iCareLoop: Data Management System for Monitoring Gerontological Social Isolation and Loneliness

Xiayan Ji[1], Ahhyun Yuh[1], Hyonyoung Choi[1], Viktor Erdélyi[2], Teruhiro Mizumoto[2,3], Sean Lee Harrison[1], James Weimer[4], George Demiris[1], Takeshi Nakagawa[6], Takashi Suehiro[2], Yasuyuki Gondo[2], Hajime Nagahara[2], Oleg Sokolsky[1], Teruo Higashino[2,5], Insup Lee[1]

1. University of Pennsylvania, U.S., 2. Osaka University, Japan, 3. Chiba Institute of Technology, Japan,
4. Vanderbilt University, U.S., 5. Kyoto Tachibana University, Japan, 6. National Center for Geriatrics and Gerontology, Japan.

{xjiae, lucy0828, hyonchoi}@seas.upenn.edu, viktor@ist.osaka-u.ac.jp, teruhiro.mizumoto@p.chibakoudai.jp, seanha@nursing.upenn.edu, james.weimer@vanderbilt.edu, gdemiris@nursing.upenn.edu, nakag@fc.ritsumei.ac.jp, nagahara@ids.osaka-u.ac.jp, higashino-t@tachibana-u.ac.jp, {sokolsky, lee}@cis.upenn.edu

***Abstract*—The COVID-19 pandemic has amplified social isolation and loneliness among the elderly, necessitating robust monitoring solutions. However, the effective management of a multitude of sensors, each with potentially different protocols and unreliable connections, poses a substantial challenge. Additionally, the administration of regular paper-based surveys to elderly individuals can prove problematic due to potential forgetfulness. To address these challenges, we have developed iCareLoop, a comprehensive data collection and management system equipped with an intuitive user interface (UI) specifically designed for the elderly. iCareLoop includes a user-friendly survey application, delivers visualizations of sensor and survey statuses, and features alert mechanisms for missing data, thereby streamlining data management for researchers. The current iteration of iCareLoop integrates initial stakeholder feedback and evaluates user satisfaction. Furthermore, preliminary analysis of the survey and sensor data provides an illustration of the potential uses and data quality of our system. We believe that the insights gleaned from this study can significantly inform future research on mobile elderly care in the post-COVID-19 era.**

***Index Terms*—Mobile Data Management, Mobile User Interface, Mobile User Experience**

I. Introduction

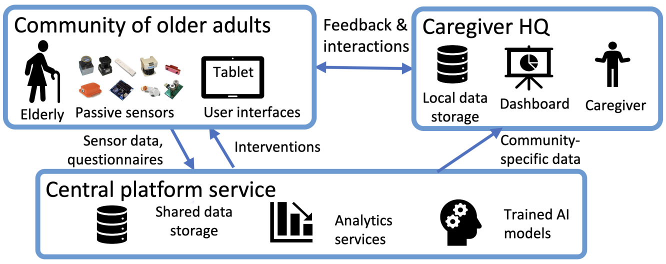
The COVID-19 pandemic has brought about many challenges for society, particularly affecting vulnerable populations such as the elderly [1], [2]. One of the most significant impacts of the pandemic on older adults has been increased social isolation and loneliness, leading to negative health outcomes such as depression, anxiety, and cognitive decline [3]–[7]. As a result, there is an urgent need for effective monitoring solutions to ensure the well-being of the elderly during this time [8]. Existing technologies and methodologies face limitations in terms of efficiency, reliability, and usability [9]. Therefore, there is a critical need for innovative approaches that address these shortcomings while catering to the unique needs of the elderly population.

One such approach is the development of comprehensive monitoring systems, incorporating both sensors [10], [11] and surveys to collect relevant data on the physical and mental states of the elderly. However, implementing and managing such systems presents several challenges, including dealing with numerous sensors having varying communication protocols and intermittent connectivity, as well as ensuring timely completion of daily or weekly paper-based surveys by the elderly participants. These difficulties make it difficult to maintain high-quality data, which is essential for meaningful research findings [12].

To overcome these obstacles, we propose iCareLoop, a data collection and management system designed to simplify data acquisition, processing, and analysis for community stakeholders. iCareLoop features an easy-to-use UI tailored for the elderly, enabling them to participate actively without facing undue burden. Furthermore, iCareLoop streamlines the process of managing substantial volumes of data generated by numerous sensors and surveys, thereby enabling efficient decision-making within the elderly community. For instance, caregivers such as family members and nurses can utilize iCareLoop to gain timely insights into the mental condition of the elderly and make informed decisions regarding the provision of necessary care. Finally, the system's built-in alert function notifies community stakeholders if a sensor stops sending data or participants fail to answer questionnaires, making it easier to ensure continuous data collection. The overview of iCareLoop is shown in Figure 1.

Our development of iCareLoop builds on prior research in elderly care technology, underscoring the significance of creating user-centered solutions that accommodate the unique traits of the target population. To verify iCareLoop's efficacy, we carried out initial tests in actual elderly communities and collected feedback from a range of stakeholders, including volunteers, regular elderly individuals, and geriatric experts such as geriatric psychiatrists. Overall, based on the 17 survey responses gathered, iCareLoop received favorable feedback from both the elderly and researchers. By incorporating this invaluable feedback, we enhanced the system's functionality, rendering it more adaptable for diverse com-

Fig. 1: A high-level overview of the iCareLoop system, designed for the elder community, includes feedback incorporation and interaction with the Caregiver Headquarters (HQ), offering various central platform services.



munity applications. Additionally, we assessed the potential usage of iCareLoop through preliminary data analysis and activity pattern recognition spanning over two-month period. The empirical results corroborated our hypothesis regarding the correlation between emotions and loneliness, indicating the high quality of data gathered.

II. Literature Review

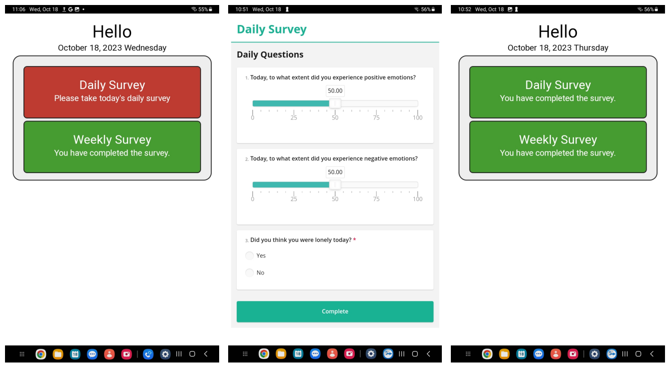
A. Digital Technologies in Elderly Healthcare

Digital technologies hold substantial potential for enhancing health monitoring and the overall social well-being of the elderly. However, several considerations need to be made when introducing these technologies. Developers should prioritize simplicity and intuitive functionality in these systems, as the elderly may be hesitant to adopt such tools long-term, despite their usability [13]. The deployment process should be centered on enhancing the quality of life for the elderly, rather than solely focusing on performing predefined tasks [14]. In addition, it is essential to provide effective digital literacy training to the elderly, as this demographic often faces challenges with the digital divide [15]. With these considerations in mind, digital technologies can significantly reduce social isolation among older adults and improve their social well-being [16].

B. Existing Dashboards and Platforms

Numerous dashboards and platforms for monitoring sensor data exist in the current landscape. For instance, [17] introduces a personal health dashboard designed and evaluated based on user studies, aimed at supporting reflective behavior change. VitalCore [18], on the other hand, is a platform specifically created for the scalable monitoring of medical sensors. However, these platforms do not accommodate data collection from questionnaires. Filling this void, RADAR-Base [19] provides an Active aRMT Questionnaire app, thereby establishing a platform for continuous mobile health (mHealth) streaming data collection from multiple sources. Nonetheless, it is not specifically designed for elderly users. The LAMP platform [20], a smartphone platform for mental health monitoring, caters to patient demands for trust, control, and community and clinician requirements for transparency in design. Yet, it lacks a sensor monitoring component. Overall, the technology readiness level for smart homes and home health monitoring

Fig. 2: Survey Application User Interfaces: When a survey is completed, the survey tab turns green.



technologies tailored for the elderly remains low [21]. In our approach, the combination of sensors and surveys is designed to create a synergistic effect, with surveys providing the initial ground truth for building future predictive models based on sensor data.

III. iCareLoop System

A. Survey Application

In the iCareLoop system, we use a user-friendly survey application for efficient data collection, as shown in Figure 2. Participants are provided with tablets pre-installed with the application. Remote access capabilities using TeamViewer are integrated to ensure smooth operation and prompt issue resolution. All survey responses are automatically stored on a local server, serving as the central database for collected data.

a) MMSE: Before participants join the study, certified clinicians administer the Mini-Mental State Examination (MMSE) [22] to screen for cognitive impairment. The MMSE is composed of 11 questions designed to assess various cognitive domains such as attention, memory, orientation, and language skills. The results of this test help us to determine the suitability of participants for our study.

b) Baseline Surveys: After passing the MMSE, participants complete a comprehensive, one-time survey covering sociodemographic information, psychological factors, medical history, loneliness, and social isolation. UCLA [23] and Lubben scales [24] measure social isolation and loneliness. This allows us to gather a broad spectrum of basic information about the participants, ranging from their personality traits to their physical and mental health statuses.

c) Daily and Weekly Surveys: Following the system's initial installation, we request participants to respond to daily and weekly surveys. The daily surveys consist of four questions about participants' daily emotions and state of loneliness. The weekly surveys repeat the questionnaires from the UCLA Loneliness Scale, capturing their levels of loneliness for the respective week. To help participants in remembering to complete the surveys, we've designed the user interface of the daily and weekly survey buttons to turn from green to red upon completion of the surveys. Besides, we also implement a push notification function to remind the elderly users.

Fig. 3: iCareLoop management dashboard

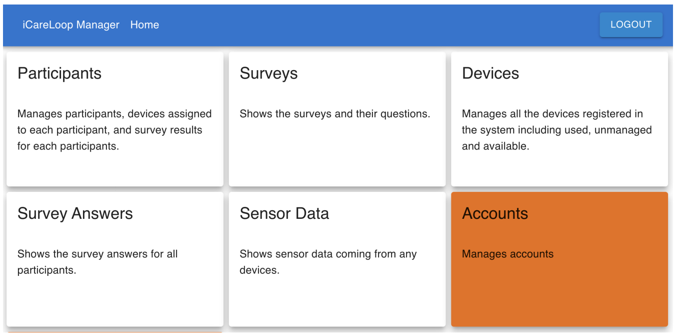
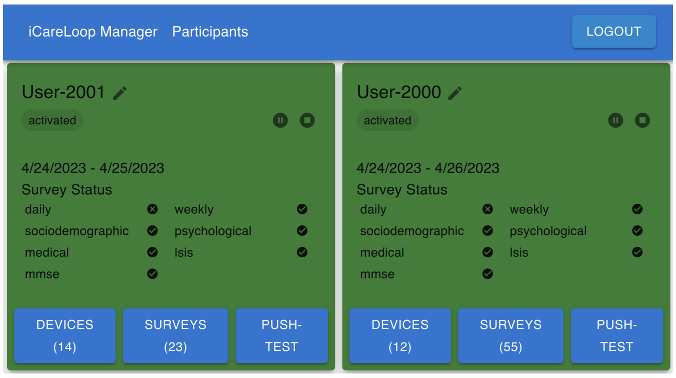


Fig. 4: iCareLoop participant management



B. Management Dashboard

Our management dashboard comprises three key components: participant management, survey response visualization, and sensor data display, as shown in Figure 3.

a) Participant management: Within the `Participants` tab, we display all enrolled participants as shown in Figure 4. For each user, the number of sensors installed at their residence is shown, along with the total count of surveys they have completed to date. If a user clicks on the `SURVEYS` icon, a calendar view of daily and weekly survey responses appears, highlighting any missing responses. Clicking on the `DEVICES` icon leads to a page that displays the current connection status of the sensors. This succinct display provides immediate access to a user's status, allowing researchers to quickly obtain an overview of the users and contact a specific user if sensor data or survey responses reveal any anomalies.

b) Sensor data display: The `Devices` tab displays all sensors currently in use for the project. Users can search by user ID to retrieve all relevant records for a specific participant, depicted in Figure 5. Additionally, we have implemented filter tabs for different sensor brands, such as Withings, and sensor management statuses, including assigned and retired. This page is convenient for verifying the most recent data received from the sensors, thereby facilitating troubleshooting during sensor installation. The `Sensor Data` tab provides a detailed view of the data collected by each sensor.

c) Survey data display: The `Survey answers` tab displays all baseline, weekly, and daily questionnaire responses from participants, shown in Figure 6. Researchers can filter by

Fig. 5: iCareLoop sensor management

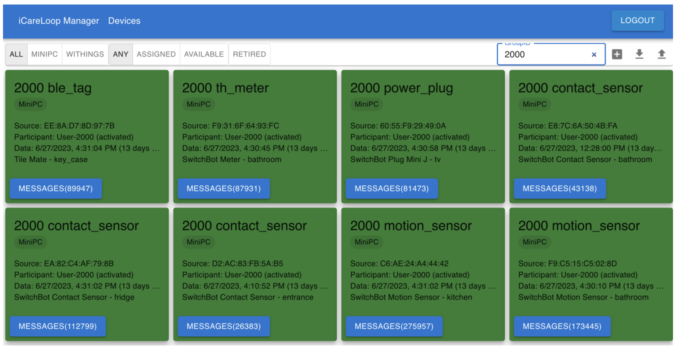
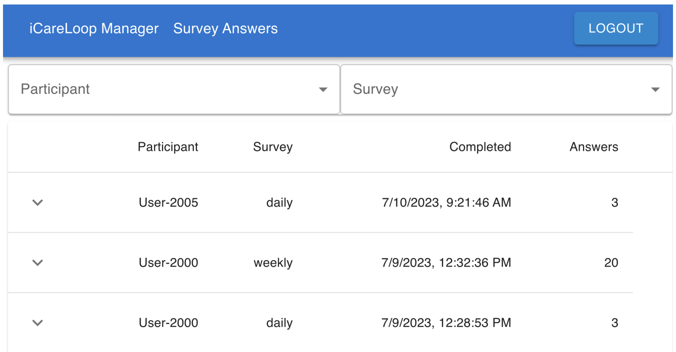


Fig. 6: iCareLoop survey management



participant ID to view all surveys a participant has answered to date. Moreover, filters by survey type are also available. Detailed responses can be viewed by clicking on the dropdown button.

C. Alert Function

Given the numerous sensors and surveys that researchers must monitor, keeping track of everything can be challenging. Issues such as device online status and whether participants have missed any surveys need constant monitoring. To address this, iCareLoop includes an alert function that sends out alerts if a device has not sent data within a pre-specified deadline. Additionally, a daily survey completion report is delivered to help monitor questionnaire responses. Table I presents an example of the deadlines for our current system.

TABLE I: Monitoring rules for sensors

Device	Deadline	Device	Deadline
Motion Sensor	1 day	BLE Tag Sensor	1 day
Contact Sensor	1 day	Smart Scale	1 week
Smart Plug	1 day	Sleep Mat	3 days
Bathroom Meter	1 day	Fitness Tracker	3 days

D. Backend platform

On the backend side, we employ a data management platform that can securely collect sensor data from participants. This platform consists of a mini PC (located in the elderly home) that collects data from the sensors deployed in the home, and it allows us to share data collected from two completely separate sensor deployments (one in the USA and one in Japan) in an automated way. The mini PC encrypts the data it collects and uploads it to a cloud server. The cloud server only acts as a broker to distribute the data to our local servers, which decrypt the data and store it for analysis purposes. Additionally, the platform supports obtaining data from a third-party cloud (Withings public cloud) via OAuth authentication. The dashboard then interacts with both the cloud server and local server to obtain the necessary information to display.

E. Customization for Elderly

iCareLoop is conceptualized around a low-maintenance, low-burden design, meant to function unobtrusively in the background until it detects an issue to report. The objective is to let elderly users live their daily lives undisturbed by the sensing system with minimal user interaction. This is achieved by choosing long-life battery sensors that unintrusively collect data. For instance, BLE tags attached to keychains help track outdoor activities by recording time spent away from home, potentially indicating social interactions or physical exercise. Similarly, strategically positioned motion sensors and door contact sensors within the home can capture movement and daily activities, thereby detecting potential signs of social isolation and loneliness.

We discovered that elderly individuals may unintentionally disrupt the sensors or the mini PC, underscoring the need for extra safeguards. In-person technical troubleshooting was challenging due to COVID-related visitor restrictions and a desire to minimize disturbances for the elderly. Additionally, assisting the elderly with technical issues proved complex. Therefore, we enhanced user-friendliness and convenience by introducing a plug-and-play feature. We set up remote access to the mini PC and tablet using TeamViewer, allowing administrators to perform remote troubleshooting. In case of accidental disconnections, the user merely needs to reconnect the mini PC to power and the system will automatically reconnect to the network and accept remote debugging connections, bypassing the need for intricate manual start-ups and technical knowledge.

F. Real-world Deployment

a) Community Engagement: Our community outreach involves collaborations with elderly communities in both the USA and Japan. In the USA, we partnered with senior apartments in the greater Philadelphia area, encouraging older adult participation from diverse socioeconomic backgrounds, with a focus on combating social isolation. In Japan, our partner is the larger-scale Shikanodai community in Nara prefecture, home to approximately 7,000 residents, 40% of whom are older adults. Unlike typical retirement communities, Shikanodai primarily consists of single-family, detached homes, and emphasizes keeping older adults engaged with the wider community.

b) Sensor Installation: Before visiting a participant's home, we ensure that all their dedicated sensors function properly by testing the tablet and mini PC in our lab. To streamline our 12-sensor deployments, we've developed a comprehensive preparation checklist, which has reduced the sensor mis-installation rate by 10%. Our deployment team comprises two developers and a clinician, each with specific roles. The clinician conducts the MMSE and surveys with the participant, while one developer connects the mini PC to local WiFi and launches the sensor data collection program. The other developer installs sensors around the house, verifying their connections with the tablet. This concurrent task execution minimizes deployment time to under an hour, greatly enhancing our efficiency. For future deployments, we've compiled a detailed manual outlining each step.

c) Lessons learned: In implementing and testing iCareLoop, we learned several lessons for future iterations. In the US, participants found the survey burdensome, indicating the need for a more user-friendly approach. The instability of contact sensors suggests a potential switch to motion sensors, which might capture daily activity more effectively. For example, toilet use and refrigerator usage can be measured accurately with motion sensors, even when doors are left open, an issue that challenges contact sensors. In Japan, participants had no concerns about the measurement process. However, we observed intermittent data from door sensors, likely due to weak transmission and potential packet loss. In addition, sensors may detach within a day if the adhesive surface and tape strength are inadequate. These findings underscore areas for improvement to ensure consistent, dependable data collection.

In the event of missing or incomplete sensor data, we could use statistical techniques or machine learning to analyze existing data patterns and fill in gaps. Time series analysis tools can smooth out short-term fluctuations, emphasizing long-term trends. Despite occasional data gaps, this approach allows us to gain insights into shifts in social isolation and loneliness, informing community support initiatives. To reduce the amount of missing survey responses, we also implement a push notification function to remind the elderly to fill out surveys daily.

IV. Evaluation

A. User Satisfaction

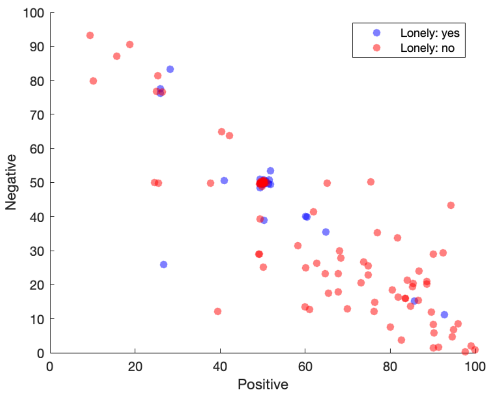
We conducted two separate user satisfaction surveys: one focused on the elderly individuals who utilized the survey application to answer questionnaires, and the other concerning the management dashboard used by researchers. We collected 6 survey responses from elderly users and another 11 responses related to the dashboard and alerts from researchers in relevant fields. Table II presents the average scores for each question across the two surveys.

1) Survey application: As per Table II, participants 50% of participants gave the highest score to the user interface design and the length of the questionnaires. Satisfaction levels regarding font size varied according to each participant's eyesight, but 83% of them reported no issues with font sizes during the surveys. Interestingly, all participants, including the elderly who may not have regular exposure to technology, preferred using tablets over paper for survey completion. However, the

TABLE II: Average points of user satisfactions

Survey application	**points (0 - 5)**
Ease of using user interface	4.5
Length of daily and weekly surveys	4.5
Font size of the app	4.5
Preference for using a tablet over paper	4.6
Remembering to complete the surveys	2.8
Dashboard and alerts	**points (0 - 5)**
Sensor status and sensor data display	4.3
Survey response display	4.4
Participant status display	4.6
Alert function	3.9
Recommend to future users	4.5

Fig. 7: Participants' responses to daily surveys



greatest challenge faced by all participants was remembering to complete the surveys each day. Notably, 33% of participants rated this task a three, indicating a constant need for reminders to fulfill it

2) Dashboard and alerts: The results of the survey indicate that the features of the iCareLoop dashboard were generally well-received by the participants, with an average rating of 4.4 out of 5. Displaying the participant status, which received 81.8% of five-score rating from all participants, and the survey answers, which 54.5% of participants scored as five, were found to be especially helpful. Another feature, the sensor display, also received positive feedback. About 45.5% of the participants rated it with a score of five, which suggests a good level of satisfaction with this feature. On the other hand, the alert function had a mixed reception, with 9.1% of researchers ranking a score of two, 27.3% assigning it a mid-level score of three, 27.3% for the score of four, and 36.4% for the score of five. Given these findings, we plan to refine the alert frequency to better align with the users' needs and to prevent them from being overwhelmed by too many alerts, a condition known as alarm fatigue. Overall, a majority of researchers, about 63.6%, expressed their intent to use the dashboard in their future projects. They also indicated they would recommend it to their colleagues in the research community.

B. Analysis of the Survey Answer

By utilizing the iCareLoop survey app on tablets instead of paper surveys, we were able to effortlessly gather daily and weekly responses from participants. This efficient method facilitated the collection of 116 responses from 8 participants over a span of approximately two months, enabling us to conduct data analysis. Each day, participants were requested to answer four questions specifically designed to assess their levels of loneliness. The questions were as follows:

- To what extent did you experience positive emotions today? (Scale: 1-100)
- To what extent did you experience negative emotions today? (Scale: 1-100)
- Did you feel lonely at any point today? (Yes/No)
- When did you feel lonely? (Morning/Evening/Night)

From the survey responses, we obtained continuous data reflecting participants' levels of positive and negative emotions (ranging from 0 to 100). We also collected categorical data on loneliness (yes/no). Figure 7 illustrates that participants reported feeling lonely 24 times and not lonely 92 times. To quantify the impact of emotions on loneliness, we used logistic regression analysis, considering the inverse correlation between positive and negative emotions.

We employed three binomial logistic regression models using positive emotions, negative emotions, and the difference between positive and negative emotions (calculated by subtracting the positive from the negative) as predictors. The response variable was the loneliness label. The p-values for all models were less than 0.05, indicating significant associations. The difference between positive and negative emotions showed the strongest significance (p-value = 0.0017), followed by negative emotions (p-value = 0.0019), and then positive emotions (p-value = 0.0027).

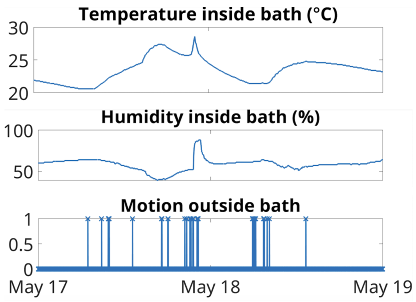
C. Activity Recognition with Sensor Data

In this section, we perform a qualitative evaluation of the sensor data quality collected by iCareLoop by comparing it to known activities, as described in [25]. An example of the collected sensor data for monitoring a bathing event is presented in Figure 8. The humidity and temperature data are visualized as standard line plots, while the motion sensor data is represented as binary values (0 for no motion and 1 for motion detection). Notably, in the middle of the time axis, there is a sudden spike observed in the humidity graph. We argue that this occurrence indicates bathing behavior due to the release of humidity during bathing. Supporting evidence is found in the motion sensor's reaction during the same time frame. While there is a temperature spike at the same time, the signal is weaker, suggesting that humidity is a more reliable indicator. To further investigate meaningful patterns for detecting loneliness, we are currently accumulating data from multiple sensors in our database for future studies.

V. Discussion

In future work, we will employ sensor fusion methods to extract meaningful features for social isolation detection.

Fig. 8: Bathing area (temperature, humidity, motion)



Integrating these features with survey responses, we aim to uncover correlations between an elder's isolation and their reported loneliness. Our goal is to develop predictive models for effective detection and potential prevention of loneliness through targeted interventions for the elderly population.

VI. Conclusion

This paper introduces iCareLoop, an innovative platform addressing COVID-19 challenges in elderly loneliness and social isolation. With a user-friendly interface, data visualization, and alert mechanisms, it improves data management in elderly communities. User evaluations favor our digital survey tool over paper surveys, and researchers are satisfied with its user management. Initial data analysis identified areas for future refinement. iCareLoop offers a blueprint for post-pandemic elderly care and community resilience research and interventions.

VII. Acknowledgment

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