A Novel Approach in Testing Life-Monitoring Technologies for Ageing in Place: A Focus on Fall Detection and Behavioural Alerts

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Abstract: Addressing the issues of age and disability, our study presents a systematic technique for evaluating smart home technology designed to improve independent living. While acknowledging companies' efforts in this field, we created a framework to assess potential solutions using a rigorous demographic study that defined various user profiles - or personae - as the foundation for our comparison research. Our methodology is based on a dual-focused analytical approach: analysing installation processes and operating performance, with a particular emphasis on fall detection and behaviour analysis. To evaluate fall detection, we developed a test protocol, which resulted in the compilation of a large database. We pioneered the use of virtual personae in a game engine for behavioural analysis, which are simulated in living contexts via probabilistic activity generation. This novel approach allowed the creation of virtual sensor data, which was then analysed by AI algorithms thus generating alerts. This study emphasises the possibility for combining IoT and AI to reduce the need for institutional care by offering real-time help and monitoring. Our methodology takes a thorough approach to assessing the efficacy of smart home devices, ensuring that they are adaptable to the real-world demands of the ageing population and people with disabilities.

1 INTRODUCTION

Currently, many ageing people or people with disabilities are unable to live independently due to issues within their daily lives such as cognitive problems, general health issues or a simple fall down a flight of stairs… the responsibility often falls on family members, commonly resulting in their placement in specialised institutions or retirement homes. This practice not only impacts the emotional and physical well being of the older population but also represents a significant ficial burden for governments, which invest heavily in subsidising these facilities.

Recent studies have shown that the life expectancy of individuals in long-term care facilities, including nursing homes, can be notably lower compared to those living independently. For instance, an older people moving to a long-term care facility might see a drastic reduction in life expectancy, with mortality rates as high as $50\% - 60\%$ within the first year of residence. In contrast, seniors living in retirement communities, which offer a more supportive and engaging environment, might enjoy a longer and stronger life (Boucaud-Maitre et al., 2023), (Lubitz et al., 2003), (Nugraha and Aprilia, 2019).

This contrast raises an important question: Could smart home IoT technologies, combined with Artificial Intelligence (IA), offer a sustainable alternative for elder and disabled care? Integrating these technologies into daily routines may delay institutionalisation by assisting, monitoring, and alerting caregivers in real-time.

Several companies have asked themselves this

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question and propose different kinds of solutions to support beneficiaries in their lives such as falls detector, behavioural monitoring, sensors and emotion detectors . . .

Through this paper, we aim to propose a new framework that allows for an easy yet thorough testing of these technologies, assessing their practical capabilities in real-world scenarios. This endeavor is not just a technological assessment but a step towards re-imagining care for this specific population, offering a vision where the older and disabled can lead happier, longer lives within the comfort of their homes, supported by ethical applications of AI and IoT sensors.

2 DEFINING THE PROBLEM

The increasing prevalence of older institutionalization poses significant challenges for healthcare systems worldwide. Understanding the determits that lead to institutionalization is crucial for developing strategies to extend the period that older individuals can safely live at home. This section explores five determits identified during a specialized conference held in March 2023.

2.1 Sleep and Aging

Sleep quality significantly affects cognitive functioning and aging. Age-related changes in sleep needs and patterns can lead to insomnia and other sleep disorders, which are prevalent in the older resulting from commorbities induced by age (Ancoli-Israel, 2009). Poor sleep quality, including issues like sleep fragmentation and sleep apnea, is linked to reduced cognitive abilities and daily functioning, potentially accelerating the institutionalization process (Foley et al., 2004).

2.2 Malnourishment in Ageing

Malnutrition in ageing individuals, often resulting from an imbalance in energy and protein intake, is a critical factor contributing to frailty and dependency (Kaiser et al., 2010). Factors like involuntary weight loss, appetite control disorders, dental problems, medication side effects, and changes in body composition exacerbate this issue, leading to muscle loss, physical weakness, and cognitive impairments, which can hasten the loss of autonomy (Volkert, 2013).

2.3 Social Isolation

Social isolation has profound impacts on both mental and physical health. Prolonged loneliness can decrease life quality, even in institutional settings (Cornwell and Waite, 2009). A lack of social interaction can increase mortality risk and negatively affect brain function, highlighting the necessity of meaningful social engagement to prevent institutionalization (Holt-Lunstad et al., 2015).

2.4 Physical Activity and Aging

Physical inactivity in the older leads to muscle mass loss, reduced endurance, and weakness. Regular physical activity is crucial for preventing falls, a major reason for institutionalization (Rubenstein, 2006). It also slows cognitive decline, enhances oxygen consumption, and prevents sarcopenia, underscoring the importance of an active lifestyle for maintaining independence (Ferrucci et al., 2016).

2.5 Cognitive Disorders

Cognitive impairments affect daily routines and decision-making, leading to disorientation and confusion. Introducing technology to maintain routines can be beneficial, but simplicity is key, as learning new technologies can be stressful for those with cognitive disorders (Mowszowski et al., 2012). Personalized activities and routines are vital for maintaining self-esteem and autonomy in these individuals (Klompstra et al., 2013).

Understanding the determits of institutionalization is essential for developing effective interventions to extend the independent living of ageing adults. This section highlighted the importance of addressing sleep quality, nutrition, social engagement, physical activity, and cognitive health. The judicious use of technology can support these efforts, though it should be implemented with consideration of the individual's capabilities and preferences.

A number of companies offer solutions to enable the ageing people or people with disabilities to remain in their own homes. The solutions offered by these companies are diverse. This paper considers solutions that detect punctual problems such as falls and analyse the person's behaviour in order to detect any problems in their lifestyle. The objective is to present a framework to study and compare these technologies in order to select one or more technologies that meets the needs of these people and provides them with the best possible support.

3 PERSONA ANALYSIS

Personae are designed to create representations of human behaviour as a way to support project development. According to (Nielsen, 2018), “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.

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 provides, 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 11158 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 included disabilities linked to motor, cognitive, or vital functions and whether the person was totally isolated, lived with others, or received formal and informal support.

This first layer was then crossed with data about different types of domiciles. Characteristics included whether the person lived in a single-story apartment, and multi-story home, or other alternative living situations (such as living in a camper / Recreational vehicle (RV) during the summer). Pairings were validated with some regression analyses but were found to overweight mainstream lifestyles and overshadow any diversity. Driven by the project framing and to create a variety of personae on which the technologies could be tested, reasonable pairings were made. 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 help combat social isolation.

The third layer added factors related to the installation and use of new in-home monitoring technologies. Here, 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.

Finally, to breathe life into the personae, 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 though new technologies.

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

4 METHODICAL APPROACH

The objective of this section is to elucidate the process of comparing and classifying the different services to be installed inside homes to launch alerts. Specifically, the study aims to bring together a range personal assistance solutions that enable alerts to be issued in the event of problems.

The comparison process comprises several distinct steps. Firstly, the installation process is compared, considering that time is a precious resource for large-scale installations and must be taken into account. Secondly, two categories of alert triggers are considered: alerts resulting from a fall and alerts resulting from a change in daily routines.

4.1 Installation

The transition through aging should be navigated smoothly. This is why the installation of technologies is a critical point that must meet a number of criteria. To be installed in a home, they need to be as discreet as possible and put into operation as quickly as possible, without causing any damage. In addition, it shouldn't be noticeable on the electricity bill, either for the wallet or for the planet. These criteria are summarized on table 1 and are the reference for the installation testing.

Table 1: installation criteria.

Criteria	Description
Kit supplied	All components for the installation are provided and safe.
Installation time	Total time to install the solution.
Discretion	All components are seemlessly integrated in a home.
Damage	Installation caused permanent damage on the wall, ground, etc.
Consumption	Electrical power consumption of all devices.

4.2 Alerting

Tasks such as fall detection and triggering alerts for behavioural changes belong to the broader classification tasks family, as they involve distinguishing between positive and negative outcomes. In this paper, we counted the number of True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) to find the F1-score.

- True Positives (TP) are instances where the system correctly predicts the positive alert.
- False Positives (FP) are instances where the system incorrectly predicts the positive alert when it is actually negative.
- True Negatives (TN) are instances where the system correctly predicts the negative alert.
- False Negatives (FN) are instances where the system incorrectly predicts the negative alert when it is actually positive.

This F1-score considers the balance between precision and recall. Precision measures the accuracy of positive predictions, calculated as the ratio of true positives to the sum of true positives and false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{1}$$

Recall, on the other hand, measures the proportion of actual positives that were correctly identified, calculated as the ratio of true positives to the sum of true positives and false negatives.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

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

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

This score ranges from 0 to 1, where a higher value indicates better performance in terms of both precision and recall.

5 METHOD IMPLEMENTATION

This section explain how experiments are conducted in order to compare solutions from different companies.

5.1 Falls

Fall detectors utilize various sensor types, including wearables and wall-mounted devices. To conduct a comprehensive comparative study, the authors established a simulated living room environment. Modular rooms representing bedrooms, kitchens, or living rooms were created by arranging furniture and decorations. A set of predefined environments facilitated a reproducible set of experiments. Wall-mounted sensors were strategically placed according to the manufacturer's guidelines as shown in Figure 1.

Figure 1: Example of set-up falls.

The authors conducted a series of falling scenarios, totaling over 300 falls in the experimental room. For each fall, experimenters recorded which sensors detected the event and applied the scoring method outlined in the previous section.

One significant contribution of this study is the creation of a comprehensive database. Bascom cameras recorded every fall during testing, providing high-quality footage (1920 x 1080 resolution, 25 fps) with wide-angle lenses (112°) and infrared night vision (up to 20 meters) in complete darkness. This database comprises over 300 recorded falls, along with various other situations (such as interactions with animals or sitting on a sofa), resulting in many hours of footage from the experimental room. Additionally, recordings were made in a real home to enhance contextual variability. These recordings, categorized into falls and non-falls, are available upon request to the authors.

5.2 Behaviour Analysis

Among the solutions commercialized by companies, some use learning aptitudes to capture the behaviour of beneficiaries by recording and analysing their movements within their homes. This is accomplished through various means such as movement sensors, door-opening sensors, or wearable sensors. Behind these solutions, machine learning algorithms were employed. These algorithms require data to learn beneficiaries' habits and detect outliers that may correspond to alerts.

A straightforward approach to test these algorithms involved installing each solution in multiple homes and then requesting feedback from the beneficiaries to confirm or deny the triggering of alerts. However, evidently, this approach was ultimately discarded to prevent any potential inconvenience and ethical issues due to monitoring.

The primary novelty of this paper lies in its unique approach. Rather than using real homes, the authors opted for virtual homes along with virtual beneficiaries, effectively forming a digital twin. To model habits within this virtual environment, the authors employed a sophisticated system of layers, combining various statistical tools explained in Appendix A.

A set of characters are accommodated for each simulation, residing in various homes according to the personae identified in the section 3. Indeed, in a real individual's life, it's crucial to incorporate their entire environment (family, friends and pets). We decided to represent the entire environment by forming a family consisting of several personae whose lives intertwine. Each persona is characterized by a set of attributes, as outlined in Table 2. Ultimately, once the simulation has run, our aim is to generate a comprehensive list of visited rooms within the home for each time step (1 minute).

The lives of personae are structured around various activities, such as breakfast, reading or family visits. Activities were divided in two sections; planned activities (daily, weekly and monthly activities) and unplanned activities (such as episodical events, see Figure 2). In the simulation, each activity is comprised of different attributes, as detailed in Table 3.

Table 2: Attributes of persona.

Attribute	Description
Name	This unique name identifying the persona
Family	This binds the persona to a group of persona represented by family friends and pets.
Owner	This value represents if the persona is a home owner.
Stack	Data structure gathering current running activities.

Table 3: Attributes of activity.

Attribute	Description
Name	This unique name identifying the activity
Priority	Integer representing the relative importance of an activity
Activation distribution	Statistical distribution representing the probability that this activity is activated.
List of rooms	Rooms visited in this activity.

The priority assigned to an activity reflects its relative importance compared to other activities, as illustrated in Figure 2. What is referred to as daily activities are what were classified as activities of "unimportance" or leisure activities. The priority of each activity can be adjusted in regards to the situation and the persona.

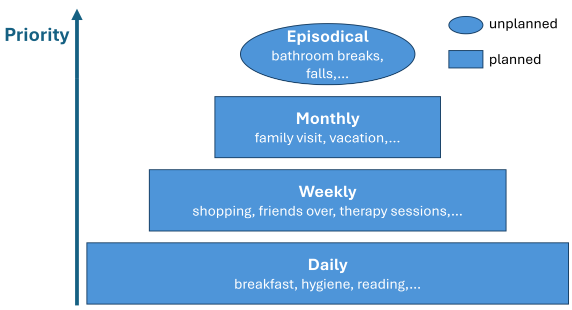

Figure 2: Activities priority level.

As an example if a person reads in their living room around 10 a.m, then one would usually find them reading there. Say now that a bathroom break

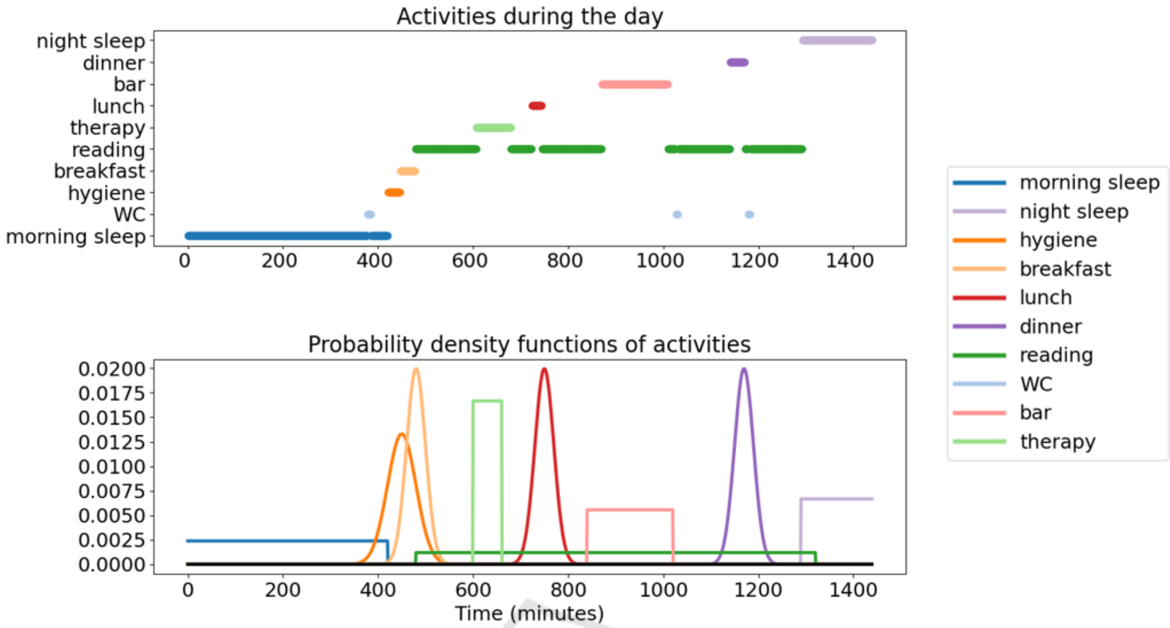

Figure 3: Activation function based on probability density functions (on the bottom) for each activity (on top) a persona may undertake during a standard day.

is selected, the priority will ensure that the persona will not finish its reading activity before going to the bathroom. The bathroom break activity will directly kick-in and reading will resume after the bathroom break finishes. Note that once resuming, the remaining amount of time for reading will have been reduced by the time spent in the bathroom.

In that same regard, if a shopping session (considered a weekly event) overlaps with a reading activity, the shopping session takes precedence. This layered system enables the simulation of different days while maintaining the same daily routine meaning each day is based on the same pattern but is never quite the same. At the highest level of the priority hierarchy are episodic activities, which are unpredictable compared to planned activities. Episodic activities regroup things like urinary urgencies, trips to the hospital, falling and other unforseen events.

For every persona, a stack is maintained to monitor their current activity. A stack is a linear data structure ordered by priority rules, where activities are arranged based on their urgency or importance, with the highest priority at the top. The activity with the highest priority is treated as the current activity and is pushed onto the stack.

Two scenarios can introduce a new activity to the stack. First, if a higher priority activity than the current one is activated, it's added on top of the stack and reconsidered as the current one. During each time step, the duration of all activities in the stack is reduced by one minute. When an activity's remaining duration reaches zero minutes, it's removed from the stack. This process ensures that the most urgent or important activities are promptly addressed for each persona. Secondly, if the current activity terminates without another activity in the stack, all activation functions of activities are triggered, and the activity with the highest value of the activation function is chosen as the new current activity. An example of generated activities and probability density functions are illustrated in Figure 3.

To introduce sociological interaction into the simulation, the authors introduced a special type of activity known as ”common activities”. These activities, initiated by one persona, are added to the stack of other personas who are involved. This method fosters interaction between personas, a crucial element for creating a realistic simulation that mirrors real-life scenarios.

The global randomness of each day resides in the selection of each activities and the randomness of their duration in a set of predefined possible activities and duration. Based on personas description, a set of possible activities are established. An example of activities for one personna is given in Appendix C. When an activity begins, a set of rooms are visited to complete this activity. Each room is visited during a certain amount of time. This time is also given by a random distribution. As an example, when one wakes up in the morning, usually a hygiene activity is initiated. This entails 3 rooms: the toilet, the bathroom and the bedroom, where waking up, taking a shower or washing up, urinating and getting dressed successfully take place. The order in which these take place leaves more room for randomness.

After generating all activities and visited rooms for each persona, the next step is to create a virtual environment to model displacement inside homes. Unreal Engine[1] was selected as the platform to construct the digital twin. Each persona is represented by a meta-human[2]. These meta-humans move within the home based on generated data.

The solutions proposed by the companies we aimed to test rely on motion detectors to provide alerts. To simulate these sensors within Unreal Engine, virtual sensors are created. These sensors activate when a meta-human is in motion inside the virtual environment as shown in Figure 4. All data collected by the virtual sensors is stored in memory for analysis.

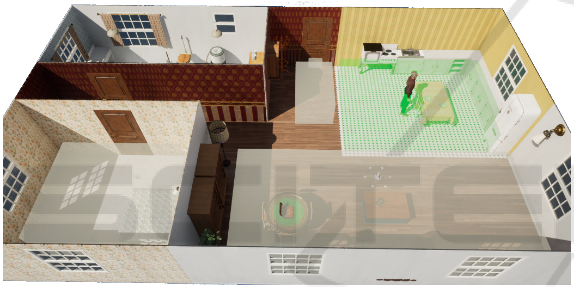

Figure 4: Example of simulation where a meta-human is in motion in one room (green box). The other empty room has a white box.

At the conclusion of this process, we gather all the data extracted from the virtual sensors. This data encompasses the movements and interactions of the meta-humans within the simulated environment, providing a comprehensive record of their presence in different rooms. With the generated data in the form of a CSV file, the companies could successfully test their algorithms. The authors manually changed activities to correspond to outliers to simulate abnormal activities. As an example, a fall could be translated by an abnormal 3 hours stay in the toilet or bathroom. Dementia or a loss of memory could be translated by an extended amount of time shopping; instead of a typical 2 hours shopping session, we'd have a 5 hours shopping session. By recovering the output of these algorithms, we are therefore capable of assessing their precision by comparing and matching inputs and outputs.

[1]Unreal Engine (UE) is a series of 3D computer graphics game engines developed by Epic Games

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

6 CONCLUSION

This paper has outlined a thorough framework for assessing life-monitoring technologies intended to support aging individuals in maintaining independence at home, with specific emphasis on fall detection and behavioral alerts. Through our analysis and experimentation, we have developed a structured approach that facilitates comparison and evaluation of solutions offered by various companies in this domain. Grounded in persona analysis, our methodology provides a systematic framework for assessing the practical capabilities of smart home devices in real-world settings. By simulating living environments and conducting extensive experiments using digital representations of defined personas, we have gained insights into alert triggers and behavior analysis within smart homes.

However, it is important to recognize the limitations of our study. While our framework introduces a novel methodology for evaluating life-monitoring technologies, there are inherent challenges and complexities that must be addressed. For instance, the simulated environment may not fully replicate the intricacies of real-life situations, particularly regarding the subtle nuances of human behavior. Additionally, this environment aimed to capture data from motion sensors only. More sophisticated sensors like cameras cannot be replicated in this software.

Moving forward, future research should prioritize addressing these limitations and refining our methodology to improve its effectiveness and relevance. This includes conducting more extensive user studies to gather feedback and insights from aging individuals and individuals with disabilities. Furthermore, ongoing collaboration between researchers, industry stakeholders, and end-users is essential to drive innovation and advancement in the realm of smart home technologies tailored for aging in place.

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APPENDIX

A Statistic Tools

The uniform distribution is characterized by a constant probability density function over a specified interval. In the context of behaviour modeling, it's often used to represent situations where all outcomes within a range are equally likely. For example, it can be used to model the probability to sit in the living room over the afternoon. The distribution is defined by two parameters: the minimum and maximum values of the interval.

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

The Gaussian distribution, also known as the normal distribution, is one of the most widely used distributions in statistics. It's characterized by a symmetric bell-shaped curve, with the mean (average) at the center and the majority of the data clustered around the mean. Many natural phenomena follow a normal distribution, making it particularly useful for modeling behaviour when the underlying process is influenced by multiple independent factors. An example is the morning wake-up time, which revolves around a certain mean (μ) with a certain standard deviation (σ).

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

behaviour modeling often involves analyzing the time intervals between successive events. The exponential distribution provides a mathematical framework for modeling these inter-event times.

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

Where λ represents the mean.

A Poisson process is a stochastic process that models a sequence of events occurring randomly in time or space. It is widely used in various fields such as queueing theory, telecommunications, and reliability engineering. The defining characteristics of a Poisson process are:

1 Independence: Events occur independently of each other.

2 Stationarity: The probability of an event occurring in a given interval of time or space is the same for all equivalent intervals.

3 Ordinariness: The process has no simultaneous events; events occur singularly.

The key formulae associated with a Poisson process include:

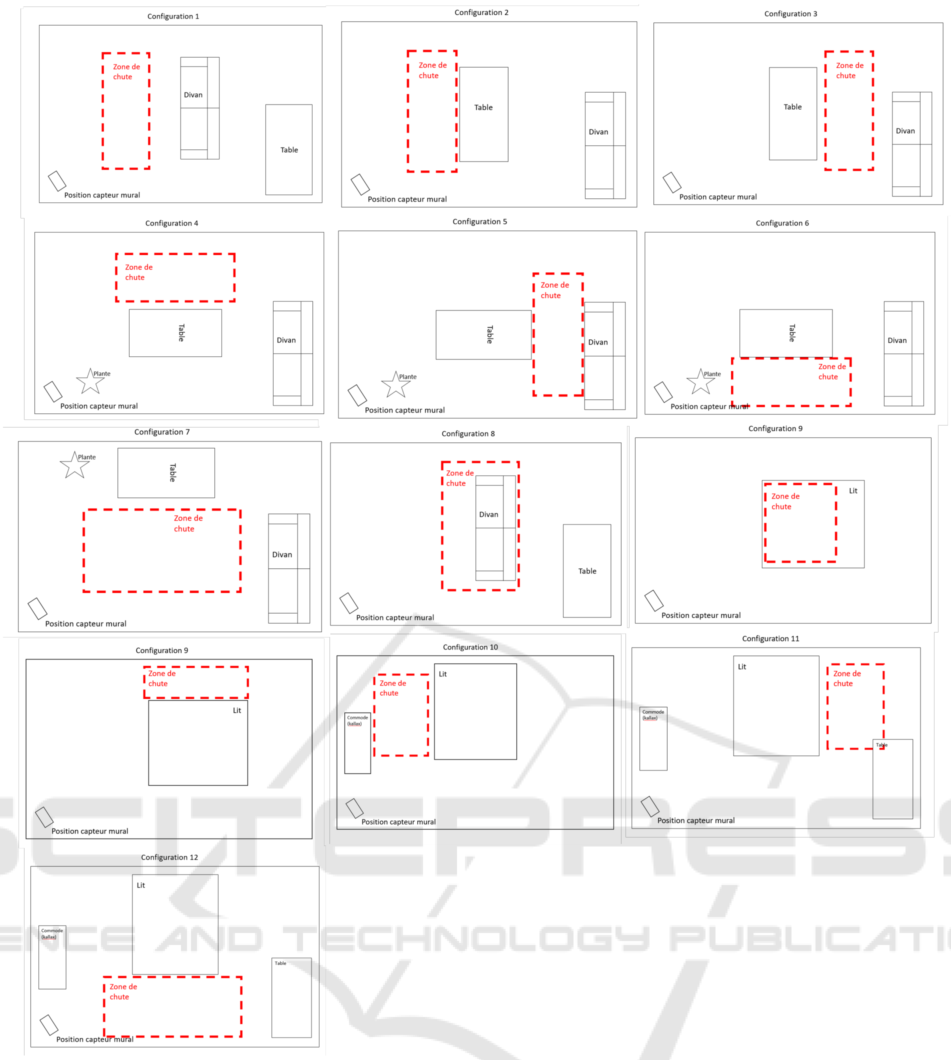

Figure 5: Different room configurations for fall detection.

Table 4: Example of possible activity for one personna.

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 5: Example of rooms to visit for one personna.

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

- Probability of n events in time t: The probability that exactly n events occur in a fixed interval of time t is given by the Poisson distribution formula:

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

  where $N(t)$ is the number of events occurring by time t, λ is the rate parameter of the process (average rate at which events occur per time unit), e is the base of the natural logarithm (approximately equal to 2.71828), and $n!$ denotes n factorial.

- Inter-arrival Times: The time between consecutive events in a Poisson process follows an exponential distribution with probability density function defined in equation 6.

These formulae encapsulate the mathematical structure of a Poisson process, describing both the distribution of the number of events within a given time frame and the statistical properties of the intervals between these events. For example, the Poisson process can be used to model the time between going to the toilet.

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 Personna

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 distribution based on the average time and standard deviation in the following tables. The distribution type is dictated by the activity (see table 4) and appears chronically depending on the frequence (column *Activity Type* in table 4.) 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.