, A. Trofimova, Matteo Matteucci, and Fabio Salice. "Realistic human behaviour simulation for quantitative ambient intelligence studies". In: *Technology and Disability* 28 (2017), pp. 159–177.

[87] Sara Casaccia, Riccardo Rosati, Lorenzo Scalise, and Gian Marco Revel. "Measurement of Activities of Daily Living: a simulation tool for the optimisation of a Passive Infrared sensor network in a Smart Home environment". In: *2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. IEEE. 2020, pp. 1–6.

[88] Can Jiang and Akira Mita. "Automatic Daily Activity Schedule Planning for Simulating Smart House with Elderly People Living Alone". In: *International Conference on Smart Homes and Health Telematics*. Springer. 2020, pp. 171–183.

[89] Stein Kristiansen, Thomas P. Plagemann, and Vera Goebel. "An Activity Rule Based Approach to Simulate ADL Sequences". In: *IEEE Access* 6 (2018), pp. 12551–12572. DOI: 10.1109/ACCESS.2018.2807761.

[90] Diane J Cook and Maureen Schmitter-Edgecombe. "Assessing the quality of activities in a smart environment". In: *Methods of information in medicine* 48.05 (2009), pp. 480–485.

[91] Helena Eriksson and Anna Isaksson. *Trygg om natten: En studie av kunders, anhörigas och personals perspektiv på införandet av ny teknik inom nattpatrullens arbete*. 2011.

[92] Yannick Francillette, Bruno Bouchard, Kévin Bouchard, and Sébastien Gaboury. "Modeling, learning, and simulating human activities of daily living with behavior trees". In: *Knowledge and Information Systems* 62 (2020), pp. 3881–3910.

[93] Norbert Noury and Tareq Hadidi. "Computer simulation of the activity of the elderly person living independently in a Health Smart Home". In: *Computer methods and programs in biomedicine* 108 3 (2012), pp. 1216–1228.

[94] Wonsik Lee, Seoungjae Cho, Phuong Minh Chu, Hoang Vu, Abdelsalam Helal, Wei Song, Y. S. Jeong, and Kyungeun Cho. "Automatic agent generation for IoT-based smart house simulator". In: *Neurocomputing* 209 (2016), pp. 14–24.

[95] Oihane Kamara-Esteban, Gorka Azkune, Ander Pijoan, Cruz E. Borges, Ainhoa Alonso-Vicario, and Diego López-de-Ipiña. "MASSHA: An agent-based approach for human activity simulation in intelligent environments". In: *Pervasive and Mobile Computing* 40 (2017), pp. 279–300. ISSN: 1574-1192. DOI: https://doi.org/10.1016/j.pmcj.2017.07.007. URL: https://www.sciencedirect.com/science/article/pii/S1574119216304072.

[96] An C Tran, Stephen Marsland, Jens Dietrich, Hans W Guesgen, and Paul Lyons. "Use cases for abnormal behaviour detection in smart homes". In: *Aging Friendly Technology for Health and Independence: 8th International Conference on Smart Homes and Health Telematics, ICOST 2010, Seoul, Korea, June 22-24, 2010. Proceedings 8*. Springer. 2010, pp. 144–151.

[97] UABUA Bakar, Hemant Ghayvat, SF Hasanm, and Subhas Chandra Mukhopadhyay. "Activity and anomaly detection in smart home: A survey". In: *Next generation sensors and systems* (2015), pp. 191–220.

[98] Rami Yared and Bessam Abdulrazak. "Ambient technology to assist elderly people in indoor risks". In: *Computers* 5.4 (2016), p. 22.

[99] Nhu Khue Vuong, Syin Chan, and Chiew Tong Lau. "Automated detection of wandering patterns in people with dementia". In: *Gerontechnology* 12.3 (2014), pp. 127–147.

[100] Mihail Popescu, Benjapon Hotrabhavananda, Michael Moore, and Marjorie Skubic. "VAMPIR-an automatic fall detection system using a vertical PIR sensor array". In: *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*. IEEE. 2012, pp. 163–166.

[101] Henry Rimminen, Juha Lindström, Matti Linnavuo, and Raimo Sepponen. "Detection of falls among the elderly by a floor sensor using the electric near field". In: *IEEE Transactions on Information Technology in Biomedicine* 14.6 (2010), pp. 1475–1476.

[102] Ahmet Yazar, Furkan Keskin, B Ugur Töreyin, and A Enis Çetin. "Fall detection using single-tree complex wavelet transform". In: *Pattern Recognition Letters* 34.15 (2013), pp. 1945–1952.

[103] Kabalan Chaccour, Rony Darazi, Amir Hajjam el Hassans, and Emmanuel Andres. "Smart carpet using differential piezoresistive pressure sensors for elderly fall detection". In: *2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE. 2015, pp. 225–229.

[104] Rafael Oliveira, Rafael Feres, Fabio Barreto, and Raphael Abreu. "CNN for Elderly Wandering Prediction in Indoor Scenarios". In: *SN Computer Science* 3.3 (2022), p. 230.

[105] Rita Zgheib, Stein Kristiansen, Emmanuel Conchon, Thomas Plageman, Vera Goebel, and Rémi Bastide. "A scalable semantic framework for IoT healthcare applications". In: *Journal of Ambient Intelligence and Humanized Computing* 14.5 (2023), pp. 4883–4901.

[106] Jennifer A Williams and Diane J Cook. "Forecasting behavior in smart homes based on sleep and wake patterns". In: *Technology and Health Care* 25.1 (2017), pp. 89–110.

[107] Tamara L Hayes, Thomas Riley, Misha Pavel, and Jeffrey A Kaye. "Estimation of rest-activity patterns using motion sensors". In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*. IEEE. 2010, pp. 2147–2150.

[108] Zahraa Khais Shahid, Saguna Saguna, and Christer Åhlund. "Recognizing long-term sleep behaviour change using clustering for elderly in smart homes". In: *2022 IEEE International Smart Cities Conference (ISC2)*. IEEE. 2022, pp. 1–7.

[109] Shoji Tominaga, Masamichi Shimosaka, Rui Fukui, and Tomomasa Sato. "A unified framework for modeling and predicting going-out behavior". In: *Pervasive Computing: 10th International Conference, Pervasive 2012, Newcastle, UK, June 18-22, 2012. Proceedings 10*. Springer. 2012, pp. 73–90.

[110] M Logeshwaran and J Joselin Jeya Sheela ME. "Designing an IoT based Kitchen Monitoring and Automation System for Gas and Fire Detection". In: *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*. IEEE. 2022, pp. 346–353.

[111] Wei-Ling Hsu, Ji-Yun Jhuang, Chien-Shiun Huang, Chiu-Kuo Liang, and Yan-Chyuan Shiau. "Application of Internet of Things in a kitchen fire prevention system". In: *Applied Sciences* 9.17 (2019), p. 3520.

[112] Aung Aung Phyo Wai, Sivasubramaniam Shanthini Devi, Jit Biswas, and Sanjib Kumar Panda. "Pervasive intelligence system to enable safety and assistance in kitchen for home-alone elderly". In: *Toward Useful Services for Elderly and People with Disabilities: 9th International Conference on Smart Homes and Health Telematics, ICOST 2011, Montreal, Canada, June 20-22, 2011. Proceedings 9*. Springer. 2011, pp. 276–280.

[113] Qiang Lin, Daqing Zhang, Liming Chen, Hongbo Ni, and Xingshe Zhou. "Managing elders' wandering behavior using sensors-based solutions: a survey". In: *International Journal of Gerontology* 8.2 (2014), pp. 49–55.

[114] David Martino-Saltzman, Bruce B. Blasch, Robin D. Morris, and Lisa Wynn McNeal. "Travel Behavior of Nursing Home Residents Perceived as Wanderers and Nonwanderers". In: *The Gerontologist* 31.5 (Oct. 1991), pp. 666–672. ISSN: 0016-9013. DOI: 10.1093/geront/31.5.666. eprint: https://academic.oup.com/gerontologist/article-pdf/31/5/666/1702376/31-5-666.pdf. URL: https://doi.org/10.1093/geront/31.5.666.

[115] Kyohei Ota, Yuki Ota, Mitsugu Otsu, and Akihiro Kajiwara. "Elderly-care motion sensor using UWB-IR". In: *2011 IEEE Sensors Applications Symposium*. IEEE. 2011, pp. 159–162.

[116] Qiang Lin, Weichao Zhao, and Weilan Wang. "Detecting dementia-related wandering locomotion of elders by leveraging active infrared sensors". In: *Journal of Computer and Communications* 6.5 (2018), pp. 94–105.

[117] Elham Khodabandehloo and Daniele Riboni. "Collaborative trajectory mining in smart-homes to support early diagnosis of cognitive decline". In: *IEEE Transactions on Emerging Topics in Computing* 9.3 (2020), pp. 1194–1205.

[118] AJ Blake, Karen Morgan, MJ Bendall, H Dallosso, SBJ Ebrahim, THD al Arie, PH Fentem, and EJ Bassey. "Falls by elderly people at home: prevalence and associated factors". In: *Age and ageing* 17.6 (1988), pp. 365–372.

[119] Kaishun Wu, Yandao Huang, Minghui Qiu, Zhenkan Peng, and Lu Wang. "Toward Device-free and User-independent Fall Detection Using Floor Vibration". In: *ACM Transactions on Sensor Networks* 19.1 (2023), pp. 1–20.

[120] Majd Alwan, Prabhu Jude Rajendran, Steve Kell, David Mack, Siddharth Dalal, Matt Wolfe, and Robin Felder. "A smart and passive floor-vibration based fall detector for elderly". In: *2006 2nd International Conference on Information & Communication Technologies*. Vol. 1. IEEE. 2006, pp. 1003–1007.

[121] Tamara L Hayes, Francena Abendroth, Andre Adami, Misha Pavel, Tracy A Zitzelberger, and Jeffrey A Kaye. "Unobtrusive assessment of activity patterns associated with mild cognitive impairment". In: *Alzheimer's & Dementia* 4.6 (2008), pp. 395–405.

[122] Colleen Galambos, Marjorie Skubic, Shaung Wang, and Marilyn Rantz. "Management of dementia and depression utilizing in-home passive sensor data". In: *Gerontechnology: international journal on the fundamental aspects of technology to serve the ageing society* 11.3 (2013), p. 457.

[123] Larry Christensen. "A method of assessing change in a single subject: An alteration of the RC index". In: *Behav Ther* 17 (1986), pp. 305–308.

[124] Taketoshi Mori, Ryo Urushibata, Masamichi Shimosaka, Hiroshi Noguchi, and Tomomasa Sato. "Anomaly detection algorithm based on life pattern extraction from accumulated pyroelectric sensor data". In: *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. 2008, pp. 2545–2552.

[125] C Jiang and A Mita. "Automatic floorplan generation of living space for simulating a life of an elderly resident supported by a mobile robot". In: *Proceedings of 36th International Symposium on Automation and Robotics in Construction (ISARC 2019), Banff*. 2019, pp. 688–695.

[126] Can Jiang and Akira Mita. "Automatic spatial attribute and travel pattern generation for simulating living spaces for elderly individuals living alone". In: *Building and Environment* 176 (2020), p. 106776. ISSN: 0360-1323. DOI: https://doi.org/10.1016/j.buildenv.2020.106776.

[127] Sidney Katz, Thomas D Downs, Helen R Cash, and Robert C Grotz. "Progress in development of the index of ADL". In: *The gerontologist* 10.1_Part_1 (1970), pp. 20–30.

[128] M Powell Lawton and Elaine M Brody. "Assessment of older people: self-maintaining and instrumental activities of daily living." In: *The gerontologist* (1969).

[129] Statistics Bureau of Japan. *Statistics Bureau Home Page/Outline of the 2016 Survey on Time Use and Leisure Activities*. URL: https://www.stat.go.jp/english/data/shakai/2016/gaiyo.html.

[130] Kai Tanaka, Mineichi Kudo, and Keigo Kimura. "Sensor Data Simulation for Anomaly Detection of the Elderly Living Alone". In: *arXiv preprint arXiv:2312.16852* (2023).

[131] Martin M Oken, Richard H Creech, Douglass C Tormey, John Horton, Thomas E Davis, Eleanor T McFadden, and Paul P Carbone. "Toxicity and response criteria of the Eastern Cooperative Oncology Group". In: *American journal of clinical oncology* 5.6 (1982), pp. 649–656.

[132] R Normala and ZM Lukman. "Bedridden Elderly: Factors and Risks". In: *International Journal of Research and Scientific Innovation* 7.8 (2020), pp. 46–49.

[133] Miyuki Ishikawa, Koji Tamakoshi, Hiroshi Yatsuya, Kazutaka Suma, Keiko Wada, Rei Otsuka, Kunihiro Matsushita, Huiming Zhang, Chiyoe Murata, Takaaki Kondo, et al. "Factors related to frequency of engaging in outside activities among elderly persons living an independent life at home". In: *Nagoya journal of medical science* 68.3/4 (2006), p. 121.

[134] Mary Ganguli, Andrea Fox, Joanne Gilby, and Steven Belle. "Characteristics of rural homebound older adults: a community-based study". In: *Journal of the American Geriatrics Society* 44.4 (1996), pp. 363–370.

[135] James Lindesay and Catherine Thompson. *Housebound elderly people: Definition, prevalence and characteristics*. 1993.

[136] Amanda N Szabo, Edward McAuley, Kirk I Erickson, Michelle Voss, Ruchika S Prakash, Emily L Mailey, Thomas R Wójcicki, Siobhan M White, Neha Gothe, Erin A Olson, et al. "Cardiorespiratory fitness, hippocampal volume, and frequency of forgetting in older adults." In: *Neuropsychology* 25.5 (2011), p. 545.

[137] Marshal F Folstein, Susan E Folstein, and Paul R McHugh. ""Mini-mental state": a practical method for grading the cognitive state of patients for the clinician". In: *Journal of psychiatric research* 12.3 (1975), pp. 189–198.

[138] Kabalan Chaccour, Rony Darazi, Amir Hajjam El Hassani, and Emmanuel Andres. "From fall detection to fall prevention: A generic classification of fall-related systems". In: *IEEE Sensors Journal* 17.3 (2016), pp. 812–822.

[139] Lars Nyberg and Yngve Gustafson. "Patient falls in stroke rehabilitation: a challenge to rehabilitation strategies". In: *Stroke* 26.5 (1995), pp. 838–842.

[140] Misato Nihei, Tetsuaki Okada, and Minoru Kamata. "Proposal of a Method to Predict Fall Frequency Based on Internal Factors Analysis". In: *Japanese Journal of Fall Prevention* 3.1 (2016), pp. 3–12.

[141] Tim Van Kasteren, Athanasios Noulas, Gwenn Englebienne, and Ben Kröse. "Accurate activity recognition in a home setting". In: *Proceedings of the 10th international conference on Ubiquitous computing*. 2008, pp. 1–9.

[142] Vladimir I. Levenshtein. "Binary codes capable of correcting deletions, insertions, and reversals". In: *Soviet physics. Doklady* 10 (1965), pp. 707–710.

[143] Tim LM van Kasteren, Gwenn Englebienne, and Ben JA Kröse. "Human activity recognition from wireless sensor network data: Benchmark and software". In: *Activity recognition in pervasive intelligent environments*. Springer, 2011, pp. 165–186.

[144] Wei-Yin Loh. "Classification and regression trees". In: *Wiley interdisciplinary reviews: data mining and knowledge discovery* 1.1 (2011), pp. 14–23.

[145] HH Avilés-Arriaga, LE Sucar-Succar, CE Mendoza-Durán, and LA Pineda-Cortés. "A comparison of dynamic naive bayesian classifiers and hidden markov models for gesture recognition". In: *Journal of applied research and technology* 9.1 (2011), pp. 81–102.

[146] Lawrence R Rabiner. "A tutorial on hidden Markov models and selected applications in speech recognition". In: *Proceedings of the IEEE* 77.2 (1989), pp. 257–286.

[147] Leo Breiman. "Random forests". In: *Machine learning* 45 (2001), pp. 5–32.

[148] Maarit Kangas, Raija Korpelainen, Irene Vikman, Lars Nyberg, and Timo Jämsä. "Sensitivity and false alarm rate of a fall sensor in long-term fall detection in the elderly". In: *Gerontology* 61.1 (2014), pp. 61–68.

[149] Emma Stack. "Falls are unintentional: Studying simulations is a waste of faking time". In: *Journal of Rehabilitation and Assistive Technologies Engineering* 4 (2017), p. 2055668317732945.

[150] Raed Abdel Sater and A Ben Hamza. "A federated learning approach to anomaly detection in smart buildings". In: *ACM Transactions on Internet of Things* 2.4 (2021), pp. 1–23.

[151] Björn Friedrich, Taishi Sawabe, and Andreas Hein. "Unsupervised statistical concept drift detection for behaviour abnormality detection". In: *Applied Intelligence* 53.3 (2023), pp. 2527–2537.