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Assisted Living Using Sensor Based Ambient Intelligence

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***Abstract*: This research paper reviews the methodologies used to monitor and enable the elderly population to live a safe lifestyle. The four different methodologies reviewed primarily revolve around the concept of Ambient Intelligence and behavior monitoring where-in the elderly person's activities of daily living are monitored and deviations are analyzed as possible emergencies. Most of the methodologies were found to have good success rates and confidence levels and areas of improvements were also determined. A survey was also initiated to about 60 participants from different geographies and demographics to know about the awareness and acceptance of such technologies. While awareness will need to be built up, most respondents were in favor of self-reliance for elderly people. An opinion of an expert working in the field of elderly care was also taken and it corroborated the findings from literature review and survey results that the method of assisted living using sensor based ambient intelligence will gain prevalence to provide well-being of elderly people.**

***Keywords*: Assisted living, Ambient intelligence, Elderly care, Unobtrusive monitoring, Behavior based monitoring.**

1. Introduction

The world is currently faced with an increase in elderly population, with around 10% of the population being over 65 years as of 2021[1]. The number of persons aged 80 years or over is projected to reach more than 400 million in 2050[2]. While older persons are seen as contributors to development due to their experience, they also need to be cared for during the most vulnerable years of their lives. A host of mechanisms have been put in place and technologies have been under development to ensure that the aging population is taken care of in the best manner possible.

Each of the mechanisms & technologies comes with their own pros and cons, quite notably on the aspects of cost, implementation complexity, usability, and maintainability. The key challenge has been to design solutions which provide techniques which respect the privacy of the individuals. While closed circuit television cameras and on-body sensors are an effective way to monitor the elderly individual for any sudden onset of inactivity, there exists obvious challenges with privacy and management with these types of sensing mechanisms. This has led to an interest in various attempts to design & develop unobtrusive means of monitoring using the concept of sensor based ambient intelligence. Various studies and research projects have been undertaken on this concept in almost all universities globally including collaboration with industry. This research project hypothesizes that Assisted Living using Sensor Based Ambient Intelligence will become prevalent in the coming two decades.

2. Method

As part of the project, four proposed solutions have been studied with the author expressing his understanding of the solutions with reference to the hypothesis and concluding this report by presenting statistical results from the survey conducted from a wide range of population. While the available literature is from global academia, the survey has been conducted predominantly sampling Indian respondents.

A. Review of Literature

The literature has been reviewed considering methodology of detecting inactivity of elderly people in the house, whether it uses ambient sensors or on-body sensors, whether the detection model uses Artificial Intelligence or Machine Learning principles, results of the tests, learnings, and conclusions.

1) Towards detecting inactivity using an in-home monitoring system [3]

This literature has been published by the authors Masud Moshtaghi, Ingrid Zukerman, R. Andrew Russell, and David Albrecht belonging to the Faculty of Information Technology, Faculty of Engineering, Monash University, Australia.

The authors conducted the research using the concept of Monitoring, Interacting and Assisting. The method proposed was to use non-intrusive ambient sensors like Infra-Red based motion sensors, Reed Sensors attached to doors & windows, Infra-Red based Beam Breakers and Pressure sensors like pressure mats. A statistical model was built using available sensor data on normal periods of activity & inactivity and deviations were detected from the model based on periods of unexpected inactivity which crossed a threshold.

The distribution of the data was modelled using the statistical technique of Exponential Distribution of data and calculating a Coefficient of Variation (ratio of standard deviation to the mean. $CV = \sigma/ \mu$). The threshold was adjusted to cater for rare events, for example, activity in the kitchen normally occurs prior to breakfast, lunch & dinner and not at 3 a.m. in the night.

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Thus, a weighted average of the threshold is calculated for that region of the house for that specific period. This detection model was not adaptive, i.e., the thresholds were not re-generated or re-computed based on any continuous adaptive mechanism. Thus, there is no AI or ML built into the system.

The tests conducted demonstrated average weekly false alerts between 2 for entire house-based approach & 10 for region-based approach. The system was implemented using 17 sensors in the entire house. The region-based approach did produce more false alerts, but thus it allowed identifying areas of the house which would require better monitoring. It may require additional sensors thereby increasing the cost. Another observation from the authors is that in the regions in the house like lounge and study, people make relatively small movements and thus additional sensors may be needed to detect these movements accurately.

Better thresholds are seen in Region Based approach, for e.g., in Bedroom (blue curve) the threshold is seen to be higher in periods of extreme inactivity in mid of the night. Similarly in the study (green dotted curve in fig. 2), the thresholds are seen to be the highest during evening hours.

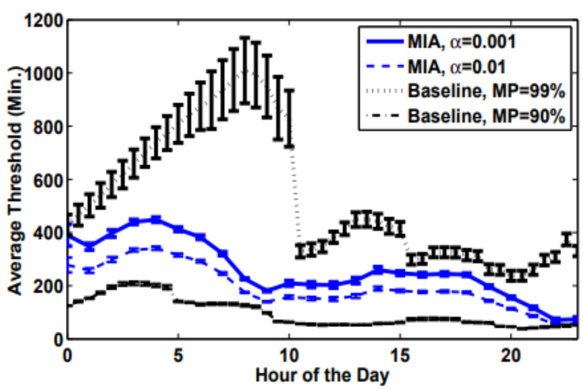

Fig. 1. Entire house approach

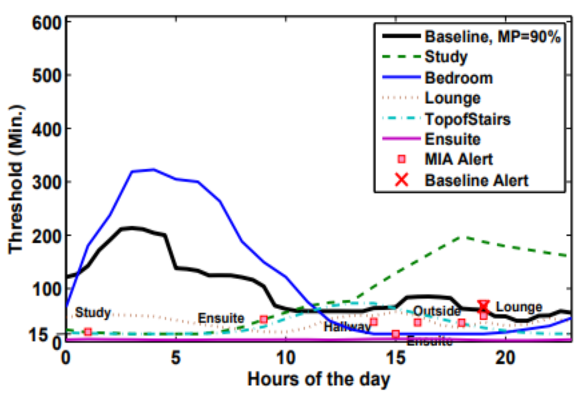

Fig. 2. Region based approach

2) A Behavior Monitoring System (BMS) for ambient assisted living [4]

This literature has been published by the authors Samih Eisa and Adriano Moreira at the University of Minho in Portugal.

The authors experimented on an ambient sensor-based Behavior Monitoring System to detect the activity of elderly people within their house. Observations were used to create a Learning Module to learn the subject's activity and a Detection Module to detect any abnormality in the subject's activity and raise alerts on its detection.

Concepts of Machine Learning and statistical probability were used to build the model of a behavior monitoring system, taking two aspects of the subject's behavior, Stay & Transition. Stay was defined as the time elapsed between two consecutive observations detected within the same room and Transition represented the room-to-room mobility of the subject.

As part of the experiments, researchers used two datasets for validation, Synthetic and Aruba datasets. Synthetic was a data generator to simulate a subject's mobility profile. The researchers generated two profiles and experimented with different behaviors: sleeping in the bedroom, being out of the home, or staying in the living room. Aruba dataset was collected from the CASAS Smart Home project of Washington State University containing sensor data from the home of a volunteer adult woman [7]. The researchers considered only the data that was collected from Passive Infra-Red motion sensors.

Quality of the Learning Module was determined by how well it described the behavior of the subject and distinguished between a normal and an abnormal behavior of the subject. The results drawn from the experiments show that the Learning Module successfully learnt the normal daily behavior (stay and transition periods) of the subject. The Anomaly Confirmation Time (ACT) was the ability of the model in terms of time required to detect an anomaly. The results of the experiments with the Synthetic dataset were similar for both the experimented profiles. The Aruba dataset results, however, showed a lower Anomaly Confirmation Time than those of the Synthetic dataset.

The Average Number of False Positives per week was higher for the Aruba dataset than the Synthetic dataset. The researchers concluded that the cause of the high number of false positives for the Aruba dataset was due to the presence of multiple people excluding the subject within the same house. According to the researchers, to avoid this, the system needs to be designed in a way such that the days when the subject is visited by guests should be ignored during the learning of the subject's daily behavior.

Classification of behavior based on a rule-based classifier resulted in high accuracy (more than 90%) in most observations. Advantage of this behavior monitoring system was that it provided alarms on abnormal activity detection in quasi-real time, unlike most existing behavior monitoring systems. Thus, it reduced the rate of wrong detection or false alarms.

One of the challenges noted was that the cost of the sensing technologies was high.

Another challenge faced was the difficulty in perfectly defining human behavior. Each system or model has its own way of defining behaviors, leading to heterogeneity in the data and difficulty in evaluation and comparison of these models. Also, the difficulty in sensing the difference between the subject and possibly a relative led to false alerts and undermined the quality of the model.

3) The smart habits, An intelligent privacy-aware home care assistance system [5]

This literature has been published by the authors Andrej Grguri´c, Miran Mošmondor and Darko Huljeni´c belonging to the organization Ericsson Nikola Tesla in Zagreb, Croatia.

The main objective of the Smart Habits system was to answer the question "Is My Loved One Ok?". The system comprised three main parts: The Home-Sensing Platform residing in the home of the elderly person, The SmartHabits Expert System in the Cloud, and thirdly the underlying communications. The Home-Sensing Platform consisted of following sensors - Reed Sensors for Doors & Windows, Motion, Luminance, Temperature, Humidity & Pressure amongst others to answer the questions who, where, when, what, why.

The sensors were integrated with a Device Gateway, Home Gateway, and Local Database, which provided the basic connections & configurations to the sensor system along with temporary data storage in case of loss of network connectivity. The SmartHabits Expert System resided in the Cloud and consisted of the following: a) A Knowledge Base with facts & rules with an editor to define rules. b) A Pattern Recognition Engine which analyzed the facts with reference to the set rules c) An Anomaly Detection Engine which decides if an event is to be considered anomalous and finally d) A Notification Management Engine to notify the caregiver in case of any anomaly detected.

Data collection included gathering data for pattern recognition for a day, week, or month. Based on the pattern, the profile of the user is characterized. The pattern recognition thus provides boundaries to be presented to the caregiver to accept a rule. Clustering Method was used for anomaly detection as it provided low time complexity. K Means Clustering method was used to identify natural clusters in the data. Bayesian Information Criterion was used to define optimum number of clusters.

Pilot testing was conducted in the city of Zagreb. The test subjects did not have to interact with the system since there was no Body Area Technology involved in this system. During the pilot and testing phase, the system was able to learn 23 patterns per household in the first 30 days with approximately 3 patterns per sensor. On an average 61% of the rules were accepted by the caregivers, indicating that the majority of learned patterns were adequate with a confidence level of 95%. The feedback from users at the end of the pilot phase was satisfactory with an average rating of 4.67 out of 5 on around 14 parameters which were evaluated.

4) An ambient intelligence based human behavior monitoring framework for ubiquitous environment [6]

This literature has been published by the authors Nirmalya Thakur and Chia Y Han belonging to the Department of Electrical Engineering and Computer Science, University of Cincinnati, OH.

This framework took an approach to make a detailed study of human behavior during activities of daily living (ADL) to list behavioral patterns associated with complex activities. It incorporated an intelligent decision-making algorithm to analyze those patterns and detect anomalies in user behavior to identify emergencies. The model considered five characteristics of Activities of Daily Living: Whether an activity is Sequential, Concurrent, Interleaved, False Start or a Social Interaction. The analysis of these characteristics with respect to the area or space and time helped in understanding the user's performance during the ADL as well as in determining anomalies.

To describe a performed activity, it was broken down into atomic and core atomic activities which describe the macro and micro level tasks and sub-tasks. Both wearable and unobtrusive sensors were used to capture the context of the user as well as the user behavior for each of the atomic activities which they performed. The resultant data set provided the context in which the atomic activity was carried out.

The wearable sensors included those supporting the accelerometer and gyroscope. The data was split into training and test sets. The machine learning model was fed the training data and tested on the test data. The model used for machine learning was the K-Nearest Neighbor algorithm (K-NN classifier). To predict emergency or non-emergency, the K-NN classifier model assigned a confidence value to every behavior pattern there-by arriving at a conclusion whether the exhibited behavior is to be flagged off as an emergency.

While wearable sensors have their set of challenges, use of such sensors helped in analyzing the activities at a fine grain level, e.g., postures and gestures, which provided a detailed data set as against purely a contextual data set used by unobtrusive sensors alone.

The framework with its dataset was able to achieve an overall performance accuracy of 76.71% while the intelligent algorithm it used which considered context information, the area or space & time, resulted in a performance accuracy of 83.87%.

B. Survey Methodology

The survey was conducted to get responses from people of varied backgrounds and demographics. A Google Forms link was created with 22 questions out of which 9 were single selection, 2 were multiple selection, 3 were short answer types and remaining 8 were long answer type of questions. The Google Forms link was in form of a standard questionnaire and not a quiz format

The survey was responded to over a one and half month period. Approximately 50% of the respondents were based in India while the others were from diverse geographies of North America, Central Europe, Nordics, and Australasian regions. The age group selected were 18-25 years, 26 to 35 years, 35 to 45 years and 45 and above, thus allowing for those age demographics who were likely to have either parents or grandparents as elderly persons who may need some form of assisted living and those who in two decades will be senior citizens themselves.

The questionnaire was composed to get the respondents views on the research topic: - whether they were aware of the concept of assisted living, whether they had elderly people whom they had to care for, their views on technology-based solutions. The questions are given in Appendix for reference. The survey questionnaire Google Forms link was shared with the respondents using various social media channels like WhatsApp, Email and Facebook messenger.

While the name of the person was solicited, it was a non-mandatory field in case anyone had any privacy concern. The rest of the questions were made mandatory.

C. *Analysis of Survey Results*

59 respondents provided their responses. Majority of them (44 %) were in the age group 26-35 years (Fig. 3), who would have elderly parents or relatives in the 60 years plus age group. More than 94% of all respondents had elderly members in the family above the age of 60 years (Fig. 4). A good 56% of the respondents had the elderly members living by themselves in their own households (Fig. 5).

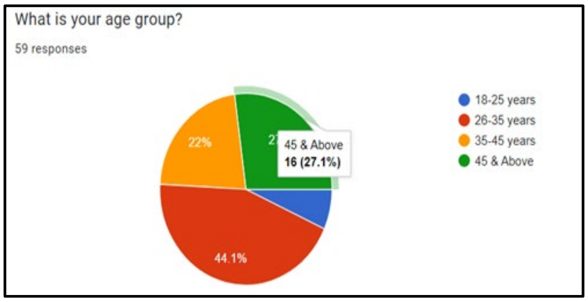

Fig. 3.

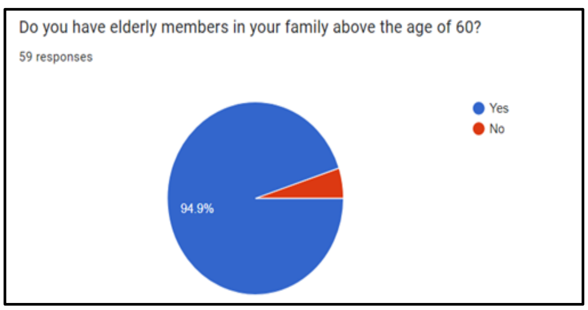

Fig. 4.

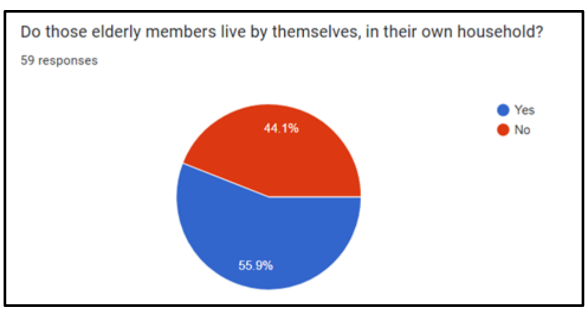

Fig. 5.

From the total survey population, more than 50% of the respondents have stated that they value self-reliance of the elderly in conducting activities of daily living (Fig. 6). When cross-referenced with age, this number jumps to 68.75% for the age group of 45 and above (Fig. 7). In about two decades, this age group will be in elderly population age group and this figure is therefore a critical indicator of the value being given to self-reliance, which can be achieved by using mechanisms of Assisted Living.

Close to 16% of the respondents have responded with the highest comfort level of 5, indicating that their elderly family members would be comfortable with technology-based solutions monitoring their daily activities with the intention to improve their well-being. When cross referenced with age, this number jumps to 25% for the age group of 45 and above (Fig. 8). While 25% does not indicate most of the population, however, when coupled with data for comfort level 4, the number becomes 37.5%. This is a good indicator that individuals currently in the 45 and above age group would also be comfortable with technology when they enter a senior citizen age group.

A key observation is that from the total respondent population, 29% feel that privacy concern may be the reason Assisted Living would not be adopted. While this is not a trivial percentage (11 out of 59), it is also important to note that 40 out of 59, almost 68% feel that learning curve would be the key reason for non-adoption. It is therefore important to educate current and future generations on aspects of privacy and the learning curve.

Ease of Use has been a key criterion reported from the survey respondents. In Assisted Living, the system does not have to be used by the elderly individual at all. There is no intervention from the elderly individual since the system is meant to be unobtrusive and blends into the home environment seamlessly. 59% of the respondents were found to be not aware of any innovative techniques for elderly care (Fig. 9).

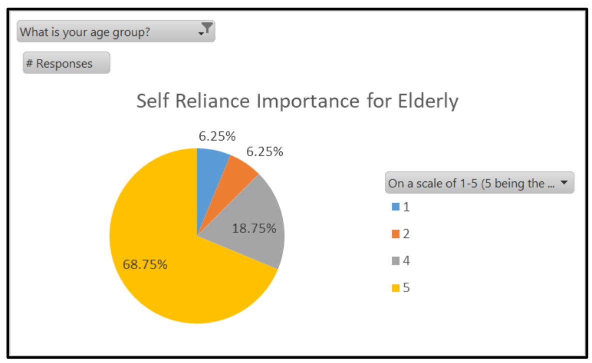

Fig. 6.

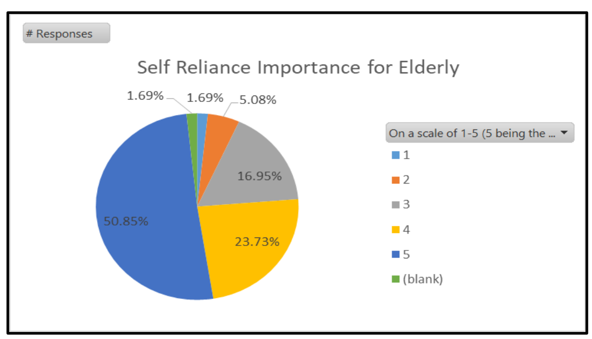

Fig. 7.

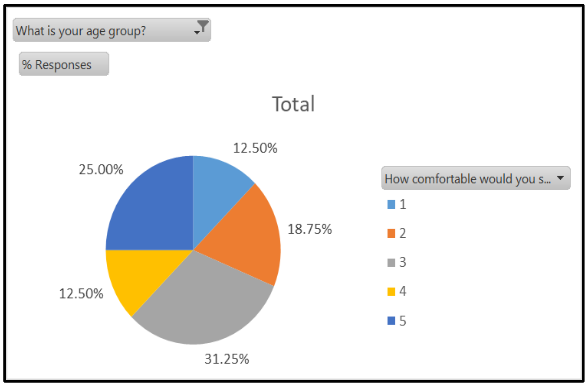

Fig. 8.

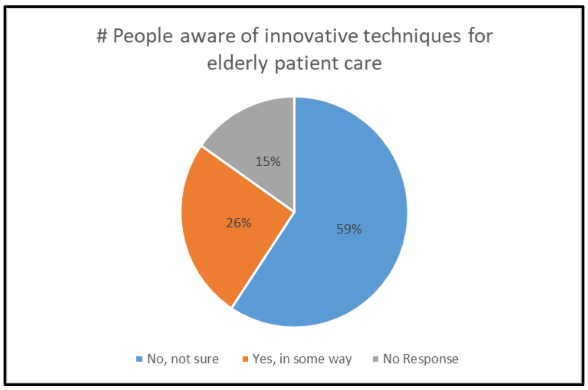

Fig. 9.

D. Expert View

A meeting was held with Mrs. Prajakta Wadhavkar, Founder, Tapas Health Care [8], Pune, India. The author apprised Mrs. Wadhavkar with an overview of the project and on the concept of Assisted Living Using Sensor Based Ambient Intelligence to seek her feedback. Mrs. Wadhavkar is a veteran in the field of health care for the elderly and provided valuable feedback and suggestions.

She believed such a mechanism is of use to two categories of elderly population, first those who are aging normally but are otherwise healthy individuals, living by themselves and secondly those with normal aging with onset of aging disorders but with ability to carry out day to day activities by themselves.

Mrs. Wadhavkar suggested that deviations in behavior patterns of Activities of Daily Living (ADL) can give indications on onset of possible disorders like dementia or Alzheimer amongst others.

On the point of caregivers, a valuable insight was provided that in developed nations, caregivers are expensive and not available easily, hence mechanisms such as this can play a wider role. On the other hand, in countries like India, caregivers are available relatively easily, however, in recent times there have been multiple challenges experienced with caregivers due to their carelessness and lack of proper training and hence such systems can help fill the gap.

She suggested that key emergency events to track include the following a) Fall b) Being locked into a room or toilet and being unable to open and c) Monitoring if the individual is maintaining a daily routine of walking / exercising around the house. According to Mrs. Wadhavkar, currently the lifestyle of senior citizens has also changed for e.g., many of them in India have started leading a modern lifestyle with attending late night events, movies etc. and any model created would need to adapt to such changing lifestyles.

To summarize, she said that the concept of Assisted Living using discrete, unobtrusive sensor elements to monitor the elderly individual and detect abnormal behavioral activity which may suggest a medical emergency, does hold a lot of good scope to develop further. While initially the model can be simple, it can evolve over time.

3. Conclusion

Almost all the literature surveyed stated good test results with one of them having a confidence level of more than 95%. While areas of improvement have been found, like the need for additional sensors and the need of additional algorithms to differentiate subjects and relatives or guests, overall, the methodologies and technologies used provided satisfactory results.

A high percentage of respondents from the survey were in favor of self-reliance regarding elderly people living by themselves, which is a key factor in support of the concept of Assisted Living. A good number of respondents are in favor of technological solutions for elderly care and since cameras and on-body sensors have privacy concerns, an unobtrusive, discrete method may find wider acceptance.

As very little awareness is observed in these areas, it is thus necessary that awareness campaigns be conducted to make both the elderly population and their families aware of such technologies. The opinion from experts from the field is also positive for this method of elderly care as it can also be used to detect onset of conditions as age progresses.

The conclusion can therefore be drawn that "the hypothesis that Assisted Living using Sensor Based Ambient Intelligence will become prevalent in the coming two decades" can thus be said to be valid.

Appendix – Survey Questionnaire

1. What is your age group?
2. Are you aware about the concept of Assisted Living using Sensor Based Ambient Intelligence Technology?
3. Do you have elderly members in your family above the age of 60?
4. Do those elderly members live by themselves, in their own household?
5. Do those elderly members suffer from any significant neuro-degenerative disease?
6. Are your elderly family members able to locomote around the house by themselves?
7. What activities do they perform throughout the house by themselves?
8. What are you most worried about, regarding your elderly family member being by themselves in their household?
9. In what ways are you currently ensuring the safety of the elderly members who are by themselves?
10. Are you using any technology-based solution which is assisting in alerting either you or a caregiver in case any risk is foreseen to the elderly family member?
11. If the answer to the above question is Yes, please elaborate on the technology.
12. If you would not like a technology-based solution, please elaborate what alternative mechanisms or ways you would prefer to determine if there is an emergency requiring attention?
13. Do you know of any innovative techniques that can be used to ensure their safety?

14. In case a technology-based solution is available, what would some of your criteria be, that you would expect that solution to fulfil?
15. How comfortable would you say are the elderly family members with technology-based solutions monitoring their daily activities intended to improve their well-being?
16. On a scale of 1-5 (5 being the highest), how much would you say the elderly members in your family or the ones you care for, wish to be self-reliant in conducting their fundamental daily activities?
17. Which of the following use-cases for Sensor-Based Ambient Assisted Living Technology would be most persuasive in driving adoption amongst the elderly family members or caregivers? (Select Any/All that Apply)?
    a) Fall Detection & Alerting on Emergencies
    b) Assistance in Daily Activities (Grooming/Walking/Standing/ Lighting Controls/Pill Dispenser, etc.)
    c) Passive monitoring of parameters to detect on-set of neurodegenerative conditions
    d) Presence Detection
    e) Others
18. If you selected Others in the above question, please elaborate.
19. Select from the reasons below as to why would elderly family members or caregivers NOT adopt Sensor-Based Ambient Assisted Living Technology?
    a) Affordability
    b) Privacy Concerns with the data being collected
    c) Uncomfortable learning new technology
    d) Others
20. If selected Others for above question, please elaborate
21. How many hours in an entire day would you spend time as a caregiver for your elderly family members assisting them with daily/routine activities (0-24 hours)?
22. If you hire a caregiver, how much would you spend approximately on the caregiver as a percentage of your household income (10% to 25%)?

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