

Assessing AI-Driven Care Solutions For Ageing and Disabled Individuals: A Proposed Framework And Tool

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Abstract. As the global population ages, there is an increasing need for innovative solutions that enable ageing and disabled individuals to live independently and safely in their own homes. This paper presents a comprehensive framework for evaluating AI-driven smart home technologies designed to address this challenge. By leveraging virtual personae and digital simulations, the study provides a methodical approach to testing and comparing various in-home assistance systems, with a focus on fall detection and behavior monitoring.

The research involved the creation of a detailed simulation environment that mirrors real-life scenarios, allowing for the rigorous assessment of different technologies. Key aspects such as installation ease, energy consumption, and alert accuracy were analyzed to determine the effectiveness of each solution. The study also developed a robust database of simulated events, including over 300 falls, to further enhance the reliability of the evaluations.

Ethical considerations played a crucial role in the selection and assessment process, guided by principles of Responsible Research and Innovation (RRI) and the Eight Caring Technology Principles (8 CTPs). The findings emphasize the importance of user-centered design and ethical development in creating technologies that truly meet the needs of aging populations.

Keywords: AI · Digital Simulation · Silver Economy · Innovative Testing Methods · Fall Detection · Assistive Technology · Geriatrics · Software tool.

Acknowledgments. We extend our special thanks to Alonso Peralta, Brayden Donovan, and Adam Hussain of Texas A&M University for their valuable contributions to this paper. We also acknowledge CIAS asbl(Olivier Feralli) for leading the project and providing this research topic, Mani ASBL (Cindy Bertijn) for their meticulous tracking and mapping of findings, Telesecours (Axel De Roover) for their ground experience, insight, and database, and all other affiliated actors of the project for their precious help. Additionally, we thank the various institutions for their material support.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

1 Introduction

Many ageing individuals and people with disabilities currently struggle to live independently due to various daily challenges, such as cognitive impairments, health issues, or accidents like falling down stairs. This often places a significant burden on family members, leading to their placement in specialized institutions or retirement homes. Such arrangements not only affect the emotional and physical well-being of the ageing population but also place a substantial financial strain on governments, which heavily subsidize these facilities.

Recent research indicates that life expectancy in long-term care facilities, including nursing homes, can be significantly shorter than for those living independently. For example, an ageing person moving to a long-term care facility may experience a sharp decline in life expectancy, with mortality rates reaching 50% – 60% within the first year of residence. In contrast, seniors residing in retirement communities, which offer a more engaging and supportive environment, tend to live longer and healthier lives [3], [14], [18].

This disparity brings an essential question: Could smart home Internet of Things (IoT) technologies, combined with Artificial Intelligence (AI), provide a sustainable alternative for elder and disabled care? By integrating these technologies into daily routines, it may be possible to delay the need for institutionalization by offering real-time assistance, monitoring, and alerts for caregivers. Several companies have explored this idea, offering solutions such as fall detectors, behavioral monitoring, sensors, and emotion detectors to support individuals in their daily lives.

In this paper, we propose a new framework designed for comprehensive yet accessible testing of these technologies, evaluating their practical capabilities in real-world scenarios along with a new tool for real-time testing of behavioral alert

algorithms. This effort goes beyond mere technological evaluation; it represents a step toward reimagining care for this population, envisioning a future where the ageing and disabled populations can enjoy longer, happier lives within the comfort of their homes, supported by ethical applications of AI and IoT sensors. This entire framework draws its inspiration from the principles of P4 medicine: predictive, preventive, personalized and participatory [7].

The remainder of this paper is organized as follows. Section 2 explores the factors leading to the institutionalization of ageing and disabled individuals. Section 3 details the construction of personae based on interviews with these populations, providing a foundation for the user-centered design of assistive technologies. Then, section 4 introduces the relevant metrics and criteria for evaluating assistive technologies, focusing on their usability and effectiveness followed by section 5; presenting a novel methodology for assessing these technologies, with a specific emphasis on fall prevention and behavioral deviation analysis. In Section 6, we introduce a real-time tool designed for companies to evaluate their technologies using our proposed methodology. Finally, Section 7 addresses the ethical and social considerations underlying the selection and evaluation of life-monitoring technologies

2 Understanding the societal challenge

The rising trend of institutionalization among the ageing population presents significant challenges for healthcare systems across the globe. It is vital to understand the factors that contribute to this outcome to develop strategies that can extend the period during which older individuals can safely remain in their homes. This section examines five key factors identified during a specialized conference held in March 2023 at OpenHub regrouping information and communication technology professors, geriatrics specialists, health insurances, Social and Behavioral experts and emergency assistance companies.

Sleep and Aging Sleep quality plays a crucial role in cognitive function and the aging process. Changes in sleep patterns and requirements with age can lead to insomnia and other sleep disorders, which are common in older adults due to age-related comorbidities [1]. Poor sleep quality, characterized by issues such as sleep fragmentation and sleep apnea, is associated with diminished cognitive abilities and daily functioning, potentially speeding up the process of institutionalization [8].

Malnutrition in Aging Malnutrition among the elderly, often caused by imbalances in energy and protein intake, is a significant factor that contributes to frailty and dependency [12]. Conditions such as involuntary weight loss, appetite disorders, dental issues, medication side effects, and changes in body composition exacerbate this problem, leading to muscle loss, physical weakness, and cognitive decline, which can accelerate the loss of independence [22].

Social Isolation Social isolation has severe repercussions on both mental and physical health. Prolonged loneliness can reduce the quality of life, even in institutional settings [5]. The lack of social interaction can increase mortality risk and adversely affect brain function, emphasizing the need for meaningful social engagement to prevent institutionalization [10].

Physical Activity and Aging Physical inactivity in older adults leads to the loss of muscle mass, decreased endurance, and overall weakness. Regular physical activity is essential for preventing falls, a leading cause of institutionalization [21]. It also slows cognitive decline, improves oxygen consumption, and prevents sarcopenia, highlighting the importance of an active lifestyle for maintaining independence [6].

Cognitive Disorders Cognitive impairments disrupt daily routines and decision-making, causing disorientation and confusion. While technology can help maintain routines, it is important to keep it simple, as learning new technologies can be stressful for those with cognitive disorders [16]. Personalized activities and routines are crucial for preserving self-esteem and autonomy in these individuals [13].

Understanding the factors that lead to institutionalization is essential for developing effective interventions and solutions to extend the independent living of aging adults. This section has highlighted the importance of addressing sleep quality, nutrition, social engagement, physical activity, and cognitive health. While technology can support these efforts, it must be implemented with careful consideration of the individual’s abilities and preferences. In other words, working together with the patient to provide patient centered care.

3 Persona analysis

Personae are designed to create representations of human behaviour as a way to support project development. According to [17], “To get product design closer to the everyday lives of the users, design personae are a means to capture the everyday experiences and needs of users and customers”. In this research project, personae were devised to frame the representations of a specific target audience. In total seven personae were created who each capture different key characteristics of both mainstream and outlying user groups. This diversity provides fertile grounds to explore and understand our target audience as well as open the project to explore new or under-researched areas. The personae were iteratively and cumulatively constructed using four layers of quantitative and qualitative data (see section 3.1). Furthermore, the personae are undergoing continuous qualitative participatory assessment with older adults and adults with disabilities, and as such, the results are not yet available, as the study is still ongoing during the writing of this paper. (see section 3.2).

3.1 Personae development

In this section, we wish to understand our target demographic; their habits and way of life in order to be able to replicate it digitally. Understand our target demographic, empathizing with them enables more accurate and realistic simulation and ultimately results in a more focused product.

Personae are defined as fictional user profiles built according to real data that is representative of a target group [9]. Here, personae were constructed by crossing raw data provided by our research partners, testimonials from 32 semi-structured interviews conducted in Spring 2023 with older adults, adults with disabilities, and professional care providers, as well as census data published by the Belgian governments, and World Health Organisation. Key research partners include four non-profit organizations who either provide human support to older adults or adults with disabilities, or technological support in the form of medical alert bracelets and necklaces that connect the caller to a dedicated helpline. Data was extracted and analyzed from 11 158 beneficiaries across Belgium, as well as the medical alert calls made to the provider between 2020 and 2022 (292 251 calls).

The personae were constructed using four layers that incrementally crossed and compiled new characteristics: The first layer identified user pathologies crossed with the types of support provided. This information was extracted from two databases provided by the research partners. Both contained a “free text” entry in which technicians and social workers compiled various information about each beneficiary (or household) in an unstructured way: general state of health, known illnesses, type of treatment or medication, family structure, help from relatives or professionals, etc.

Through a systematic search for keywords and rational groupings, a limited number of harmonized categories was built and allocated to each beneficiary. As shown in Table 1, the categories of different pathologies included disabilities linked to motor, sensory, vital, or cognitive functions, as well as “other” health problems (conditions that do not directly affect day to day abilities, such as early stage cancers or allergies) or “none” (a person in good health). Otherwise, the categories of different types of support distinguish between people who were totally isolated, lived with others, or received formal and informal support.

To build the personae, combinations of pathologies and types of support were selected among all the possibilities according to their ability to represent a large number of people from the initial population, or to represent specific cases that are less frequent but just as relevant to this study. In total, four mainstream profiles (AC03, G01, ABC11, D04) and three outlying profiles (E04, F13, A23) served as the basis for the seven personae.

This first layer was then crossed with other data retrieved from the “free text” field: age, gender and types of housing. The resulting second layer specified whether the person lived in a single-story apartment, a multi-story home, or another alternative accommodation (such as a camper / recreational vehicle during the summer). Pairings were tested with some regression analyses but were found to overweight mainstream lifestyles and overshadow any diversity.

Table 1: Categories linked to pathologies and types of support.

Pathologies	Types of Support
A Physical and motor functions	01 Living alone without assistance
B Sensory functions	02 Living alone with professional help
C Vital functions	03 Living alone with informal help
D Cognitive and behavioural functions	04 Living alone with professional and informal help
E Other illnesses and health problems	11 Couple without assistance
F In good health	12 Couple with professional help
G No relevant health information	13 Couple with informal help
+ All possible hybrid situations: AB, AC, AD, BC, BD, CD, ABC, ABD, ACD, BCD, ABCD	14 Couple with professional and informal help
	21 Cohabitants without assistance
	22 Cohabitants with professional help
	23 Cohabitants with informal help
	24 Cohabitants with professional and informal help

Indeed, the strict respect of the mean case for each profile would systematically lead to a similar personal situation, considering that women aged around 75 and residing in single-family homes are over-represented in our sample.

Driven by the project framing and to create a variety of personae on which the technologies could be tested, reasonable pairings were made on the basis of census data and our own understanding gained through semi-structured interviews. For instance, it seemed more reasonable for an older couple living with their daughter and grandchildren and who have minor health issues to be paired with a multi-story home whereas a widowed woman with mobility concerns was paired with a small furnished studio in the city center to ease mobility issues, enabling both easier independent access to services and social networks.

The third layer added factors related to the installation and use of new in-home monitoring technologies. As such information was only partially provided in the databases, a balanced distribution of reasonable characteristics supported by census data were paired with the developing personae. This includes whether the persona rents or owns the apartment (and can make permanent changes to the space), if they have Wi-Fi access, or if they have stable and continuous access to electricity.

The fourth layer was included to breathe life into the personae [4]. Testimonials and user characteristics from semi-structured interviews were combined with compatible personae to provide human qualities, such as a reluctance to try new technologies, a newfound sense of freedom, a stubbornness to refuse help, a fear of bothering friends, family, and service providers, or a desire to stay connected with younger family members through new technologies.

Overall, from these personae, many features were taken into consideration when constructing their digital simulation, as detailed in section 5.2. Key categories include types of assistance (formal and informal), health conditions (phys-

ical, sensory, vital, cognitive, and other health issues), autonomy levels, and living situations (house types and technological access). Common features across personae involve a detailed consideration of their living environments, health challenges, and the support network, ensuring a nuanced simulation base for technology testing.

3.2 Personae evaluation

To test and strengthen their applicability, the seven personae are now undergoing additional qualitative participatory assessment, which is still in progress. A limited range of technologies allowing fall detection and daily routines modifications has been installed for 2 to 3 months at the personal home of 50 beneficiaries (senior or disabled individuals). Taking advantage of this opportunity, a team of field experts been gathered, has received specific training and has to conduct additional data collection. Semi-structured interviews (in average 30 minutes in duration and fully audio-recorded) explore whether the 50 beneficiaries consider being more or less faithfully represented by the persona which is supposedly aligned with their own personal situation.

The seven designed personae have been translated into a synthetic visual A3 sheet, adding sketched representations to ease the beneficiaries' impregnation exercise. Interviewers are equipped with a memo sheet summarizing the main coherencies and incoherencies between the selected persona and the beneficiary life situation, according to data already gathered thanks to the provider databases. Based on the A3 visual persona and the memo sheet, the interviewer then solicit life experience anecdotes from each beneficiary (using the narrative biographical interviews method [20]). While relying on the persona itself and its various components, the beneficiary is thus invited to unfold memories and extracts from their personal life; everyday living habits; own pathologies or solicited types of support.

Conventional content analysis will be conducted [11] on basis of the transcribed audio-recordings, and the seven personae will be adapted iteratively thanks to additional insights gathered through these 50 semi-structured interviews. Expected modifications involve more nuanced appraisal of living situations; of technology acceptability levels and of everyday living patterns.

4 Evaluation criteria and methods

This section aims to outline the methodology used to evaluate and categorize various in-home services designed to generate alerts. The goal is to consolidate a variety of personal assistance solutions that are capable of issuing notifications when issues arise.

The evaluation process is composed of several key stages. Initially, the focus is on comparing the installation process, acknowledging that efficiency is crucial for large-scale deployments. Following this, the analysis distinguishes between

two primary types of alert triggers: those prompted by falls and those initiated by deviations in routine behaviors.

4.1 Installation

As individuals age, the transition should be as seamless as possible. Thus, the installation of these technologies must adhere to several important criteria. For a system to be successfully integrated into a home, it must be discreet, easily and quickly operational, and non-disruptive. Additionally, it should have minimal impact on the household’s electricity consumption, both in terms of cost and environmental footprint. These criteria are detailed in Table 2 and serve as the benchmarks for assessing the installation process.

Table 2: Installation Criteria.[2]

Criteria	Description
Kit Supplied	All necessary components for the installation are included and meet safety standards.
Installation Time	The total duration required to set up the system.
Discretion	The components are unobtrusively integrated within the home environment.
Damage	The extent to which the installation causes permanent alterations to walls, floors, etc.
Consumption	The electrical power usage of the entire setup.

4.2 Alerting

Detecting incidents like falls or signaling changes in behavior falls under the category of classification tasks, where the system differentiates between correct and incorrect outcomes. In this study, we measured the system’s performance by calculating the True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), leading to the computation of the F1-score.

- True Positives (TP) occur when the system correctly identifies a positive alert.
- False Positives (FP) occur when the system mistakenly signals a positive alert when there is none.

- True Negatives (TN) occur when the system correctly identifies that no alert is needed.
- False Negatives (FN) occur when the system fails to generate a positive alert when one is actually needed.

The F1-score is derived to balance precision and recall. Precision indicates the proportion of correct positive alerts out of all positive alerts issued, calculated as the ratio of true positives to the sum of true positives and false positives.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (1)$$

Recall, in contrast, reflects the system’s ability to correctly identify actual positive cases, computed as the ratio of true positives to the sum of true positives and false negatives.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

The F1-score synthesizes these two metrics into a single value, representing the harmonic mean of precision and recall. It is calculated using the formula:

$$F1\text{-score} = \frac{2 \cdot (\text{Precision} \cdot \text{Recall})}{\text{Precision} + \text{Recall}} \quad (3)$$

This score ranges from 0 to 1, with a higher score indicating superior performance in balancing both precision and recall.

5 Application of Developed Frameworks

This section details the procedures used to conduct experiments for evaluating and comparing solutions provided by different companies.

5.1 Fall Detection

Various sensor types, including wearable and wall-mounted devices, are employed in fall detection systems. To perform a thorough comparison, the researchers created a simulated home environment, specifically focusing on a living room setup. Modular spaces were constructed to represent different rooms like bedrooms, kitchens, and living areas by arranging furniture and decorations. These standardized environments allowed for consistent and repeatable experiments. Wall-mounted sensors were positioned according to the manufacturers’ specifications, as illustrated in Figure 1.

The researchers conducted over 300 simulated falls in this experimental setting. For each incident, they recorded which sensors detected the fall and evaluated the results using the scoring method described earlier (see 5).

One of the key contributions of this study is the development of a comprehensive database. High-resolution (1920 x 1080, 25 fps) recordings were captured



Fig. 1: Example of fall detection setup.[2]

using Bascom cameras with wide-angle lenses (112°) and infrared night vision capabilities (up to 20 meters) in complete darkness. This database includes more than 300 recorded falls, as well as other scenarios such as interactions with pets or sitting on a sofa, resulting in extensive footage from the experimental environment. Additional recordings were made in real homes to add context and variability. These recordings, categorized as falls and non-falls, are available to researchers upon request to the authors.

5.2 Behavioral Analysis

Some commercial solutions utilize machine learning algorithms to monitor and analyze the behavior of individuals by tracking their movements within their homes. These systems use various sensors, such as motion detectors, door-opening sensors, and wearable devices, to gather data. The algorithms behind these solutions learn the routines of the individuals and identify deviations that may indicate potential issues.

A straightforward method to test these algorithms would involve installing each system in multiple homes and soliciting feedback from residents to verify whether alerts were triggered correctly. However, this approach was ultimately rejected due to the potential inconvenience and ethical concerns associated with constant monitoring.

The innovative aspect of this study lies in its unique approach. Instead of using real homes, the researchers opted for virtual environments populated by virtual individuals, effectively creating digital simulations. To simulate behavior within this virtual world, the researchers used a layered system of statistical tools, which are further explained in Appendix A.

Each simulation involves a set of characters residing in different virtual homes, modeled after the personae identified in Section 3. In real life, a person’s environment includes family, friends, and pets, so the simulation represents this by creating families composed of multiple personae whose lives intersect. Each persona is defined by a set of attributes, as shown in Table 3. The goal of the simulation is to generate a detailed record of room usage within the home, updated every minute.

Table 3: Persona Attributes.[2]

Attribute	Description
Name	A unique identifier for the persona
Family	Links the persona to a group of personae, representing family, friends, and pets.
Owner	Indicates whether the persona owns the home.
Stack	A data structure that tracks ongoing activities.

The personae’ daily lives are structured around various activities, such as eating breakfast, reading, or receiving visitors. These activities are categorized into planned activities (daily, weekly, monthly) and unplanned activities (such as episodic events, see Figure 2). Each activity in the simulation has specific attributes, detailed in Table 4.

Table 4: Activity Attributes.[2]

Attribute	Description
Name	A unique identifier for the activity
Priority	An integer representing the importance of the activity
Activation Distribution	A statistical distribution indicating the probability of the activity being initiated.
List of Rooms	The rooms visited during this activity.
Frequency	The occurrence of the activity (daily, weekly,...) associated with number of the day it takes place

The priority assigned to an activity determines its importance relative to other activities, as depicted in Figure 2. Daily activities are generally classified as "low priority" or leisure activities. The priority of each activity can be adjusted according to the situation and the persona involved.

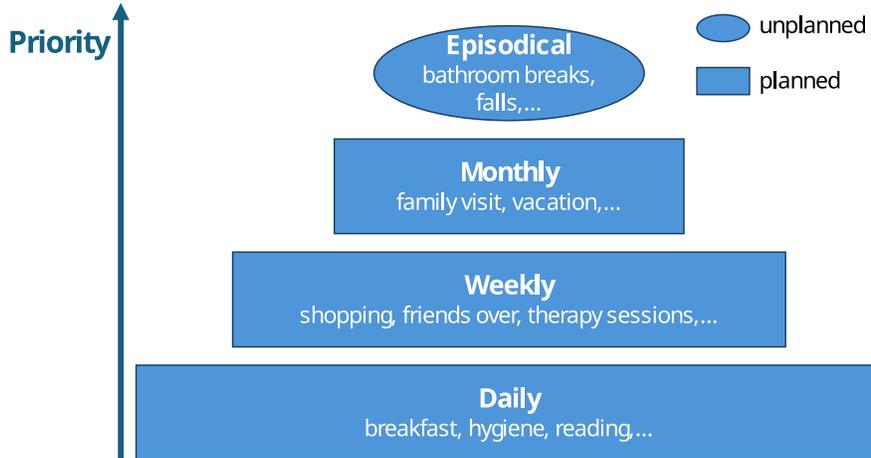


Fig. 2: Activity priority levels.[2]

For instance, if a persona is reading in the living room at 10 a.m., they are likely to remain there for the activity's duration. If a bathroom break is needed, the priority system ensures that the persona interrupts their reading to attend to the more urgent activity, after which they resume reading with the remaining time adjusted accordingly. Similarly, if a higher priority activity, like a shopping trip, overlaps with reading, the shopping trip takes precedence. This layered system allows the simulation to mimic daily routines that follow a pattern but vary slightly each day. The most critical activities, such as emergency situations or unexpected events, sit at the top of the priority hierarchy.

Each persona has a stack that tracks their current activities. This stack is a data structure where activities are arranged by priority, with the most urgent tasks at the top. The activity at the top of the stack is treated as the current task.

Two scenarios can trigger a new activity to be added to the stack. First, if a higher priority activity becomes relevant, it is added to the stack and becomes the current task. During each simulation minute, the remaining duration of all activities in the stack decreases by one minute. When an activity's duration reaches zero, it is removed from the stack. This ensures that the most urgent tasks are always addressed promptly. Second, if the current activity ends and no other activities are in the stack, all possible activities are evaluated, and the one with the highest activation function value becomes the new current task.

Figure 3 illustrates an example of generated activities and their corresponding probability distributions during one day.

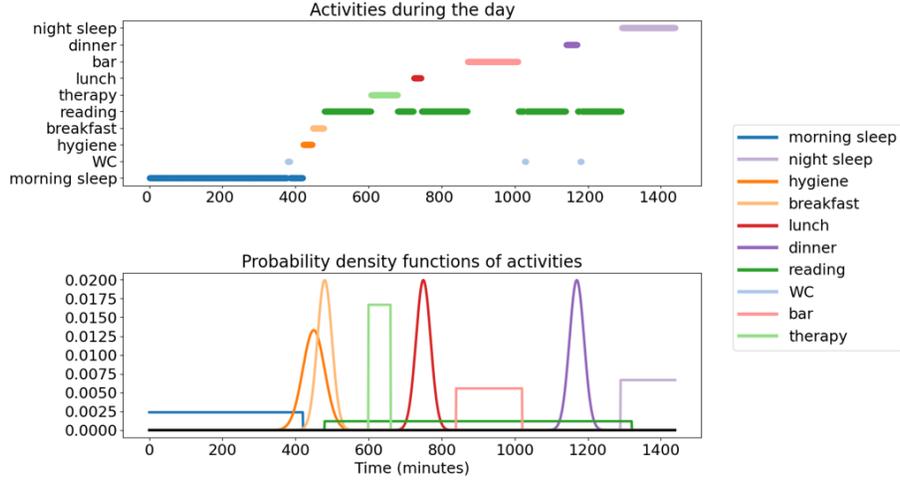


Fig. 3: Activation function based on probability density functions (on the bottom) for each activity (on top) a persona may undertake during a standard day.[2]

To simulate social interactions, the researchers introduced a special type of activity called "common activities", which, when initiated by one persona, are added to the stacks of other involved personae. This mechanism fosters interactions between personae, adding realism to the simulation by reflecting real-world dynamics.

The randomness of each simulated day comes from the selection and duration of activities within a predefined set. Based on persona descriptions, a set of possible activities is generated. An example of possible activities for one persona is provided in Appendix C. When an activity is triggered, it involves visiting certain rooms, with the duration of each visit determined by a random distribution. For example, after waking up in the morning, a hygiene routine might be initiated, involving visits to the toilet, bathroom, and bedroom. The order and duration of these actions introduce variability into the routine.

Once all activities and room visits are generated for each persona, the next step is to simulate movement within the home. Unreal Engine⁷ was selected to build the digital simulation environment. Each persona is represented by a meta-

⁷Unreal Engine (UE) is a series of 3D computer graphics game engines developed by Epic Games.

human⁸. These meta-humans navigate the virtual home based on the generated activity data.

The solutions from the companies under evaluation rely on motion detectors to trigger alerts. To simulate these sensors in Unreal Engine, virtual sensors were created. These sensors activate when a meta-human moves within the virtual environment, as shown in Figure 4. All data collected by the virtual sensors are stored for further analysis.



Fig. 4: Example of simulation where a meta-human is in motion in one room (green box). The other empty room has a white box.[2]

At the end of the simulation, the data gathered from the virtual sensors provide a comprehensive record of the meta-humans' movements and interactions within the simulated environment. This data, formatted into CSV files, is then used by the companies to test their algorithms. The researchers manually altered certain activities to create outliers and simulate abnormal behaviors. For instance, a fall might be simulated by extending the time a persona spends in the bathroom to three hours. Cognitive impairments, such as memory loss, could be represented by a prolonged shopping trip, lasting five hours instead of the usual two. By comparing the algorithms' outputs to the known inputs, the precision of each solution can be assessed.

6 The Digital patient: a tool for real-time testing

The ability to simulate various scenarios on demand represents a powerful tool for both training and testing predictive models. As the digital simulation and

⁸A Meta-human is a hyper-realistic digital representation of a human. These digital entities are designed to mimic human emotions, actions, and intricacies perfectly.

simulation concepts evolve, offering an interactive and customizable tool for real-time testing becomes crucial. This tool would allow researchers and developers to simulate an aging individual’s daily life, facilitating the creation and refinement of AI-driven monitoring systems. This section introduces a beta version of a tool developed for this purpose, as well as potential future expansions.

6.1 Beta Version of real time digital simulation

The initial version of the tool enables users to construct and control digital simulations of personae, simulating their daily life activities in real-time. This beta version provides a user-friendly interface that allows for the creation of detailed personae, each of which can act as a digital simulation of the target audience. The tool is designed to mimic the behaviors of elderly individuals or individuals with disabilities, thus serving as a valuable asset for the training of predictive models, particularly for detecting abnormal or hazardous behaviors.

Persona Creation and Environment Setup Through the interface, users can design a central persona and build an entourage around them, which can include family members, friends, or other individuals. The user is able to control whether these additional personae live with the central persona or interact with them randomly. The central persona’s behavior is guided by algorithms that replicate realistic daily routines, while the interaction with the surrounding environment is simulated in real time.

Users can further define the central persona’s living environment by selecting from a range of three pre-designed houses, all of which have been constructed to reflect typical residential settings for aging individuals. This choice of environment is critical for simulating the spatial dynamics involved in everyday activities and ensuring the realism of the digital simulation.

Activity Definition and Customization The tool allows users to create a variety of activities that the central persona can engage in throughout the day. Each activity is defined by several parameters:

- **Name:** A unique identifier for the activity.
- **Persona(e):** The participant(s) involved in the activity. If more than one persona is involved, it becomes a common activity.
- **Type:** The nature of the activity (e.g., daily, weekly, monthly, or punctual).
- **Location:** The specific place(s) within the house where the activity occurs (e.g., kitchen, bathroom, living room).
- **Statistical parameters:** Parameters necessary to use any of the probability functions defined in Appendix A

Once these parameters are set, the user initiates the daily life activities algorithm (see Section 5), which simulates the persona’s behavior over the course of a day, a week, or a longer period. The user can view the sequence of activities generated

by the algorithm and make adjustments by interacting with the interface. For example, an unexpected event such as a fall or an extended trip to the bathroom can be added to test the system's response.

This dynamic capability is particularly valuable for testing fall detection and behavioral alert systems in real-time, as it allows for the continuous streaming of sensor data via an API. The tool broadcasts sensor data at regular intervals to any machine learning model connected to the system, thereby enabling on-the-fly model training without the need to preload extensive datasets.

6.2 Future Add-Ons

The future of this tool lies in expanding its capabilities to offer deeper insights and more refined simulations. Two key extensions have been identified for further development

State Transition Mapping One proposed enhancement is the addition of an interactive graph that visualizes the different states within an activity, especially when the activity spans multiple locations. For example, in a "morning routine" that involves visiting the bathroom, bedroom, and kitchen, the user would be able to define and adjust the probabilities associated with transitions between these locations. By modifying the transition matrix, users could simulate more complex behavioral patterns and introduce variations in how activities are performed. This would be particularly useful for understanding the variability in daily routines and how deviations might trigger alerts in monitoring systems.

Real-Time Visualization Another significant add-on would be the integration of real-time visualizations using the Unreal Engine. This feature would allow users to observe the central persona and their entourage navigating the virtual house in real-time. By rendering the movements and activities of the persona in a simulated 3D environment, researchers could visually track how different scenarios unfold, providing a more intuitive understanding of the interplay between environmental factors, persona behavior, and sensor data. Such visualization would not only serve as a diagnostic tool but also enhance the design of future smart home technologies by highlighting any discrepancies between predicted and actual behavior.

These expansions would further enhance the tool's capacity to simulate life-like behaviors in virtual environments, helping to refine AI models and better equip them to handle real-world scenarios. By integrating sophisticated modeling and visualization capabilities, the tool will push the boundaries of what can be achieved in the field of life-monitoring technologies for aging in place.

The development of this real-time testing tool marks a significant step forward in the evaluation of smart home technologies aimed at supporting independent living for elderly individuals. The ability to create, control, and modify digital simulations offers unparalleled flexibility for testing predictive models and sensor systems. As the tool evolves, its capacity to simulate complex behaviors

in real-time will only enhance its value to researchers and developers alike, contributing to the advancement of AI-driven solutions that improve the quality of life for aging and disabled populations.

7 Ethics and social impact

While this article primarily addresses the development of a systematic approach to testing life-monitoring technologies from a technological standpoint, it is essential to highlight the ethical and social considerations that guided the selection of the technologies tested. The selection criteria were established through an interdisciplinary process involving a diverse consortium, including mutual aid organizations, home care services, a telemonitoring organization, technology experts, psychologists, disability specialists, and experts in user-centered innovation approaches.

Each consortium member had the opportunity to contribute criteria relevant to their expertise and the project's objectives. These criteria were categorized into three main areas: acceptability, feasibility, and viability. A particular focus was placed on the concept of Responsible Research and Innovation (RRI), defined as:

"a transparent, interactive process by which societal actors and innovators become mutually responsive to each other with a view to the (ethical) acceptability, sustainability, and societal desirability of the innovation process and its marketable products (in order to allow a proper embedding of scientific and technological advances in our society)." [23]

Despite the theoretical and normative nature of RRI, which is often hindered by a lack of practical governance processes and guidelines for implementation, the consortium prioritized selecting technologies developed within the context of responsible innovation [19]. This prioritization was guided by the Eight Caring Technology Principles (8 CTPs), a framework specifically tailored to health technologies and supported by the Dr. Daniël De Coninck Fund, managed by the Belgian philanthropic organization, the King Baudouin Foundation. [15]

The 8 CTPs framework emphasizes responsible health technology innovation by prioritizing user and societal needs, data security, equity, participatory governance, and quality control. These principles are grounded in three central overarching values: autonomy, justice, and trust.

Although some criteria from the 8 CTPs overlapped with those already proposed by experts—such as data security, quality control (including scientific validation of the technology), minimization of stigmatization, promotion of user autonomy, adaptability to various disabilities, and environmental impact through life cycle analysis—additional elements were integrated thanks to this framework. For instance, the inclusion of end-users, namely seniors and their caregivers, in the development process enhanced the likelihood of producing a solution that truly meets their needs. Moreover, the requirement for transparent, comprehensible, and accessible information provided both about and by the technology (e.g., alerts) and the necessity for patients to give informed consent were also empha-

sized.

However, not all criteria from the 8 CTPs, nor those proposed by the experts, could be retained. To ensure the criteria were implementable within the project's framework—particularly as evaluation criteria in a public procurement process to select the technologies for testing—the initial list of 126 criteria was refined to 53. The overlap of certain criteria allowed for the prioritization of some over others, ensuring that the final selection was both comprehensive and manageable within the project's scope.

8 Conclusion

This paper presented a comprehensive framework for evaluating AI-driven smart home solutions designed to support aging and disabled individuals. Through the use of virtual personae and digital simulations, the research explored the potential of these technologies to enhance independent living and reduce the need for institutionalization. The study introduces a novel testing framework designed to compare various solutions, with a focus on their installation processes, alerting capabilities, and adaptability to the diverse needs of different user profiles.

The creation of a robust database of simulated falls and other behaviors has provided a valuable resource for further research and development in this field. Additionally, the introduction of a real-time testing tool using digital simulations has opened new avenues for refining predictive models and improving the responsiveness of smart home systems. More importantly, this framework should help professionals, doctors, geriatric institutions and any concerned individuals, benchmark technologies and select the most fit for their needs.

Ethical considerations were integral to the selection and evaluation of the technologies tested. The interdisciplinary approach, guided by principles of Responsible Research and Innovation (RRI) and the Eight Caring Technology Principles (8 CTPs), ensured that the solutions not only meet technological standards but also align with societal values, user autonomy, and environmental sustainability.

The study's methodology contribute significantly to the ongoing efforts to improve the quality of life for aging and disabled populations. By rigorously testing and validating advanced AI technologies with a deep understanding of user needs and ethical imperatives, this research offers a promising path forward for developing solutions that allow individuals to age with dignity and independence in their own homes. Future work will focus on refining the digital simulation models, expanding real-time testing capabilities, and further engaging end-users in the development process to ensure that these technologies continue to evolve in a way that truly serves the needs of the communities they are designed to help.

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Appendix [2]

A Statistic tools

The uniform distribution is defined by a constant probability density function across a specified range, making it suitable for scenarios where all outcomes within that range have an equal chance of occurring. In behavior modeling, it can represent situations such as the likelihood of spending time in the living room during the afternoon. This distribution is determined by two parameters: the minimum and maximum values of the interval.

$$f(x) = \frac{1}{t_2 - t_1} \quad \text{for } t_1 \leq x \leq t_2 \quad (4)$$

The Gaussian distribution, also known as the normal distribution, is a fundamental statistical distribution characterized by its symmetric bell-shaped curve, centered around the mean. Most data points cluster around this mean, making it ideal for modeling behaviors influenced by multiple independent factors. For instance, the time a person wakes up in the morning can be modeled using a normal distribution, centered around a specific mean (μ) with an associated standard deviation (σ).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (5)$$

The exponential distribution is a crucial tool in behavior modeling, especially when it comes to analyzing the time intervals between consecutive events. This distribution is particularly well-suited for scenarios where the events occur independently and at a constant average rate over time. In behavior modeling, understanding these inter-event times is essential for accurately simulating and predicting patterns of behavior.

$$f(x; \lambda) = \lambda e^{-\lambda x} \quad (6)$$

where λ represents the rate parameter.

The Poisson process is a stochastic model used to describe a sequence of events that occur randomly over time or space. It is widely applied in fields such as queueing theory, telecommunications, and reliability engineering. The key characteristics of a Poisson process are:

- 1 Independence: Each event occurs independently of others.
- 2 Stationarity: The probability of an event occurring within a given time or space interval remains consistent across equivalent intervals.
- 3 Ordinarity: Events occur one at a time, without any overlap.

The essential formulas associated with a Poisson process include:

- **Probability of n events in time t :** The likelihood that exactly n events occur within a fixed time interval t is described by the Poisson distribution:

$$P(N(t) = n) = \frac{e^{-\lambda t} (\lambda t)^n}{n!} \quad (7)$$

where $N(t)$ represents the number of events by time t , λ is the rate parameter (average rate of occurrence per time unit), e is the base of the natural logarithm (approximately 2.71828), and $n!$ denotes n factorial.

- **Inter-arrival Times:** The time between successive events in a Poisson process follows an exponential distribution, as defined by the probability density function in equation 6.

These formulas describe the mathematical foundation of a Poisson process, outlining both the distribution of event occurrences within a set time frame and the statistical properties of the intervals between these events. For instance, a Poisson process can model the time intervals between visits to the bathroom.

B More on sensor testing

During sensor testing, various configurations of room setups were systematically analysed to evaluate the efficacy of sensor-based monitoring systems designed to detect falls and behavioural anomalies among the elderly living independently. The testing environments mimicked typical residential settings, incorporating common furniture arrangements and living spaces. Twelve distinct configurations were assessed (see Figure 5), each varying in the spatial layout and positioning of key furniture pieces such as sofas, tables, and beds, as well as the strategic placement of wall-mounted sensors to maximise coverage and minimise blind spots. These configurations also included open spaces to simulate potential fall zones, delimited by red dashed lines, indicating the areas where fall incidents were emulated during the trials. The diversity in room setups provided a comprehensive range of scenarios to test the sensors' responsiveness to actual falls versus routine activities, ensuring robustness in varied domestic landscapes. The sensor systems were challenged with different angles and distances from the fall zones, furniture obstructions, and varying levels of ambient lighting, all of which are critical factors in the real-world application of such technologies.

C Possible activities for a persona

As described in section 5.2, days are statistically generated using a specifically written algorithm. However this algorithm has a base. This base is comprised of activity names, states and important parameters for each distribution. That is, each activity will be a series of states and each state will yield a specific



Fig. 5: Different room configurations for fall detection [2]

distribution based on the average time and standard deviation in the following tables. The distribution type is dictated by the activity (see table 5) and appears chronically depending on the frequency (column *Activity Type* in table 5.) As can be noticed, some distributions don't require average time and standard deviation.

For the more complexe activities, some have starting and ending points (in order to avoid morning sleep at 10pm at night) and others are unique in order to avoid, for example, having lunch twice. Finally for the non-daily activities, days of the week and month are given in order to make this activities happen only on these given dyas. Keep in mind that for weekly activities, the given days range from 0 to 6 while for monthly activities, these days are given from 0 to 30. Within the month, weekly activities loop using a 7 day congruence in order to loop. That is of every Monday, the persona goes swimming, then the date of the month will be converted into the day of the week using the residue of the euclidienne division by seven.

Table 5: Example of possible activity for one persona [2]

Activity Name	Activity Type	Distribution Type	Average	Standard Deviation	Start	End	Common	Unique	Day
morning_sleep	Routine	uniforme			0	420			
night_sleep	Routine	uniforme			1290	1440			
hygiene	Routine	normale	450	30				TRUE	
breakfast	Routine	normale	480	20				TRUE	
lunch	Routine	normale	750	20				TRUE	
diner	Routine	normale	1170	20				TRUE	
reading	Routine	uniforme			480	1320		FALSE	
WC	Episodical	poisson	300					FALSE	
coffee	Weekly	uniforme			840	1020		TRUE	0;1;3;5
therapist	Weekly	uniforme			600	660			0;
friends_over	Monthly	normale					TRUE	TRUE	2;27
friends_support	Weekly	normale			900	1140			2;4;5
family_diner	Monthly	normale					TRUE	TRUE	12;30
escapade	Monthly	uniforme			660	780			16;
shopping	Weekly	uniforme			600	660		TRUE	4;
random_kitchen	Episodical	poisson	960		540	1020		FALSE	

Table 6: Example of rooms to visit for one persona[2]

Activity Name	State Name	Average Time	Standard Deviation
morning_sleep	Bedroom	40	20
night_sleep	Bathroom	10	2
night_sleep	Bedroom	240	30
hygiene	Bathroom	20	5
hygiene	Bedroom	15	3
hygiene	WC	5	1
breakfast	Kitchen	30	5
lunch	Kitchen	30	5
diner	Kitchen	40	10
reading	Living Room	30	10
wc	WC	5	1
coffee	Outdoor	180	40
therapist	Outdoor	70	10
friends_over	Living Room	30	5
friends_over	Kitchen	40	5
friends_over	Living Room	30	10
friends_support	Living Room	30	5
friends_support	Kitchen	40	5
family_diner	Kitchen	15	5
family_diner	Living Room	40	10
family_diner	Living Room	20	5
escapade	Outdoor	2880	50
shopping	Outdoor	180	20
random_kitchen	Kitchen	15	5