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Sensor-Driven Detection of Social Isolation in Community-Dwelling Elderly

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Abstract. Ageing-in-place, the ability to age holistically in the community, is increasingly gaining recognition as a solution to address resource limitations in the elderly care sector. Effective elderly care models require a personalised and all-encompassing approach to caregiving. In this regard, sensor technologies have gained attention as an effective means to monitor the wellbeing of elderly living alone. In this study, we seek to investigate the potential of non-intrusive sensor systems to detect socially isolated community dwelling elderly. Using a mixed method approach, our results showed that sensor-derived features such as going-out behavior, daytime napping and time spent in the living room are associated with different social isolation dimensions. The average time spent outside home is associated with the social loneliness level, social network score and the overall social isolation level of the elderly and the time spent in the living room is positively associated with the emotional loneliness level. Further, elderly who perceived themselves as socially lonely tend to take more naps during the day time. The findings of this study provide implications on how a non-intrusive sensor-based monitoring system comprising of motion-sensors and a door contact sensor can be utilized to detect elderly who are at risk of social isolation.

Keywords: Non-intrusive sensors · Ageing-in-place · Social isolation

1 Introduction

According to the United Nations, countries across the world are facing an upward trend of population ageing [1]. Along with this, is the upward trend towards the elderly living alone. In order to meet rapidly changing elderly needs, nations are increasingly adopting cost effective home and community based care models to substitute costly and labor intensive institutionalized elderly care system. Community care models allow elderly to age-in-place, i.e., to live in their own home, thus giving them the freedom and independency in life. Although such care models would alleviate the resource shortfall in care facilities, it could also lead to various social and health issues.

The risks faced by elderly people living alone could range from their safety and health to their psychological well-being. Further, as the elderly are living alone and often have a limited network of family and friends, they may be at a high risk of social deprivation, which could lead to pertinent issues such as loneliness and social isolation. Social isolation has been often identified as an objective measure of network size and diversity, and frequency of interpersonal contact. On the other hand, loneliness is a qualitative, subjective evaluation related to one's expectations and satisfaction with the frequency and closeness of interpersonal contacts [3]. However, both loneliness and social isolation have often been associated with various negative health repercussions, such as greater risk of cardiovascular disease [4], cognitive impairment [5, 6] and worsened sleep quality [7]. They have also been found to be correlated with higher mortality rates among the elderly [8, 9].

The prevalence of social isolation and loneliness amongst older people aged 60 or above is substantial, (estimated to be up to 17% [10–12]) and loneliness is reported to be experienced by approximately 40% within this age group [13]. The trend towards elderly living alone, and the impact of social isolation on individuals' health highlight the need to target social isolation as an emergent societal issue. However, challenges to care provision and social interventions could arise when identifying the elderly who are lonely and socially isolated. Direct self-reported methods are most commonly used to measure the loneliness and social isolation of an individual. However, these subjective responses may not be accurate as existing social stigmas associated with being lonely can be potential obstacles.

In Singapore, elderly aged 65 and above who live alone has grown exponentially from 14,500 in 2000 to 42,100 in 2015 [2]. From 2007 to 2011, at least 50 elderly living alone have passed away in their own homes, only to be discovered after a prolonged period [2]. Past studies have shown the potential of sensor technologies to identify elderly with physical, psychological and cognitive impairments [14, 15]. Sensor-enabled 'Smart Homes' have the ability to effectively monitor the wellbeing of elderly living alone. Therefore, in recent years, many technology-based initiatives have been carried out to transform the face of ageing [17] in Singapore. However, past studies have acknowledged that privacy concerns with installing monitoring cameras in the elderly's homes and memory lapses in remembering to put on their wearables are some challenges in building a sensor-enabled smart home environment [16].

The Smart Homes and Intelligent Neighbors to Enable Seniors (SHINESeniors) project aims to create up to 100 sensor-enabled homes in support of ageing-in-place, through the use of non-intrusive and non-participative sensor technologies such as passive infrared (PIR) motion and door contact sensors. In this study, we use a mixed method approach with data gathered from surveys, observations and objective measures derived from PIR sensors to present an all-encompassing approach for caregivers to detect socially isolated elderly who are living in their own homes.

2 Methodology

2.1 Data Collection

The data in this study was collected from sensor-enabled homes of 50 elderly participants in the SHINESeniors project. These participants were selected on a voluntarily basis if they meet the following criteria: living alone in government-subsidized flats, aged 65 or above and affiliated to a Voluntary Welfare Organization (VWO) operating in the neighborhood. All the participants agreed to have the sensors installed in their homes and the consent to obtain data for research purposes was obtained prior to the installation.

The sensor-based monitoring system was deployed in early 2015 for 50 flats [18]. Specifically, passive infrared (PIR) motion sensors have been installed in every room of the apartment, including the living room, bedroom, kitchen and bathroom. Each sensor, at 10 s intervals, reports if motion has been detected within its coverage area. Additionally, a door contact sensor has been installed on the main door to report every door opening or closing event. Together with the motion sensors, we can monitor if the elderly is in or out of home, as well as their daily living patterns observed by sensor data at home, in an unobtrusive manner.

In order to obtain ground truth such as daily routines, unusual events etc., two researchers conduct home visits to the elderly homes twice a month from the day of the installation of the system. Further, a survey has been conducted in early 2016 to gather information pertaining to participants' demographics and wellbeing. The survey comprised of questions to assess participants in terms of both the physical and mental health wellbeing. The main aspects of the survey include: demographic characteristics, social isolation, depression, cognition, physical health status and subjective wellbeing. Although the system has been installed since 2015, we limit the scope of this study to 7 months (January 2016 to July 2016). Further, at the quantitative data analysis stage, we have considered sensor data from two months prior to the survey date of the particular elderly.

Social isolation. Social isolation has been defined and explored in myriad ways in past literature. It is often referred to the lack of interpersonal contacts with the society [11]. On the other hand, loneliness refers to the subjective state of negative feelings associated with perceived social isolation [19]. In this study we measure social isolation as a combination of three factors: (1) relative lack of a social network, including both family and friends, (2) the subjective loneliness and (3) attendance in social activities. All dimensions were assessed using self-reported measures.

First, the presence of a social network was measured using the Lubben Social Network Scale [20]. This scale includes questions to evaluate the family and friendship network of individuals. The scale includes questions such as: 'How many relatives do you see or hear from at least once a month?' and 'How many friends do you feel close to such that you could call on them for help?' Second, loneliness of elderly was subjectively measured using the De Jong Gierveld Loneliness Scale [3]. All items were measured using a five-point likert-scale with anchors from 'strongly disagree' to 'strongly agree'. It is a multidimensional measure of loneliness, which consists of two factors encompassing 6 emotional loneliness items and 5 social loneliness items. In this study, we refer to emotional loneliness as the absence of an attachment figure in one's life and someone to turn to. On the other hand, social loneliness refers to the absence of an acceptable social network that can provide a sense of belonging, of companionship and of being a member of a community [3, 21].

Items under emotional loneliness include questions such as: 'I miss having people around me' and 'I miss the pleasure of the company of others,' and social loneliness items include: 'There are plenty of people I can lean on when I have problems' and

‘There are enough people I feel close to.’ Finally, elderly’s frequency of attendance in four activities was surveyed to derive a score on their social functions. Specifically, the survey included questions on their frequency of meeting friends, visiting family, attending religious activities and having meals outside.

Geriatric depression. Loneliness and depression are often identified to be correlated [22]. The subjective feeling of loneliness as a result of lack of interpersonal contact could lead to the development of depressive symptomatology in the elderly. On the other hand, symptoms of depression could also result in avoidance behavior. Thus, the reciprocal relationship between the depression and the lack of social contact could result in an upward spiral, causing the elderly to become more socially isolated. The geriatric depression was measured using the 15 item Geriatric Depression Scale (GDS) and a cutoff score of 5 was used to screen for the elderly with depressive symptoms [23].

Cognition. Perceived social isolation has been extensively recognized in the literature as a contributing factor to poorer overall cognitive performance, faster cognitive decline and poorer executive functioning [6]. In this study, we assess the cognition using the Abbreviated Mental Test score [24]. The scale is popularly used to assess the elderly for the possibility of cognitive impairment. A score above 7 out of 10 is considered normal.

Other wellbeing indices. Other wellbeing indices that were measured in the survey include subjective sleep quality, chronic conditions, Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL). Past studies have shown the association between social isolation and the quality of sleep [7]. Therefore, factors such as sleep duration, daytime tiredness, napping and the quality of night time sleep can be used as important indicators when detecting the socially isolated elderly. In our survey, we measure the subjective sleep quality using the items of Pittsburgh Sleep Quality Index (PSQI) [25]. Independence in performing activities of daily living and instrumental activities of daily living were assessed using the Katz, et al. [26] and Lawton and Brody [27] respectively.

2.2 Feature Extraction

There are several aspects of elderly daily living that can be inferred using an in-home sensor-based monitoring system. In SHINESeniors project, we have designed algorithms to derive elderly’s behavioral patterns such as sleep, going out and toileting from sensor readings. Then we use different features derived from sensor data to examine the association with elderly’s social isolation level.

Going out. We consider that the elderly has gone out if the flat is empty, i.e., no motion is detected between consecutive door contact events of duration longer than 30 min but less than 24 h. Two measures were derived based on the going-out pattern: average daily away duration and the number of times the elderly went out (away count).

Sleep. The sleep duration was calculated based on the bedroom sensor and personalized to living habits of the elderly. If the elderly is sleeping in the room, the number of sensor firings should be very low. Assuming one sleep event last for at least 30 min, the elderly is identified as sleeping if there is no motion detected in any other area of the flat other than the bedroom for 30 min. After identifying the sleep intervals objectively, findings were compared against the subjective data collected through surveys and ground truth data collected regularly through observations. Two features were derived from the sleep intervals: (1) day time napping duration was calculated using the sum of all sleep durations between 7 am and 7 pm and (2) night time sleeping duration was calculated based on the sleep durations after 7 pm and before 7 am.

Time spent in the living room. Individuals who are alone may spend prolonged periods of time in the living room watching TV, reading or just relaxing on the sofa. Therefore, the time spent in the living room could be an indicator of the elderly's overall activity level and thus may relate to their subjective isolation level. As with the sleep duration assessment, the time spent in the living room was determined based on the sensor signal in the living room, but without considering minimum time duration.

Activity level in the kitchen. The ability to perform activities of daily living is often related to the perceived loneliness level of individuals [28]. Elderly who are fully independent in performing activities of daily living are likely to perform more household chores, thus triggering more sensor signals. Therefore, the total count of sensor firings from the kitchen sensor was captured as an indicator of the activities elderly perform in the kitchen area. When the elderly is active in a particular area of the flat, the number of sensor firings has to be higher than when the elderly is stationary.

2.3 Data Analysis

The main analysis has been carried out in two stages: (1) analysis of the relationship between the sensor-derived features, wellness indices and social isolation measures and (2) qualitative analysis of elderly's daily living patterns observed by sensor data. First, the Pearson product-moment r correlation is computed to investigate the factors associated with social isolation dimensions, as it provides a bivariate measure of the relationship strength between two variables. The association of social isolation dimensions with the survey indices and sensor-derived features were examined at this stage of the analysis. Second, a more in-depth qualitative analysis has been carried out to validate the findings of the quantitative analysis. Specifically, individual elderly profiles which are generated using data gathered by periodic observations, interviews and the survey were examined against the long-term sensor-derived daily living patterns to identify trends of socially isolated elderly. Figure 1 illustrates the process of data analysis and validation.

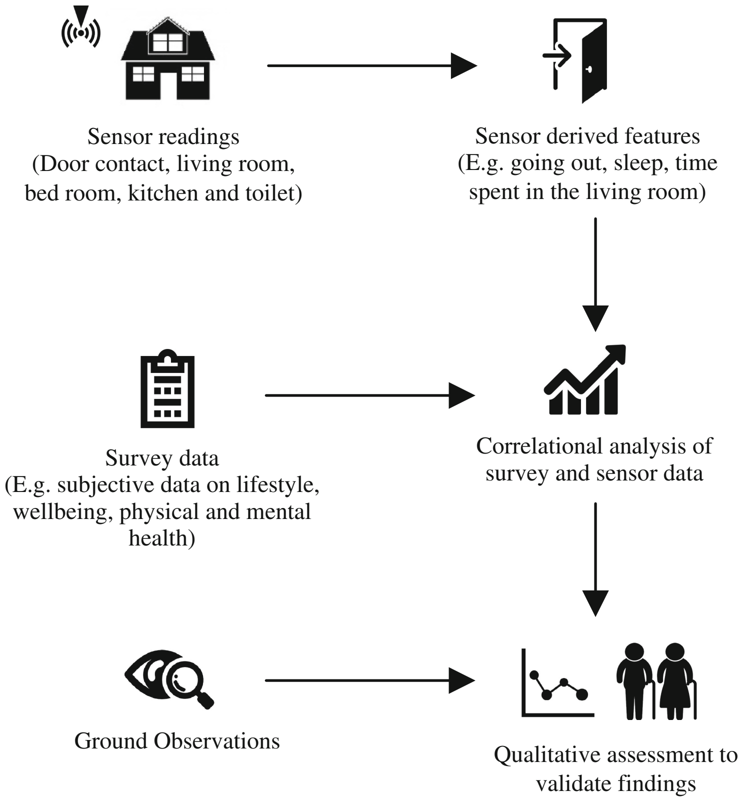

Fig. 1. Process diagram of the data analysis

3 Results and Findings

3.1 Descriptive Statistics

Table 1 illustrates the demographic characteristics of 46 elderly who participated in the survey, out of 50 elderly participants of the project. All 46 elderly were within the age range of 60 to 91 and 27 were female and 19 were male. The majority of the elderly were of Chinese descent (87%), had no formal (39%) or only primary (39%) education and only 3 were married at the time of the survey. Further, only one elderly performed poorly in AMT (<5) test, indicating cognitive impairment, while 16 elderly showed GDS score of 5 or above. Therefore, in subsequent quantitative analysis, we have not considered the AMT scores of the elderly.

Table 1. Demographic statistics

Demographic characteristic	Category	Number of elderly	Percentage %
Age group	60–64	3	6.5
	65–74	12	26.0
	75–84	25	54.3
	85 and above	6	13.0
Gender	Female	27	57.8
	Male	19	42.2
Race	Chinese	40	87.0
	Malay	2	4.3
	Indian	2	4.3
	Others	2	4.3
Language	English	13	28.2
	Mandarin	12	26.1
	Malay	1	2.2
	Tamil	1	2.2
	Dialect	19	41.3
Education	No formal qualifications	18	39.1
	Primary (PSLE)	18	39.1
	Secondary	9	19.6
	Junior College	1	2.2
	Diploma	0	–
	Degree or higher	0	–
Marital status	Single (never married)	18	39.1
	Currently married	3	6.5
	Separated	1	2.2
	Divorced	9	19.6
	Widowed	15	32.6

The distribution of the loneliness score and the social networking score is presented in the Fig. 2. The total loneliness score was calculated based on two factors, subjective social loneliness and emotional loneliness levels. The Fig. 2 illustrates the normalized scores of total loneliness level and social networking. According to the graph, elderly who have a low social network tend to perceive higher loneliness levels.

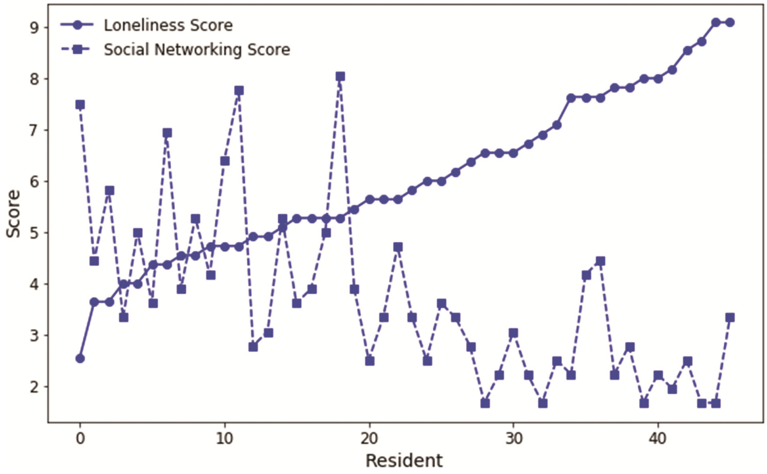

Fig. 2. Distribution of the loneliness and social network

3.2 Social Isolation and Sensor-Derived Features

Table 2 shows the results of the correlation analysis. The table shows the correlations between the sensor-derived features, wellness indices derived by the survey and the social isolation dimensions (i.e., emotional loneliness, social loneliness and social networking scores). The overall social isolation score was calculated based on the loneliness scores (emotional and social loneliness), social network and attendance in social activities. A composite score of social isolation was computed based on the standard loadings of each dimension. Thus, the composite social isolation is a weighted score of three dimensions which could measure one's overall isolation level.

Results showed that the average daily away duration is negatively correlated with the social loneliness score ($p < 0.05$) and the social isolation score ($p < 0.01$) and positively correlated with the social networking score ($p < 0.05$). In a related work by Austin, et al. [29], the time out duration was related to the overall perceived loneliness level using the UCLA loneliness scale [30], a unidimensional measure of the perceived loneliness [21]. However, according to our results, average daily away duration is associated with the social loneliness, a component of the multi-dimensional loneliness, but did not show a strong association with the emotional loneliness.

Further, time spent in the living room is significantly correlated with the emotional loneliness score ($p < 0.05$). This suggests that the elderly who lack of an attachment figure or who do not have anyone to turn to when they need emotional comfort, would spend more time in the living room. Daytime napping duration showed a significant and positive correlation with social loneliness ($p < 0.05$), suggesting that the elderly who lack a sense of belonging or companionship tend to sleep more during the day time.

Geriatric Depression Score (GDS) showed a significant positive correlation with all social isolation dimensions and the overall social isolation score. IADL and the sleep quality (PSQI) scores showed significant correlation with the emotional loneliness score.

The correlation analysis showed that the average daily away duration of elderly is strongly associated with the social isolation score. Figure 3 shows the correlation of both variables. As we could see from the figure, two variables are negatively correlated and the coefficient shows high significance ($r = -0.43$, $p < 0.01$), i.e., elderly who are more isolated spent less time outside the home. This is consistent with the findings of Austin, et al. [29] and Petersen, et al. [31] which show the association between the perceived loneliness and the time spent outside the home.

Table 2. Results of the correlation analysis

Sensor-derived feature	Emotional loneliness	Social loneliness	Social network	Social isolation score
Average daily away duration	−0.22 (0.144)	**−0.38* (0.011)**	**0.31* (0.037)**	**−0.42** (0.005)**
Away count	0.13 (0.392)	−0.10 (0.503)	−0.07 (0.656)	0.08 (0.606)
Napping duration	−0.08 (0.597)	**0.32* (0.038)**	−0.26 (0.101)	−0.05 (0.777)
Night time sleep duration	−0.12 (0.448)	0.24 (0.133)	−0.14 (0.373)	−0.16) (0.297
Average time spent in the living room	**0.31* (0.049)**	−0.01 (0.973)	−0.23 (0.149)	0.17 (0.292)
Kitchen activity	−0.11 (0.48)	0.03 (0.854)	0.03 (0.852)	0.10 (0.508)
Gender	0.09 (0.534)	−0.08 (0.611)	0.14 (0.374)	0.17 (0.255)
Geriatric Depression Score (GDS)	**0.49*** (0.001)**	**0.50*** (0.000)**	**−0.34* (0.021)**	**0.59*** (0.000)**
Instrumental activities of daily living (IADL)	**−0.31* (0.042)**	−0.15 (0.33)	0.20 (0.193)	−0.27 (0.067)
Sleep Quality (PSQI)	**0.35* (0.021)**	0.25 (0.101)	−0.25 (0.092)	0.29 (0.053)

P values are in parenthesis
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

The correlation analysis highlighted the factors that are associated with social isolation dimensions. Next, a qualitative analysis of the daily living patterns of elderly, based on the sensor-derived features and ground truth data gathered through the survey and periodic visits, was carried out to validate the findings of the correlation analysis.

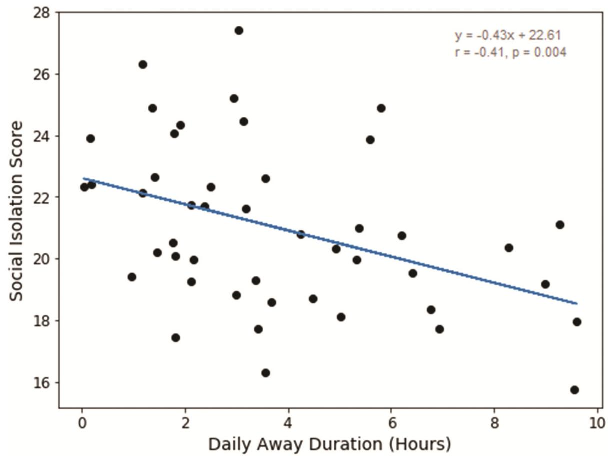

Fig. 3. The relationship between the social isolation score and the daily away duration

3.3 Qualitative Analysis

Going Out Patterns and Social Isolation. Long-term trends of the elderly's going out patterns, defined by the away frequency and durations, could reveal changes in their perception of social isolation. Further, our quantitative analysis revealed a significant correlation between the away duration and the social isolation level. Hence, to gain a relative idea of one's social isolation level with respect to the community, we can compare the going out patterns of each elderly against the average going out pattern of all the elderly in the sample. As all the elderly live in the same neighborhood, external factors such as community activities, seasonal effect and weather changes, which could influence the going out behavior, are common for all the elderly.

The case of two elderly is illustrated in this section using multiple data sources to triangulate the results. Figure 4 illustrates their weekly going out frequency and away duration. As can be seen in Fig. 4, going out trend consistently lies below the average of the community, except for one week. The social and emotional loneliness levels of elderly 1 were 21 and 23 respectively (community medians: 15 and 17), which were significantly above the average loneliness level of the community. Further, the GDS score showed that she suffers from mild depression. Face-to-face interviews revealed that the elderly had suicidal thoughts and would like to stay home and watch TV during the day. On the other hand, elderly 2 perceived a moderately well loneliness level (social loneliness 19 and emotional loneliness 14), but had a poor social network. The going out duration of the elderly showed a downward trend over time. Ground observations revealed that the elderly suffers from lack of social connections as her children have stopped visiting or calling her. Such qualitative observations provide ground truth evidence for the association between the going-out pattern and the social isolation level.

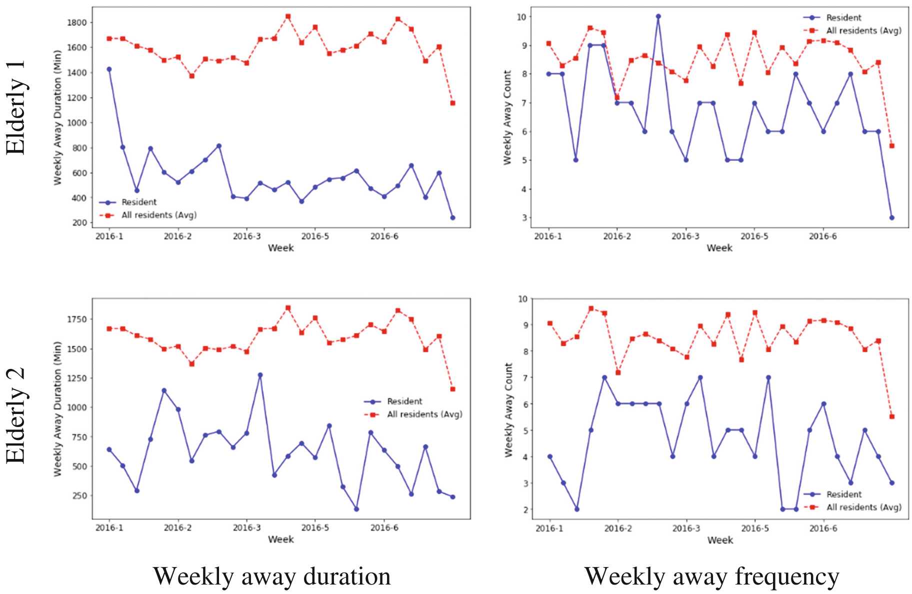

Fig. 4. Going out pattern

Daily In-home Living Patterns and Social Isolation. In this section, we analyze the elderly's in-home daily living patterns observed by sensor data and the social isolation dimensions. Our correlation analysis revealed that, the time spent in the living room is associated with the emotional loneliness and the day-time napping duration (sleep between 7:00 am and 7:00 pm) is associated with the social loneliness level. Therefore, we have qualitatively examined elderly's in-home behavior detected by PIR sensors (i.e. bedroom, bathroom, living room and kitchen sensors) to identify how different loneliness levels can be reflected in their daily living patterns.

As discussed above, elderly 2 showed moderately high loneliness levels and a poor social networking score and a going out pattern that was below the community average. Therefore, we have analyzed elderly 2's daily living pattern in-depth to apply our findings. The heat maps in Fig. 5 show the daily living patterns of the elderly 2 captured by each sensor. Signals of sensors in each area was aggregated on an hourly basis to generate the heat maps. Thus, areas with lighter shades represent high activity time periods. From the heat map of the bed room sensor, it is evident that this elderly had consistently stayed in the bedroom from midnight until after 10:00 am. The survey data revealed that, the elderly usually wakes up at 8:00 am but frequently goes back to sleep after waking up in the morning, thus starting the day very late. After waking up in the morning and using the bathroom, she would mostly stay in the living room area and the kitchen.

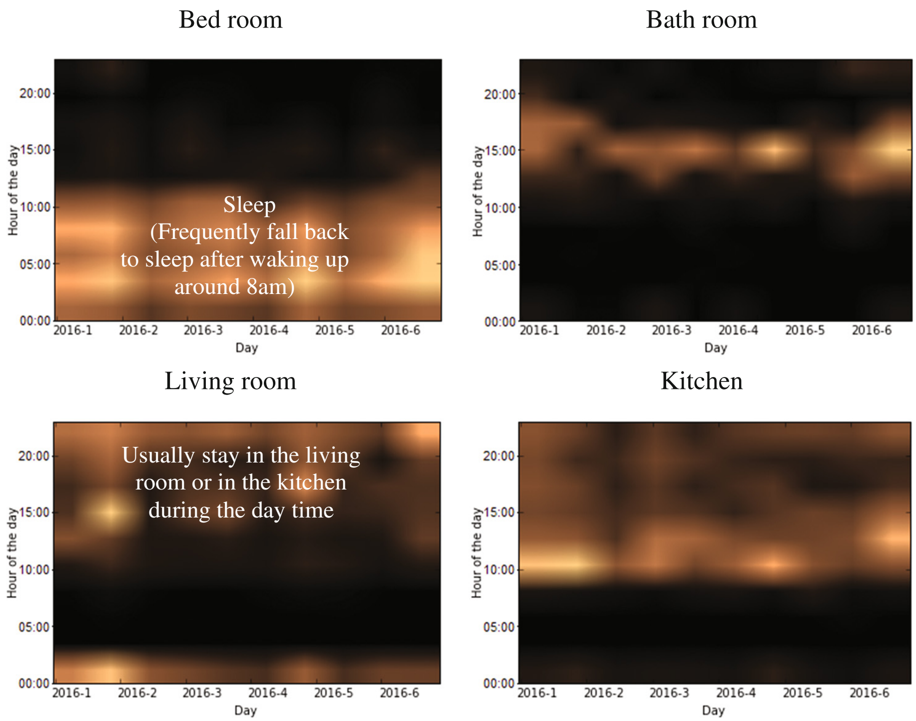

Fig. 5. Daily living pattern of elderly 2

4 Conclusion

This study used a mixed method approach to detect elderly who are at risk of social isolation using in-home sensors. Our results showed that the average time spent outside home is associated with the social loneliness and the social networking score of the elderly. Further, elderly who perceived themselves as socially lonely have taken more naps during the daytime. Average time spent in the living room was significantly associated with the perceived emotional loneliness level of the elderly. We also correlated the overall social isolation level calculated based on the social and emotional loneliness, social network and attendance in social activities, with the daily away duration and results showed a linear negative relationship.

The qualitative analysis of the in-home daily living patterns observed by sensor data validated the findings of the correlation analysis. In-home behavior and going out behavior captured by the motion sensors and the door contact sensor revealed different patterns for elderly with different perceived social isolation levels. However, there can be other confounding factors, which influence both the social isolation and their behavioral patterns. Further, as highlighted by Petersen, et al. [31], it is also possible that some elderly do not experience loneliness but display somewhat similar daily living patterns.

Therefore, when determining social isolation, a model including plausible confounding variables such as depression or mobility could give better results.

The ability to detect socially isolated elderly, solely by observing their daily living patterns through sensor data, is important for the provision of care. Our study is an attempt to detect socially isolated, community dwelling elderly living alone, using a minimum number of in-home sensors. Our results provide implications on how the sensor-based monitoring systems can be utilized to detect elderly who are at risk of social isolation, using motion-sensors and a door contact sensor. The caregivers should look into the individual daily living patterns and specific circumstances in order to design interventions to improve social functions of elderly living alone.

This study used cross-sectional data to examine the association between sensor-derived features and social isolation dimensions. As the quantitative analysis is based on bivariate correlations, our findings did not establish the causality of the relationships. Future research will be carried out to apply multivariate estimation models to identify the predictors of social isolation. Moreover, longitudinal analysis using multiple waves of data could establish the causal relationship between variables. Therefore, longitudinal analysis using the data gathered through follow-up surveys will be carried out in the future.

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