Short: Integrated Sensing Platform for Detecting Social Isolation and Loneliness In the Elderly Community

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ABSTRACT

Social isolation is an objective absence or paucity of contacts and interactions between a person and a social network. Loneliness is a subjective feeling of being alone, separated, or apart from others. These two highly correlated mental health concerns significantly increase the elderly’s risk of premature death from all causes, a risk that may rival those of smoking, obesity, and physical inactivity. In this work, we propose an integrated design for technology usage to tackle the aforementioned mental healthcare concerns involving the elderly community. The technology infrastructure is an Internet-of-Things (IoT) monitoring system aiming to detect social isolation and promptly predict the risk of loneliness. With our system, interventions can be developed to maintain the mental well-being of the elderly, a salient need due to the social disruptions incurred by COVID-19.

1 INTRODUCTION

Social isolation is a status of lacking social contact or support. It is an objective measure that captures the lack of connections and interactions between people and their social networks. On the other hand, loneliness is a subjective feeling associated with feelings of isolation or detachment due to being alone. It is a mismatch between expected social contacts and real social contacts. Social isolation and loneliness are mental health concerns in gerontology with severe impacts. For example, premature death, dementia, heart disease, stroke, depression, anxiety, and suicide are all potential impacts of social isolation or loneliness [24]. Specifically, social isolation is associated with a 50% increase in the risk of dementia, while loneliness is associated with a higher chance of depression, anxiety, and suicide. In addition, loneliness increases the vulnerability to chronic disease by 41% and a higher risk of death in heart failure patients by four times [24]. Due to the preventative measures during the COVID-19 pandemic, many elderly community organizations were...
shut down, and the elderly were constrained from visits with family members, which significantly restricted their social participation [8]. Therefore, the decreasing social interaction caused by social distancing could negatively impact the mental and physical health of the elderly [33].

This work aims to support the prognosis and diagnosis of loneliness and social isolation in the elderly community and suggest targeted personalized interventions. To create an infrastructure to support this, we encounter many challenges, including limited applicable sensing implementations, the elderly’s lack of familiarity and resistance to technology, energy efficiency, and privacy.

Questionnaire [7] is straightforward for diagnosing loneliness and social isolation. However, it imposes an additional burden on those being monitored. Therefore, we propose using sensors that can monitor the mental status of the elderly directly and indirectly. Thus far, existing works [35] target a limited number of aspects that explain social isolation and loneliness. Therefore, we adopt a systematic method to categorize and monitor a comprehensive list of variables. As we age, staying up to date with the newest technologies becomes increasingly challenging. Thus, the person and sensor interaction should be simple and require minimal operation. At the device level, day-to-day monitoring poses a stringent requirement on the battery of sensors. Hence, the sensor suites should be energy efficient and not require frequent battery replacement. Finally, collecting sensor data brings privacy or data leakage concerns which should be addressed through sensor selection.

In this work, we propose an integrated sensor and questionnaire platform to comprehensively capture and quantify the mental health status of the elderly. Our sensor suite seeks to combine various sensing methods to get a more holistic view of the elderly and their habits to prevent mental health concerns while being both energy-efficient and privacy-preserving. We summarize our contributions toward this goal as follows:

1. We conduct a comprehensive related work search and systematically analyze factors correlated with social isolation and loneliness;
2. We derive seven critical variables based on related work search and regression analysis to guide our design;
3. We propose an integrated IoT platform to holistically monitor the mental health status of the elderly.

The rest of the paper is structured as follows. First, we start with Section 2 to summarize the related work of metrics for loneliness and social isolation, together with existing sensing methodologies. Then, in Section 3 we identify the critical variables to monitor using systematic categorization and regression analysis. Next, in Section 4, we propose a sensing suite design that comprehensively monitor the mental health status of the elderly. Finally, we discuss potential limitations in Section 5 and conclude our work in Section 6.

3 CRITICAL VARIABLE IDENTIFICATION

To determine the most relevant variables to monitor, we conduct a regression analysis on the National Social Life, Health, and Aging Project (NSHAP) dataset [17]. This dataset is a population-based study of health and social factors on a national scale, aiming to understand the well-being of community-dwelling elderly. It published three rounds of data in 2005–06, 2010–11, and 2015–16, with 3005, 3377, and 4777 interviews, respectively, having a response rate of over 74%. While this dataset contains many variables we identified in Section 2, it limits our analysis with its lack of sensor data that captures mobility, sleep quality, activity level, and home usage. UCLA Loneliness Scale [30] is provided and thus used as ground truth in this analysis.

3.1 Systematic Categorization

We categorize the variables into mediating, and moderating variables [3]. A mediating variable (or mediator) explains the process through which two variables are related, while a moderating variable (or moderator) affects the strength and direction of that relationship. Although we adopt the mediator-moderator categorization, we do not argue for the existence of a causal relationship. Instead, we seek to systematically review the correlated variables and identify the critical ones to monitor.

Mediators: In the case of social isolation, loneliness, and their effect on health, we summarize the following mediators. First, substantial evidence links loneliness, social isolation, and social support to changes in cardiovascular [42], neuroendocrine [6] and the immune function [14], and the physiological stress response [13]. A
lack of social connections has been linked to higher levels of inflammation [20], which may point to a plausible biological mechanism for associating social isolation and loneliness with various adverse health outcomes. Second, social isolation and loneliness have been linked to decreased sleep quality [44, 15], which can influence multiple physical health conditions, including cardiovascular disease, weight gain, obesity, diabetes, metabolic syndrome, and increased risk for mortality. Finally, mobility pattern [34] and physical activity level [16] are also commonly identified mediators of social isolation and health.

**Moderators:** On the other hand, we also come across many moderators. There is evidence that demographic factors moderate the influence of social connection and health [28, 29], such as ethnicity, Socioeconomic Status (SES). Recent evidence suggests that social isolation and loneliness may carry a higher risk among those under age 65 than those over age 65 [38]. However, no reliable gender differences have emerged. In Figure 1, we summarize the mediator and moderator between social isolation, loneliness, and health.

![Figure 1: Mediators (green box) and moderators (yellow box) for social isolation, loneliness, and health.](image)

### 3.2 Regression Analysis

Based on systematic categorization in Section 3.1, we select ten mediators and four moderators from the NSHAP dataset, as shown in Table 2. We then run a regression analysis on the ground truth and the selected features to evaluate their feature importance. After applying min-max normalization, we compare the performance of Random Forest (RF) [5], Isolation Forest (IF) [21], Support Vector Regression (SVR) [2], and Multi-layer Perceptron (MLP) [18]. Finally, we use 10-fold cross-validation for evaluations on explained variance (EV), $R^2$ score ($R^2$), and mean squared error (MSE) for testing. The results are shown in Table 3.

We find that weight and cardiovascular parameters are the most important variables to predict change in loneliness. Since RF has the best regression performance for loneliness across three rounds of data collection, we show the feature importance of the RF model in Figure 2. We observe that the change in systolic blood pressure measurement and weight ranked at the top in feature importance. The higher rank indicates a stronger correlation between these variables and loneliness, which does not necessarily suggest causation. However, we conjecture that the correlation coefficient could be sufficient for comparison purposes.

To have a well-rounded understanding of the variables' effects, we then show in Figure 3 the variance of the coefficient of a Ridge regression model with cross-validation to check for the robustness of the variable effect. From Figure 3, we observe that although cardiovascular parameters have a more significant coefficient than weight, weight has a tighter interval, which implies a more robust impact on social isolation and loneliness. Therefore, both weight and cardiovascular metrics should be included in the monitoring platform, but most works on sensing gerontological loneliness tend to overlook them.

### 4 SENSING SUITE DESIGN

Based on the analysis in Section 3, we will pay special attention to weight, blood pressure, and other cardiovascular readings in our monitoring list. In addition, we include sleep behavior, mobility/activity level, and ambient environment based on our related work search. Finally, we design our sensing suite by solving the following challenges: limited applicable sensing implementations, the elderly lack of familiarity and resistance to technology, difficulty acquiring ground truth, energy efficiency, and data privacy.

**Sensing Implementations:** In Table 4, we list the corresponding sensors we use to monitor the variables and their commercial product examples. It is at the users’ discretion to replace the sensor with an alternative within their budgets, for instance, using Fitbit.

![Figure 2: Top ten variables of importance. Variables with ‘c’ are the changes between round 1 and round 2, and variables with ‘c1’ are the changes between round 2 and round 3.](image)

![Figure 3: Variable coefficient variance.](image)

<table>
<thead>
<tr>
<th>Round</th>
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<th>RF</th>
<th>MLP</th>
<th>IF</th>
<th>SVR</th>
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<td>EV</td>
<td>0.9040</td>
<td>0.8585</td>
<td>0.0161</td>
<td>0.8188</td>
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<tr>
<td>$R^2$</td>
<td>0.9037</td>
<td>0.8435</td>
<td>0.0104</td>
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<td>EV</td>
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<tr>
<td>$R^2$</td>
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<td>0.6251</td>
<td>-0.0027</td>
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Table 3: Models comparison. For explained variance and $R^2$ score, the closer to one, the better the model. For the mean squared error, the smaller, the better. The best-performing ones are in bold.
indirectly monitor activities like eating and bathing. In addition, the sensors store data to replace GPS sensors to track activities and mobility. For indirect monitoring, we use the SwicBot Contact Sensor and anonymization of users. Additionally, we monitor our variable strategies include file encryption and decryption, access control, and privacy risks, consent, and participatory feedback. To address these concerns, we plan to conduct a usability test on two international elderly communities, one in the US and the other in Japan. We aim to create a generally applicable system by engaging with these communities.

We recognize the trade-off between collecting more data and respecting user privacy. To balance this, we monitor behaviors indirectly and use converted inference to protect user privacy.

5 DISCUSSION

Our design may have surface-level limitations regarding ethics, privacy risks, consent, and participatory feedback. To address these concerns, we plan to conduct a usability test on two international elderly communities. In the future, we would like to leverage our system for personalized intervention to mitigate loneliness problems for elderly.

7 ACKNOWLEDGMENTS

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REFERENCES

<table>
<thead>
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<th>Variables</th>
<th>Sensor</th>
<th>Example</th>
<th>Monitor</th>
<th>Battery Life</th>
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<td>Weight</td>
<td>Smart scale</td>
<td>Withings Body+</td>
<td>Direct</td>
<td>~18 months</td>
</tr>
<tr>
<td>Blood pressure</td>
<td>Tablet questionnaire</td>
<td>Any Android Tablet</td>
<td>Indirect</td>
<td>N/A</td>
</tr>
<tr>
<td>Cardiovascular</td>
<td>Activity tracker</td>
<td>Withings Move</td>
<td>Indirect</td>
<td>~18 months</td>
</tr>
<tr>
<td>Sleep Quality</td>
<td>Sleep tracking mat</td>
<td>Withings Sleep</td>
<td>Direct</td>
<td>N/A</td>
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<tr>
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<td>Bluetooth LE tag</td>
<td>Tile Mate BLE</td>
<td>Indirect</td>
<td>~36 months</td>
</tr>
<tr>
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<td>Contact sensors</td>
<td>SwitchBot Contact sensor</td>
<td>Indirect</td>
<td>&gt; 94 months</td>
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<tr>
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<td>Temperature and humidity sensors</td>
<td>EnOcean ETHS</td>
<td>Direct</td>
<td>&gt; 60 months</td>
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</table>

Table 4: Variables that our sensor system monitors. Critical variables in bold.