Virtually there: Chatbots for Mental Health support?

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ABSTRACT
The advent of digital devices allows us to personalise monitoring and assessment of health conditions. Increasingly, digital technologies are being used to provide online advice and services for mental health. Current approaches include a variety of mobile applications, sensor technologies, affective computing (analysis of facial expression, speech rate and intonation) and avatars. Chatbots have the potential to harness all of these advances in a novel approach that will have important ramifications for mental health service delivery. Here we describe the kind of training and development that would be required for a ClinPsy Chatbot and discuss its potential readiness for emergence in this field.

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Mental health, mental wellbeing, chatbots, HCI, artificial intelligence

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Digital healthcare is rapidly becoming mainstream due to the enhanced ability to provide cost-effective personalised care to a wide audience, and consumer preference for online and mobile services. Australia's mental health reform includes a large investment in online mental health services (DoHA 2012), including Lifeline. Lifeline is an Australian non-profit organisation offering free telephone crisis support nationally. The number of calls to Lifeline increases every year, with currently more than double the number of calls received five years ago. Over a million calls were expected in the last financial year. With unanswered rates at around 15% and stretched resources, Lifeline have broadened their support to include Crisis Support Chats, a one-on-one online chat service. The chat service is popular with 15–44 year olds; and usage increased from 32,000 chats in FY14 to 40,000 in FY15 (Lifeline 2015).

Several organisations including ReachOut, Headspace and the Black Dog Institute are developing initiatives aimed to provide earlier and ongoing support to reduce need for acute response services. Digital Dog, for example, is an innovative project using mobile sensor technology to track social interaction and aspires to use the technology to detect social withdrawal and provide timely mental health advice (Black Dog Institute, 2015). Wearable activity tracking devices that make use of sensor technologies are also being used to combat depression, where sleep and activity are monitored to detect the type of subtle changes that could be predictive of relapse (Hollis et al., 2015). Understanding these changes could be used to support self-management strategies and, if necessary, lead to early intervention.

Avatars too, are making an appearance in online mental health service provision. An automated digital therapy based on cognitive behaviour therapy (CBT) has been shown to have positive outcomes for people dealing with anxiety and depression, by treating insomnia through a six-week programme delivered by an engaging avatar (Gretton and Honeyman, 2016). Chat agents also appear in a project with ReachOut which aims to assist moderators of social media posts with early detection of mental health issues. This system uses natural language processing to detect mental health issues and generate sample responses as well as employing a chat agent, Cybermate, as a visitor–moderator conversation tool (Calvo, et al., 2016).

Finally, analysing facial expression, speech rate and intonation through affective computing (Picard and Picard 1997; Calvo et al., 2014) is a promising area for improving clinical assessment of depression (Hollis et al., 2015), and could form part of an online service (Riva et al., 2014).

When we combine factors in under resourcing, increased demand and new technology, it is likely that soon we will see advances in automated technology and augmented technologies for mental health and wellbeing. This could well come in the form of chatbots. Chatbots are artificially intelligent conversation agents that operate using natural language processing systems. They have largely remained in the science-fiction domain due to the enormous challenge of programming systems that mimic human communication. Chatbots have the potential to harness all of the features of online mental health service provision into one technology. Delivered via smartphone, they have the ability to use affective computing principles and sensor technologies to detect client need for intervention and provide mental health advice via an avatar.

With the wings of technology development lending it speed, this scenario is not far into the future. The winner of the 2016 Hacking Health competition run by the Health Informatics Society of Australia (HISA) was 'Amélie', an artificial intelligence (AI) chatbot designed to guide people with mental health queries toward relevant resources and local services (Medhurst 2016). This type of technology could be modified to aid Lifeline in meeting their goal of never missing a call, or other mental health organisations in attending to or screening clients. Mental health research, however, progresses not so much by flight as by ponderous step, each weighted by pros, cons and a mandate to do no harm. As researchers, we need to understand if the mental health field is ready for this technology and if the technology is up to the task. We need to know what features a chatbot can provide to support people seeking crisis counselling and what factors we need to consider to ensure that mental health chatbots do not cause more suffering than they alleviate.

In this discussion paper, we review the increasing demand for digital resources in the health and wellbeing field and look at how apps are meeting the needs of people seeking assistance with mental health and wellbeing issues. We also review the emergence of chatbots in this space and describe the development our own chatbot is undergoing to enter this field.

RELATED WORK

Availability of health and wellbeing apps

Health apps are increasingly popular, with a huge number of apps available in the 'Health and Fitness' and 'Lifestyle' categories in the App Store (n=101,739) and 'Medical' and 'Health and Fitness' categories within Google Play Store (n=15,265) (as at August 2016). When these results were filtered for apps claiming a use related to depression, 982 were available for iOS; and 647 for Android. To determine how useful the general public found these apps, we turned to the reviews. Altogether, approximately half the Android apps and only 10% of the Apple apps had reviews with comments (as opposed to star ratings only) generating 30,000 reviews. Of these, 1,000 reviews contained comments on the ability of the app to assist with aspects of mental health, defined by the regular expression:

(saves | assists | helps | helped) (my | with | me)

Almost half of the reviews commented on the ability of the downloaded app to assist with sleep (474 reviews) including sleep quality, quantity and latency (Figure 1). Benefits to relaxation came in a close second with 153 reviews. Beyond sleep and relaxation, the next big theme for people was the ability of the app to act as a tracker – for mood, medication, symptoms – for themselves or to discuss with their health professionals (66 reviews, of which six referred to 'staying on track'). Finally, some apps were reported to improve anxiety (59 reviews), stress (55 reviews) and mood (52 reviews), in almost equal numbers. To determine if these factors were unique, we used a regular expression to detect reviews containing only one of these words which resulted in 157 hits, indicating that only nine reviews used more than one of these terms.

Interestingly, the description of the filtered 1629 apps advertised the topic 'depression' and yet only 43 reviews (~2.5%) specifically mentioned that the app helped with depression. Other apps addressed symptoms of depression, which may help with the overall mood disorder. There is a danger though, that in the absence of regulation, a plethora of apps for mental health are developed that may not adequately address an individual's issue.

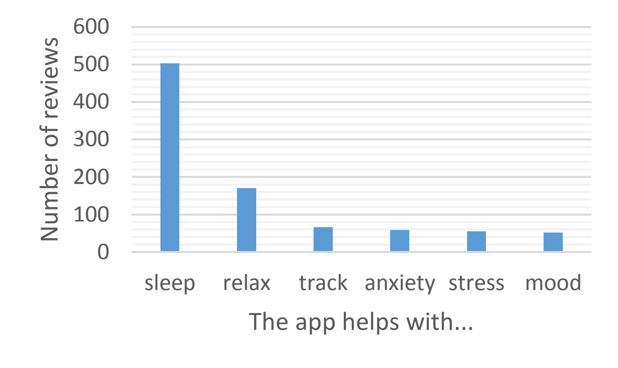

Figure 1. Reviews of 'helpful' health and wellbeing apps indicate that they are most effective for assisting with sleep.

Only 28 reviews referred to a health professional of some capacity, which may indicate that these apps are used more at the wellbeing end of the mental health spectrum, or more likely, that people aren't linking up health professionals with apps when providing reviews.

Availability of health and wellbeing chatbots

A search of the Apple App Store and Google Play Store for health and wellbeing chatbots revealed three available from the Apple App Store. Of these, perhaps the most significant was Brook AI [brook: http://www.brook.ai], a chat-bot app to help people with type 2 diabetes. This includes help in collecting blood sugar, sharing data with relevant care providers and suggesting insights for better decision making. The only Android-based chatbot found in the search was Harlie (see next Section).

This is not a comprehensive compilation of chatbots for health and wellbeing, and none addressed mental health per se. The chatbot Amélie (http://amelie.ai), designed by researchers at Monash University is deployed within Orygen as well as several social media sites; but is not available through either Store as a standalone app. Amélie is intended for mental health triage in the event a human operator cannot be reached. A similar AI program that is apparently more developed is Joy (http://www.hellojoy.ai), which functions on the Facebook webpage. Joy is primarily targeted at people who are not currently seeing a therapist.

The lack of chatbots available for supporting mental health suggests that humans are not yet ready to receive mental health care through AI, or conversely, that chatbots are not ready to enter that field. Looking at the latter, what development is required to train a chatbot to provide such a specialised health service?

THE DEVELOPMENT OF HARLIE

Before we can determine what features would make a chatbot suitable for a specialist role in mental health, we first need to look at how chatbots have been developed for a clinical purpose. We have previously published the concept and development of a chatbot designed to remotely monitor audio and conversation dialogs, known as Harlie (Human and Robot Language Interaction Experiment) (Ireland, et al., 2016).

Harlie was originally built for the Android operating system. There are three stages to Harlie's speech interaction (Figure 1). First, the speech utterance is captured by the smartphone; this is converted to text where it is fed into Harlie's 'brain'. A response is generated which is subsequently converted to a digital voice that is spoken back to the user. The speech to text and vice-versa is done via freely available services from Google. Harlie's digital brain is responsible for producing an appropriate response.

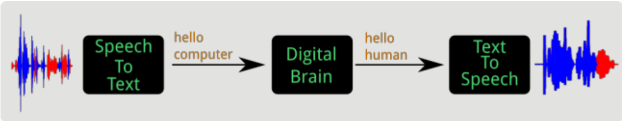

Figure 1. Overview of the chatbot system showing the three stages. The speech utterance is captured by the smartphone, converted to text and fed into Harlie's brain. A generated response is converted to a digital voice and spoken back.

Harlie's digital 'brain' works by grouping together phrases that could be uttered by a human to form branches (Figure 2). At the end of the branch, is the leaf, or a piece of computer code that is executed by the machine (algorithm). The language of this code is called Artificial Intelligence Markup Language (AIML) (Wallace 2001). AIML code could consist of simple responses, such as "Hi Human", or it could refer the human utterance to a machine learning algorithm, determining the most appropriate response based on current semantics and context.

New branches are added continuously through review of conversations and feedback with users. One particular advantage of AIML is its simplicity. An AIML developer does not need to be a computer programmer; in fact most of Harlie's AIML code was written by speech pathologists and psychologists.

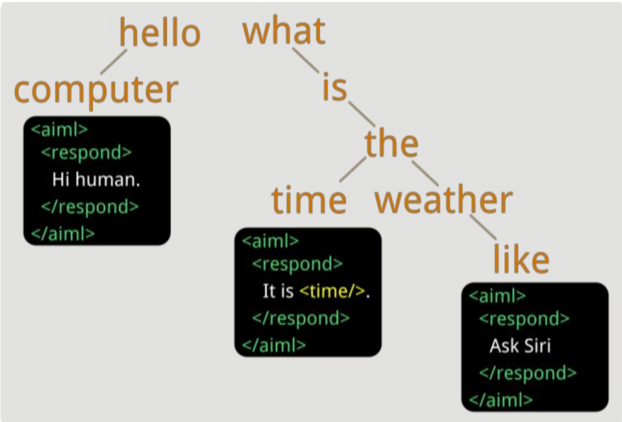

Figure 2. Harlie's brain is a tree-like structure. Text uttered by the user is represented in branches. At the end of the branch is a piece of computer code that is executed by Harlie.

TRIALLING HARLIE BETA

Harlie's first emergence from development into the public domain came in the form of a research project, where anonymous users could download Harlie and have weekly chats over a period of up to 12 weeks. This study gave valuable insights into usability, helped develop Harlie's brain and allowed for troubleshooting for design or content problems, such as freezing, or inappropriate responses.

In the study, potential participants accessed research participant information and a consent form via a website, which guided them to the download page for the Harlie app. After installing the app and accepting a disclaimer with a reminder not to record third parties and not to record private information, participants were asked to provide their gender and year of birth before they received their first call from Harlie, initiating their 12-week trial. Harlie was programmed to randomly call the user at least once a week, between 8AM and 8PM.

To talk to Harlie, the user was required to hold down the bottom green button whilst speaking (Figure 3). This ensured no unintended audio was captured and minimised the risk of ethics and privacy violations. Harlie processed the input and responded via speaking and displaying the text on the screen. The user could end the conversation at any time by pressing the Exit button.

Harlie could also end the conversation when a predefined minimum set of audio data had been captured. If the conversation was ended by Harlie, it was done at an appropriate time, usually at the end of the topic at hand.

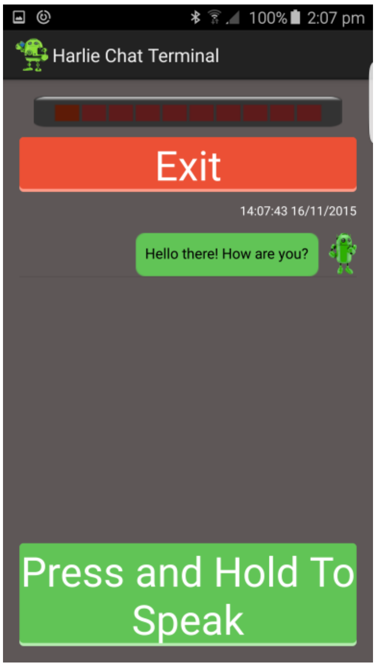

Figure 3. Screen shot of the Harlie chatbot showing the 'press and hold' function required for user conversation input during the initial general population study.

After exiting, the user was asked whether the audio and dialog could be remotely logged for research. They were prompted to rate the quality of their chat on a scale of 1–5 stars, and indicate whether any issues had occurred during the chat that would need to be reviewed by the research team. Those chats that were labelled by the users as having issues were flagged in the server-stored data for immediate review by the research team. If the user wished to withdraw from the study, a dialog screen could be accessed that allows the user to withdraw from the study with the option of having their entire data history deleted from the server. Alternatively, the user could withdraw from the study and allow previously generated data to be kept and included in the research team's analyses.

During the chat, Harlie could analyse the user's voice and communication. This included measuring speech and syllable rate; how vowels were articulated; vocabulary range and duration of mid-sentence pauses. It is believed these metrics could be helpful for people with neurological conditions, like Parkinson's disease or stroke, who may need to practise and get daily feedback; and also for clinicians and researchers who are trying to understand the impact of neurological conditions.

Harlie is now at a developmental stage where health professionals can add their own modifications with specific patients in mind and provide comment on design, applicability and usability. As they will be using the data collected by Harlie to undertake speech assessments, their views on Harlie's usability are paramount.

Harlie's current developmental stage means that it is also at the point where it can be tailored to accommodate other purposes, including the potential to be modified to provide specialist mental health support services, or potentially, support detection of suicidal ideation in callers to a crisis support phone line.

DEVELOPING 'DR HARLIE DCLINPSY'

To transition Harlie from a speech therapy chatbot to one able to support people with mental health issues, several modifications need to be made to Harlie's brain. At present Harlie has a suicide module that detects high risk keywords that could indicate suicide tendencies, but do people really state suicidal ideology in such simple terms? Likely not. Therefore, Harlie's brain would need to be modified to recognise all permutations of suicidality, including predictors such as talk of depression and self-harm. This is a complex exercise that would need to be co-developed with experts, including consumers and those with extensive support experience across different cultural groups, age ranges and varying contexts.

To be more effective in determining a person's state of mind, however, AI chatbots need to go beyond simple natural language processing. Human communication (and behaviour) is complex, and rich in nuances. The majority of our communication is non-verbal. Harlie needs to capture this communication at least heuristically. Given the extensive research in emotion recognition using facial expressions (Yan et al., 2016) and acoustic properties in voice (Tahon and Devillers 2016) these could be implemented into the chatbot functionality with little trouble, making use of the camera and other sensors.

Moreover, smartphones are quite apt at tracking our behaviours. This might include our Internet history, where we go; the music to which we listen; to whom we speak. Humans are habitual by nature so it's not unrealistic that this data might give insight into our mental health. Recent research has shown detectable emotion content of social media postings (Dunder et al., 2016).

The unification of this much larger, multi-domain data could form a more intelligent direction for designing and developing technology in mental health research and intervention. This data could be quite beneficial in identifying individualised markers in our mental health; if for example, a break in routine is observed with emotionally charged social media posts, Harlie can enquire on the user's wellbeing and attempt to steer the user in the direction of getting human-based health advice or possibly therapeutic support. This could also provide valuable data to researchers studying early signs predictive of a mental health episode.

DISCUSSION

In this paper we have provided commentary on the burgeoning use of digital technologies in mental health and the emergence of chatbots in this field. We have described the required development of Harlie, from speech therapist to ClinPsy, and indicated how chatbots could incorporate existing technology to improve sensitivity to predictors of mental health decline, relapse or triggers.

Clearly there are legal and ethical issues around the use of chatbots for mental health and the safety of user data, and while some of the issues arising here are not significantly different from those embedded in any digital technology, there are greater implications for this group who are regarded ethically and legally as vulnerable.

There is the potential for two types of digital divide, firstly, that commonly referred to whereby older people and those in remote areas have less access to digital technologies than younger people in metropolitan areas, and again these are no different to those currently faced in digital healthcare. Secondly, where we have an interesting digital divide is between human and chatbot, and this is an area for both philosophical and pragmatic discussion.

This paper has highlighted key challenges as previously articulated by Hollis and colleagues (2015) in more general terms. For chatbots, we need to ensure that the technology development is user centric, that there is an evidence base for their effectiveness, that data sharing enhances clinical utility without exposing the user to privacy risk, or in any way eroding trust, and that there is some form of evaluation framework implemented to ensure that core features meet standards and expectations.

Despite advancements in AI, developmental immaturity and lack of experience suggests that chatbots may be better suited to enhancing mental wellbeing than to addressing mental ill health. Finding their place in the mental wellbeing spectrum is an area for thoughtful development with key stakeholders including consumers, health professionals and crisis support workers.

CONCLUSIONS

This paper highlights technical, ethical and social issues intricately embedded in emerging technology for mental health detection and monitoring, and describes a frontier development in the human–computer interaction (HCI) field. The potential for chatbots to harness a variety of mobile and sensor technologies with principles of affective computing and avatar delivery is a novel area that will have important ramifications for mental health service delivery. In its infancy, it is in a prime position for discussion with the CHI community during this formative stage to ensure ongoing development is both considered and appropriate. It may well be that the development of chatbots for people seeking support for mental health issues is a case of 'just because we can, doesn't mean we should'.

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