PerMEASS – Personal Mental Health Virtual Assistant with Novel Ambient Intelligence Integration

Tine Kolenik [1] and **Martin Gjoreski** [2] and **Matjaž Gams** [3]

Abstract. This paper describes the design for a personal mental health virtual assistant with novel ambient intelligence integration – PerMEASS. It is specifically designed to provide help for three mental health issues: stress, anxiety and depression. Its assistance in these issues is based on two very closely related and trending multidisciplinary computer science fields – persuasive technology and digital behavior change intervention, which both research ways to affect human behavior or attitudes with technology, but without coercion or deception. A short overview of such assistants focuses on three of them, which represent state of the art. PerMEASS is described in more detail and compared to state of the art to showcase how it advances the existing solutions. The focus is on two parts of PerMEASS' cognitive architecture that present novel contributions: 1) a model of the theory of mind, a cognitive ability to understand other people and act appropriately, 2) an integration with ambient intelligence – artificial intelligence in the environment – in the form of a smart bracelet. PerMEASS' theory of mind is used to build a user model and utilize mental health and behavior change ontologies to devise effective and personalized strategies. At the same time, reinforcement learning is used to evaluate the strategies in real-time and use only the ones that are successful, making PerMEASS very adaptive. PerMEASS uses a smart bracelet to achieve this goal as well. The integration of the assistant with a device to collect biophysiological data in real-time pushes the assistant technology into new, so far unexplored directions. Our future work consists of firm implementation of the design and testing it in randomized controlled trials.

1 1 INTRODUCTION

Virtual assistant (VA) technology is rising in its prominence through advancements in artificial intelligence (AI), showcased by Google and Amazon VAs. However, this field of research has also been receiving more and more attention and financing for other, less commercially-oriented domain use [6, 23, 27]. VAs can be described as complex information processing agents, capable of acquiring information, putting it into action and transmitting knowledge, bringing together, much like cognitive science, things like perception, intelligence, thinking, calculation, reasoning, imagining and, in the end, conscience [23]. Research on VAs has made them understand context, adapt, learn, develop, communicate, collaborate, socialize, anticipate, predict, perceive, act, interpret, and reason. VAs are capable of doing that by having a cognitive architecture (CArch), a "hypothesis about the fixed structures that provide a mind, whether in natural or artificial systems, and how they work together – in conjunction with knowledge and skills embodied within the architecture – to yield intelligent behavior in a diversity of complex environments" [1, para. 2]. VAs are deployed either as conversational agents (aka chatbot, chatterbot, interactive agent, conversational AI, smartbot) or robots.

Another field of research in computer science that is rising in prominence is ambient intelligence (AmI). AmI is "in essence, AI in the environment" [11, p. 71], and it more specifically refers to "electronic environments that are sensitive and responsive to the presence of people," [11, p. 76] where "one of the essential tasks of AmI is to detect the physical, mental, emotional and other states of a user" [11, p. 75]. AmI is usually instantiated in platforms such as smart cities, intelligent living rooms, intelligent work places, smart public places, smart schools and playgrounds, and in ambient care and safety. To this end, AmI systems have to be embedded, context-aware, personalized, adaptive, anticipatory, unobtrusive and non-invasive [11]. Such systems have become readily available to the public due to the recent technological advances in wearables that measure biophysiological phenomena. These wearables include devices that can measure anything from heart rate and skin conductance to movement and respiratory rate [14].

VA and AmI technologies are beginning to be used for mental health (MHealth) and well-being [14, 25, 32], mostly due to the trend of progressively larger MHealth issues. Their devastating effects on an individual as well as on the society as a whole are only slowly being recognized systemically. Stress, anxiety and depression (SAD) are on the forefront of MHealth issues, with figures reaching 71% for stress, 12% for anxiety disorder and 48% for depression [31]. High suicide rates [5] contribute to revealing the lack of MHealth professionals and appropriate regulations [33]. This can therefore be an opportunity for unique technological solutions.

VAs can be purposed for MHealth treatment if used as persuasive technology (PT) [8] for digital behavior change intervention (DBCI) [21]. DBCIs attempt to "change attitudes or behaviors or both (without using coercion or deception)" [8, p. 20], where behavior change (BC) signifies a temporary or permanent effect on an individual's behavior or attitude as compared to their past [8]. Using VAs for MHealth can make an immediate impact, as they can be used without payment (which breaks down socioeconomic barriers); they are always online (making therapy available to anyone with a device that has an internet connection at any time); people feel less uneasy and anxious about sharing their feelings or personal information when

[1] Jožef Stefan Institute Jožef Stefan International Postgraduate School, Slovenia, email: tine.kolenik@ijs.si
[2] Jožef Stefan Institute Jožef Stefan International Postgraduate School, Slovenia, email: martin.gjoreski@ijs.si
[3] Jožef Stefan Institute, Slovenia, email: matjaz.gams@ijs.si

talking to a VA than to a professional or other people [7, 20]; VAs can be accessed from remote locations, and so on. Using VAs in the MHealth care therefore reduces burden on the existing system, while also reducing barriers to access it. It is also important to note that these technologies are meant to complement, rather than replace MHealth professionals [6, 25].

Section 2 shortly presents three MHealth VAs (MHVAs), which represent the current state of the art (SOTA). Section 3 presents PerMEASS in more detail, focusing on the CArch design, in order to show how it surpasses the current SOTA. Section 4 summarizes the work and sketches future directions.

2 STATE OF THE ART

The selection of the three SOTA MHVAs for this section was made according to the following conditions: 1) the MHVAs were text-based; 2) the MHVAs were researched ecologically, outside of a laboratory; 3) the MHVAs were experimentally tested. Due to the novelty of these technologies being used for MHealth, the pool of existing MHVAs that satisfied our conditions was not much larger than three.

Tess is a MHVA that "reduce[s] self-identified symptoms of depression and anxiety" [9, p. 1]. It is based on having an extensive ontology on emotions. This ontology is used on the input text from a user to discern their mood. After mood identification, Tess uses scripted conversations to help the user. The conversations are the result of three of Tess' CArch modules: a natural language understanding module, dialogue state manager and natural language response generator. Once Tess dispatches the help, it gathers journaling data and user feedback to improve them. When tested, depression and anxiety symptoms in the test group, which used Tess, were reduced by roughly 15%, while the control group, which used official self-help material, saw no change.

Yorita, Egerton, Oakman, Chan and Kubota [34] presented a MHVA that teaches its users to manage stress better and thus reduce it. Its Belief-Desire-Intention CArch has three models: "a conversation model for acquiring state information about the individual, measuring their stress level, a Sense of Coherence (SOC) model for evaluating the individuals state of stress, and Peer Support model, which uses the SOC to select a suitable peer support type and action it" [34, p. 3762]. The MHVA uses its user model, based on questionnaires on stress, to select a stress relief strategy. Strategies try to teach users to improve their stress management. The experiment with the MHVA reported that the more the subjects used the MHVA, the more they learned to manage their stress.

The last overviewed MHVA is named Woebot [7]. It primarily functions with a simple machine learning (ML) algorithm, a "decision tree with suggested responses that accepts natural language inputs with discrete sections of natural language processing techniques embedded at specific points in the tree to determine routing to subsequent conversational nodes" [7, p. 3]. Its user model has a few data points, including data on users' moods, goals, expectations and similar. The user model guides Woebot's selection of an intervention, which can be in the form of educational videos and tailored advice. When used in a randomized controlled trial, the test group, which used Woebot, saw 20% SAD symptom relief, while the control group, which used the government-approved self-help book, saw no change.

Although experimentally successful – these successes have been reported across the board [2, 17, 22, 25, 32] – such MHVAs still lack what PT and DBCI have to offer, especially in terms of user modelling, personalization and adaptation as well as working with real-time biophysiological data. This is what our research focuses on and presents in Section 3.

3 PERMEASS ARCHITECTURE DESIGN

This section describes the design of PerMEASS, a personal mental health virtual assistant with novel ambient intelligence integration. The focus is on two parts of PerMEASS' CArch: 1) the theory of mind (ToM) model, whose modules form the basis for PerMEASS' cognition, namely understanding and helping a user; 2) ambient intelligence integration with smart bracelet, which presents a novel fusion of two technologies, MHVAs and AmI, thus combining recognition powers of the latter and intervention potential of the former. These two features are why PerMEASS surpasses the current SOTA, which is described in Section 2, as they make the MHVA highly adaptive and personalized.

PerMEASS' CArch design can be seen in Figure 1. The fundamental part is labelled 'THEORY OF MIND' (top of the figure; it consists of: 'USER MODEL', 'EXPERT DOMAIN KNOWLEDGE' and the two 'STRATEGY' modules). In cognitive science, ToM describes the ability to "understand the thoughts and feelings" [18, p. 528] as well as "attributing thoughts and goals to others" [18, p. 528]. The ToM in PerMEASS' CArch is not as general as cognitive science deems it, but more domain-specific in terms of its functionality – with it, PerMEASS tries to understand a user in terms of their MHealth issues and help them with a reasonable action – a personalized and adaptive strategy – to solve those issues. AmI integration happens at the bottom of Figure 1, where 'PHYSIOLOGICAL INPUT' flows into 'AFFECT RECOGNITION' module.

In terms of PerMEASS' natural language processing (NLP) capabilities, they are simple and largely subservient to ToM. Since they are not the focus of our research, they are mostly outsourced to existing technologies and available software. Rasa [3], an open source conversational AI framework, is being used as one such solution. Rasa offers NLP ML for intent classification and entity recognition (word2vec algorithms) as well as reinforcement learning (RL) [29] for selecting the correct dialogue nodes. However, PerMEASS is mostly designed to be button-based, which contributes to the stated simplicity, as there is less complexity in linguistic inputs. This also presents a safer option in terms of control and precision for discerning which strategy for SAD symptom relief works best for a user. The option for certain NLP capabilities and free text options appearing at certain nodes in the scripted conversations is being researched.

The next two subsections focus on the two PerMEASS' CArch parts that are the basis of its capabilities: its ToM and its AmI integration. ToM is largely based in behavioral and cognitive sciences advances on human decision-making, BC and similar phenomena [4, 30]. These advances are rarely considered when designing such systems, which is what we want to leverage and endow PerMEASS with. There does, however, seem to be a trend in recognizing benefits of such multi- and interdisciplinary efforts, as PTs are being progressively used to help, motivate and guide people towards well-being [16, 24]. Using behavioral and cognitive sciences knowledge in PerMEASS should therefore prove to be crucial for its success.

3.1 Model of the theory of mind in PerMEASS

PerMEASS' ToM consists of three larger subparts (see Figure 1): the user model ('USER MODEL'), a module with ontologies on expert and domain knowledge ('EXPERT DOMAIN KNOWLEDGE'), and modules on strategy selection ('STRATEGY SELEC-

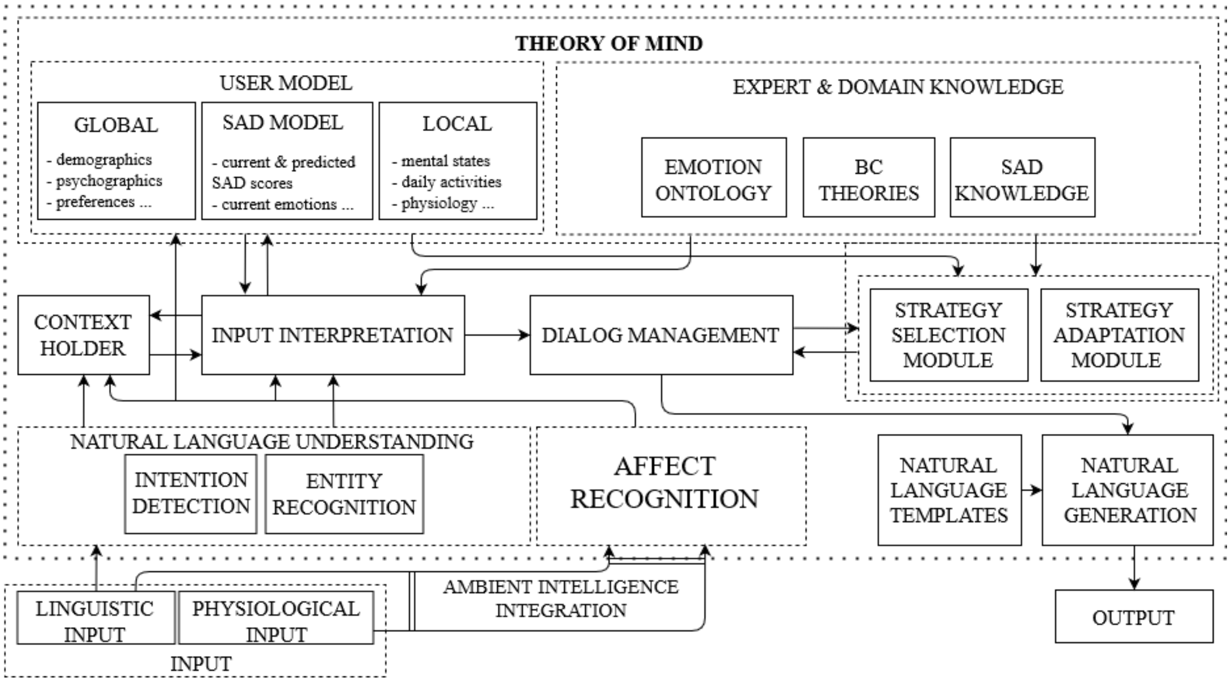

Figure 1. PerMEASS' CArch

TION MODULE') and adaptation ('STRATEGY ADAPTATION MODULE'). These are described in depth below.

3.1.1 User Model

The user model [13] is an essential part of PerMEASS to effectively dispatch its strategies. These range from passively – when the user is not actively conversing with PerMEASS – delivered nudges, which are "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options" [30, p. 6], to active in-conversation help. For increased rates of success, PerMEASS continually updates a model of its user. It dialogically delivers a questionnaire on the Big Five personality traits (B5) [26], which model the user's personality. The Big 5 model of a user is a global aspect of the user model, meaning that it is not changing or updating. For local – or continuously updating – aspects of the user model, SAD scores are the most important. They are determined through the Depression Anxiety Stress Scales 21 questionnaire [19], which measures short-term SAD. These scores get regularly updated through continuous posing of the questionnaire. Sentiment analysis also presents a dimension in the user model, used for discerning emotional valence. Collecting data on other user dimensions is being considered as well.

3.1.2 Expert and Domain Knowledge

The expert and domain knowledge module is made of various ontologies. This means that the knowledge on emotions, BC and SAD is, through rules, transformed into a computer-readable language. Ontological relations then serve other VA's functions that can use them. PerMEASS uses the expert and domain knowledge module, which utilizes the user model, to personalize its behavior and tailor its strategies to the user: B5 is used to personalize the messages PerMEASS dispatches (e.g., the dominant B5 dimension of a user guides the strategy selection [15]); the ontology on emotions is used in connection with the local aspects of the user model to guide the conversation (see Tess in Section 2); the SAD knowledge determines the SAD severity and type for selecting the correct thematic strategy (e.g., self-education on the SAD type); the most helpful form of BC is selected, which ranges from self-reflection (that, e.g., comes from monitoring) to tailored emotion elicitation [4].

3.1.3 Strategy Selection and Adaptation

Strategy selection for dispatching tailored help to the user is largely based on the latter's B5 profile, but also on SAD scores. B5 is one of the most stable psychological and cognitive constructs, highly reproduced and successful in determining the right kind of influence on specific personalities [15, 26]. This makes it fundamental for strategy selection. The expert and domain knowledge module provides multiple different strategies that compete with each other for deployment. They have to contend according to multiple criteria [10] for selection. However, this is only one part of how the strategies are dependent on the user. The other mechanism for strategies is their adaptation, which is dependent on their success in certain timespan with a certain user. ML, namely RL [29], enables PerMEASS to learn from its historical interactions and conversations with its users to discern which strategies work better and which do not work. If the strategy selection is a top-down approach, dependent on our knowledge and presuppositions on what works with certain psychological and cognitive profiles, this adaptive approach is a bottom-up process. Combined, they form a powerful capability to discern the most effective strategies. Currently, the main problem of strategy adaptation with RL is determining the reward function in the algorithm. The reward function in PerMEASS' RL algorithm is represented by the SAD score as well as the length of the time that it takes to evaluate a certain strategy and whether it works (meaning it helps the user). Since timespan evaluation is difficult and becomes accurate only when not using short-term strategies, only some strategies can work from this bottom-up aspect. Experiments and user studies are planned to determine the timespan threshold of strategies as well as to select the strategies for RL usage.

The three modules that form ToM are a fruitful testing ground for fusing MHVA technology with AmI. Integrating PerMEASS with AmI, namely connecting a smart bracelet to be part of its 'cognition', can be beneficial and enhance existing functionalities to a new level.

3.2 Ambient Intelligence Integration

A smart bracelet – specifically, Empatica [12] is being tested – provides PerMEASS with biophysiological measurements (e.g., heart rate, sweating rate and skin temperature). These measurements are used for automatic monitoring of SAD [14]. The bracelet readings are fed into a neural network to build a model that can predict a user's SAD symptoms, which eliminates the need for PerMEASS to pose the SAD questionnaire or at least lower the frequency of it being posed, improving the user experience. Therefore, the user model is updated with SAD scores in real time and continuously. To establish such a process, the SAD model is built in the following way: when the measurements start, the SAD answers from the questionnaire are used to label the biophysiological data from the smart bracelet. The accuracy of the model is dependent on the amount of data, so through time, enough data results in personalized ML models that become accurate enough to predict SAD scores. The affect recognition module ('AFFECT RECOGNITION' in Figure 1) is used for this PerMEASS' capability.

With such a model, the smart bracelet can be used to improve nudging. Nudges can be utilized at times that most benefit the user. When the user model reflects certain real-time SAD scores, a nudge can be dispatched as a passive intervention (which means that the user will not have to use PerMEASS actively to receive help).

4 CONCLUSION

This paper outlines PerMEASS, a personal mental health virtual assistant with novel ambient intelligence integration. We show, through overviewing SOTA MHVA systems, how PerMEASS advances current state of the art in this field. We believe that PerMEASS achieves that with: 1) modelling ToM, a cognitive ability to understand and properly act in social interactions with people, and 2) introducing a novel fusion between two technologies, MHVAs and AmI, through integrating a smart bracelet into PerMEASS' CArch. ToM consists of: a user model with SAD, global and local user data; a RL algorithm to model historical interactions between PerMEASS and the user, thus reasoning on which strategies work and which do not; so far inexistent ontologies, especially on BC and SAD. PerMEASS also represents a technological fusion between MHVA and AmI, which we have not come across in the existing literature yet, and we want to continue exploring this novel symbiosis. Combining ToM and AmI integration results in an effective way of selecting and adapting multiple strategies for help in people with SAD symptoms.

In our next steps, we plan to make the final implementation [28] of PerMEASS as described. User studies and experiments will be carried out to test PerMEASS in an ecological environment – Fitzgerald et al [7] study will be replicated by replacing Woebot with PerMEASS – as well as to find out how to improve PerMEASS in other aspects.

Using AI as PT in the personalized health and well-being domain should be, in our belief, a societal priority. This makes relevant research important, and we feel that our ideas can contribute to realizing the promise the MHVA technology is exhibiting.

ACKNOWLEDGEMENTS

This work is supported by Slovenian Research Agency's Young researchers postgraduate research funding.

REFERENCES

[1] Cognitive architecture. http://cogarch.ict.usc.edu/. Accessed: 2020-05-30.

[2] David Bakker, Nikolaos Kazantzis, Debra Rickwood, and Nikki Rickard, 'Mental health smartphone apps: Review and evidence-based recommendations for future developments', *JMIR Mental Health*, **3**(1), e7, (Mar 2016).

[3] Tom Bocklisch, Joey Faulkner, Nick Pawlowski, and Alan Nichol, 'Rasa: Open source language understanding and dialogue management', *CoRR*, **abs/1712.05181**, (2017).

[4] Rachel Carey, Lauren Connell, Marie Johnston, Alexander Rothman, Marijn Bruin, Michael Kelly, and Susan Michie, 'Behavior change techniques and their mechanisms of action: A synthesis of links described in published intervention literature', *Annals of Behavioral Medicine*, **53**, 693–707, (10 2018).

[5] S. C. Curtin, M. Warner, and H. Hedegaard, 'Increase in Suicide in the United States, 1999-2014', *NCHS Data Brief*, (241), 1–8, (Apr 2016).

[6] Ahmed Fadhil and Gianluca Schiavo, 'Designing for health chatbots', *arXiv*, (1902.09022), (2019).

[7] Kathleen Kara Fitzpatrick, Alison Darcy, and Molly Vierhile, 'Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (woebot): A randomized controlled trial', *JMIR Ment Health*, **4**(2), e19, (Jun 2017).

[8] B.J. Fogg, *Persuasive Technology: Using Computers to Change What We Think and Do*, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2003.

[9] Russell Fulmer, Angela Joerin, Breanna Gentile, Lysanne Lakerink, and Michiel Rauws, 'Using psychological artificial intelligence (tess) to relieve symptoms of depression and anxiety: Randomized controlled trial', *JMIR Ment Health*, **5**(4), e64, (Dec 2018).

[10] M. Gamg, *Weak Intelligence: Through the Principle and Paradox of Multiple Knowledge*, Nova Science Pub Inc, New York, USA, 2001.

[11] Matjaz Gams, Irene Gu, Aki Härmä, Andrés Muñoz, and Vincent Tam, 'Artificial intelligence and ambient intelligence', *Journal of Ambient Intelligence and Smart Environments*, **11**, 71–86, (01 2019).

[12] M. Garbarino, M. Lai, D. Bender, R. W. Picard, and S. Tognetti, 'Empatica e3 — a wearable wireless multi-sensor device for real-time computerized biofeedback and data acquisition', in *2014 4th International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH)*, pp. 39–42, (Nov 2014).

[13] Suparna Ghanvatkar, Atreyi Kankanhalli, and Vaibhav Rajan, 'User models for personalized physical activity interventions: Scoping review', *JMIR Mhealth Uhealth*, **7**(1), e11098, (Jan 2019).

[14] Martin Gjoreski, Mitja Luštrek, Matjaž Gams, and Hristijan Gjoreski, 'Monitoring stress with a wrist device using context', *Journal of Biomedical Informatics*, **73**, 159 – 170, (2017).

[15] Jacob B. Hirsh, Sonia K. Kang, and Galen V. Bodenhausen, 'Personalized persuasion: Tailoring persuasive appeals to recipients' personality traits', *Psychological Science*, **23**(6), 578–581, (2012). PMID: 22547658.

[16] Catriona M Kennedy, John Powell, Thomas H Payne, John Ainsworth, Alan Boyd, and Iain Buchan, 'Active assistance technology for health-related behavior change: An interdisciplinary review', *J Med Internet Res*, **14**(3), e80, (Jun 2012).

[17] L. Laranjo, A. G. Dunn, H. L. Tong, A. B. Kocaballi, J. Chen, R. Bashir, D. Surian, B. Gallego, F. Magrabi, A. Y. S. Lau, and E. Coiera, 'Conversational agents in healthcare: a systematic review', *J Am Med Inform Assoc*, **25**(9), 1248–1258, (09 2018).

[18] Alan M. Leslie, Ori Friedman, and Tim P. German, 'Core mechanisms in 'theory of mind'', *Trends in Cognitive Sciences*, **8**(12), 528 – 533, (2004).

[19] S.H. Lovibond and P.F. Lovibond, *Manual for the Depression Anxiety Stress Scales*, Psychology Foundation monograph, Psychology Foundation of Australia, 1996.

[20] Gale M. Lucas, Jonathan Gratch, Aisha King, and Louis-Philippe Morency, 'It's only a computer: Virtual humans increase willingness to disclose', *Computers in Human Behavior*, **37**, 94 – 100, (2014).

[21] D. C. Mohr, M. N. Burns, S. M. Schueller, G. Clarke, and M. Klinkman, 'Behavioral intervention technologies: evidence review and recommendations for future research in mental health', *Gen Hosp Psychiatry*, **35**(4), 332–338, (2013).

[22] Joao Luis Zeni Montenegro, Cristiano André da Costa, and Rodrigo da Rosa Righi, 'Survey of conversational agents in health', *Expert Systems with Applications*, **129**, 56 – 67, (2019).

[23] J. Oakley. Intelligent cognitive assistants (ica).

[24] Rita Orji and Karyn Moffatt, 'Persuasive technology for health and wellness: State-of-the-art and emerging trends', *Health Informatics Journal*, **24**(1), 66–91, (2018).

[25] S. Provoost, H. M. Lau, J. Ruwaard, and H. Riper, 'Embodied Conversational Agents in Clinical Psychology: A Scoping Review', *J. Med. Internet Res.*, **19**(5), e151, (05 2017).

[26] Beatrice Rammstedt and Oliver P. John, 'Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german', *Journal of Research in Personality*, **41**(1), 203 – 212, (2007).

[27] A. Sheth, H. Y. Yip, and S. Shekarpour, 'Extending patient-chatbot experience with internet-of-things and background knowledge: Case studies with healthcare applications', *IEEE Intelligent Systems*, **34**(4), 24–30, (2019).

[28] Ian Sommerville, *Software Engineering*, Addison-Wesley, Harlow, England, 9 edn., 2010.

[29] Richard S. Sutton and Andrew G. Barto, *Reinforcement Learning: An Introduction*, The MIT Press, second edn., 2018.

[30] R.H. Thaler and C.R. Sunstein, *Nudge: Improving Decisions about Health, Wealth, and Happiness*, Yale University Press, 2008.

[31] Jean Twenge, 'Time Period and Birth Cohort Differences in Depressive Symptoms in the U.S., 1982–2013', *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement*, **121**(2), 437–454, (April 2015).

[32] A. N. Vaidyam, H. Wisniewski, J. D. Halamka, M. S. Kashavan, and J. B. Torous, 'Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape', *Can J Psychiatry*, **64**(7), 456–464, (07 2019).

[33] P. Winkler, D. Krupchanka, T. Roberts, L. Kondratova, V. Mach?, C. H?schl, N. Sartorius, R. Van Voren, O. Aizberg, I. Bitter, A. Cerga-Pashoja, A. Deljkovic, N. Fanaj, A. Germanavicius, H. Hinkov, A. Hovsepyan, F. N. Ismayilov, S. S. Ivezic, M. Jarema, V. Jordanova, S. Kuki?, N. Makhashvili, B. N. ?arotar, O. Plevachuk, D. Smirnova, B. I. Voinescu, J. Vrublevska, and G. Thornicroft, 'A blind spot on the global mental health map: a scoping review of 25 years' development of mental health care for people with severe mental illnesses in central and eastern Europe', *Lancet Psychiatry*, **4**(8), 634–642, (08 2017).

[34] A. Yorita, S. Egerton, J. Oakman, C. Chan, and N. Kubota, 'A robot assisted stress management framework: Using conversation to measure occupational stress', in *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 3761–3767, (2018).