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.

CCS CONCEPTS

• **Applied computing → Health care information systems**; • **Social and professional topics → Seniors**; • **Human-centered computing → Ambient intelligence**.

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KEYWORDS

IoT, social isolation, loneliness, gerontology, machine learning

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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.

2 RELATED WORK

Standard metrics for loneliness include the Lubben Social Network Scale [23], the UCLA Loneliness Scale [30], and the Duke Social Support Index [19]. Each metric's definition of social isolation and loneliness varies slightly. In Table 1, we show the common standard for determining social isolation and loneliness using UCLA loneliness scale [30] and Lubben Social Network Scale [23], which we plan to incorporate into our questionnaire for ground truth.

UCLA Loneliness Scale	Lubben Social Network Scale
20–34 a low degree of loneliness	0-11: at risk for social isolation
35–49 a moderate degree of loneliness	12-30: not at risk for social isolation
50–64 a moderately high degree of loneliness	
65–80 a high degree of loneliness	

Table 1: Ground truth interpretation of the scales.

Existing work predicts social isolation and loneliness with sensors from a multidisciplinary perspective. Previous studies include investigating the anthropocentric data [35], mobility or activity levels [31, 34, 12, 1, 26], daytime napping [12], and interactivity with others [27, 22, 43]. Many sensors are used to extract such patterns, for instance, GPS sensors, contact sensors, Passive Infrared Sensors (PIR), and wearable devices [34, 32]. In addition, the environmental quality [41, 4, 10] and the elderly's Activity of Daily Living (ADL) such as sleep quality [12, 45, 35], and usage of home appliances [45, 41, 4] could also reveal the loneliness status. For example, some works [4, 10, 25] monitor the environmental quality with light and gas sensors. Others [41, 45] use the power and water consumption sensors to capture utility usage. In colder ambient environments, for example, people report greater loneliness, and they pursue both physical warmth and social affiliation [11]. Besides, weather affects people's emotions, which can be captured using humidity and temperature [9]. Thus, our related work search identified mobility, activity, sleep quality, and ambient environment as the expository variables to monitor.

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.

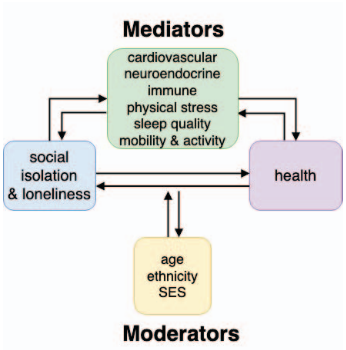

Figure 1: Mediators (green box) and moderators (yellow box) for social isolation, loneliness, and health.

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 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.

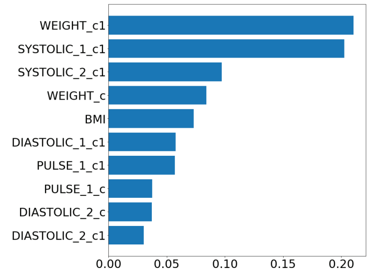

Figure 2: Top ten variables of importance. Variables with '_c' are the changes between round 1 and round 2, and variables with '_c1' are the changes between round 2 and round 3.

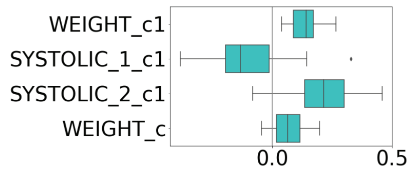

Figure 3: Variable coefficient variance.

Round	Metrics	RF	MLP	IF	SVR
1	EV	**0.9040**	0.8585	0.0161	0.8188
	R^2	**0.9037**	0.8435	0.0104	0.8137
	MSE	**5.3134**	8.6559	54.6782	10.1926
2	EV	**0.7571**	0.6458	0.0087	0.5400
	R^2	**0.7560**	0.6251	-0.0027	0.5342
	MSE	**10.5743**	16.4171	43.7718	20.2421
3	EV	**0.8019**	0.7230	0.0303	0.6557
	R^2	**0.8013**	0.6779	0.0179	0.6516
	MSE	**9.4571**	15.3810	46.8033	16.5033

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.

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

Mediators	Moderators	Ground Truth
SYSTOLIC_1: first systolic value (mm Hg)	GENDER gender of respondent	LEFTOUT: feel left out (4 categories)
SYSTOLIC_2: second systolic value (mm Hg)	AGE age of respondent (calculated in CAPI from dob)	ISOLATED: feel isolated (4 categories)
DIASTOLIC_1: first diastolic value (mm Hg)	BMI body mass index (kg/m^2)	COMPANION: lack companionship (4 categories)
DIASTOLIC_2: second diastolic value (mm Hg)	WEIGHT weight (lbs)	
PULSE_1: final status of first pulse reading	INCOME: household income relative to American families	
PULSE_2: final status of second pulse reading		
IMMUNOSUPPRESSIV: meds: immunosuppressive agents / IMMUNOLOGICAGENT: meds: immunologic agents		
HORMONES: meds: hormones / HORMONESANTINEOP: meds: hormones/antineoplastics		

Table 2: Moderators, mediators and ground truth used for regression analysis.

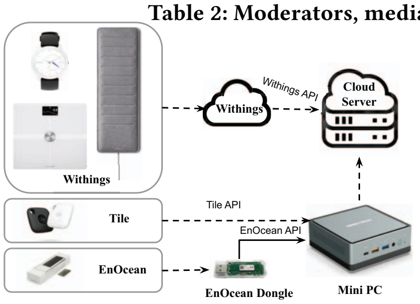

Figure 4: Data flow diagram in the sensor system.

or other smartwatches to replace Withings Move. We show the data flow diagram in the Figure 4. Overall, our sensor system will target the known factors of social isolation and loneliness: physiological measurements, sleep quality, indoor and outdoor mobility/activity level, and home usage.

Ease of Use of the Technology: Considering the unfamiliarity of using technology for the elderly, we focus on sensors that provide passive sensing and require minimal operation while setting up the sensor system. For instance, we will place a Withings Sleep tracking mat under the mattress in the bed to monitor the sleeping behaviors like going to sleep and getting up. The elderly can go about their daily routines without being interrupted by passive sensors.

Ground Truth: Questionnaires to collect ground truth run into accuracy and compliance challenges. Thus we will pre-install and provide a questionnaire application on Android tablets, which includes two ground truth metrics for accuracy, i.e., UCLA Loneliness Scale and Lubben Social Network Scale. In addition, a timely reminder via notification will be presented to remind the participants to complete the questionnaire.

Energy Efficiency: To make our sensors as seamless as possible for the elderly, we avoid battery changes and charging in favor of energy-efficient devices. For instance, the Withings Body+ smart scale [39] and Withings Move smartwatch [40] have an approximate battery life of as long as 18 months. The Tile Mate tag has an expected battery life of three years. The battery life of each device is shown in Table 4.

Data Privacy: We encourage data privacy by employing security strategies and monitoring variables indirectly. The security strategies include file encryption and decryption, access control, and anonymization of users. Additionally, we monitor our variable indirectly. As an illustration, we use the SwictBot Contact Sensors [36] to replace GPS sensors to track activities and mobility. For example, we attach contact sensors to the fridge and bathroom to indirectly monitor activities like eating and bathing. In addition, the Tile Mate BLE tag [37] can be attached to regularly used items like a handbag for presence detection, i.e., whether an elderly is indoors or outdoors, without revealing the precise location information.

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, 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.

6 CONCLUSION

In this work, we target the problem of diagnosing loneliness and isolation in the elderly community. To start with, we systematically review the factors correlated with social isolation and loneliness in the elderly. Then we run a regression analysis to derive the critical variables based on the NSHAP dataset. Finally, we propose an integrated sensor system design that could comprehensively monitor the mental health status of the elderly, addressing the challenges we discover for technology usage in elderly monitoring. As a next step, we plan to conduct usability testing to gather feedback on the design. Then, we will apply the sensor setup for two international elderly communities to collect data and evaluate the usefulness of our system. In the future, we would like to leverage our system for personalized intervention to mitigate loneliness problems for elderly.

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REFERENCES

[1] Johanna Austin, Hiroko H Dodge, Thomas Riley, Peter G Jacobs, Stephen Thielke, and Jeffrey Kaye. 2016. A smart-home system to unobtrusively and continuously assess loneliness in older adults. *IEEE journal of translational engineering in health and medicine*, 4, 1–11.

[2] Mariette Awad and Rahul Khanna. 2015. Support vector regression. In *Efficient learning machines*. Springer, 67–80.

[3] Reuben M Baron and David A Kenny. 1986. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, 51, 6, 1173.

Variables	Sensor	Example	Monitor	Battery Life
Weight	Smart scale	Withings Body+	Direct	~18 months
Blood pressure	Tablet questionnaire	*Any Android Tablet*	Indirect	N/A
Cardiovascular	Activity tracker	Withings Move	Indirect	~18 months
Sleep Quality	Sleep tracking mat	Withings Sleep	Direct	N/A
Outdoor Mobility	Bluetooth LE tag	Tile Mate BLE	Indirect	~36 months
Indoor Activity	Contact sensors	SwitchBot Contact sensor	Indirect	> 94 months
Ambient environment	Temperature and humidity sensors	EnOcean ETHS	Direct	> 60 months

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

[4] Mohamed Bennasar et al. 2019. A sensor platform for non-invasive remote monitoring of older adults in real time. In *Innovation in Medicine and Healthcare Systems, and Multimedia*. Springer, 125–135.

[5] Leo Breiman. 2001. Random forests. *Machine learning*, 45, 1, 5–32.

[6] John T Cacioppo, Stephanie Cacioppo, John P Capitanio, and Steven W Cole. 2015. The neuroendocrinology of social isolation. *Annual review of psychology*, 66, 733.

[7] Caitlin E Coyle and Elizabeth Dugan. 2012. Social isolation, loneliness and health among older adults. *Journal of aging and health*, 24, 8, 1346–1363.

[8] Thomas KM Cudjoe and Ashwin A Kotwal. 2020. "social distancing" amid a crisis in social isolation and loneliness. *Journal of the American Geriatrics Society*.

[9] Jaap JA Denissen, Ligaya Butalid, Lars Penke, and Marcel AG Van Aken. 2008. The effects of weather on daily mood: a multilevel approach. *Emotion*, 8, 5, 662.

[10] Satu Elo, Reetta Saarnio, and Arja Isola. 2011. The physical, social and symbolic environment supporting the well-being of home-dwelling elderly people. *International Journal of Circumpolar Health*, 70, 1, 90–100.

[11] Adam J Fay and Jon K Maner. 2019. Interactive effects of tactile warmth and ambient temperature on the search for social affiliation. *Social Psychology*.

[12] Nadee Goonawardene, XiaoPing Toh, and Hwee-Pink Tan. 2017. Sensor-driven detection of social isolation in community-dwelling elderly. In *International Conference on Human Aspects of IT for the Aged Population*. Springer, 378–392.

[13] Nina Grant, Mark Hamer, and Andrew Steptoe. 2009. Social isolation and stress-related cardiovascular, lipid, and cortisol responses. *Annals of Behavioral Medicine*, 37, 1, 29–37.

[14] Louise C Hawkley and John T Cacioppo. 2003. Loneliness and pathways to disease. *Brain, behavior, and immunity*, 17, 1, 98–105.

[15] Louise C Hawkley and John T Cacioppo. 2010. Loneliness matters: a theoretical and empirical review of consequences and mechanisms. *Annals of behavioral medicine*, 40, 2, 218–227.

[16] Louise C Hawkley, Ronald A Thisted, and John T Cacioppo. 2009. Loneliness predicts reduced physical activity: cross-sectional & longitudinal analyses. *Health psychology*, 28, 3, 354.

[17] Louise C Hawkley and Linda J Waite. 2022. National social life, health, and aging project (NSHAP). In *Encyclopedia of Gerontology and Population Aging*. Springer, 3394–3401.

[18] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2015. Delving deep into rectifiers: surpassing human-level performance on imagenet classification. (2015). DOI: 10.48550/ARXIV.1502.01852.

[19] Harold G Koenig, Ron E Westlund, Linda K George, Dana C Hughes, Dan G Blazer, and Celia Hybels. 1993. Abbreviating the duke social support index for use in chronically ill elderly individuals. *Psychosomatics*, 34, 1, 61–69.

[20] Carrianne J Leschak and Naomi I Eisenberger. 2019. Two distinct immune pathways linking social relationships with health: inflammatory and antiviral processes. *Psychosomatic medicine*, 81, 8, 711.

[21] Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. 2008. Isolation forest. In *2008 eighth ieee international conference on data mining*. IEEE, 413–422.

[22] Pengcheng Liu, Sing-Kiong Nguang, and Ashton Partridge. 2015. Occupancy inference using pyroelectric infrared sensors through hidden markov models. *IEEE Sensors Journal*, 16, 4, 1062–1068.

[23] James Lubben, Eva Blozik, Gerhard Gillmann, Steve Iliffe, Wolfgang von Renteln Kruse, John C Beck, and Andreas E Stuck. 2006. Performance of an abbreviated version of the lubben social network scale among three european community-dwelling older adult populations. *The Gerontologist*, 46, 4, 503–513.

[24] National Academies of Sciences, Engineering, and Medicine and others. 2020. *Social isolation and loneliness in older adults: Opportunities for the health care system*. National Academies Press.

[25] Yu Jin Park, Seol Young Jung, Tae Yong Son, and Soon Ju Kang. 2021. Self-organizing iot device-based smart diagnosing assistance system for activities of daily living. *Sensors*, 21, 3, 785.

[26] Johanna Petersen, Daniel Austin, Jeffrey A Kaye, Misha Pavel, and Tamara L Hayes. 2013. Unobtrusive in-home detection of time spent out-of-home with applications to loneliness and physical activity. *IEEE journal of biomedical and health informatics*, 18, 5, 1590–1596.

[27] Johanna Petersen, Nicole Larimer, Jeffrey A Kaye, Misha Pavel, and Tamara L Hayes. 2012. Svm to detect the presence of visitors in a smart home environment. In *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 5850–5853.

[28] Jo C Phelan and Bruce G Link. 2015. Is racism a fundamental cause of inequalities in health? *Annual Review of Sociology*, 41, 311–330.

[29] Jo C Phelan, Bruce G Link, and Parisa Tehranifar. 2010. Social conditions as fundamental causes of health inequalities: theory, evidence, and policy implications. *Journal of health and social behavior*, 51, 1_suppl, S28–S40.

[30] Daniel W Russell. 1996. Ucla loneliness scale (version 3): reliability, validity, and factor structure. *Journal of personality assessment*, 66, 1, 20–40.

[31] Stephanie Schrempft, Marta Jackowska, Mark Hamer, and Andrew Steptoe. 2019. Associations between social isolation, loneliness, and objective physical activity in older men and women. *BMC public health*, 19, 1, 1–10.

[32] Narayan Schütz et al. 2021. A sensor-driven visit detection system in older adults' homes: towards digital late-life depression marker extraction. *IEEE Journal of Biomedical and Health Informatics*, 26, 4, 1560–1569.

[33] W Sepúlveda-Loyola, I Rodrıguez-Sánchez, P Pérez-Rodrıguez, F Ganz, R Torralba, DV Oliveira, and Leocadio Rodrıguez-Mañas. 2020. Impact of social isolation due to covid-19 on health in older people: mental and physical effects and recommendations. *The journal of nutrition, health & aging*, 24, 9, 938–947.

[34] Aditi Site, Saigopal Vasudevan, Samuel Olaiya Afolaranmi, Jose L Martinez Lastra, Jari Nurmi, and Elena Simona Lohan. 2022. A machine-learning-based analysis of the relationships between loneliness metrics and mobility patterns for elderly. *Sensors*, 22, 13, 4946.

[35] Aditi Site et al. 2022. Managing perceived loneliness and social-isolation levels for older adults: a survey with focus on wearables-based solutions. *Sensors*, 22, 3, 1108.

[36] 2022. Switchbot contact sensor. https://us.switch-bot.com/products/contact-sensor.

[37] 2022. Tile mate ble tag. https://www.tile.com/product/mate-2-pack?categorySlug=tile-mate.

[38] Christina Victor, Sasha Scambler, John Bond, and Ann Bowling. 2000. Being alone in later life: loneliness, social isolation and living alone. *Reviews in Clinical Gerontology*, 10, 4, 407–417.

[39] 2022. Withings body+ smart scale. https://www.withings.com/us/en/body-plus.

[40] 2022. Withings move smartwatch. https://www.withings.com/us/en/withings-move/.

[41] Przemyslaw Woznowski et al. 2015. A multi-modal sensor infrastructure for healthcare in a residential environment. In *2015 IEEE International Conference on Communication Workshop (ICCW)*. IEEE, 271–277.

[42] Ning Xia and Huige Li. 2018. Loneliness, social isolation, and cardiovascular health. *Antioxidants & redox signaling*, 28, 9, 837–851.

[43] Masahiro Yoshida, Sofia Kleisarchaki, Levent Gtirgen, and Hiroaki Nishi. 2018. Indoor occupancy estimation via location-aware hmm: an iot approach. In *2018 IEEE 19th International Symposium on" A World of Wireless, Mobile and Multimedia Networks"(WoWMoM)*. IEEE, 14–19.

[44] Bin Yu, Andrew Steptoe, Kaijun Niu, Po-Wen Ku, and Li-Jung Chen. 2018. Prospective associations of social isolation and loneliness with poor sleep quality in older adults. *Quality of Life Research*, 27, 3, 683–691.

[45] Nadia Zouba, François Brémond, Monique Thonnat, Alain Anfosso, Eric Pascual, Patrick Mallea, Veronique Mailland, and Olivier Guerin. 2009. A computer system to monitor older adults at home: preliminary results. *Gerontechnology*, 8, 3, 129–139.