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Design Concept of a Mental Health Monitoring Application with Explainable Assessments

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Abstract

Mental health has become a global issue with growing numbers of cases. Digital phenotyping in mental healthcare provides a highly effective, scaled, cost-effective approach to handling global mental health problems. Monitoring and diagnosis of mental health through mobile technologies are at an early stage. This paper proposes a novel architecture for a mobile application design based on speech and behavioural analysis that can lead to evidence-based monitoring outside of clinical settings. The application is designed to monitor the overall mental health status of individuals based on mood, stress, behaviour, and personality. It proposes to integrate objective mental health assessment from smartphone data with subjective assessments via periodic, short, self-reported, standardized questionnaires. The solution proposes explainable assessments for individual users and clinicians to build user trust and system credibility. This research provides insight into how digitally assisted mental health monitoring can be implemented in future mobile digital technologies using passive sensing.

Keywords Mental Health Monitoring, Smartphone, Explainable Assessments, Digital Health

1 Introduction

Mental Health (MH) is an integral part of the overall wellness of an individual (WHO 2008). MH conditions expand into mental disorders, psychosocial disabilities, and other psychological conditions connected to substantial distress, difficulty functioning, or probable self-harm (WHO 2022). Mental and physical health are fundamentally linked; people with serious mental illnesses are at higher risk of experiencing a wide range of chronic physical conditions, which diminish the quality of life and lead to worse health outcomes (Scott et al. 2016). For example, depression increases the risk of coronary heart disease among healthy adults and mortality among patients with coronary heart disease (Krittanawong et al. 2023).

MH problems are a global challenge. According to World Health Organisation (WHO) about one in every eight persons lives with a mental disorder globally. Anxiety and depression have become more prominent with a substantial increase after COVID-19 (Madanian et al. 2023b). This is exacerbated in low and middle-income countries where MH services and resources are limited, or their affordability and accessibility remain unsatisfactory. Individuals also avoid seeking MH support due to societal and personal factors such as low MH literacy, stigma, and discrimination (WHO 2022). More than 80% of people who died from suicide had contacted health services in the year prior to their death, emphasizing the opportunity for digitally assisted mental health management in clinical settings (Erwin and Daniel 2020).

To tackle growing concerns in MH management, digital mental health applications have the potential to empower traditional mental health screening and monitoring tools such as questionnaires and interviews. They are promising in enabling scaled, cost-effective, personalized applications for timely support, and tackling stigma as discussed in (Madanian et al. 2022). These applications can provide non-invasive and non-intrusive support to the management of MH with a low burden to individuals. There are more than 10,000 MH–related apps to address various MH disorders such as stress, depression, and anxiety. However, low retention and poor user engagement are common in many interventions when applied in real-world contexts (Seiferth et al. 2023). Further, the limited empirical and theoretical evidence and the lack of clinical guideline conformity have made most apps less effective (Kaveladze et al. 2022; Torous and Roberts 2017).

The integration of digital tools in early intervention systems is promising in MH care services where there are resource and practitioner constraints. Nevertheless, clinicians have not adequately accepted digital decision support systems, mainly due to the low interpretability and meaning of their outcomes (Schoonderwoerd et al. 2021). Moreover, applications that integrate advances of empirically validated MH monitoring approaches are lacking to provide insights on overall mental wellness with reflections on to classical MH monitoring tools. To address these issues, we propose a new conceptual design of a MH monitoring application that (a) evaluates MH and well-being based on a theoretical model, (b) integrates evidence-based monitoring approaches, and (c) provides explainable MH assessments. This solution is designed as both a self-monitoring and clinician decision-support tool. This paper is structured as follows. The required design elements for MH applications are discussed in section two. In section three we explain our proposed MH application conceptual design followed by its usability assessments in section four. A comparison of our proposed MH app with the available apps and solution benefits and limitations are provided in sections five and six. The article is concluded in section seven.

2 Design Elements

2.1 Theoretical Model on Evaluating MH Well-being

In general, self-report questionnaires and interviews are used to diagnosis mental disorders based on the Diagnostic and Statistical Manual of Mental Disorders V (Mahsa et al. 2021). Validated screening tools exist to monitor general mental health status as well as specific mental health conditions. General Health Questionnaires-28 (GHQ-28)(Goldberg and Williams 1988), Beck Depression Inventory (BDI) (Beck et al. 1988) are some examples for self-report psychological tests. Hamilton depression rating scale (HAM-D)(Hamilton 1967) is used by health professionals to assess depression. Perceived Stress Scale (PSS), Stress Self-Rating Scale (SSRS), Self-Assessment Manikin and Positive and Negative Affect Schedule (PANAS) are some commonly used tools in psychological stress evaluation (Can et al. 2019). Typical questions range from the ability to cope with household activities, through social interactions, agitation, level of activity, to quality of sleep.

However, MH is not the mere absence of psychopathological symptoms but rather the presence of feelings and well-being (Lamers et al. 2012). Composite scores from psychological measures that reflect positive and negative attributes, are used in literature to evaluate MH (Jeste et al. 2019). The bio-psycho-social profile can provide a holistic view of individuals' MH (Jeste et al. 2019). The Mental Health Continuum (MHC) model considers five aspects of mood, thinking and attitudes, behaviour and performance, physical changes, and substance use. It conceptualizes MH along a continuum between health and illness, avoiding specific diagnostic labels (Persson et al. 2022). MH significantly links affective states such as emotions, stress, and moods (Gross et al. 2019) while affective experiences are highly subjective and are dependent on an individual's mood, personality, age, culture, and environment (Bota et al. 2019). Therefore, our solution identifies mood, stress, behaviour, and personality as vital concepts in modelling a person's overall MH well-being.

2.2 Integrated Evidence-based Monitoring Approaches

To objectively evaluate mental health conditions, biomarker based methods are also available based on saliva and blood (Hagiwara et al. 2016). To detect stress, physiological parameters such as hormone levels, Electro-Cardiogram (ECG), Blood Pressure (BP), Skin Temperature (ST), and functional Magnetic Resonance Imaging (fMRI) are also being of interest (Can et al. 2019). However, methods relying on biomarkers are usually costly, invasive, and demand special equipment. On the other hand, most mental disorders cause mood variation over time and conventional periodical self-report assessments may limitedly reflect the true experience of the patient due to subjectivity and memory limitations. Experience sampling, where individuals are prompted periodically throughout the day to report their states, symptoms, and surroundings, can also lead to burden on human participants, imposing challenges for long term treatments.

To overcome the physical and economical challenges imposed by traditional mental health screening tools, we propose to integrate empirically proven monitoring approaches in both passive monitoring and self-reporting assessments to complement each other. Practitioners use self-reported screening questionnaires to query indicative symptoms of MH disorders requiring further assessment (Shields et al. 2021). Several MH apps automatically monitor behaviour and speech features to evaluate different aspects of MH objectively (Mahsa et al. 2021). Studies have assessed factors related to MH including mood (Likamwa et al. 2013), happiness (Bogomolov et al. 2013), and social interactions (Matthews et al. 2016) from behavioural indicators derived from smartphone data such as call and text logs, app and battery usage, screen activity, and internet browsing. This has yielded insights into MH monitoring (Hagiwara et al. 2016) , emotion recognition (Madanian et al. 2022), and stress detection (Mahsa et al. 2021).

2.3 Explainable MH Assessments

Explainable outcomes build user trust in automatic assessments (Madanian et al. 2023a). This could be especially useful for individuals with low mental health literacy and clinicians who trust medical oriented interpretations. In this regard, Explainable Artificial Intelligence (XAI) can provide human-understandable explanations on AI outcomes ensuring credibility, accountability, and trust in critical areas of MH (Balcombe and De Leo 2021). Particularly, explainable models in MH applications enable professionals to interpret their patients' behaviours (Mendes et al. 2022). Different XAI concepts such as rule-based or visual explanations, explanation by simplification or feature relevance have been studied to provide interpretable results in the domain. Required explanations depend on the users' background (e.g., domain experts, and lay users) (Schoonderwoerd et al. 2021). Interactive explanations enable greater user involvement such as live explanations, feature explanations, and ask-the-app explanations (Weitz et al. 2022).

Usability of explanations for users are crucial in integrating XAI methods. A framework named as TIFU (Transparency and Interpretability For Understandability framework) recommends transparency and interpretability to operationalize explainability (Dan et al. 2023). Transparency is referred to as the representation of the feature space in a way that aligns with clinical context. Interpretability is recommended through either via interpretable computational processes, clinically interpretable structural descriptions, or ability to explore qualitative relationships between inputs and outputs (Dan et al. 2023).

3 Proposed App and Conceptual Design

Here we suggest a design concept of an MH app and present its conceptual design (Figure 1). The app aims to model users' MH status using profilers. It incorporates objective assessments with passive monitoring of smartphone data and subjective assessment using periodic self-report standard short questionnaires. Proposed application does not aim to diagnose a particular MH condition. Literature states the demerits of targeting specific disorders due to potential of commodities and labelling users with a diagnosis via an application can be harmful as well. Instead, it is recommend addressing both anxiety and low mood as emotional disorders are the most common psychological conditions in worldwide (Bakker et al. 2016).

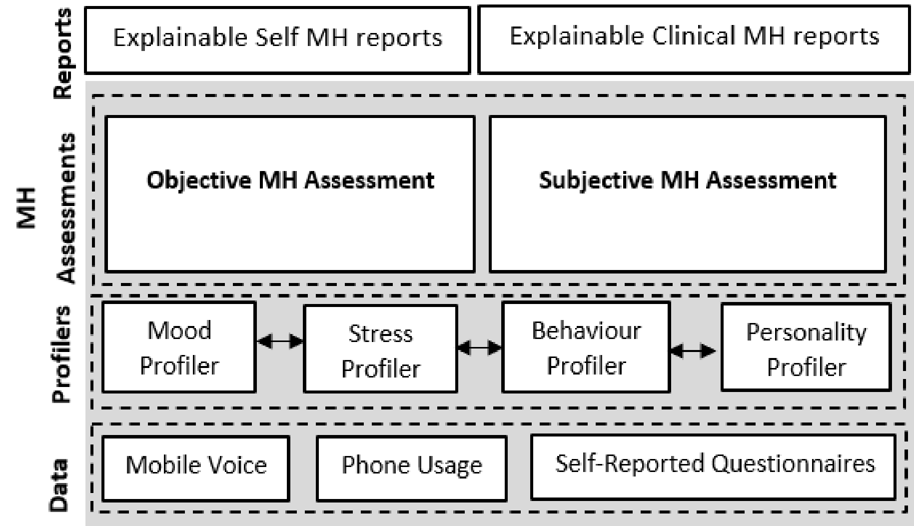

Figure 1: High Level System Architecture

3.1 Mood Profiling

Mood is an experience of feeling that can last for a long period while emotion is a brief reaction to a specific stimulus (Chen et al. 2020). For example, a person can quickly get angry, but will not remain angry for a longer period. However, the emotion 'anger' can lead the person to an irritable mood for a long time (Philip et al. 2019). Multiple emotions contribute to the two main positive and negative mood dimensions. Moods can be profiled by analysing emotional intensity and emotional state transitions. Emotions are modelled in discrete and continuous space. In discrete space, emotions are classified into several feelings (e.g., anger and joy). In continuous space, the valence-arousal two-dimensional model (named as the circumplex model) (Russell 1979) is widely adapted. The valence axis denotes the positivity of an emotion (e.g., pleasant versus unpleasant), while the arousal axis indicates its activeness or intensity level. The model can be easily assessed using the Self-Assessment Manikins (SAM) which provides a graphical interface (Bota et al. 2019). Our solution recommends emotion modelling in valence-arousal spaces. Objective emotion recognition and user-perceived emotional assessment can be periodically measured using speech analysis, and using SAM, respectively.

3.2 Stress Profiling

Stress is linked to emotions and is mapped to the high arousal/ negative valence of the circumplex model (Philip et al. 2019). Stress levels can be presented as a binary classification or a multi-label classification of the stress levels. Studies have investigated the relationship between emotions derived from speech and stress (Tokuno et al. 2011) and have also derived stress directly from speech (Lu et al. 2012). Objective stress assessment is recommended from speech while self-report stress screening is recommended with periodic Perceived Stress Scale (PSS) (Cohen et al. 1983) or Kessler Psychological Distress Scale (K10) (Kessler et al. 2002).

3.3 Behavioural Profiling

Behaviour impacts the affective states of emotions, mood, and stress. Behavioural style models are derived from smartphone usage patterns to infer affective states (Bogomolov et al. 2013; Likamwa et al. 2013). Behavioural indicators derived from mobile phone sensors had been proven clinically meaningful to track symptoms in different MH disorders (Place et al. 2017). Behavioural profiling is proposed over social interactions, mobility and device activity pattern dimensions using call and text logs, location variables and mobile app usage patterns over time. The app can identify user behavioural changes that can link to MH. This could exploit the relationship between behavioural patterns and affective states of mood and stress.

3.4 Personality Profiling

Individuals' personality impacts event response, hence, the affective states. Relationships between personality traits and stress have been widely studied in social psychology; where more negative personalities experience greater distress (Bogomolov et al. 2014). Personality traits had been considered in individual impact on automatic recognition of daily happiness (Bogomolov et al. 2013), and stress (Bogomolov et al. 2014) from smartphone usage patterns. Most studies focus on the Big Five traits (Gosling et al. 2003) in personality assessment. Our app will incorporate personality traits and demographics to bring individual impacts on mood, stress, and behavioural profiling.

3.5 Mental Health Assessments

Both objective and subjective MH assessments are proposed based on the outcome of the main profilers. Subjective MH assessment would consider mood and stress profiling derived on corresponding self-report questionnaires which include SAMs and PSS or K10 assessments respectively. A brief subjective MH assessment is proposed with a periodic Five-Item Mental Health Inventory (MHI-5) for self-report screening questionnaire for affective and anxiety disorders (Schoonderwoerd et al. 2021). It would complement the objective mental health assessment derived on mood and stress which considers behaviour patterns as well. Both types of assessments would consider individual personality which are acquired via Big Five traits and demographics. Assessments can mainly focus on daily variation of mood and stress, periodic MH assessments, and relationships between mood and stress with behavioural characteristics.

3.6 Explainable AI-based Reports

Explainable AI-based reports are recommended on MH assessments. Different levels of explanations are recommended for individuals and clinicians. Clinicians would be interested in explanations that would help in analysing hypotheses related to clinical diagnoses. In addition to descriptive information on diagnosis, clinicians are interested in input variables, certainty and evidence for evaluations, counterfactual and contrastive information, case-based examples as well as history of system performance (Likamwa et al. 2013). We recommend generating explainable reports based on MH assessment including information elements such as feature importance, support/contrast evaluations with their certainty and case-based examples on evaluations. For individual users, feature explanations, and ask-the app explanations as presented in (Weitz et al. 2022) and are recommended to obtain clear self-reflections on system assessments. Feature explanations provide the influence of each feature considered in the assessment while ask-the-app explanations provide a dialog-based explanation of system outcomes.

4 Usability Assessments

We propose an experimental phase of the application for usability assessment of the proposed features. Since, the application is positioned as a clinical decision supportive tool to monitor patients and track symptoms in between their clinical visits with a visibility to their behavioural patterns and personality, a feasibility analysis of the application from the clinicians' perspectives is required to validate the effectiveness of the design elements in clinical environment. A mixed methodological approach which utilizes application usage, qualitative interviews and questionnaires like in (Betthauser et al. 2020) is recommended for usability assessment from a clinician's perspective.

Self-usability for individuals can be assessed separately since the expectation of the application is to provide insights into one's own MH well-being in a realistic environment. We identify university students as an interested population due to identified higher rates of MH concerns among them and the high probability of avoiding professional guidance due to misconceptions on stress, stigma and uncertainty on effectiveness (Lee and Jung 2018). A study with university students can provide feedback on potential of capitalizing insights and explanations to monitor and manage own MH well-being before a more general population-based study.

5 Comparison with other MH Mobile Apps

The design of the proposed app can be positioned distinctively compared to some of the available MH monitoring apps (e.g., MoodPrism (Rickard et al. 2016), Moodable (Dogrucu et al. 2020), MIMOSYS (Hagiwara et al. 2016) , MoodRhythm (Matthews et al. 2016), EmotionSense (Rachuri et al. 2010) and MoodScope (Likamwa et al. 2013).

MoodPrism monitors emotion well-being from self-report assessments, user online behaviour and weekly short voice samples. Moodable app uses contextual data from social networks and mobile sensors together with brief voice samples. Compared to them, relying on voice analytics for emotion and stress detection has the benefit of the possibility of generalizing across languages due to similar vocal anatomy and is especially useful for low-resource languages when natural language processing technology is not available.

MIMOSYS evaluates short-term and midterm MH conditions based on emotional components of the voice in fixed phrases and call recordings. Compared to MIMOSYS, our app incorporates wider aspects of MH via behavioural analytics and personality. MoodRhythm and EmotionSense apps have explored analytics of voice records on bipolar disorder and for experimental social psychology research respectively. MoodScope infers users' mood from their smartphone usage patterns where application usage and phone calls had been the most moods sensitive. Personalized models had been more accurate than general models. Personality profiling in the proposed application aims to address individual differences in MH monitoring in a generalized approach for a wider population. None of the above applications integrate explainable assessments which can turn the applications more clinical oriented. Compared to above applications, the proposed solution leverages the advances of voice analytics together with behavioural analytics in empirical investigations of MH monitoring. The added functionality of explainable assessments makes it clinically appealing.

6 Discussion

Despite the availability of many MH monitoring apps, many of them lack theoretical and empirical evidence on their approaches or focus on a particular MH disorder. Our proposed app is a generic MH app which suggests indications on overall mental wellness based on common MH-related concepts and integrates passive and self-report MH assessments. While passive monitoring on mobile data provides objective assessments, standard short questionnaires reduce user resistance on manual reporting. The combination of complemented passive monitoring and standard screening enables integration of system for standard clinical practice and clinical research. Most importantly, the presentation of interpretable results can ensure user trust and credibility of system assessments with meaningful reports for individuals and clinicians.

However, the design is to be integrated with the methodologies to protect privacy and security concerns of the user data. The experimental phase is to be supported with a working prototype of the proposed solution which will be developed utilizing public datasets. Therefore, we expect that the experimental phase can provide valuable insights into user experience to finalize solution with user feedback considering ethical considerations including privacy, security, and user consent on data sharing. Finalization of design and tuning of the models for a wider use is expected at the end of the experimental phase. Since AI based algorithms have a risk of bias in giving poor performance for populations outside model validations, the identification, quantification, and mitigation of risk of bias is required during the development life cycle.

The presented concepts have the potential in spanning over more advanced approaches. For example, to provide a holistic view of MH, our proposed system has the potential of moving into a more comprehensive MH model such as the MHC model by integrating relevant monitoring approaches. Also, user personalities can be incorporated to personalize presented explanations as explored in (Weitz et al. 2022).

7 Conclusion

The paper presents the conceptual design of a MH monitoring application taking into account the need for more effective apps with evidence-based research support and clinical integration. This research provides insight into objective MH monitoring through speech and behavioural analytics to complement periodic subjective assessments. Explainable assessments consider the need of transparency from both individuals and mental health professionals. Existing knowledge is integrated in designing process and the experimental phase is presented for usability assessments. It is acknowledged that the design might have limitations from both selected MH screening tools as well as empirical approaches in real world context. Life cycle management of the application needs systematically assess and mitigate risk and limitations.

8 References

Bakker, D., Kazantzis, N., Rickwood, D., and Rickard, N. 2016. "Mental Health Smartphone Apps: Review and Evidence-Based Recommendations for Future Developments," *JMIR mental health* (3:1), p. e7.

Balcombe, L., and De Leo, D. 2021. "Digital Mental Health Challenges and the Horizon Ahead for Solutions Comment," *JMIR Mental Health* (8:3), p. e26811.

Beck, A. T., Steer, R. A., and Carbin, M. G. 1988. "Psychometric Properties of the Beck Depression Inventory: Twenty-Five Years of Evaluation," *Clinical Psychology Review* (8:1), pp. 77-100-100.

Betthauser, L. M., Stearns-Yoder, K. A., McGarity, S., Brenner, L. A., Smith, V., and Place, S. 2020. "Mobile App for Mental Health Monitoring and Clinical Outreach in Veterans: Mixed Methods Feasibility and Acceptability Study," *Journal of Medical Internet Research* (22:8).

Bogomolov, A., Lepri, B., Ferron, M., Pianesi, F., and Pentland, A. 2014. "Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits," Association for Computing Machinery, pp. 477-486-486.

Bogomolov, A., Lepri, B., and Pianesi, F. 2013. "Happiness Recognition from Mobile Phone Data." IEEE, pp. 790-795.

Bota, P. J., Wang, C., Fred, A. L. N., and Placido Da Silva, H. 2019. "A Review, Current Challenges, and Future Possibilities on Emotion Recognition Using Machine Learning and Physiological Signals," *IEEE Access, Access, IEEE* (7), pp. 140990-141020.

Can, Y. S., Arnrich, B., and Ersoy, C. 2019. "Stress Detection in Daily Life Scenarios Using Smart Phones and Wearable Sensors: A Survey," *Journal of Biomedical Informatics* (92), p. 103139.

Chen, L., Magdy, W., Whalley, H., and Wolters, M. K. 2020. "Examining the Role of Mood Patterns in Predicting Self-Reported Depressive Symptoms," Association for Computing Machinery, Inc, pp. 164-173-173.

Cohen, S., Kamarck, T., and Mermelstein, R. 1983. "A Global Measure of Perceived Stress," *Journal of Health and Social Behavior* (24:4), pp. 385-396.

Dan, W. J., Andrey, K., Katharine, A. S., and Andrea, C. 2023. "Explainable Artificial Intelligence for Mental Health through Transparency and Interpretability for Understandability," *npj Digital Medicine* (6:1), pp. 1-7.

Dogrucu, A., Perucic, A., Isaro, A., Ball, D., Toto, E., Rundensteiner, E. A., Agu, E., Davis-Martin, R., and Boudreaux, E. 2020. "Moodable: On Feasibility of Instantaneous Depression Assessment Using Machine Learning on Voice Samples with Retrospectively Harvested Smartphone and Social Media Data," *Smart Health* (17), p. 100118.

Erwin, L., and Daniel, D. H. 2020. "Ai Enabled Suicide Prediction Tools: A Qualitative Narrative Review," *BMJ Health & Care Informatics* (27:3).

Goldberg, D., and Williams, P. 1988. *A User's Guide to the General Health Questionnaire*. Windsor, UK: NFER-Nelson:.

Gosling, S. D., Rentfrow, P. J., and Swann Jr, W. B. 2003. "A Very Brief Measure of the Big-Five Personality Domains," *Journal of Research in Personality* (37:6), pp. 504-528-528.

Gross, J. J., Uusberg, H., and Uusberg, A. 2019. "Mental Illness and Well-Being: An Affect Regulation Perspective," *World Psychiatry* (18:2), pp. 130-139-139.

Hagiwara, N., Omiya, Y., Shinohara, S., Nakamura, M., Higuchi, M., Yasunaga, H., Mitsuyoshi, S., and Tokuno, S. 2016. "Validity of the Mind Monitoring System as a Mental Health Indicator Using Voice," in: *Advances in Science, Technology and Engineering Systems Journal*. pp. 262-265.

Hamilton, M. 1967. "Development of a Rating Scale for Primary Depressive Illness," *British Journal of Social and Clinical Psychology* (6:4), pp. 278-296-296.

Jeste, D. V., Glorioso, D., Lee, E. E., Daly, R., Graham, S., Paredes, A. M., Twamley, E. W., Van Patten, R., Depp, C., Liu, J., Tu, X. M., Nebeker, C., Yamada, Y., and Kim, H. C. 2019. "Study of Independent Living Residents of a Continuing Care Senior Housing Community: Sociodemographic and Clinical Associations of Cognitive, Physical, and Mental Health," *American Journal of Geriatric Psychiatry* (27:9), pp. 895-907-907.

Kaveladze, B. T., Wasil, A. R., Bunyi, J. B., Ramirez, V., and Schueller, S. M. 2022. "User Experience, Engagement, and Popularity in Mental Health Apps: Secondary Analysis of App Analytics and Expert App Reviews," *JMIR Hum Factors* (9:1), p. e30766.

Kessler, R. C., Andrews, G., Colpe, L. J., Hiripi, E., Mroczek, D. K., Normand, S. L. T., Walters, E. E., and Zaslavsky, A. M. 2002. "Short Screening Scales to Monitor Population Prevalences and Trends in Non-Specific Psychological Distress," *Psychological Medicine* (32:6), pp. 959-976.

Krittanawong, C., Maitra, N. S., Qadeer, Y. K., Wang, Z., Fogg, S., Storch, E. A., Celano, C. M., Huffman, J. C., Jha, M., Charney, D. S., and Lavie, C. J. 2023. "Association of Depression and Cardiovascular Disease," *American Journal of Medicine* (136:9), pp. 881-895-895.

Lamers, S. M. A., Westerhof, G. J., Bohlmeijer, E. T., and Kovács, V. 2012. "Differential Relationships in the Association of the Big Five Personality Traits with Positive Mental Health and Psychopathology," *Journal of Research in Personality* (46:5), pp. 517-524-524.

Lee, R. A., and Jung, M. E. 2018. "Evaluation of an Mhealth App (Destressify) on University Students' Mental Health: Pilot Trial," *JMIR Mental Health* (5:1), p. e2.

Likamwa, R., Zhong, L., Liu, Y., and Lane, N. D. 2013. "Moodscope: Building a Mood Sensor from Smartphone Usage Patterns," pp. 389-401-401.

Lu, H., Rabbi, M., Choudhury, T., Chittaranjan, G. T., Frauendorfer, D., Mast, M. S., Campbell, A. T., and Gatica-Perez, D. 2012. "Stresssense: Detecting Stress in Unconstrained Acoustic Environments Using Smartphones," pp. 351-360-360.

Madanian, S., Nakarada-Kordic, I., Reay, S., and Chetty, T. 2023a. "Patients' Perspectives on Digital Health Tools," *PEC Innovation* (2).

Madanian, S., Parry, D., Adeleye, O., Poellabauer, C., Mirza, F., Mathew, S., and Schneider, S. 2022. "Automatic Speech Emotion Recognition Using Machine Learning: Digital Transformation of Mental Health," *PACIS 2022*.

Madanian, S., Rasoulipanah, H., and Yu, J. 2023b. "Stress Detection on Social Network: Public Mental Health Surveillance: Public Mental Health Surveillance," Association for Computing Machinery, pp. 170-175-175.

Mahsa, S., Qassem, M., and Panicos, A. K. 2021. "Wearable, Environmental, and Smartphone-Based Passive Sensing for Mental Health Monitoring," *Frontiers in Digital Health* (3).

Matthews, M., Abdullah, S., Murnane, E., Choudhury, T., Gay, G., Voida, S., and Frank, E. 2016. "Development and Evaluation of a Smartphone-Based Measure of Social Rhythms for Bipolar Disorder," *Assessment* (23:4), pp. 472-483-483.

Mendes, J. P. M., Moura, I. R., Van de Ven, P., Viana, D., Silva, F. J. S., Coutinho, L. R., Teixeira, S., Rodrigues, J. J. P. C., and Teles, A. S. 2022. "Sensing Apps and Public Data Sets for Digital Phenotyping of Mental Health: Systematic Review," *J Med Internet Res* (24:2), p. e28735.

Persson, L., Dobson, K. S., and Frampton, N. M. A. 2022. "Evaluation of a Mental Health Continuum Model in Two Samples," *Canadian Journal of Behavioural Science* (54:3), pp. 206-212.

Philip, S., Attila, R., Robert, D., and Kristof Van, L. 2019. "Wearable-Based Affect Recognition—a Review," *Sensors* (19:19), pp. 4079-4079.

Place, S., Blanch-Hartigan, D., Rubin, C., Gorrostieta, C., Mead, C., Kane, J., Marx, B. P., Feast, J., Deckersbach, T., Pentland, A. S., Nierenberg, A., and Azarbayejani, A. 2017. "Behavioral Indicators on a Mobile Sensing Platform Predict Clinically Validated Psychiatric Symptoms of Mood and Anxiety Disorders," *J Med Internet Res* (19:3), p. e75.

Rachuri, K. K., Musolesi, M., Mascolo, C., Rentfrow, P. J., Longworth, C., and Aucinas, A. 2010. "Emotionsense," *Proceedings of the 12th ACM International Conference: Ubiquitous Computing*), pp. 281-290.

Rickard, N., Arjmand, H. A., Bakker, D., and Seabrook, E. 2016. "Development of a Mobile Phone App to Support Self-Monitoring of Emotional Well-Being: A Mental Health Digital Innovation," *JMIR Mental Health* (3:4), p. e49.

Russell, J. A. 1979. "Affective Space Is Bipolar," *Journal of Personality and Social Psychology* (37:3), pp. 345-356.

Schoonderwoerd, T. A. J., Jorritsma, W., Neerincx, M. A., and van den Bosch, K. 2021. "Human-Centered Xai: Developing Design Patterns for Explanations of Clinical Decision Support Systems," *International Journal of Human Computer Studies* (154).

Scott, K. M., Lim, C., Al-Hamzawi, A., Alonso, J., Bruffaerts, R., Caldas-de-Almeida, J. M., Florescu, S., Girolamo, G. d., Hu, C., Jonge, P. d., Kawakami, N., Medina-Mora, M. E., Moskalewicz, J., Navarro-Mateu, F., O'Neill, S., Piazza, M., Posada-Villa, J., Torres, Y., and Kessler, R. C. 2016. "Association of Mental Disorders with Subsequent Chronic Physical Conditions World Mental Health Surveys from 17 Countries," *AMA Psychiatry*), pp. 150-158.

Seiferth, C., Vogel, L., Aas, B., Brandhorst, I., Carlbring, P., Conzelmann, A., Esfandiari, N., Finkbeiner, M., Hollmann, K., Lautenbacher, H., Meinzinger, E., Newbold, A., Opitz, A., Renner, T. J., Sander, L. B., Santangelo, P. S., Schoedel, R., Schuller, B., Stachl, C., Tank, s. T., Terhorst, Y., Torous, J., Wac, K., Werner-Seidler, A., Wolf, S., and Löchner, J. 2023. "How to E-Mental Health: A Guideline for Researchers and Practitioners Using Digital Technology in the Context of Mental Health," *Nature Mental Health*), pp. pages542–554.

Shields, R. E., Korol, S., Carleton, R. N., McElheran, M., Stelnicki, A. M., Groll, D., and Anderson, G. S. 2021. "Brief Mental Health Disorder Screening Questionnaires and Use with Public Safety Personnel: A Review," *International Journal of Environmental Research and Public Health* (18:7).

Tokuno, S., Tsumatori, G., Shono, S., Takei, E., Suzuki, G., Yamamoto, T., Mituyoshi, S., and Shimura, M. 2011. "Usage of Emotion Recognition in Military Health Care." pp. 1-5.

Torous, J., and Roberts, L. W. 2017. "Needed Innovation in Digital Health and Smartphone Applications for Mental Health Transparency and Trust," *JAMA Psychiatry*).

Weitz, K., Zellner, A., and André, E. 2022. "What Do End-Users Really Want? Investigation of Human-Centered Xai for Mobile Health Apps," *arXiv preprint arXiv:2210.03506*).

WHO. 2008. "Mhgap : Mental Health Gap Action Programme : Scaling up Care for Mental, Neurological and Substance Use Disorders,").

WHO. 2022. "World Mental Health Report: Transforming Mental Health for All."

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