Reaching out : Towards a sustainable allocation strategy between users and therapists

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Abstract

During recent times, a wide range of mental health apps have become quite popular. While most mental health apps in recent years focuses on having self help modules to assist users towards their wellbeing, most apps do not include a dedicated system towards connecting such users with mental health experts or professionals. In this paper we hence present the idea of a socio-technical system that can act as an auxillary component to such mental health apps by providing seamless connection with therapists based on their availability and keeping in mind user privacy.

1 Related Work

Recent mental health applications focus more towards empowering an individual through self-help [9], often expecting users to go through the self-help programs entirely on their own. While automated therapy based on Cognitive Behavioural Therapy (CBT) [6] has been popular in recent apps like Woebot [1], Wysa [3] which uses conversational AI models [2] to detect user sentiments from text message and generate relevant replies. While such automated therapy is a good option considering limited resources, the human-human interaction still remains missing, and most people feel comfortable confiding their feelings to an actual human, rather a bot. Also a unique challenge in such platforms is how to preserve user privacy when performing analytics on user text messages and deploying such conversational AI models.

2 Problem Setting

We present the idea of a socio-technical system that can be presented as a future product like a mobile application or website interface. The system should supporting a one-to-one message feature with varying modality (audio/text), whereby users can send a message directly to a professional and vice-versa. We first describe the stakeholders who will be involved in this socio-technical system (app/ web interface.)

- **Mental Health Experts** Mental health professionals who have required expertise and can allocate some time during their daily therapeutic sessions on this app/web interface to interact with potential clients/general user. Each therapist has a limited time to respond to a user's query (e.g. 24 hours)
- **Users** General users of the app or the web interface. Such users also have a limited timeline to respond back to professionals, otherwise the session gets closed.
- **Volunteers** Volunteers/Caregivers play an undoubtedly important role in mental health domains specifically in responding to helpline numbers. In this case volunteers would be responding back to users whose message requests are in pending by the assigned professional.

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2.1 Research Questions

- Each professional on average can handle only a specific bandwidth of users (let's say 3-4 users per day). *Maybe we can propose a followUp rate based learning approach*
- Depending on the severity of their symptoms users are currently experiencing, getting access to a consultation with a professional is crucial. How can we make it a more efficient allocation process? *PHQ-9, GAD-7 scores, unstructured notes like worry journal/ negative thought writings can act as feature points. But can we present a deanonymized fair (like considering gender biases in depression texts [8]) sentiment analysis model that can assign users scores based on them in a privacy-preserving manner*
- For volunteers, since they would be looking into pending requests for a set of professionals, how can we make a good allocation strategy so as to not overburden them when responding to multiple requests.

3 Possible Solutions using Machine Learning

Given for a particular user/client u_i from the entier User Set $\mathbb{U}$, they have $\mathbb{P} = p_1, p_2, \ldots, p_2$ set of professionals to chose from, each therapist p_k ranked in order of best *Criteria* (Level of matching in symptoms and experience/area of expertise, reply/response time (r_i) and availability of the therapists).

Similarly for a given therapist p_i, given average reply time r_i and average number of requests transferred to volunteers from the previous sessions (tr_i), how many users from the user set $\mathbb{U}$ can we allocate to p_i, to optimise lesser overburden on the corresponding therapist, but at the same time optimizing for the users who are assigned to p_i. This is classic case of a multi-objective optimization problem and some the recent machine learning solutions include *Pareto based learning* [4], [7] or using reinforcement learning and reward policies [5]

4 A Solution Towards Public Health

While in-person interactions with therapists maybe preferable for someone, often due to certain circumstances, therapy at home via online medium may be a better viable option. This is particularly relevant during recent times due to the global pandemic where in-person interactions have been highly compromised. Existing therapists/professional experts can thus employ through such an online system to connect with more clients who need their help much more efficiently, while users can easily connect through an app with a therapist, without having to face any barriers towards finding any such resources.

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