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Informal Caregivers Disclose Increasingly More to a Social Robot Over Time

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Figure 1: The interaction from the eyes of the participants (and the experimenter). Participants were exposed to the robot Pepper (SoftBank Robotics) only via the Zoom chats.

ABSTRACT

Informal caregivers often struggle in managing to cope with both the stress and the practical demands of the caregiving situation. It has been suggested that digital solutions might be useful to monitor caregivers' health and well-being, by providing early intervention and support. Given the importance of self-disclosure for psychological health, here we aimed to investigate the potential of employing a social robot for eliciting self-disclosure among informal caregivers over time. We conducted a longitudinal experiment across a five-week period, measuring participants' disclosure duration (in seconds) and length (in number of words). Our preliminary results show a positive trend where informal caregivers speak for a longer time and share more information in their disclosures to a social robot across the five-week period. These results provide useful evidence supporting the potential deployment of social robots as intervention tools to help provide support for individuals suffering from stress and experiencing challenging life situations.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; *Field studies*; **User studies**; **HCI theory, concepts and models**; **Auditory feedback**; *Natural language interfaces*; • **Applied computing** → **Psychology**; • **Social and professional topics** → **People with disabilities**; • **Computer systems organization** → **Robotics**; • **Computing methodologies** → *Cognitive science*.

KEYWORDS

Caregiving, Informal Caregivers, Human-Robot Interaction, HRI, Social Robot, Self-Disclosure, Intervention, Ecological Momentary Intervention, EMI, Stress

1 INTRODUCTION

Informal caregivers provide care and support to a friend or family member while being unpaid and non-formally trained. Their care recipients often suffer from chronic health condition that are related to old age or a variety of physical and mental health conditions [52]. While many informal caregivers find the caregiving experience to be rewarding [61, 62], this experience is also often associated with serious health and well-being implications for the informal caregiver [49, 51, 52]. The caregiving situation is considered to be a potential stressor [40], which might lead to a variety of negative health and well-being outcomes including strain, burden, and depression [15, 21]. Previous empirical findings emphasize that caregiving as a stressor can have serious implications to the caregiver's physical and mental health [28, 47]. The role of a caregiver, which requires time and resources [6, 42, 52], can limit informal caregivers from receiving professional mental and physical health treatment for themselves. This is a substantial psychological factor as caregivers struggle with managing to cope with stress and practical demands of the caregiving role while experiencing the loss (of a person and their independence), they often do not receive necessary help [10, 26, 49]. Moreover, informal caregivers are at a higher risk of hidden morbidity [8, 55], suffering from a condition without receiving a proper diagnosis, being aware of it or acknowledging one's condition. As informal caregivers struggle in managing to cope with both the stress and the practical demands of the caregiving situation, they often receive no formal mental health treatment or help themselves [10, 49]. Accordingly, it has been suggested that online and digital solutions [e.g., 3, 4, 45, 46, 48], as well as ecological momentary assessment (EMA) and intervention (EMI) measures, can be used to monitor informal caregivers' health and well-being, as well as to provide early intervention and support across several different domains [e.g., 25, 38, 57]. This would be especially meaningful to caregivers considering their natural limitations of receiving formal support due to the caregiving role [49, 50]. Moreover, while eHealth solutions, as well as health-technologies in general for care recipients, are widely addressed and studied in the Human-Computer Interaction (HCI) research field, eHealth solutions and interventions for caregivers receives very little attention [45]. While these might not be suffering from a diagnosed condition, they are living with considerably difficult life situations and could use the support of various digital solutions.

Self-disclosure plays a critical role in successful treatment outcomes [58] and has a positive impact on mental and physical health [22]. Furthermore, there is substantial supporting evidence for engaging in emotional disclosure as part of a therapeutic process and as an intervention for stress and coping trauma, especially as a self-help intervention [41, 43, 44, 60]. Here we investigated the potential of employing a social robot as a tool for delivering EMI for eliciting self-disclosure among informal caregivers over time. Social robots, autonomous machines that interact and communicate with humans or other agents by following social behaviours and rules relevant to their role [9], are gradually being deployed across various health and well-being settings due to their ability to function autonomously or semi-autonomously in physical and social spaces alongside humans [see 27]. Social robots are being studied and introduced in psychosocial health interventions [see 53, 54], within mental health settings [see 33, 56], showing potential for overcoming some of the social barriers of EMA and EMI techniques [see 33]. EMA and EMI tools oriented towards caregiving stress and burden are often noninteractional, are highly dependent on caregivers' active participation and are not as time-effective [7, 39, 45]. These interventions are often mobile or application-based and require full engagement on behalf of the caregiver to log information independently as these are highly dependent on users' initiative and responsibility [see 11, 14, 20], which can be challenging when going through the caregiving experience [51].

Due to social robots' embodiment and human-like design, previous studies show how social robots could encourage humans to self-disclose information and emotions [e.g., 34]. Moreover, previous studies stress how richer modalities of communication like flowing dialogue [see 13, 19] can influence users' perceptions of a system and provide a better user experience than traditional noninteractional systems [32]. Accordingly, social robots might just fall at the ideal intersection between being an autonomous and physically present technology [see 27] that can capture emotion and information while also being able to demonstrate social and cognitive cues that might help to elicit rich and valuable disclosures from informal caregivers [33]. Given the importance of self-disclosure for psychological health, in this late-breaking work, we introduce recent results from a long-term online mediated experiment with informal caregivers looking at informal caregivers' self-disclosures to social robots over time.

2 METHODS

The study methodology followed an experimental design protocol for mediated online experimental design with a social robot [35]. For a detailed description of the experimental design, stimuli, task, procedure and measurements, please see the experimental design protocol [35]. All study procedures were approved by the research ethics committee of the University of Glasgow (ethics approval number: 300200132).

2.1 Experimental Design and Procedure

A 10 (chat sessions across time) repeated measures experimental design was conducted. Participants conversed with the social robot Pepper (SoftBank Robotics) via Zoom video chats about general everyday topics (e.g., social relationships, work-life balance, health and well-being). Each interaction consisted of the robot asking the participant 3 questions (x3 repetitions). The topic of each interaction was assigned randomly before the experimental procedure started, as was the order of the questions. Participants were scheduled to interact with the robot twice a week during prearranged times, and each interaction with the robot lasted between 5 to 10 minutes at most, and another 10-20 minutes were taken up for completing questionnaires. These interactions took place across five weeks

between 21/07/21 and 24/08/21. When recruited, participants completed an induction questionnaire (Session 0) approximately one week before beginning their video chat interactions with Pepper (Sessions 1 to 10).

Each interaction with the robot Pepper followed the same order, starting with greetings followed by 3 questions (x3 repetitions). The participants were instructed to have a short conversation with the robot, following the robot's lead in the interaction and answering the robot's questions. Participants were instructed that no time limit applied for the interactions and that the interactions usually took about five to ten minutes. They were further encouraged to participate in the interactions the way they saw fit - speaking as little or as much as they wished. In addition, participants were instructed that there were no correct or incorrect answers, and they were encouraged to provide honest answers according to what they felt comfortable with. In the first interaction with the robot (Session 1), participants were asked for their name by the robot as part of the robot introduction (i.e., "Hello there, my name is Pepper, what is your name?), as such a question would be part of a normal introduction in on-going social exchanges with another person. Before the interaction started, participants were instructed that they were not obliged to share their name with the robot and that they could give a fake name if they preferred to do so. From the second interaction (Session 2) onwards, the robot addressed each participant by the name they gave during the first interaction (Session 1), to provide a sense of natural and personalized interactions.

Each short interaction was guided by the robot as a semi-structured interview discussing non-sensitive topics regarding general every-day experiences. The task followed the following structure and order:

- Short greetings/introduction (e.g., "Hi there, how are you doing?").
- One pre-defined general question about the participant day, week, or weekend, to build rapport (e.g., "How was your weekend? Did you do anything interesting?").
- An opening statement introducing the topic of the question (e.g., "I am going to ask you about your social life").
- Two pre-defined, non-sensitive questions that correspond to the topic that was randomly allocated to the interaction (e.g., "Can you tell me about your social-life? How often do you socialize, and how do you feel about it?").

The ten topics for the ten sessions describe one or more of the six themes described by [16, 17], aiming to elicit meaningful disclosures following [30] and [2] guidelines. Following [16, 17] framework, these topics were aimed to initiate self-reflection and capture meaningful information regarding one's quality of life and mental health. The ten topics were: Work Situation, Leisure and Passions (Life), Finances, Relationships, Social Life, Mental Health, Physical Health, Personality, Goals and Ambitions, and Routine and Daily Activities. After each interaction with Pepper, participants completed several questionnaires. For a detailed description of the procedure (including the questionnaires that participants were asked to complete), please see the experimental design protocol [35].

2.2 Participants

The target population for this study is exclusively informal caregivers. These are adults from the general population aged 18 or over who are having extra responsibilities looking after a friend or a family member due to a long-term physical or mental ill-health or disability, or problem-related to old age [52]. Moreover, participants reported to have normal to corrected to normal vision, not suffer from hearing loss or difficulties, or physical handicap, are native English speakers, and currently reside in Great Britain. Due to the technical requirements of the mediated experimental design, the target population of this study consist of individuals with access to a personal computer with Zoom installed, a functioning web camera, stable internet connection, microphone, and speakers/headphones.

Participants were recruited via Prolific and were allowed to participate only after confirming that they were older than 18 years, are informal caregivers, are the main caregiver of their care recipient, are native English speakers, residing in the UK, and have access to a computer with Zoom installed as well as a decent web camera, stable internet connection, microphone, and speakers/headphones. Also, Prolific users were asked to commit to attending 2 sessions a week across a 5 week period. Participants were paid a total of £3 for every 30 minutes of participation or participation session if it lasted less than 30 minutes. Participants who completed all 10 sessions were paid an extra £20 after their final interaction.

A priori power calculations using G*power software [23, 24] suggest that for reasonable power (0.83) to detect small to medium effect sizes, a sample size of 22 participants would be required. Due to the relatively complex data collection procedure and the potential for a high dropout rate, we recruited 40 participants via the Prolific website. Two participants who were recruited for the study ended up not participating in any of the sessions. Additionally, throughout the study four more participants dropped out, mainly due to their caregiving responsibilities, resulting in a final sample size of 34 participants.

2.3 Stimuli

Conversational interactions were guided by the robot Pepper (Soft-Bank Robotics), a humanoid robot capable of communicating via speech and body language or gestures. Pepper was placed in front of a web camera (Logi-tech, 1080p), connected to the experimenter computer (see Figure 2). Pepper communicated with participants in this study via the WoZ technique controlled by the experimenter via a PC laptop, whereas participants could only see Pepper on their Zoom screen (see Figure 1). All pre-scripted questions and speech items were written and coded in the WoZ system, with the experimenter controlling Pepper by pressing buttons on a PC laptop. Accordingly, the procedure followed a clear pre-programmed protocol where the experimenter did not need to speak or type anything during the interaction, but only pressed the relevant keys to trigger the required or appropriate text delivery via Pepper.

Pepper responded to participants' answers and statements with neutral or empathetic responses. Pepper's vocabulary was limited and constrained to reflect the current state of speech recognition technology in social robotics. A limited set of responses were pre-defined for answers and statements with neutral sentiment or containing factual information (e.g., "I understand", "I see", "okay"), for

Figure 2: The lab settings, including the robot Pepper (SoftBank Robotics) in front of a web camera, while the experimenter in the back is controlling the robot using the Wizard of Oz technique.

answers and statements of positive sentiment (e.g., "I am happy to hear that", "This is really interesting", "That's amazing"), and for answers and statements of negative sentiment (e.g., "I am sorry to hear that", "This sounds very challenging", "These are not easy times"). Moreover, Pepper had pre-defined statements for opening an interaction (e.g., "Hello there", "Hi!", "How are you doing today?"), closing an interaction ("That's it for now", "See you next time", "Have a good weekend", "Goodbye"), answer with basic polite gratitude (e.g., "I am fine, thank you!", "Thank you", "That is lovely of you to say so", "It was nice to chat with you too!"), and thank participants for their cooperation and disclosures (e.g., "Thank you for sharing with me", "Thank you for telling me", "What a nice memory. Thank you for sharing with me"). Pepper communicated using a cheerful, high-pitched voice, and expressive and animated body language that corresponded to the spoken content and Pepper's physical capabilities. Pepper's movements were self-initiated based on Pepper's demo software's "animation" function, in order to provide a sense of neutral interaction and to ensure replicability by future studies using the same functionality that all Pepper robots are equipped with.

2.4 Measurements and data units

For this late-breaking work, we are focusing on the features of disclosure's duration, which is the duration of the speech in seconds, and disclosure's length, which is the number of words used per disclosure. These two features were selected as measures for disclosure due to their objective essence to convey disclosure quantitatively [see 31, 34–36]. Using these two measures ensures high replicability, allowing other researchers to compare their results

in relation to the length and duration of self-disclosure. Accordingly, these objective measurements provide a common language for HRI and HCI researchers studying self-disclosure, as well as researchers from different fields studying interventions aimed at encouraging self-disclosure. These measures do not indicate for latent aspects of the concept like depth and breadth [1], as well as for subjective perceptions of disclosure [see 30, 31]. Nevertheless, other measures were collected to provide further information regarding participants' disclosures, including their subjective perceptions and qualitative evidence of the interaction [see 35].

The disclosure's duration was extracted and processed from the audio recordings using Parselmouth [29], a Python library for Praat [5]. Disclosure's length was extracted from the audio files using the IBM Watson speech recognition engine. To ensure capturing all utterances within each disclosure we amplified the audio files with 7 decibels and slowed the audio file's pitch.

To ensure that our models only include high-quality data, in these preliminary models we included only cases that were processed correctly and did not require any further diagnosis. This resulted in a final sample size of 987 data units. We further investigated changes in disclosure (duration and length) and constructed two additional models without the rapport item of each session, focusing only on items that corresponded to the topics of disclosure. These models included a sample size of 659 data units.
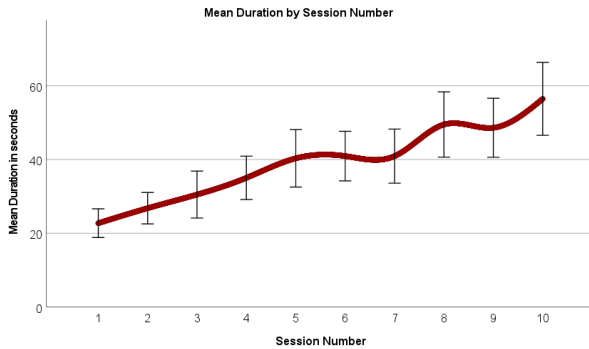
3 RESULTS

3.1 Duration

Simple linear regression was used to test if the session number significantly predicted the disclosure duration when interacting with the social robot Pepper. The overall regression was statistically

significant, $F(1, 985) = 90.16$, $p < .001$, explaining 8.4% ($R^2 = .084$) of the variance in participants' disclosure duration. It was found that the session number has a significant positive effect on participants' disclosure duration ($\beta = 2.80$, $SE = .30$, $p < .001$).

Another simple linear regression was used to test if the session number significantly predicted the disclosure duration when interacting with the social robot Pepper, including only the items that corresponded to the topic of disclosure. The overall regression was statistically significant, $F(1, 657) = 78.98$, $p < .001$, explaining 11% ($R^2 = .107$) of the variance in participants' disclosure duration. It was found that the session number has a significant positive effect on participants' disclosure duration ($\beta = 3.46$, $SE = .39$, $p < .001$).

Figure 3: Mean duration in seconds by the session number, including only the items that corresponded to the topic of disclosure.
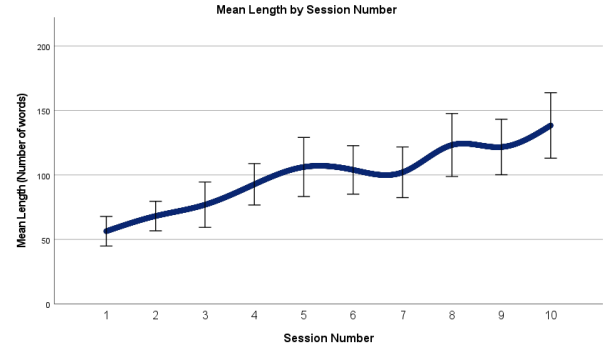
3.2 Length

Simple linear regression was used to test if the session number significantly predicted the disclosure length, in terms of the number of words used, when interacting with the social robot Pepper. The overall regression was statistically significant, $F(1, 985) = 70.46$, $p < .001$, explaining 7% ($R^2 = .067$) of the variance in participants' disclosure length. It was found that the session number has a significant positive effect on participants' disclosure length ($\beta = 6.70$, $SE = .80$, $p < .001$).

Another simple linear regression was used to test if the session number significantly predicted the disclosure length, in terms of the number of words used, when interacting with the social robot Pepper, including only the items that corresponded to the topic of disclosure. The overall regression was statistically significant, $F(1, 657) = 61.15$, $p < .001$, explaining 9% ($R^2 = .085$) of the variance in participants' disclosure length. It was found that the session number has a significant positive effect on participants' disclosure length ($\beta = 8.32$, $SE = 1.06$, $p < .001$).

4 DISCUSSION AND CONCLUSIONS

In order to evaluate informal caregivers' self-disclosures to social robots, we conducted a longitudinal online mediated experiment with 10 repetitions that took place over a 5 week period. Our preliminary results show a clear positive trend where informal caregivers

Figure 4: Mean length in number of words by the session number, including only the items that corresponded to the topic of disclosure.

speak for a longer time and share more information in their disclosures to the social robot Pepper across the 10 sessions. While previous longitudinal studies often report novelty effects in human–machine communication encounters [59][e.g., 18], here we see a clear opposing trend with the length and quality of participant disclosures increasing over time. These results provide meaningful evidence for user experience, acceptance, and trust of social robots in care settings [see 37]. This is in line with users' [see 54] and experts' [see 12] views addressing the importance of user experience factors when using robots in care settings and psychosocial interventions, on behalf of both care recipients and caregivers.

These preliminary results are particularly interesting due to the unique life situation of the target population, informal caregivers [see 52]. These individuals are under significant stress and deal with many complex burdens [42, 49, 51]. Accordingly, from the results of this study, we can learn about the value of social robot-led interactions with stressed individuals who might not be suffering from a diagnosed mental condition themselves, but are living with considerably difficult life situations. Furthermore, these results provide important evidence concerning the potential of introducing social robots in real-life applications of EMAs and EMIs. Social robots could therefore elicit rich interactions with stressed individuals over time, acquire relevant information from their disclosures, and potentially (and this will need to be further investigated and empirically evaluated) relieve their stress and burden via engaging them in ongoing discussions that elicit rich self-disclosures.

REFERENCES

[1] Irwin Altman and Dalmas A Taylor. 1973. *Social penetration: The development of interpersonal relationships*. Holt, Rinehart & Winston, Oxford, England. viii,

212−viii, 212 pages.

[2] Arthur Aron, Edward Melinat, Elaine N. Aron, Robert Darrin Vallone, and Renee J. Bator. 1997. The experimental generation of interpersonal closeness: A procedure and some preliminary findings. *Personality and Social Psychology Bulletin* 23, 4 (7 1997), 363−377. https://doi.org/10.1177/0146167297234003

[3] Ieva Biliunaite, Austeja Dumarkaite, Evaldas Kazlauskas, Robbert Sanderman, and Gerhard Andersson. 2021. ICBT program for improving informal caregiver well-being: A qualitative study. *Internet Interventions* 23 (3 2021), 100361. https://doi.org/10.1016/J.INVENT.2021.100361

[4] Ieva Biliunaite, Evaldas Kazlauskas, Robbert Sanderman, and Gerhard Andersson. 2021. Process Evaluation of Internet-Based Cognitive Behavioral Therapy Intervention for Informal Caregivers. *Frontiers in Medicine* 8 (11 2021), 2227. https://doi.org/10.3389/FMED.2021.725510/BIBTEX

[5] Paul Boersma and David Weenink. 2001. PRAAT, a system for doing phonetics by computer. *Glot international* 5 (2001), 341−345.

[6] Judith Bom, Pieter Bakx, Frederik Schut, and Eddy Van Doorslaer. 2019. The Impact of Informal Caregiving for Older Adults on the Health of Various Types of Caregivers: A Systematic Review. *The Gerontologist* 59, 5 (9 2019), e629−e642. https://doi.org/10.1093/GERONT/GNY137

[7] L. M.M. Boots, M. E. De Vugt, R. J.M. Van Knippenberg, G. I.J.M. Kempen, and F. R.J. Verhey. 2014. A systematic review of Internet-based supportive interventions for caregivers of patients with dementia. *International Journal of Geriatric Psychiatry* 29, 4 (4 2014), 331−344. https://doi.org/10.1002/GPS.4016

[8] Michal Braun, Mario Mikulincer, Anne Rydall, Andrew Walsh, and Gary Rodin. 2007. Hidden morbidity in cancer: Spouse caregivers. *Journal of Clinical Oncology* 25, 30 (10 2007), 4829−4834. https://doi.org/10.1200/JCO.2006.10.0909

[9] Cynthia Breazeal. 2003. Toward sociable robots. *Robotics and Autonomous Systems* 42, 3 (2003), 167−175. https://doi.org/10.1016/S0921-8890(02)00373-1

[10] Henry Brodaty and Marika Donkin. 2009. Family caregivers of people with dementia. *Dialogues in Clinical Neuroscience* 11, 2 (2009), 217. https://doi.org/10.31887/DCNS.2009.11.2/HBRODATY

[11] Lora E. Burke, Saul Shiffman, Edvin Music, Mindi A. Styn, Andrea Kriska, Asim Smailagic, Daniel Siewiorek, Linda J. Ewing, Eileen Chasens, Brian French, Juliet Mancino, Dara Mendez, Patrick Strollo, and Stephen L. Rathbun. 2017. Ecological Momentary Assessment in Behavioral Research: Addressing Technological and Human Participant Challenges. *Journal of Medical Internet Research* 19, 3 (3 2017). https://doi.org/10.2196/JMIR.7138

[12] Theresa Sophie Busse, Sven Kernebeck, Larissa Nef, Patrick Rebacz, Ilona Kick-busch, and Jan Peter Ehlers. 2021. Views on Using Social Robots in Professional Caregiving: Content Analysis of a Scenario Method Workshop. *Journal of medical Internet research* 23, 11 (11 2021). https://doi.org/10.2196/20046

[13] John R Carlson and Robert W Zmud. 1999. Channel Expansion Theory and the Experiential Nature of Media Richness Perceptions. *The Academy of Management Journal* 42, 2 (1999), 153−170. https://doi.org/10.2307/257090

[14] Kelly J. Chandler, Camilla J. Hodge, Kara McElvaine, Ericka J. Olschewski, Karen K. Melton, and Pascal Deboeck. 2021. Challenges of ecological momentary assessments to study family leisure: Participants' perspectives. *https://doi.org/10.1080/00222216.2021.2001398* (11 2021), 1−7. https://doi.org/10.1080/00222216.2021.2001398

[15] Rebecca N Collins and Naoko Kishita. 2020. Prevalence of depression and burden among informal care-givers of people with dementia: a meta-analysis. *Ageing and Society* 40, 11 (2020), 2355−2392. https://doi.org/DOI:10.1017/S0144686X19000527

[16] Janice Connell, John Brazier, Alicia O'Cathain, Myfanwy Lloyd-Jones, and Suzy Paisley. 2012. Quality of life of people with mental health problems: a synthesis of qualitative research. *Health and Quality of Life Outcomes* 10, 1 (2012), 138. https://doi.org/10.1186/1477-7525-10-138

[17] Janice Connell, Alicia O'Cathain, and John Brazier. 2014. Measuring quality of life in mental health: Are we asking the right questions? *Social Science and Medicine* 120 (8 2014), 12−20. https://doi.org/10.1016/j.socscimed.2014.08.026

[18] Emmelyn A J Croes and Marjolijn L Antheunis. 2020. Can we be friends with Mitsuku? A longitudinal study on the process of relationship formation between humans and a social chatbot. *Journal of Social and Personal Relationships* 38, 1 (9 2020), 279−300. https://doi.org/10.1177/0265407520959463

[19] Richard L Daft and Robert H Lengel. 1986. Organizational Information Require-ments, Media Richness and Structural Design. *Management Science* 32, 5 (1986), 554−571. https://doi.org/10.1287/mnsc.32.5.554

[20] Kim Phuong Dao, Katrien De Cocker, Huong Ly Tong, A Baki Kocaballi, Clara Chow, and Liliana Laranjo. 2021. Smartphone-Delivered Ecological Momentary Interventions Based on Ecological Momentary Assessments to Promote Health Behaviors: Systematic Review and Adapted Checklist for Reporting Ecologi-cal Momentary Assessment and Intervention Studies. *JMIR Mhealth Uhealth 2021;9(11):e22890 https://mhealth.jmir.org/2021/11/e22890* 9, 11 (11 2021), e22890. https://doi.org/10.2196/22890

[21] P. L. de Zwart, P. Bakx, and E. K.A. van Doorslaer. 2017. Will you still need me, will you still feed me when I'm 64? The health impact of caregiving to one's spouse. *Health economics* 26 Suppl 2, Suppl Suppl 2 (9 2017), 127−138. https://doi.org/10.1002/HEC.3542

[22] Valerian J Derlega, Barbara A Winstead, Robin J Lewis, and James Maddux. 1993. Clients' responses to dissatisfaction in psychotherapy: A test of Rusbult's exit-voice-loyalty-neglect model. *Journal of Social and Clinical Psychology* 12, 3 (1993), 307−318. https://doi.org/10.1521/jscp.1993.12.3.307

[23] Franz Faul, Edgar Erdfelder, Axel Buchner, and Albert-Georg Lang. 2009. Sta-tistical power analyses using G*Power 3.1: Tests for correlation and regres-sion analyses. *Behavior Research Methods* 41, 4 (2009), 1149−1160. https://doi.org/10.3758/BRM.41.4.1149

[24] Franz Faul, Edgar Erdfelder, Albert-Georg Lang, and Axel Buchner. 2007. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods* 39, 2 (2007), 175−191. https://doi.org/10.3758/BF03193146

[25] Irina Fonareva, Alexandra M. Amen, Roger M. Ellingson, and Barry S. Oken. 2012. Differences in stress-related ratings between research center and home environments in dementia caregivers using ecological momentary assessment. *International Psychogeriatrics* 24, 1 (1 2012), 90−98. https://doi.org/10.1017/S1041610211001414

[26] Pierre Gérain and Emmanuelle Zech. 2019. Informal Caregiver burnout? De-velopment of a theoretical framework to understand the impact of caregiving. *Frontiers in Psychology* 10, JULY (2019), 1748. https://doi.org/10.3389/FPSYG.2019.01748/BIBTEX

[27] Anna Henschel, Guy Laban, and Emily S Cross. 2021. What Makes a Robot Social? A Review of Social Robots from Science Fiction to a Home or Hospital Near You. *Current Robotics Reports* 2 (2021), 9−19. https://doi.org/10.1007/s43154-020-00035-0

[28] Laura Hiel, Mariëlle A. Beenackers, Carry M. Renders, Suzan J.W. Robroek, Alex Burdorf, and Simone Croezen. 2015. Providing personal informal care to older European adults: should we care about the caregivers' health? *Preventive medicine* 70 (1 2015), 64−68. https://doi.org/10.1016/J.YPMED.2014.10.028

[29] Yannick Jadoul, Bill Thompson, and Bart de Boer. 2018. Introducing Parselmouth: A Python interface to Praat. *Journal of Phonetics* 71 (11 2018), 1−15. https://doi.org/10.1016/j.wocn.2018.07.001

[30] Sidney M Jourard. 1971. *Self-disclosure: An experimental analysis of the transparent self.* John Wiley, Oxford, England. xiii, 248−xiii, 248 pages.

[31] Hamutal Kreiner and Yossi Levi-Belz. 2019. Self-Disclosure Here and Now: Com-bining Retrospective Perceived Assessment With Dynamic Behavioral Measures. *Frontiers in Psychology* 10 (2019), 558. https://doi.org/10.3389/fpsyg.2019.00558

[32] Guy Laban. 2021. Perceptions of Anthropomorphism in a Chatbot Dialogue: The Role of Animacy and Intelligence. In *Proceedings of the 9th International Conference on Human-Agent Interaction.* ACM, New York, NY, USA, 305−310. https://doi.org/10.1145/3472307.3484686

[33] Guy Laban, Ziv Ben-Zion, and Emily S. Cross. 2022. Social Robots for Supporting Post-traumatic Stress Disorder Diagnosis and Treatment. *Frontiers in psychiatry* 12 (2 2022). https://doi.org/10.3389/FPSYT.2021.752874

[34] Guy Laban, Jean-Noël George, Val Morrison, and Emily S. Cross. 2021. Tell me more! Assessing interactions with social robots from speech. *Paladyn, Journal of Behavioral Robotics* 12, 1 (2021), 136−159. https://doi.org/10.1515/pjbr-2021-0011

[35] Guy Laban, Arvid Kappas, Val Morrison, and Emily S. Cross. 2021. Protocol for a Mediated Long-Term Experiment with a Social Robot. *PsyArXiv* (2021). https://doi.org/10.31234/OSF.IO/4Z3AW

[36] Guy Laban, Val Morrison, and Emily S Cross. 2020. Let's Talk About It! Subjective and Objective Disclosures to Social Robots. In *Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction.* Associ-ation for Computing Machinery, Cambridge, United Kingdom, 328−330. https://doi.org/10.1145/3371382.3378252

[37] Effie Lai-Chong Law, Asbjørn Følstad, Jonathan Grudin, and Björn Schuller. 2022. Conversational Agent as Trustworthy Autonomous System (Trust-CA) (Dagstuhl Seminar 21381). *Dagstuhl Reports* 11, 8 (2022), 76−114. https://doi.org/10.4230/DagRep.11.8.76

[38] Carlo Lazzari. 2018. Ecological Momentary Assessments and Interventions in Alzheimer's Caregiving. *Current Alzheimer Research* 15, 11 (7 2018), 1027−1031. https://doi.org/10.2174/1567205015666180702111523

[39] Yunhuan Li, Juejin Li, Yalin Zhang, Yuxin Ding, and Xiaolin Hu. 2022. The effectiveness of e-Health interventions on caregiver burden, depression, and quality of life in informal caregivers of patients with cancer: A systematic review and meta-analysis of randomized controlled trials. *International journal of nursing studies* 127 (3 2022). https://doi.org/10.1016/J.IJNURSTU.2022.104179

[40] SJ Semple MM Skaff LI Pearlin, JT Mullan. 1990. Caregiving and the stress process: an overview of concepts and their measures. *Gerontologist* 30, 5 (1990), 583−594. https://doi.org/10.1093/geront/30.5.583

[41] Michael J Mahoney. 1995. Emotionality and health: Lessons from and for psy-chotherapy. In *Emotion, disclosure, & health.* American Psychological Association, Washington, DC, US, 241−253. https://doi.org/10.1037/10182-011

[42] Leonard I. Pearlin, Joseph T. Mullan, Shirley J. Semple, and Marilyn M. Skaff. 1990. Caregiving and the stress process: an overview of concepts and their measures. *The Gerontologist* 30, 5 (1990), 583−594. https://doi.org/10.1093/GERONT/30.5.583

[43] James W Pennebaker. 1997. *Opening up: The healing power of expressing emotions, Rev. ed.* Guilford Press, New York, NY, US. 249, xii, 249–xii pages.

[44] James W Pennebaker. 1997. Writing about Emotional Experiences as a Therapeutic Process. *Psychological Science* 8, 3 (1997), 162–166. http://www.jstor.org/stable/40063169

[45] Milica Petrovic and Andrea Gaggioli. 2020. Digital Mental Health Tools for Caregivers of Older Adults—A Scoping Review. *Frontiers in Public Health* 8 (2020), 128. https://doi.org/10.3389/fpubh.2020.00128

[46] Milica Petrovic and Andrea Gaggioli. 2021. The potential of transformative video design for improving caregiver's wellbeing. *Health psychology open* 8, 1 (4 2021), 20551029211009098. https://doi.org/10.1177/20551029211009098

[47] Martin Pinquart and Silvia Sörensen. 2007. Correlates of physical health of informal caregivers: a meta-analysis. *The journals of gerontology. Series B, Psychological sciences and social sciences* 62, 2 (2007). https://doi.org/10.1093/GERONB/62.2.P126

[48] Jenny Ploeg, Maureen Markle-Reid, Ruta Valaitis, Carrie McAiney, Wendy Duggleby, Amy Bartholomew, and Diana Sherifali. 2017. Web-based interventions to improve mental health, general caregiving outcomes, and general health for informal caregivers of adults with chronic conditions living in the community: Rapid evidence review. *Journal of Medical Internet Research* 19, 7 (2017). https://doi.org/10.2196/jmir.7564

[49] Tracey A. Revenson, Konstadina Griva, Aleksandra Luszczynska, Val Morrison, Efharis Panagopoulou, Noa Vilchinsky, and Mariët Hagedoorn. 2016. Caregiving Outcomes. *Caregiving in the Illness Context* (2016), 15–24. https://doi.org/10.1057/9781137558985_2

[50] Tracey A. Revenson, Konstadina Griva, Aleksandra Luszczynska, Val Morrison, Efharis Panagopoulou, Noa Vilchinsky, and Mariët Hagedoorn. 2016. Interventions to Support Caregivers. *Caregiving in the Illness Context* (2016), 90–104. https://doi.org/10.1057/9781137558985_8

[51] Tracey A. Revenson, Konstadina Griva, Aleksandra Luszczynska, Val Morrison, Efharis Panagopoulou, Noa Vilchinsky, and Mariët Hagedoorn. 2016. The Emotional Experience of Caregiving. *Caregiving in the Illness Context* (2016), 38–47. https://doi.org/10.1057/9781137558985_4

[52] Tracey A Revenson, Konstadina Griva, Aleksandra Luszczynska, Val Morrison, Efharis Panagopoulou, Noa Vilchinsky, and Mariët Hagedoorn. 2016. What Is Caregiving and How Should We Study It? In *Caregiving in the Illness Context*, Tracey A Revenson, Konstadina Griva, Aleksandra Luszczynska, Val Morrison, Efharis Panagopoulou, Noa Vilchinsky, and Mariët Hagedoorn (Eds.). Palgrave Macmillan UK, London, 1–14. https://doi.org/10.1057/9781137558985_1

[53] Nicole Lee Robinson, Timothy Vaughan Cottier, and David John Kavanagh. 2019. Psychosocial Health Interventions by Social Robots: Systematic Review of Randomized Controlled Trials. *J Med Internet Res* 21, 5 (2019), 1–20. https://doi.org/10.2196/13203

[54] Nicole L. Robinson and David J. Kavanagh. 2021. A social robot to deliver a psychotherapeutic treatment: Qualitative responses by participants in a randomized controlled trial and future design recommendations. *International Journal of Human-Computer Studies* 155 (11 2021), 102700. https://doi.org/10.1016/J.IJHCS.2021.102700

[55] Rajeswari Sambasivam, Jianlin Liu, Janhavi A. Vaingankar, Hui L. Ong, Min En Tan, Restria Fauziana, Louisa Picco, Siow Ann Chong, and Mythily Subramaniam. 2019. The hidden patient: chronic physical morbidity, psychological distress, and quality of life in caregivers of older adults. *Psychogeriatrics* 19, 1 (1 2019), 65. https://doi.org/10.1111/PSYG.12365

[56] Arielle A J Scoglio, Erin D Reilly, Jay A Gorman, and Charles E Drebing. 2019. Use of Social Robots in Mental Health and Well-Being Research: Systematic Review. *J Med Internet Res* 21, 7 (2019), e13322. https://doi.org/10.2196/13322

[57] Kelly M. Shaffer, Philip I. Chow, Jillian V. Glazer, Tri Le, Matthew J. Reilley, Mark J. Jameson, and Lee M. Ritterband. 2021. Feasibility of ecological momentary assessment to study depressive symptoms among cancer caregivers. *Psycho-Oncology* 30, 5 (5 2021), 756–764. https://doi.org/10.1002/PON.5627

[58] Denise M Sloan. 2010. Self-disclosure and psychological well-being. The Guilford Press, New York, NY, US, 212–225.

[59] Catharina Vesterager Smedegaard. 2019. Reframing the Role of Novelty within Social HRI: From Noise to Information. In *Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI '19)*. IEEE Press, 411–420. https://doi.org/10.1109/HRI.2019.8673219

[60] William B. Stiles. 2004. Disclosure as a speech act: Is it psychotherapeutic to disclose? *Emotion, disclosure, & health.* (10 2004), 71–91. https://doi.org/10.1037/10182-004

[61] Mikołaj Zarzycki and Val Morrison. 2021. Getting back or giving back: understanding caregiver motivations and willingness to provide informal care. *http://mc.manuscriptcentral.com/HPBM* 9, 1 (2021), 636–661. https://doi.org/10.1080/21642850.2021.1951737

[62] Mikołaj Zarzycki, Val Morrison, Eva Bei, and Diane Seddon. 2022. Cultural and societal motivations for being informal caregivers: a qualitative systematic review and meta-synthesis. *https://doi.org/10.1080/17437199.2022.2032259* (2022). https://doi.org/10.1080/17437199.2022.2032259