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

Raida Karim
University of Washington
Seattle, Washington, United States
rk1997@cs.washington.edu

Yufei Zhang
University of Washington
Seattle, Washington, United States
yufeiz6@uw.edu

Patrícia Alves-Oliveira
University of Washington
Seattle, Washington, United States
patri@cs.washington.edu

Elin A. Björling
University of Washington
Seattle, Washington, United States
bjorling@uw.edu

Maya Cakmak
University of Washington
Seattle, Washington, United States
mcakmak@cs.washington.edu

***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**

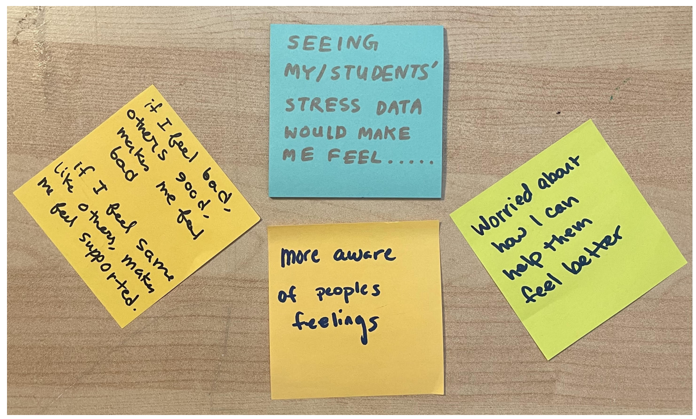

Fig. 1. Written prompt used in study and corresponding responses in post-its about feelings of people seeing community's mental health data visualization.

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 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.

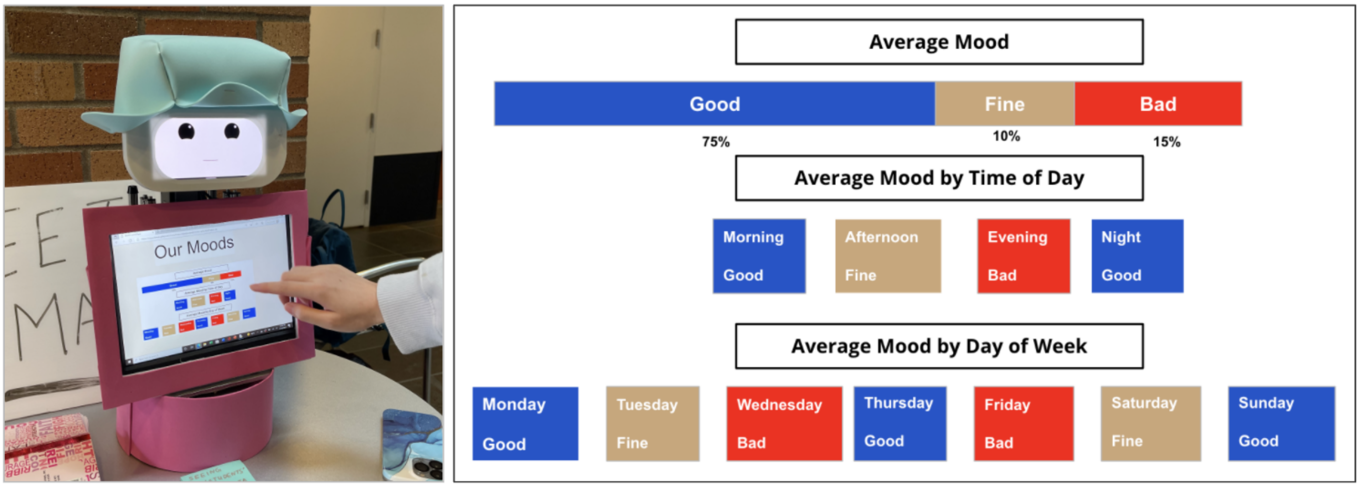

Fig. 2. *Left:* The mental health data visualization template on a social robot being interacted by a participant during study. *Right:* The template used in study.

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

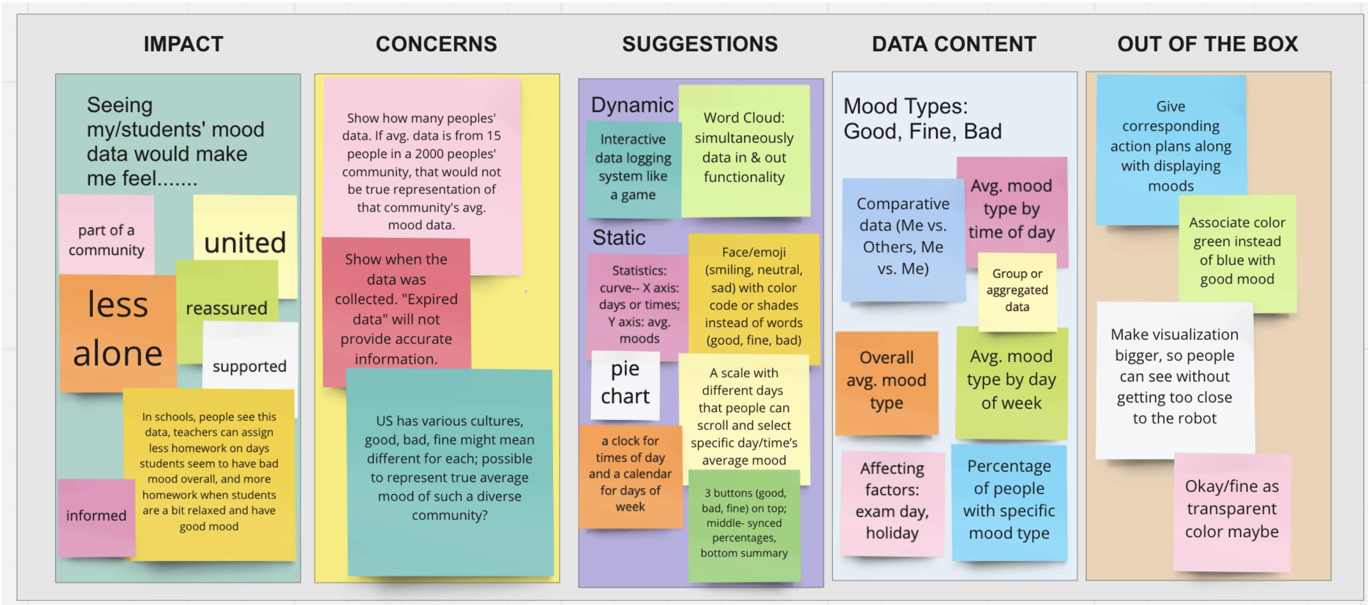

Fig. 3. Qualitative analysis of the user study.

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 post-its 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

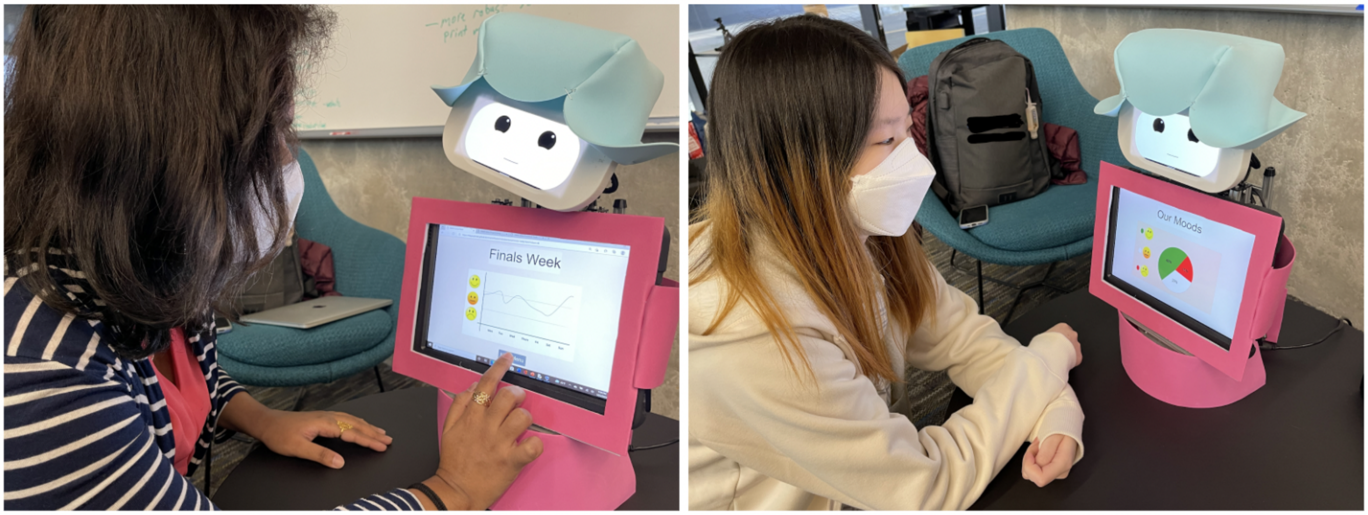

Fig. 4. Researchers interacting with improved data visualization templates – the statistical curve (left) and the pie chart (right), respectively – on the robot.

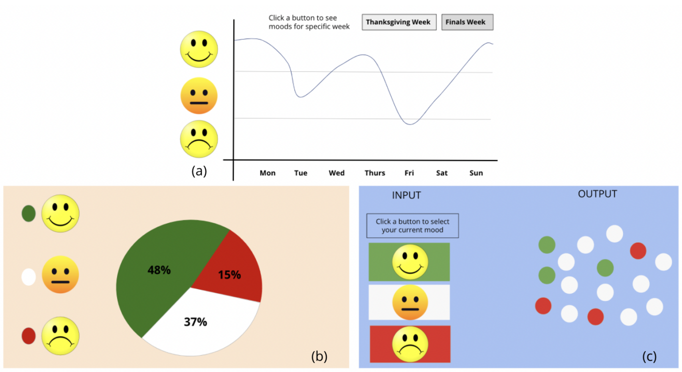

Fig. 5. Improved data visualization templates.

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))[1].
- **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 inputs and syncs up the cloud immediately (see Fig. 5(c)).

[1]Demo: https://youtu.be/AFFmWQV5Evg

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 templates (see Fig. 5). After finalizing the 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

This study was funded in part by National Science Foundation: National Robotics Initiative, SES: Award Abstract 1734100 - Design and Development of a Social Robot for Gathering Ecological Momentary Stress Data from Teens.

REFERENCES

[1] P. Gilbert, The evolution and social dynamics of compassion, Social and Personality Psychology Compass 9 (06 2015). doi:10.1111/spc3.12176.

[2] R. Jack, P. Schyns, The human face as a dynamic tool for social communication, Current Biology 25 (14) (2015) R621–R634. doi:https://doi.org/10.1016/j.cub.2015.05.052.
URL https://www.sciencedirect.com/science/article/pii/S0960982215006557

[3] M. Prince, V. Patel, S. Saxena, M. Maj, J. Maselko, M. R. Phillips, A. Rahman, No health without mental health, The Lancet 370 (9590) (2007) 859–877. doi:https://doi.org/10.1016/S0140-6736(07)61238-0.
URL https://www.sciencedirect.com/science/article/pii/S0140673607612380

[4] A. F. Jorm, Mental health literacy: empowering the community to take action for better mental health., American psychologist 67 (3) (2012) 231.

[5] N. Sartorius, Stigma and mental health, The Lancet 370 (9590) (2007) 810–811. doi:https://doi.org/10.1016/S0140-6736(07)61245-8.
URL https://www.sciencedirect.com/science/article/pii/S0140673607612458

[6] G. D. Brown, W. G. Hunter, A. Hesson, J. K. Davis, C. Kirby, J. A. Barnett, D. Byelmac, P. A. Ubel, Discussing out-of-pocket expenses during clinical appointments: an observational study of patient-psychiatrist interactions, Psychiatric Services 68 (6) (2017) 610–617.

[7] J. E. Pella, E. P. Slade, P. J. Pikulski, G. S. Ginsburg, Pediatric anxiety disorders: a cost of illness analysis, Journal of abnormal child psychology 48 (4) (2020) 551–559.

[8] E. Aboujaoude, L. Gega, M. B. Parish, D. M. Hilty, Digital interventions in mental health: current status and future directions, Frontiers in psychiatry 11 (2020) 111.

[9] C. B. Taylor, E. E. Fitzsimmons-Craft, A. K. Graham, Digital technology can revolutionize mental health services delivery: The covid-19 crisis as a catalyst for change, International Journal of Eating Disorders 53 (7) (2020) 1155–1157.

[10] A. Howells, F. J. Eiroa Orosa, I. Ivtzan, Putting the 'app' in happiness: A randomised controlled trial of a smartphone-based mindfulness intervention to enhance wellbeing, Journal of Happiness Studies 17 (01 2015). doi:10.1007/s10902-014-9589-1.

[11] M. Bowe, J. R. Wakefield, B. Kellezi, C. Stevenson, N. McNamara, B. A. Jones, A. Sumich, N. Heym, The mental health benefits of community helping during crisis: Coordinated helping, community identification and sense of unity during the covid-19 pandemic, Journal of Community & Applied Social Psychology (2021).

[12] C. M. Kelly, A. F. Jorm, B. A. Kitchener, Development of mental health first aid guidelines on how a member of the public can support a person affected by a traumatic event: a delphi study, BMC psychiatry 10 (1) (2010) 1–15.

[13] P. Alves-Oliveira, A. Paiva, P. Arriaga, G. Hoffman, Yolo, a robot for creativity: A co-design study with children, 2017. doi:10.1145/3078072.3084304.

[14] B. Scassellati, L. Boccanfuso, C.-M. Huang, M. Mademtzi, M. Qin, N. Salomons, P. Ventola, F. Shic, Improving social skills in children with asd using a long-term, in-home social robot, Science Robotics 3 (2018) eaat7544. doi:10.1126/scirobotics.aat7544.

[15] N. Jecker, You've got a friend in me: sociable robots for older adults in an age of global pandemics, Ethics and Information Technology (07 2020). doi:10.1007/s10676-020-09546-y.

[16] E. B. Onyeulo, V. Gandhi, What makes a social robot good at interacting with humans?, Information 11 (1) (2020). doi:10.3390/info11010043.
URL https://www.mdpi.com/2078-2489/11/1/43

[17] L. Bishop, A. van Maris, S. Dogramadzi, N. Zook, Social robots: The influence of human and robot characteristics on acceptance, Paladyn, Journal of Behavioral Robotics 10 (1) (2019) 346–358.

[18] S. Boucenna, A. Narzisi, E. Tilmont, F. Muratori, G. Pioggia, D. Cohen, M. Chetouani, Interactive technologies for autistic children: A review, Cognitive Computation 6 (4) (2014) 722–740.

[19] M. Zhang, A. Garcia, G. Bretones, Demographics and clinical profiles of patients visiting a free clinic in miami, florida, Frontiers in public health 7 (2019) 212.

[20] P. Benneworth, Definitions, approaches and challenges to community engagement, Mapping and Critical Synthesis of Current State-of-the-Art on (2018) 16.

[21] A. Van Der Wildt, P. Van Avermaet, M. Van Houtte, Multilingual school population: Ensuring school belonging by tolerating multilingualism, International Journal of Bilingual Education and Bilingualism 20 (7) (2017) 868–882.

[22] E. Nicolaou, J. Quach, J. Lum, G. Roberts, M. Spencer-Smith, S. Gathercole, P. Anderson, F. Mensah, M. Wake, Changes in verbal and visuospatial working memory from grade 1 to grade 3 of primary school: Population longitudinal study, Child: care, health and development 44 (3) (2018) 392–400.

[23] R.-T. Sinvani, H. Fogel-Grinvald, A. Afek, R. Ben-Avraham, A. Davidov, N. B. Cohen, A. B. Yehuda, M. Nahum, Y. Gilboa, Ecological momentary mood, resilience, and mental health status as predictors of quality of life among young adults under stress: A structural equation modeling analysis, Frontiers in Psychiatry 12 (2021).

[24] D. Szafir, D. A. Szafir, Connecting human-robot interaction and data visualization, in: Proceedings of the 2021 ACM/IEEE International Conference on Human-Robot Interaction, HRI '21, Association for Computing Machinery, New York, NY, USA, 2021, p. 281–292. doi:10.1145/3434073.3444683.
URL https://doi.org/10.1145/3434073.3444683

[25] M. Pierce, S. McManus, C. Jessop, A. John, M. Hotopf, T. Ford, S. Hatch, S. Wessely, K. M. Abel, Says who? the significance of sampling in mental health surveys during covid-19, The Lancet Psychiatry 7 (7) (2020) 567–568.

[26] Emojis: Insights, affordances, and possibilities for psychological science, Trends in Cognitive Sciences 21 (2) (2017) 66–68. doi:https://doi.org/10.1016/j.tics.2016.10.007.
URL https://www.sciencedirect.com/science/article/pii/S1364661316301784

[27] D. Feil-Seifer, K. S. Haring, S. Rossi, A. R. Wagner, T. Williams, Where to next? the impact of covid-19 on human-robot interaction research, J. Hum.-Robot Interact. 10 (1) (jun 2020). doi:10.1145/3405450.
URL https://doi.org/10.1145/3405450