Predicting Potential Alzheimer Medical Condition in Elderly using IoT Sensors - Case Study

Chong Zhi Hao Kevin, Tee Yu Xuan, Toh Ling Jing, Phang Shi Jia, Liew Jie Ying, Bertran Queck, Swapna Gottipati*
School of Information Systems
Singapore Management University
kevin.chong.2014, yuxuan.tee.2014, ljtoh.2014, sjphang.2014, jyliew.2014, klqueck.2015, swapnag@smu.edu.sg

***Abstract*— Ageing population would cause profound problems and the impact is already being felt today in many developed countries such as Singapore. The main concern for the Government is to help the citizens with active ageing through home ownership and good health care. With Internet of Things (IoT) gaining traction globally, Singapore is set to take advantage of this technology and leverage it to extend its capabilities towards a graceful Ageing-In-Place for the elderly. This ties in nicely with the expertise of SHINESeniors project by SMU-iCity Lab, which integrates IT with healthcare in ways that creates innovative IT health solutions that meet the needs of the elderlies. In this project, we study the problem of predicting potential Alzheimer conditions in the elderly through the behavioural analysis models developed from IoT sensors data. Our findings shows that IoT room sensors for location detection can enable us the capture the key three variables of elderly behaviour; excess active levels, sleeping patterns and repetitive actions. The three variables are useful in predicting the early warning signs of Alzheimer and we provide recommendations to care-givers based on the prediction analysis. We studied the task on 20 elderly living alone in the flats equipped with five sensors with the data spread over a period of 6 months.**

Keywords-IoT, Alzheimer, ageing population, prediction models, visual analytics

I. INTRODUCTION

Population ageing raises many fundamental questions for health-care providers and policy-makers. Active ageing programs enable people to be independent and prevent or delay the disabilities and chronic diseases. Most importantly in developed countries like Japan, Singapore, North America and Europe, the exponential growth of ageing population is of great concern to the Government and health-care providers [1].

Singapore Government has been working on the active ageing projects and encouraging the schools, research labs to build solutions for active ageing. SHINESeniors, or Smart Homes and Intelligent Neighbours to Enable Seniors, is a SMU-initiated effort to make community care services effective through innovations in care delivery by leveraging on Information and Communications Technology (ICT) [2]. The sensors, installed in the homes of seniors, can help community volunteers to better monitor, support them and respond in a timely manner to calls for help or falls [3, 4, 5, 6]. One of the goals of the sensors is that they can aid in behavior analysis of the seniors and predict the possible health issues. Discovering unusual patterns of the elderly daily routines can be correlated to healthcare issues.

Our objective in this report is to investigate any probable relationship between elderly behavioral patterns and potential cases of Alzheimer. In particular, we leverage sensors data and analytics to predict potential Alzheimer medical condition in elderly. Early diagnosis of Alzheimer's symptoms in an elderly using technology may provide better action plan by the health care service providers. Alzheimer's can be treated and treatment is best at the earliest stages of its onset where it has not affected as many parts of the brains [3, 6]. Therefore, there is a need for technology based simple, effective and scalable solutions that can predict the potential cases of Alzheimer. The healthcare solutions based on IoT technology are gaining popularity due to the continuous monitoring, cost effectiveness and scalability characteristics [3,4].

People with Alzheimer often carry out the same activity, make the same gesture, say the same thing, or ask the same question repeatedly [8]. Repetition is common in dementia because of memory loss and general behavioural changes. The person may repeat daily tasks, such as shaving, or they may collect items obsessively [9]. Alzheimer's patients often see changes in their sleep patterns early. For example, 20-minute daytime naps may stretch to several hours per day [10]. The most common sleep disorder symptoms in patients with Alzheimer are increased daytime sleepiness, night-time wandering, confusion, agitation. All these behaviour anomalies arises from the Alzheimer symptom identified as 'sun downing' [11, 13], a situation of confusion and restlessness.

Based on the current Alzheimer studies [10, 11, 12], we define three important patterns that enable to predict the warning signs of Alzheimer in elderly. Firstly, excessive activity levels within the residence. From empirical research, we deemed that if there are too many activities (spikes) within a short time-frame, it signifies that the person may be showing Alzheimer's symptoms in his/her activity. Secondly, unusual sleep patterns in the elderlies'. From empirical research, we found out that if an elderly has an abnormal sleeping pattern (i.e. high activity out of bedroom at night, and spend time sleeping in bedroom during the day), it could indicate a potential Alzheimer's symptom. Thirdly, high levels of repetitive behaviour. From empirical research, we found out that if an elderly has repetitive behaviour such walking in

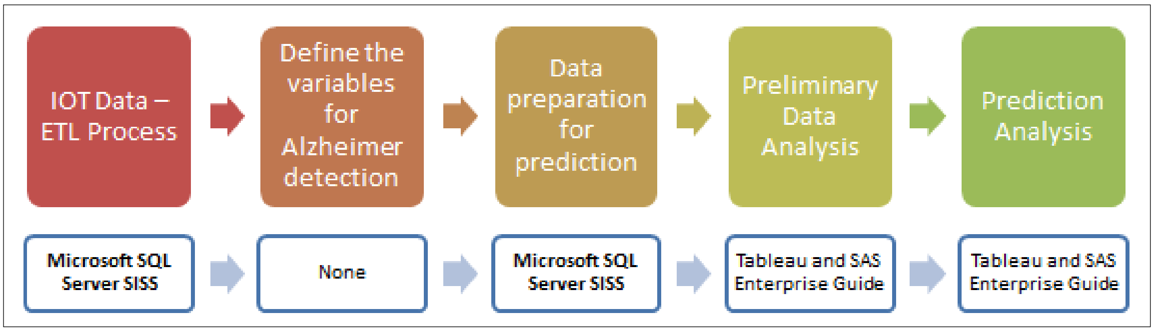

Figure 1. Alzheimer prediction analysis using IOT solution overview

between locations to search for their item or repeating the same action, we deemed this activity as a count in the "repetitive behaviour" and it may spark an outage during our analysis.

Our solution is based on IoT sensors data and three patterns or variables that are useful in predicting potential Alzheimer cases. The prediction analysis model is generated based on processed data and visualization techniques. We applied the model on the data collected from SHINESeniors project where the elderly living flats are equipped with sensors to detect the location and movements. We discovered potential cases using our solution and provided recommendations to the care givers.

The rest of the paper is organized as follows. Section II presents a brief survey of related work. Section III provides details of the dataset. Section IV gives a detailed description of the solution design for the prediction models. Section V describes our findings and insights. Section VI concludes the paper and highlights future research work.

II. RELATED WORK

Alzheimer detection: Traditional methods of Alzheimer's detection include detecting linguistic deficits [14], biomarkers combined with machine learning algorithms [15], interviews or memory tests [16]. These diagnosis methods of Alzheimer's is a challenging, time consuming and tedious process and includes limitations of patient time and conscientious participation. To overcome these challenges, the technology enabled approaches are becoming more popular among health-care providers. GPS tracking devices and video surveillance were two technologies included in this study, as these have been touted to increase freedom for patients with Alzheimer disease [17]. These techniques are not comfortable for patients as they felt stigmatized and felt they were being "watched. IoT sensors based solutions are better accepted as they are able to track the location and movement of people without stimulating their awareness.

IoTs in healthcare: IoTs enabled smart homes are not only aiming to provide an environment for assisted living [18, 20, 21], but are also enabling regular monitoring of elderly people in an unobtrusive manner [19]. The event monitoring technique collects sequences of events or activities, aiming to discover the rhythmical repetition of events that may correspond to wandering behavior. Sensors could be placed in areas to detect movement and vital signs. For example, if the patient is becoming more confused and is wandering, the sensor could detect a pattern of wandering [22]. On the other hand, if there is a sudden drop in activity, this could signal apathy of a patient who perhaps is becoming more sedentary and less social. Apart from the movements and location analysis, the sensors connected to the appliances such as gas, tap and medicine boxes provide data for analyzing the usage of the appliances. The analysis can aid in detecting the forgetfulness behavior of elderly [3].

IoTs for Alzheimer detection: Raad combined active wearable Radio Frequency Identification (RFID) wristband together with IR room locators to monitor the whereabouts of the elderly at room level [7]. The prediction models are not studied by their team yet. Yuki et al. used the IoT technology to propose the study of patient behaviour for early detection of types of dementia [4]. The key variable in their study is based on forgetfulness that is captured from the sensors on gas, taps, lights and closing door. They studied only on two patients and results are basically comparison analysis. In our project, we apply the similar approach by Yuki whereby we leverage data from IoT sensors and apply statistical models. However, the key variables in our study are sleeping disorders, extreme active levels and repetition behavior. Further, we studied our approach on twenty elderly living alone in the flats equipped with room sensors and main door sensor.

In the next section, we present our dataset and the details of IoT sensors.

III. DATSET

The data is associated with each elderly living alone in the one bedroom flat of similar structure [2]. The primary dataset for our project is IoT sensors data of 6 months. The sensors would detect movements in a specific area whereby it enables the detection the behavioral patterns of elderly living in the flats. Each record data was represented by the date and time, different areas of location in the dataset - living room, bedroom, bed, bathroom, kitchen, toilet, and main door contact. A "yes" in the dataset indicates the detection on the respective sensor while a "no" indicate otherwise. Table I shows the data description of IoT sensors from 20 different flats.

The data is collected for every 10 seconds from each sensor fixed in twenty elderly living alone flats. The dataset has in total 35422587 rows for, ensuring an appropriately large size of database to analyze. Larger datasets attribute to the better performance of prediction models. The table shows only the data columns relevant to our study.

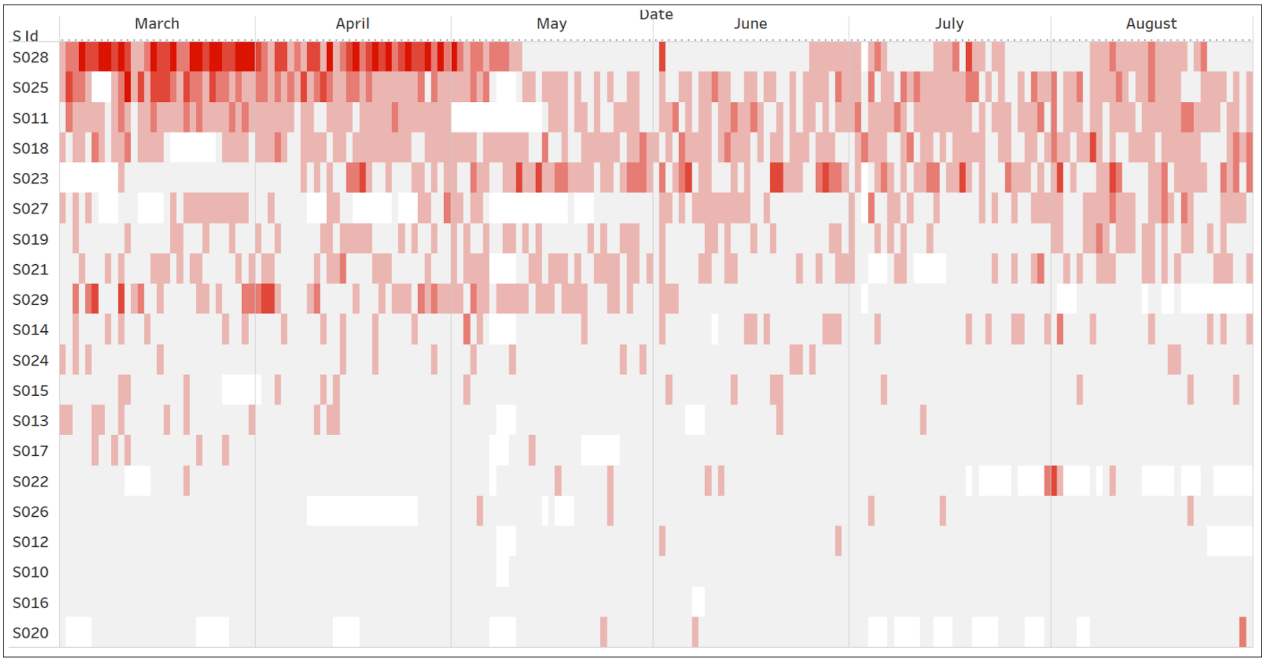

Figure 2 Sample heatmap showing number of hours that have more than 20 activities being trigger per day (Variable - excess activity levels)

TABLE I. SENSOR DATA DESCRIPTION

Attribute Name	**Description**	**Data Type**
s_id	The identifying elderly ID	ID
date	The date and time of the current sensor detection	datetime
door_contact_as	The sensor detection of any contact elderly made with the door (i.e. open door to go out / come home)	Nominal
living_room_as	The sensor detection of elderly current location in living room	Nominal
bedroom_as	The sensor detection of elderly current location in bedroom	Nominal
bathroom_as	The sensor detection of elderly current location in bathroom	Nominal
kitchen_as	The sensor detection of elderly current location in kitchen	Nominal

IV. SOLUTION

We first present the overall solution design and then provide the details of the stages.

A. *Solution Design Overview*

Figure 1 shows the overview of the solution for prediction analysis of Alzheimer's in elderly using IoT data. The stages of the design use various popular data warehouse and analytics tools as shown in the lower layer. The first stage is the data collection and data cleansing process using Microsoft tools [24]. With simple data analysis and findings from previous studies related to the Alzheimer [1, 3, 9, 10], we generated the prediction variable model from the IoT datasets. In the third stage, the data is processed to include the variables for the deeper analysis. This requires augmenting the data with more features useful for the Alzheimer detection. In the fourth stage the visualizations of the data using Tableau [23] provides a patterns and insights of the data model. We also used SAS Enterprise Guide [25] for quick data analysis and comparisons of charts. Finally, in the last stage, the predictions can be done on each elderly and the action items for the health-care providers are recommended.

B. *Details of Prediction Analysis Solution*

a) IOT data ETL process: The data is imported as 120 excel files and we used Microsoft SQL Studio to combine all the files due to capacity constraints. With that, we will be able to sort by elderly ID, as well as date and time. Two main challenges are;

- Missing data - In our data exploration, we observed that there was some missing data in the sensor readings provided. We removed the missing rows for this study.
- Data contains 'NOK's- Likewise, for 'NOK' sensor readings, we treated them as 'No' readings so that it would not artificially inflate the mobility levels of the elderly.

b) Define variables for behaviour Analysis: We performed a preliminary analysis and defined the prediction variables based on the described in introduction section We set the thresholds for the three conditions using preliminary studies. We augment the data model to aid the prediction of

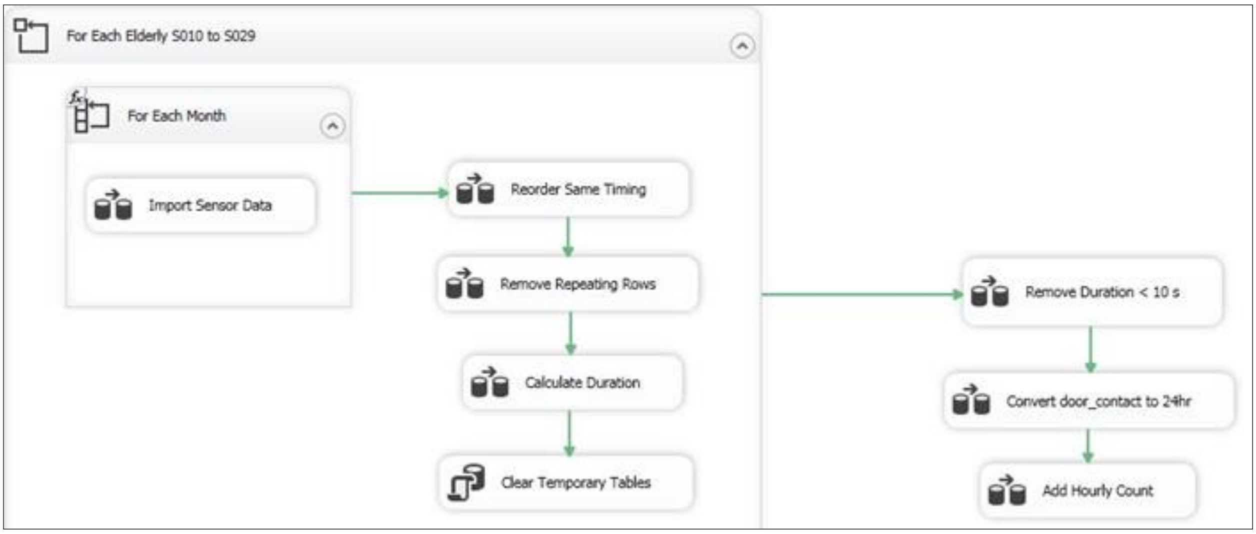

Figure 3. ETL (Extract Transform and Load) model overview for IOT data preparation

Alzheimer condition for elderly. Table II shows the details of the three variables used in the Alzheimer prediction.

TABLE II. PREDICTION ANALYSIS VARIABLES MODEL

Variables	**Threshold factors**	**Data columns aggregations**
Excessive active levels	20 activities and more and in 1 hour.	Count aggregated rows grouped by the s_id, Hour, Date
Abnormal sleeping patterns	30 activities out of bedroom in night	Count time not in bedroom at night grouped by s_id, date
Repetitive behavior	30 repetitions with "Location A - Location B - Location A" within 5 minutes.	Count aggregated rows grouped by the s_id, Hour, Date where duration <5mins

c) Data Preparation: We run the ETL process based on the variables defined in the previous stage. We used MS SQL Studio for the ETL process. We assume day time as 8am to 7.59pm and night as 8pm to 7.59am. We computed the time spent in each location based on the day and night of each day using Microsoft SQL Management studio and generated a new data model for analysis. Overall MS SQL Server ETL model is shown in the Figure 3.Figure 4 shows sample SQL script for the data preparation stage. This script is used for duration calculation.

```
SELECT [s_id]
      ,[date1]
      ,[day_night]
      ,sum(CASE WHEN location='living_room_as' THEN duration ELSE 0 END ) as [totalTimeSpentInLiv
      ,sum(CASE WHEN location='bathroom_as' THEN duration ELSE 0 END ) as [totalTimeSpentInBathro
      ,sum(CASE WHEN location='bedroom_as' THEN duration ELSE 0 END ) as [totalTimeSpentInBedroom
      ,sum(CASE WHEN location='kitchen_as' THEN duration ELSE 0 END ) as [totalTimeSpentInKitchen
      ,sum(duration) as [totalTime]
      ,sum(CASE WHEN location='bathroom_as' THEN 1 ELSE 0 END) as [frequencyOfBathrooms]
      ,sum(CASE WHEN location='door_contact_as' and duration > 20 THEN 1 ELSE 0 END) as [frequenc
  FROM [DWBA Project].[dbo].[q1e.3] group by [s_id],[date1],[day_night]
```

Figure 4. Sample SQL script for the data preparation for predcition analyis variable model

d) Preliminary Analysis: With the dataset derived above, we decided to conduct preliminary behavioural pattern analysis on the 20 elderly to have a basic understanding of their daily activities and activities undertaken. We used Tableau for the detailed prediction analysis for each elderly using various visualization graphs.

We have imported the dataset derived above to Tableau for better understanding and visualization of data on a time-series bar graph. Besides conducting preliminary behavioural pattern analysis on the individual elderly, we also run an overall analysis on the data to detect elderly with abnormal behavior in comparison with the others.

e) Prediction Analysis: We categorize each elderly into three categories of Alzheimer risk cases; abnormal, potential issue and normal. We use heatmaps from Tableau to categorize the behaviour data for each elderly by day, month and time. A sample output is shown in the Figure 2. The detailed analysis of this graph is described in Section V.

For individual Alzheimer prediction, we define a color matrix for all three variables and a risk rating matrix to demonstrate the severity of the problem. We apply levels of problem detection and profile the individuals for the reports generation. We did some preliminary analysis on the data for finding out the mean, median and standard deviations of the data for the durations. Finally, we set the thresholds to calculate the prediction scores. Table III shows the color thresholds and Table IV shows the risk-color rating scores.

TABLE III. HEATMAP COLOR THRESHOLD MATRIX

Variables	**Light Red**	**Red**	**Dark Red**
Number of hours with high triggered activities (Daily)	4-9 hours	10-14 hours	15-24 hours

Hours spent out of bedroom location (Daily)	4-9 hours	9-13 hours	>13 hours
Number of repetitions (Daily)	30-60	61-95	96-161

TABLE IV. ALZEIMEIR RISK-COLOR RATING MATRIX

Severity Rating	**Threshold for all variables**
Abnormally	>70% Light Red or 25% Red or 10% Dark Red
Potential	>30% Light Red or 10% Red or 5% Dark Red
Normal	>90% Light Red or <4% Red

V. FINDINGS ANS DISCUSSIONS

During the preliminary data analysis we conducted, we identified some of the unique trends of the elderly, and decided to give attention to these elderly. The elderly that we highlighted are "S011, S018, S023, S025 and S028". In our variable data analysis we observed that the second variable, "Abnormal sleeping patterns" is biased due to visitors, sensor reading inaccuracy and missing data that causes frequent and inflated duration calculations. Therefore, we rely only on variable 1 and variable 3 for the Alzheimer symptom analysis.

We first present our findings and then discuss the limitations and future work.

A. Findings

From Figure 2, we can observe the behavior of each elderly in the flat. We studied the heatmap for each elderly and prepared a report together with manual analysis. We then used both variables 1 and 3 and performed an overall Alzheimer prediction analysis. Table V shows the final analysis based on variables, 1 and 3.

TABLE V. PREDICTION ANALYSIS BASED ON VARIABLES 1 AND 3; EXCESS ACTIVE LEVELS AND REPETITIONS.

Elderly	**Excessive active levels (Variable 1)**	**Repetitive behaviors (Variable 3)**
S028	Abnormally	Abnormally
S011	Abnormally	Potential Issue
S018	Potential Issues	Abnormally
S025	Abnormally	Potential Issue
S023	Potential Issues	Potential Issue
S029	Potential Issues	Potential Issue
S027	Normal	Abnormally
S010, S012, S013, S014, S015, S016, S017, S019, S020, S021, S022, S024, S026	Normal	Normal

Based on current studies we genarted risk-action matrix to allocate a risk level and action to-be taken for respective residents [1, 12, 13]. Table VI shows the risk-action matrix for the predicted cases.

TABLE VI. RISK – ACTION MATRIX

Case	**Risk Level**	**Action to-be taken**
2 Abnormally present	High Risk	Schedule priority mobile doctor visit
At least 1 Abnormally present	Moderate Risk	Schedule mobile doctor visit
2 Potential issues present	Moderate-Low Risk	Schedule social workers visit
1 Potential issues present	Low Risk	Identify as potentially at risk individual, close monitoring advised

From analysinz both Table V and Table VI, we identified a few residents at risk of Alzheimer's symptoms. From the Table V and Table VI, we observe that S028 has a relatively high risk of experiencing Alzheimer's as the analysis shows him displaying highly abnormal actions related to symptoms. Hence caretakers could prioritize a mobile doctor visit to examine him as soon as possible. We observe that S011, S018, S025 and S027 has a moderate risk of experiencing Alzheimer's as they show abnormal behavioral patterns in one of our analysis and a potential issue of concern in the other. Hence caretakers could schedule mobile doctor visit to examine them.

We observe that S023 and S029 has a moderate-low risk as they shown potential issues of concern in both of our analysis. Hence, caretakers could schedule social worker visit and understand the potential issues they might be facing in their daily activities

These results actually correlate with our initial findings in our preliminary analysis that identified S011, S018, S023, S025 and S028 as individuals we wanted to deeper understanding of. The additional findings on S027 and S029 which was not identified earlier also shows that our models managed to identify behavior anomalies which the preliminary analysis might have overlooked.

B. Discussions

We observe some limitations in our findings. The first limitation is the sensor quality. Due to missing and NOKs, our analysis requires some assumptions such as: if the duration as we computed are < 10 seconds, we assume that elderly was just passing through. More efficient sensors will help in producing more accurate results. At the same time, the data should be combined with the qualitative information of elderly medical conditions and medicines intake for better prediction models.

While exploring the data prepared and visualized in our model, we discovered that apart from identifying symptoms of Alzheimer disease, this model can also be used for other medical conditions. Parkinson's disease causes a deterioration of motor functions. It results in patients to exhibit drastically slower movement and activity as compared to a healthy individual. Variable 1 which identifies the level of activity of the elderly can be used to detect such abnormal decline in activity levels for the elderly (Seyal, Smith, & Robinson, 2016). This remains our future research of leveraging pervasive technologies for active-ageing in Singapore.

VI. CONCLUSION

In this work, we study the behaviour of elderly using IoT sensors and proposed a prediction model for early detection of potential Alzheimer cases. Overall, the model serves as only a potential early diagnosis to Alzheimer diseases. A flag in behaviour does not necessary mean that the elderly is a definite Alzheimer evaluations and further medical evaluations should be performed by doctors to confirm the risks. Our project shows the potential benefits of IoT sensors in studying the behaviour of elderly citizens which can be scalable and provide recommendations to the health-care providers.

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