Personalization of mental well-being apps through AI

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Artificial intelligence (AI) has the potential to improve personalization in mental well-being technologies to facilitate users engaging with desired behaviors. To explore the current state of AI and personalization and to understand their existing personalization approaches and strategies, we explored 18 mental well-being apps that claim to use AI. We found that mental well-being apps primarily collect data on users' moods and mental states and transparent personalization strategies vary. We discuss: (1) What types of data can AI collect and use to create a more meaningful personalization in mental well-being apps and (2) How can AI support longitudinal data collection and continuous adjustment in personalized strategies.

ACM Reference Format:
Novia Wong, Preethi Seshadri, Meeshu Agnihotri, Bruna Oewel, and Elena Agapie. 2022. Personalization of mental well-being apps through AI . 1, 1 (March 2022), 4 pages. https://doi.org/XXXXXXX.XXXXXXX

1 AI BASED PERSONALIZATION: STATE-OF-THE-ART

Personalization is useful to foster engagement and sustain behavior change [5, 8, 12]. Mental health therapists often tailor skills, lessons, suggestions, and take-home activities to the needs of individual clients, to support engagement with therapeutic activities [13]. Ongoing research by coauthors found similar results, suggesting that therapists often consider the client's personal values, family background, financial condition, physical environment, and more. Similarly, health technologies that take into account an individual's contextual factors and fit to their abilities, routines, and constraints [2, 3, 10] offer better recommendations and have higher user satisfaction [7]. Artificial intelligence (AI) is also often used to personalize the experience through recommendations, chatbots, pattern recognition, and trend prediction [11]. To address the challenge of therapist shortage, mental health mobile applications (apps) can provide widely accessible support when help is needed [15]. However, recent work has shown that personalization in anxiety apps has limited scope in delivering intervention-oriented content [4], which can negatively impact user's willingness to engage with app content and affect the effectiveness of the app.

Currently, not much is known about how AI can be leveraged to improve personalization specifically in mental well-being mobile apps besides chatbots. To understand the potential of using AI to support mental well-being personalization, we first wanted to explore the current state of AI and personalization: through a small pilot study, we aimed to (1) identify the types of data that mental well-being apps transparently collect from the users

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XXXX-XXXX/2022/3-ART $15.00
https://doi.org/XXXXXXX.XXXXXXX

and its potential usage for personalization and (2) explore the existing observable and perceived personalization strategies adopted by well-being apps.

We first identified 163 unique apps on Google Play Store and Apple App Store using keywords of "Mental Health", "Well-being", "Self-care", and "Mindfulness". From those, we focused on the 18 apps [1] that mentioned personalization and AI in their app store description or on their product websites. Based on prior studies [8] and our own week-long interactions with the apps, we coded user data to understand how apps transparently might personalize content. Findings are limited to observable in-app content, manually or consented data provided by us, and perceived personalization.

2 CURRENT STATE OF AI AND PERSONALIZATION IN MENTAL WELL-BEING MOBILE APPS

PERSONALIZATION STRATEGIES OBSERVED IN MENTAL WELL-BEING MOBILE APPS: Based on our experiences interacting with the 18 reviewed apps, we inferred that primary personalization strategies were related to the content and the interface. Most apps were personalized in at least one of the following six ways: **(1) Addressing users by their name**, **(2) Content recommendation**: Based on user's responses to questions about their feelings (e.g., happy, anxious), seven apps used chatbots to provide validating messages or strategies to cope with those feelings. **(3) Descriptive feedback**: Feedback was often personalized in the form of insights and reporting. *Boom* showed users their past journal entries, *Sayana* tracked and displayed weekly mood patterns, *Balance* and *Iona* showed meditation and skill-based lesson progress, and *Mindoc* provided a visualization of in-app interaction. **(4) Interface customization**, **(5) Notification customization**: *InnerHour* users could edit their well-being goals and set preferred time for daily reminders on the Settings page. **(6) Goal-setting**: Although nearly all the apps we reviewed had the ability for users to define goals, they were limited to a small selection of pre-defined goals: *InnerHour* had 6 mental health goals to choose from, such as living happier and beating anxiety. But we observed that *Balance* recommended an initial intensity for meditation and appeared to adjust the difficulty level for meditation gradually based on user data (e.g., prior experience and in-app meditation completion). *Iona* reviewed goals with users using past journal entries and incorporated chatting history into the daily lesson plans.

DATA COLLECTED IN MENTAL WELL-BEING APPS WITH PERSONALIZATION POTENTIAL: Through questions and assessments, mental well-being apps collected information about users' mental and emotional states, name and age, and behavioral data regarding past experiences and ongoing goal assessment. Many apps had an onboarding process that involved collecting data through a questionnaire or guided workflow. For example, *Balance* asked "How often do you feel stress?" to measure the levels of anxiety and stress in the past 2 weeks, *Intellect* prompted us to "Choose one or more goals" from a list of "Feel calmer, Sleep better, and Improve self-esteem" to learn our desired behavioral and psychological goals. Apps such as *Remente* learned user preferences and needs by asking "Which area is the most important for you to focus on right now?". After the onboarding process, most apps captured in-the-moment moods or emotions (e.g., *InnerHour*: "How are you feeling right now?", *Minddoc*: "Which emotions and situations are you thinking about?") through journaling and additional questionnaires. Some apps allowed users to indicate their system preferences (e.g., preferred time for reminders and notifications) and content preferences (e.g., favoriting). Basic demographic data was also collected: *Iona* asked for preferred names and *Endel* asked for the user's age. Behavioral data focusing on the user's past behaviors and experiences with certain skills is sometimes collected during the onboarding process (e.g., *Boom*: "Have you tried mindful journaling?"). A few apps, including *Rise Sleep*, used sensors to collect data such as sleep and circadian rhythm.

[1] InnerHour, Nuna, Endel, Iona, Mental Health and Mindfulness (Boom Journal), Balance, Sayana, Sona, Reflectly, Headspace, Calm, Woebot, Wysa, Minddoc, Intellect, Rise Sleep, BetterMe Mental Health, Remente

TRANSPARENCY IN DATA AND AI USAGE: Apps usually had vague descriptions of how AI was incorporated and the how and what of personalization: examples include a *"personalised 4-week plan"* and *"optimal personalized soundscape"*. The lack of clarity can make it difficult for users to understand how the app experience is tailored to them and based on what data. Some commonly known AI-based apps (e.g., *Woebot, Calm, Wysa*) do not mention "AI" or "personalization" in their app descriptions. Only *Balance* describes in-app that each meditation lesson is built based on the user's experience, age, and goals, explaining how data is leveraged to deliver personalization.

3 DISCUSSION, OPPORTUNITIES, AND WORKSHOP CONTRIBUTION

To personalize mental well-being app experience in a more meaningful and applicable way for individual users and their unique situations, apps can adopt practices from mental health therapists. There is a need for apps to leverage AI to (1) collect and analyze complex user data, (2) actively adjust personalization based on the user's longitudinal interaction. In our preliminary analysis, we noticed that little data was collected about the user's complex identity and contextual situation, and personalization tended to base on initial goals input during onboarding.

DATA COLLECTION AND MEANINGFUL PERSONALIZATION: In therapies such as Cognitive-Behavioral Therapy (CBT), therapists support their clients in working towards goals by considering a number of different problems that are present in their lives, such as relationships with friends and family, financial problems, and basic needs (e.g. food shortage, rental assistance, job security). Therapists then adjust their clients' goals and recommendations based on these factors that change over time. In contrast, the reviewed mental well-being mobile apps only provide recommendations tailored for a handful of generic issues such as stress or anxiety. These apps do not appear to account for the underlying factors in an individual's life, unlike a therapist. This could result in making recommendations that are not aligned with the user's situation. Additionally, most apps collect only information about the user's current emotional state, unlike how therapists often bring up past unresolved issues and anticipated future challenges in addition to current needs [1] to prepare an actionable plan. Mental well-being apps can reintroduce some of the past data shared by the user - such as goals set at onboarding and goals with no recorded activity - to prompt reflection. Similarly, apps can invite users to consider upcoming events in their life or support integration with their calendars to support basic features such as timely and appropriate reminders and notifications. Opportunities exist for using AI to create a more personalized experience based on user behavior, longitudinal mood and mental wellness, additional context and constraints, etc.

LONGITUDINAL PERSONALIZATION: It is important for systems to understand that new data points can have a ripple effect on existing data and personalization strategies when making recommendations to account for the intersectional identities of the users [14]. However, users cannot easily express themselves and request additional mental wellness support from AI-focused apps the way they normally would in conventional therapy with professionals. Therapists use a combination of descriptive, dialogic and transformative reflection [1, 6]. Improved chatbots that use natural language processing to create natural dialogues could be helpful in facilitating self-reflection [1, 9]. Also, AI can make insights and reporting more actionable by distilling key takeaways, facilitating the creation of action items, and adapting lessons and strategies based on longitudinally data instead of weekly or daily data.

APP TRANSPARENCY: Finally, mobile health technologies that use AI for personalization should clarify how they leverage the data users provide [4, 11]. Mental well-being apps can provide examples of how user data influences suggested activities and lessons. This increased transparency can help users understand why they were given certain recommendations in the app and increase adoption to recommended contents.

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