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# Community-Based Data Visualization for Mental Well-being with a Social Robot

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**Abstract**—Social robots have been used to support mental health. In this work, we explored their potential as community-based tools. Visualizing mood data patterns of a community with a social robot might help the community raise awareness about the emotions people feel and affecting factors from life events. This could potentially lead to adaptation of suitable coping skills enhancing the sense of belonging and support among community members. We present preliminary findings and ongoing plans for this human-robot interaction (HRI) research work on data visualizations supporting community mental health. In a two-day study, twelve participants recruited from a university community engaged with a robot displaying mood data. Given the feedback from the study, we improved the data visualization in the robot to increase accessibility, universality, and usefulness of such visualizations. In the future, we plan on conducting studies with this improved version and deploying a social robot for a community setting.

**Index Terms**—Mental health, community, data visualization, social robots, human-robot interaction

## I. INTRODUCTION AND BACKGROUND

### A. Community and Mental Health

Although humans are social beings, they cannot always know all true information about each other [1]. We do live in communities with other community members, but we cannot always know how other members are really doing or let them know how we are really doing [2]. For an overall good health, mental well-being is as important as physical well-being [3]. Because physical illness is externally visible to others usually, other community members can easily come forward to help in resolving specific physical health issues. However, mental illness is not externally visible, so others cannot notice this and help unless our behaviors express them explicitly [4]. Also, people are not always willing to share about their mental health with others or publicly, even with family members let alone outside community members due to social stigma, personal beliefs or limitations [5]. Therefore, to tackle mental health issues, the main source of support is usually therapy, which is expensive and thus inaccessible to many [6], [7]. Digital therapy is a relatively more accessible option compared to in-person therapy because of lower cost, and availability in

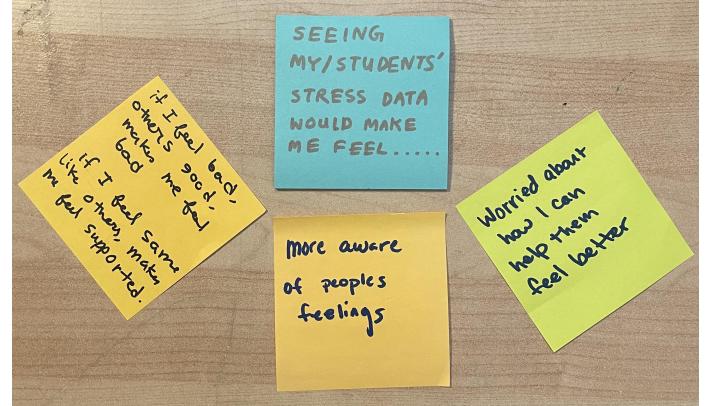


Fig. 1. Written prompt used in study and corresponding responses in post-its about feelings of people seeing community's mental health data visualization.

any location [8], [9]. However, digital therapy has drawbacks, such as lack of face-to-face interaction, user disengagement, and software incompatibility [10].

We are exploring how community members can support each other in maintaining good mental health. We hypothesize that one way to achieve this is by enabling people to know the mental states of others in their communities. This approach will allow them to compare their own mental states with others influencing their actions, behaviors, or feelings [11]. For instance, if we get to know that our current mental states are similar to that of the majority of other community members, we might feel a sense of solidarity for sharing the same mental state (see Fig. 1). If we know that our mental states are somehow better than other community members, we can take actions (e.g., share words of encouragement, behave sympathetically) to help improve their mental states [12]. Similarly, if we are having worse mental states than other community members, others could try to make us feel better and improve our mental states. In this way, a community can effectively support the mental health of its members.

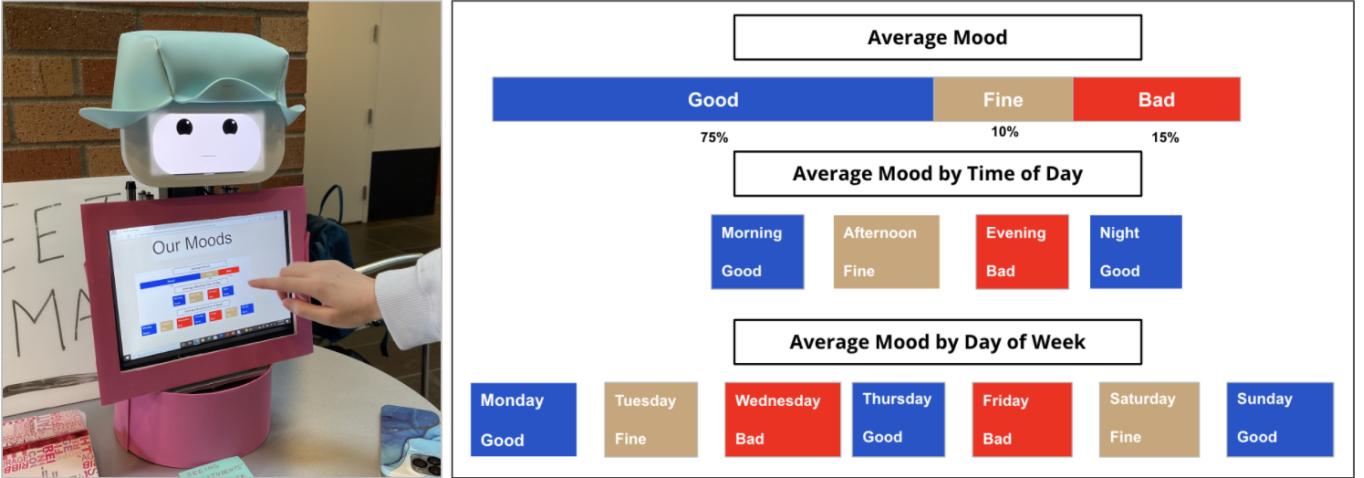


Fig. 2. *Left:* The mental health data visualization template on a social robot being interacted by a participant during study. *Right:* The template used in study.

### B. A Community-Based Social Robot for Mental Well-being

Recent HRI research shows that robots have been useful to support humans' mental well-being. The way robots have been utilized for this purpose are by enhancing robots' interactive design and capabilities for enabling people to effectively practice socio-emotional interaction skills with robots [13]–[15]. We attempt to use social robots as agents for influencing community members to support each other's mental health. We aim to investigate our hypothesis by placing a social robot in specific communities and displaying data visualization indicating the mental states of the community members through the robot in a way that would enhance social interaction and positive moods in a community. Social robots are often perceived as friendly or pet-like companions by humans for their endearing appearances (e.g., outfit, facial expressions) and capabilities that can include haptics, sounds, and movements [16]. Such perceptions or relationships boost user engagement with social robots [17]. Thus, social robots can better foster emotional support with mental health data visualization compared to other technologies (e.g., smartphone apps, websites rendered by touch screen devices) [18].

## II. PRELIMINARY STUDY IN COMMUNITY MENTAL HEALTH DATA VISUALIZATION WITH A SOCIAL ROBOT

We present the details about a preliminary study conducted to collect impressions from passerby on a mental health data visualization rendered by a community-based social robot.

### A. Defining Community

To create the data visualization template for the robot, we emphasize on accuracy and accessibility of mental health data representation of a community. We try to avoid too narrow or too broad of a scope to define a community for this purpose. For example, if we use data on an individual level, this will not be a true representation of the overall mental health of a community, namely, a group of people and thus hardly could benefit an entire community's mental

health. Conversely, data of people across all or some of the countries in the world, or different school districts of a state might not be very useful either, because this data would be drastically varied for socioeconomic and demographic differences (e.g., income, race, ethnicity, age, religion) of distinct geographic locations [19]. Therefore, we chose to visualize data of a specific institution's (e.g., school, university, hospital) community, which is neither too narrow nor too broad in its population size and diversity [20]. These communities usually consist of hundreds to thousands of people driven by a similar mission such as education and health care [21], [22]. This way of defining community is useful, as it keeps population size within a countable limit, alleviates drastic variability of factors such as demographics, and is directed by shared goals which unify community members [21]. Such community-based data visualization could inform people about the mental state of their communities, so they can take actions for the betterment of their community's mental health.

### B. Data Visualization Template

We created a data visualization template to show mental health data of a community and placed it in a social robot (see Fig. 2). To express the overall mental health of a community, we decided to visualize its moods, which more directly indicates mental states compared to other related parameters such as stress levels, and affecting life events [23]. The design choices (e.g., color codes for moods, spectrum of data varieties, mood data representation in blocks) of our template (see Fig. 2) have been chosen hypothetically in a random manner with no evidence basis from any particular community's mood data representation. This template was inspired as a generally understandable visualization in HRI [24].

### C. Study of A Social Robot Visualizing Community Mood Data

After placing the data visualization template in a social robot (see Fig. 2), we conducted a study deploying the robot in a university campus. The location chosen was the main entrance atrium of a department easily accessible to students

IMPACT	CONCERNS	SUGGESTIONS	DATA CONTENT	OUT OF THE BOX	
<p>Seeing my/students' mood data would make me feel.....</p> <p>part of a community</p> <p><b>less alone</b></p> <p>reassured</p> <p>supported</p> <p>In schools, people see this data, teachers can assign less homework on days students seem to have bad mood overall, and more homework when students are a bit relaxed and have good mood</p> <p>informed</p>	<p>Show how many peoples' data. If avg. data is from 15 people in a 2000 peoples' community, that would not be true representation of that community's avg. mood data.</p> <p>Show when the data was collected. "Expired data" will not provide accurate information.</p> <p>US has various cultures, good, bad, fine might mean different for each; possible to represent true average mood of such a diverse community?</p>	<p><b>Dynamic</b> Interactive data logging system like a game</p> <p><b>Static</b> Statistics: curve-- X axis: days or times; Y axis: avg. moods</p> <p><b>pie chart</b></p> <p>a clock for times of day and a calendar for days of week</p>	<p>Word Cloud: simultaneously data in &amp; out functionality</p> <p>Face/emoji (smiling, neutral, sad) with color code or shades instead of words (good, fine, bad)</p> <p>A scale with different days that people can scroll and select specific day/time's average mood</p> <p>3 buttons (good, bad, fine) on top; middle= synced percentages, bottom summary</p>	<p><b>Mood Types:</b> Good, Fine, Bad</p> <p>Comparative data (Me vs. Others, Me vs. Me)</p> <p><b>Avg. mood type by time of day</b></p> <p>Group or aggregated data</p> <p><b>Overall avg. mood type</b></p> <p><b>Avg. mood type by day of week</b></p> <p>Affecting factors: exam day, holiday</p> <p>Percentage of people with specific mood type</p>	<p>Give corresponding action plans along with displaying moods</p> <p>Associate color green instead of blue with good mood</p> <p>Make visualization bigger, so people can see without getting too close to the robot</p> <p>Okay/fine as transparent color maybe</p>

Fig. 3. Qualitative analysis of the user study.

and staff to interact with the robot. Below are some questions that we asked the study participants:

(Q1) *Would you improve or change the way your community's mental health data is visualized with this robot? How?*

(Q2) *How does seeing the overall mood data of your community (your own data integrated with the data of other members of your community) make you feel?*

(Q3) *If you had this robot showing this kind of data visualization at any time, how might it affect your mood? What would you say this might be like if done overtime? What this could be or mean for you in future?*

We also used a written prompt (see Fig. 1) to collect responses about their feelings. Below is an overview of the study with specifics of the community sample used, analysis procedure, and implications of the results.

**Sample:** In two days, we interviewed a total of twelve people ( $n=12$ ) from a university campus community who interacted with the robot's data visualization template (see Fig 2).

**Analysis:** We used a notebook for note-taking during the study about the main impressions of participants regarding the robot-rendered data visualization. Also, we collected posts that participants used to share feedback during the study (see Fig 1). We used emergent coding to analyse the data and extract common concerns about how data is being displayed and the effects it can have on the community. We also used a Miro board (<https://miro.com/>) to group the collected feedback in different emergent categories (see Fig. 3).

**Preliminary Results:** The responses of the study participants expressed various desires about seeing their community's mood data via a community-based social robot (see Fig. 3).

Responding to Q1, participants suggested some static data visualization templates, such as pie charts, statistical and two-dimensional curves with horizontal and vertical axes, clocks

to show data of specific times of day and calendars to show data of specific days of week, and interactive interfaces like buttons, scales, and emojis that people can click on to find out details, such as represented population size of a community (see Fig. 3). There were also suggestions to have dynamic visualization simultaneously collecting data and integrating that in itself. Participants reported to feel comfortable sharing their personal mood data with robots anonymously. We used "Good", "Bad", and "Fine" to categorize moods (see Fig. 2). However, the study results revealed that these might not work well in diverse and multilingual communities, as these words might not fully express any particular moods for all people.

Responding to Q2, study participants reported positive feelings looking at the robot-rendered visualizations containing hypothetical community mood data, and mentioned feeling 'supported', 'less alone', and 'part of a community'. They suggested that seeing their community's collective mental health data would allow them to compare their own mental states with that of other community members and take actions for improvement accordingly (see Fig. 3).

Responding to Q3, one suggestion from the study participants was that robot-rendered visualizations should include an action plan so the users can easily be informed about what shared actions could help improve their community mental health effectively. Another suggestion was to include the percentage of the community representing specific moods in the data visualization template. It could refrain people from mistakenly considering moods represented by a small portion of their community as a prevalent community mood, which might be misleading [25].

### III. IMPROVING DATA VISUALIZATIONS

Based on the feedback received from the study, we improved our data visualization template. In particular, we adopted three



Fig. 4. Researchers interacting with improved data visualization templates – the statistical curve (left) and the pie chart (right), respectively – on the robot.

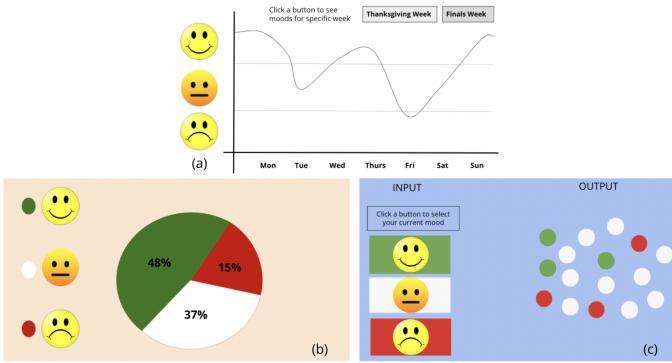


Fig. 5. Improved data visualization templates.

most suggested templates by the study participants (see Fig. 4 and 5). At least two users have suggested each of these templates instead of the old one, which is seen in Fig. 2. The newly created and improved three data visualization templates have the following specifications:

- **Template 1** contains a statistical curve with plotted mood data points, weekly mood data visualizations of a community, and buttons allowing users to choose a particular week, such as exams week and thanksgiving week (see Fig. 5(a))<sup>1</sup>.
- **Template 2** contains a pie chart, color-coded mood data visualizations, such as green for happy or good mood, white for neutral mood, and red for sad or bad mood, and percentages indicating what segment of a community population represents specific moods (see Fig. 5(b)).
- **Template 3** contains a cloud of circular mood data points categorized with color codes (same as Template 2), and a dynamic or interactive system which takes on new data

<sup>1</sup>Demo: <https://youtu.be/AFFmWQV5Evg>

inputs and syncs up the cloud immediately (see Fig. 5(c)).

Our goal was to enhance coherence and accessibility of templates by reducing the need to read text and increase dependency on universal graphics and symbols, as well as color codes. We changed the mood types from English words “Good”, “Bad”, and “Fine” to an emoji likert scale, which can be understood globally [26]. We also changed color codes adapting to the suggestions made by study participants. For instance, we have used green for good or happy mood instead of previously used blue color for this mood, and white or transparent for neutral mood instead of previously used brown color for neutral mood.

#### IV. DISCUSSION AND FUTURE DIRECTIONS

Next, we plan to conduct a second user study with the improved data visualization template(s), we will integrate them in the robot’s software system. With integrated data visualization tools in the robot, we will be able to render mental health data visualizations suitably for any community. For static visualizations (see Fig. 5(a) and 5(b)), we would collect mood data from community members using separate robot interactions. These mood data will be visualized through our finalized template(s) on the robot.

Community-based data visualizations could revolutionize HRI field with social robots displaying mental health data with maximum inclusivity and accessibility to support mental health of people across diverse communities [27]. Community-based social robots can be placed in communities like workplaces and educational institutions. Thus, this work has potential to promote mental well-being of people in various communities.

#### V. ACKNOWLEDGEMENTS

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