Data Visualization for Mental Health Monitoring in Smart Home Environment: A Case Study

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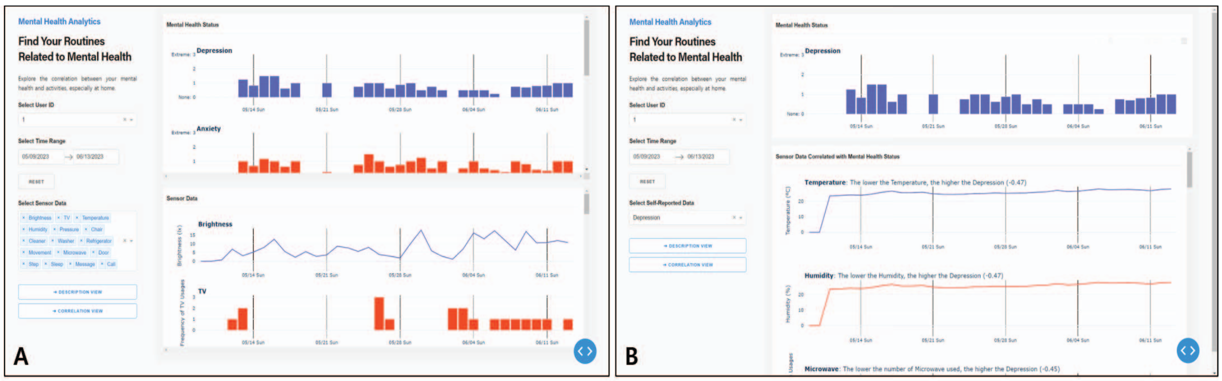

Figure 1: The screenshot of our proposed visualization system including a (A) description view, and a (B) correlation view.

Abstract

Mental health care and monitoring are important. Advancements in smart home sensing technology also make tracking people's activities easy in the home, enabling the monitoring of mental health more effectively. Some related works have demonstrated the possibilities of mental health monitoring using sensor data collected in smart homes. However, there is a lack of prior research on how to effectively utilize smart home data visualization to help people understand how their everyday behaviors are related to their mental health status. This poster presents a case study on data visualization for mental health monitoring in a smart home environment. Our web-based application allows users to browse their self-reported mental health states and home activities and visualize the correlation between mental health states and home activities.

Index Terms: Mobile health—Patient-generated health data—Mental health monitoring;

1 Introduction

Tracking of human behavioral and environmental changes can be possible early detection of the symptoms of mental illness which enables timely intervention based on their behavior data. Early detection and intervention in the initial status of mental illness can have significant to improve mental management and treatment delivery in clinical practice and general wellness.

Especially, it is important to collect behavioral data in a smart home to track mental health. People with poor mental health tend to spend more time at home [9, 13]. In the smart home environment, it is easier to track behaviors that are closely associated with mental health, such as eating and sleep patterns [7]. Additionally, the home is a place where people feel comfortable and safe [16], allowing for the minimization of external factors and enabling the tracking of individuals' naturalistic behaviors.

With the advancement of home Internet of Things (IoT) technology, it has become possible to track people's behaviors in smart home environments. Sensors can be attached to appliances, furniture, and productions in a smart home, or motion sensors can be installed. While prior studies mostly focused on analyzing cognitive declines of older adults [3], smart home sensing largely opens up novel opportunities for assessing functional health [4], which could be influenced by diverse mental health problems such as major depression symptoms and anxiety disorder. This means that we can collect various behavioral data in smart homes to help people make sense of their mental health states. However, there is a lack of studies exploring how people understand their mental health status through their home activity data.

Therefore, there is a need to visualize home activity data to assist people in making sense of their mental health status in the home environment. Data visualization aids to find relevant information and quick comprehension of massive behavioral data. Digital feedback technology through data visualization can be considered one of the solutions to enhance user participation and continuity of care. This paper aimed to develop a web application that visualizes smart home data and self-reported data to enable people to make sense of their mental health status in a smart home.

2 Related Works

Mental health monitoring in smart homes has been actively studied. For monitoring dementia, indoor location, door open/close events, and bed occupancy are utilized [10,11]. There have also been studies tracking the activities of people with mild cognitive impairment. Sensors were attached to household appliances and furniture, such as coffee machines and stoves, to track medication adherence, phone use, and coffee-making activities [6]. In another study, sensors were attached to household objects like stoves and cooking pots to track medicine adherence and food retrieval [12].

Data visualization to support self-reflection also has been studied. Health Mashups system visualized weight, sleep, step count, calendar data, location, weather, pain, food intake, and mood [1]. They present patterns between well-being data and context to promote

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Table 1: Dataset description

Category	Data Type	Descriptions
Smart home data	Frequency of Microwave Usages	Attached Aqara door sensor on the microwave
	Frequency of Refrigerator Usages	Attached Aqara vibration sensor on the refrigerator
	Frequency of Cleaner Usages	Attached Aqara vibration sensor on the washing machine
	Frequency of Washing Machine Usages	Attached Aqara vibration sensor on the washing machine
	Frequency of TV Usages	Attached Aqara smart plug on the TV
	Outing Frequency	Attached Aqara door sensor on the door
	Movement	Installed Aqara motion sensor inside the house
	Chair Movement	Attached Aqara vibration sensor on the chair
	Sleep Duration	Installed Withings sleep mat on the bed
	Environmental data	Installed Aqara temperature and humidity sensor and brightness sensor inside the house
Self-reported data	Depression	Self-reported depression data (PHQ-2)
	Anxiety Disorder	Self-reported anxiety data (GAD-2)
	Stress	Self-reported stress data
	Arousal/Valence	Self-reported arousal/valence data

behavior change. Wearable data, including devices like Fitbit and MS Band, are also visualized to support people in reflecting on their data and gaining rich insights through visual data exploration [2].

However, there is a lack of research that focuses on visualizing data collected from home appliances and furniture in smart home environments to support self-reflection on mental health. In this work, we explore how we can visualize various sensor data collected from home environments to support retrospective reviewing of their behaviors along with their self-reported mental health states.

3 Case Study

3.1 Smart Home Dataset Collection

We will collect smart home data and self-reported data as shown in Table 1. To prevent identification issues in appliance usages, we plan to collect data only from single person households. For smart home data collection, commercial sensors such as the Aqara sensor and Withings sleep tracking mat will be used. The Aqara sensor collects data on household appliance usage, furniture usage, and indoor environmental data. Specifically, we use Aqara's vibration sensor, door sensor, motion sensor, temperature and humidity sensor, brightness sensor, and smart plug. For collecting usage data of chairs, refrigerators, cleaners, and washing machines, a vibration sensor will be used to measure a vibration to be counted as one usage of the following home appliances. The door sensor is used to count one opening of the door as one usage of the following home appliances. The motion sensor is used to track the user's movement, and the brightness sensor and the temperature and humidity sensor is used to collect the user's home environment data. The Withings sleep tracking mat collects data on sleep duration. In addition, we ask people to answer the survey regarding their emotions, stress levels, depression, and anxiety. Depression and anxiety will be collected through PHQ-2 [8] and GAD-2 [5].

3.2 Data Visualization for Mental Health Monitoring

We developed a prototype for data visualization that enables users to monitor the collected data. The web application consists of a description view and a correlation view, as shown in Fig. 1. The description view visualizes summarized collected data, and the correlation view displays the relationship between sensor data and mental health.

In the description view, the left side of the screen allows users to explore data by enabling them to select a specific period and data type. This feature helps users to focus on the particular data they are interested in, facilitating the efficient exploration of the dataset [17]. On the right side of the screen, self-reported data and sensor data are visualized according to the period and data type selected by the user. For data visualization, we choose bar graphs and line graphs, which facilitate the comprehension of different information [14]. Each data was visualized as a bar graph, while the environmental information of the home was visualized using a line graph. In the case of environmental data, we use line graphs because the trends of the data are more important than individual data points. For other types of data, which encompass counts of home appliance usage or mental health statuses, the value itself is important. Consequently, bar graphs are employed [15].

In the correlation view, each sensor data is presented graphically, along with an explanation of its correlation to specific mental health aspects. The correlation between the mean of daily self-reported data and daily sensor data is calculated using the Pearson correlation coefficient. The sensor data that exhibits a high correlation with each mental health category (such as depression, anxiety, emotional arousal, and emotional valence) is displayed in descending order. This allows users to identify and explore the sensor data that show a high correlation with each specific mental health. In this view as well, users can select the time range and data types to focus on.

4 Conclusions

We presented a case study of building a visualization tool for mental health self-tracking based on self-report data and smart home activity data. We expect that the visualization tool will allow users to understand their own mental health. Furthermore, visual exploration tools will provide opportunities for clinicians and researchers to assess patients' mental health status and develop mental health care services based on smart home sensor data. As further research, we plan to analyze the individuals' own motivations and perceptions of activities correlating with mental health status for data interpretation. In addition, we will consider focusing on the correlation between positive mental status and sensor data as positive mental status (e.g., excitement, happiness) may also affect appliance usage.

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References

[1] F. Bentley, K. Tollmar, P. Stephenson, L. Levy, B. Jones, S. Robertson, E. Price, R. Catrambone, and J. Wilson. Health mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 20(5):1–27, 2013.

[2] E. K. Choe, B. Lee, H. Zhu, N. H. Riche, and D. Baur. Understanding self-reflection: how people reflect on personal data through visual data exploration. In *Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare*, pp. 173–182, 2017.

[3] D. Cook, M. Schmitter-Edgecombe, A. Crandall, C. Sanders, and B. Thomas. Collecting and disseminating smart home sensor data in the casas project. In *Proceedings of the CHI workshop on developing shared home behavior datasets to advance HCI and ubiquitous computing research*, pp. 1–7, 2009.

[4] D. J. Cook, M. Schmitter-Edgecombe, L. Jönsson, and A. V. Morant. Technology-enabled assessment of functional health. *IEEE reviews in biomedical engineering*, 12:319–332, 2018.

[5] K. Kroenke, R. L. Spitzer, J. B. Williams, P. O. Monahan, and B. Löwe. Anxiety disorders in primary care: prevalence, impairment, comorbidity, and detection. *Annals of internal medicine*, 146(5):317–325, 2007.

[6] M. L. Lee and A. K. Dey. Sensor-based observations of daily living for aging in place. *Personal and Ubiquitous Computing*, 19:27–43, 2015.

[7] L. Lianov and M. Johnson. Physician competencies for prescribing lifestyle medicine. *Jama*, 304(2):202–203, 2010.

[8] B. Löwe, K. Kroenke, and K. Gräfe. Detecting and monitoring depression with a two-item questionnaire (phq-2). *Journal of psychosomatic research*, 58(2):163–171, 2005.

[9] L. MacLeod, B. Suruliraj, D. Gall, K. Bessenyei, S. Hamm, I. Romkey, A. Bagnell, M. Mattheisen, V. Muthukumaraswamy, R. Orji, et al. A mobile sensing app to monitor youth mental health: observational pilot study. *JMIR mHealth and uHealth*, 9(10):e20638, 2021.

[10] S. Martin, J. C. Augusto, P. Mc Cullagh, W. Carswell, H. Zheng, H. Wang, J. Wallace, and M. Mulvenna. Participatory research to design a novel telehealth system to support the night-time needs of people with dementia: Nocturnal. *International journal of environmental research and public health*, 10(12):6764–6782, 2013.

[11] P. P. Morita, K. S. Sahu, and A. Oetomo. Health monitoring using smart home technologies: Scoping review. *JMIR mHealth and uHealth*, 11:e37347, 2023.

[12] D. Riboni, C. Bettini, G. Civitarese, Z. H. Janjua, and R. Helaoui. Smartfaber: Recognizing fine-grained abnormal behaviors for early detection of mild cognitive impairment. *Artificial intelligence in medicine*, 67:57–74, 2016.

[13] M. Schneider, U. Reininghaus, M. van Nierop, M. Janssens, I. Myin-Germeys, G. Investigators, et al. Does the social functioning scale reflect real-life social functioning? an experience sampling study in patients with a non-affective psychotic disorder and healthy control individuals. *Psychological Medicine*, 47(16):2777–2786, 2017.

[14] P. Shah and E. G. Freedman. Bar and line graph comprehension: An interaction of top-down and bottom-up processes. *Topics in cognitive science*, 3(3):560–578, 2011.

[15] W. A. Simcox. A method for pragmatic communication in graphic displays. *Human Factors*, 26(4):483–487, 1984.

[16] J. Sixsmith. The meaning of home: An exploratory study of environmental experience. *Journal of environmental psychology*, 6(4):281–298, 1986.

[17] J. J. Thomas and K. A. Cook. Illuminating the path: The research and development agenda for visual analytics. National Visualization and Analytics Ctr, 2005.