To Bot or Not to Bot?: Analysing Mental Health Data Disclosures

Deborah Taylor[1][0009-0006-8168-1785], Clare Melvin[2][0000-0001-5621-3417], Hane Aung[1][0000-0002-4376-0849], and Rameez Asif[1][0009-0001-8593-7956]

School of Computing Sciences, University of East Anglia, Norwich, NR4 7TJ, UK
debbie.taylor@uea.ac.uk (corresponding author), c.melvin@uea.ac.uk, min.aung@uea.ac.uk, rameez.asif@uea.ac.uk
https://www.uea.ac.uk/

Abstract. Disclosure of personal information about wellbeing and mental health is a nuanced situation requiring trust between agents. Current methods for initial mental health assessments are time and resource intensive. With increases in demand for mental health services and decreases in funding and staffing levels, this paper explores whether conversational agents can be sufficiently 'trusted' to collect the sensitive data disclosed in initial mental health assessment data, thereby reducing the workload for trained professionals.
An initial study identified the desired characteristics of a conversational agent designed for mental health assessment purposes and produced a MoSCoW design framework of desirable features.
A second study tested the framework by investigating whether a conversational agent, displaying these human-like features, could establish sufficient trust to collect data, comparable to a mental health provider online form or a social media online form. Participants (n=236; F=58%, non-binary=5%, Prefer not to say=1%, age 18-80+yrs) were recruited from a UK mental health provider and through social media.
Of the participants, 50% (n=126) engaged with the bespoke conversational agent and the remaining half completed online forms through social media and from a mental health provider.
Results indicate a conversational agent can be used to collect sensitive mental health data for initial assessment. Whilst such a tool may not be appropriate for all demographics, the conversational agent shows promise for reducing the administrative workload of those in the mental health profession, thus increasing resources for treatment and therapy.

Keywords: Conversational agents · Trust · Mental health, · Personal disclosure · Sensitive disclosure

1 Introduction

Disclosure of personal information about wellbeing and mental health is nuanced and requires trust between agents. Some countries state mental health is now being treated equally to physical health but this is not true in all cases, especially in the United Kingdom (UK), where different counties make choices based on funding and patient numbers [1].

It is also more difficult to ascertain the exact cause of mental verses physical illnesses. For example, if someone with a physical illness states 'I cannot get out of bed', a few questions, physical touches or scans, from a trained medical professional, can quickly ascertain if the patient is having a stroke, back pain, broken back, etc. and recommend the correct treatment plan. Whereas asking the same question, in relation to mental illness, is more fluid and less tangible as the issue could be due to multiple different mental health issues such as anxiety, depression, mental trauma, childhood conflicts, or a mixture thereof. As nothing can be seen, touched or scanned, the questioning technique must be open, empathetic and understanding, as a patient needs to disclose very sensitive and personal information about their innermost thoughts, feelings and belief system. If not done correctly the patient may receive a false diagnosis, which could make their symptoms worse and decrease their trust in the mental health profession [1, 2].

Following the COVID-19 Global Pandemic healthcare procedures and 'trust' of technology was changed to allow exploration of computer science and artificial intelligence (AI), for health service provision and delivery. Despite an increase in digital online functionality and usability, the utilisation of conversational agents for sensitive personal data collections is still uncommon in the mental health sector, compared to other health sectors and industry. For example, despite a range of wellbeing and therapy support applications [3] Gaggioli et al. [4] highlighted an absence of generic processes for eliciting a patient's sensitive mental health personal data, which results in initial assessments being resource intensive for healthcare processions. An initial assessments provides the necessary information to inform client treatment and support, however, these are still being completed by trained professionals, which reduces time available for them to deliver therapies [5–7].

With over 3 billion smartphones and 4.66 billion internet users worldwide it is reasonable to consider utilising conversational agents for initial mental health sensitive data collections, as a method to reduce the administrative workload for mental health professionals. [8–12].

2 Current Mental Health Conversational Agents

Current use of conversational agents in provision of mental health services varies in services offered and personal data collected. For example, the top two mental health agents are Wysa and Youper which use differing levels of Artificial Intelligence (AI) to identify potential triggers as well as offering tools such as activity monitors, mood trackers and therapeutic processes such as mindfulness and relaxation. Both target mental health issues such as poor sleep, anxiety and depression and collect a range of personal data (age, contact information, financial identifiers and medical information) in addition to identifying triggers and sources of stress [13–16].

2.1 Wysa

Wysa was released by Jo Aggarwal and Ramakant Vempati in 2015, for Android and iOS mobile users, by employing a blend of AI interaction and human communication. It was designed to decrease stress by improving sleep and mindfulness, using empathy, positive reinforcement, mindfulness suggestions and motivational interviews [13, 14].

The application enables the AI to access sensitive personal data, such as date of birth, age, contact information, addresses, financial identifiers and minimal medical information. Users can choose the level of data they wish to share, however the more data collected the more accurate the AI is at providing improved user experience [13, 14].

During 2022 Malik et.al [17] completed a study utilising Wysa user feedback, n=7929. They identified that including some low-level human-like interactions enabled the majority of users to feel more engaged, for example one user stated 'The app made me laugh with its silly jokes and play.' [17]. Some users, however, 'did not find it helpful for their specific concerns and suggested further expansion' [17].

Such feedback highlights the positive contributions these technologies can provide, however, also illustrates the complexities in meeting the mental health needs of all users. Malik et.al [17] identified that enhancements in the application, could include an improved understanding of less common mental health illnesses, more human-like interactions, and an increased level of privacy and security, to enable the AI to return more bespoke human-like replies [17].

The study's authors [17], two of whom hold equity in Wysa, acknowledge that the cross-sectional design, with reviews taken from a 'single point in time' and 'lack of knowledge on the duration of app use or the rate of attrition' limit conclusions drawn from the study [17].

Whilst collecting information from over 7,000 users, data from Apple Store users was unfortunately not accessible. Additionally, in September 2022, Wysa had over 6.5 million registered users, so the overall participant pool was 0.0012% of total available users [18].

Some of the methodological issues in Malek et.al [17] were considered by Legaspi et.al [19], as part of their 2022 review of Wysa's usefulness during the COVID-19 lock-downs.

Participants were students aged 16-19, and completed a daily form over a one week period. Results were analysed for perception of effectiveness and usability, which related to relevance and appropriateness of Wysa's responses [19].

This study was also limited by sample size (n=10) as well as, duration of the data collection window, however it was an external evaluation and run independently of Wysa.

Findings from Legaspi et.al [19] showed students were dissatisfied with 'the talk feature's repetitiveness and lack of fluidity' [19] and that the 'rigid conversation flow not only causes difficulty in communicating with Wysa but can also make the user feel neglected when the chatbot does not acknowledge the user's input.' [19].

These issues can be characterised as being the result of the conversational agent's lack of human-like responsiveness. This may be due to the low-level of personal data collected about the user, meaning the AI could not access sufficient information to create a bespoke simulated human-like conversation, thereby decreasing user engagement.

Such views were not universal across the study as one participant specifically stated they felt more comfortable relating to a conversational agent, verses a human, as they could be more open due to the application being non-judgemental, throughout the entire conversation [19].

Even though this study was also limited by the sample size, their conclusions agreed with some of the findings from Malik et.al [17]. The most essential being that simulating human-like features could be the key to increasing engagement and this could relate to the level of personal data collected. This may be particularly pertinent for certain demographics, such as the younger generation (18-39) who grew up using technology.

2.2 Youper

Youper was released by psychiatrist Dr. Jose Hamilton in 2016, for Android and iOS users, as a free and payable application, designed to 'cure the world of anxiety and depression' [20].

The free version currently provides low-level AI personality tests, ongoing mood tracking, suggests goals and encourages journal writing, to enable the user to recognise their personal mental health and wellbeing triggers. The payable version provides enhanced AI conversations and improved wellness techniques [15, 16, 20, 21].

The AI replies and suggestions, for both free and payable versions, are formulated by utilising the personal data collected when a user registers to access Youper's support. This includes email addresses, names, passwords, low-level health information and ongoing monitoring of features used within the application [15, 16, 20].

In 2021, Mehta et.al [22] completed a longitudinal observational study analysing Youper's effectiveness and acceptability. They examined data from 4,517 users, and their primary measures were user ratings gained throughout system use and retention of users, across the study's timeline of four week's from subscription [22].

They concluded that including a minimal range of human-like emotions enhanced the AI replies, and a more detailed set of human-like features could help extract a superior data collection, which the AI could utilise when replying to users. They stated that further research was needed as to what constituted the correct level of human-like features and could include a more detailed personal data collection, so the AI would be able to utilise these when creating the human-like conversations and replies [22].

Study limitations again included sample size, alongside an emotion regulation analysis measure. Youper had approximately 2 million users in 2021, but the percentage participating in the study was just 0.002%. The authors also state that 'our emotion regulation measure was not designed to assess the magnitude of emotion regulation success, meaning that our metric included only success or failure with each conversation' [22]. This narrowed the scope of the results received.

Findings from these studies, for the two market leaders in online mental health care technology, support the requirement for human-like responses and features when gaining trust by conversational agents, and the potential to increase personal data collections so the AI can utilise more data when replying.

An interesting difference found across the studies, concerned the age of the participants when utilising mental health applications and technologies. Wysa appeals to younger age participants, whereas Youper did not show any differences in trust, data collection, or engagement across demographics.

2.3 Utilising Conversational Agents for Initial Data Disclosure

Applications such as Wysa and Youper fulfil a purpose by providing a level of mental health support for clients that prefer not to access traditional face to face counselling, or do not exhibit medium to severe symptoms. This technology, however, cannot currently collect enough personal sensitive data disclosure to achieve complete engagement via human-like conversations, or reliably decrease the administrative burden on mental health professionals, when formulating treatment and support plans.

Furthermore, it is unknown whether conversational agents can be used to perform the function of a trained healthcare professional in an initial mental health assessment, particularly in light of the core therapist competencies required when developing a therapeutic rapport and relationships, for example active listening, non-judgmental, warmth, person-centred, etc.

Existing research has identified possible improvements to engagement when utilising conversational agents with some human-like features, however, which features and to what extent they facilitate engagement is yet to be explored in detail, or in relation to mental health care.

This paper, therefore, presents the results of two studies identifying the human-like features needed in a conversational agent, to elicit the level of trust required by users for personal data disclosures, and testing a conversational agent with such features for initial mental health assessments.

The current project was designed with primary objectives of (i) investigate the, as yet, unexplored scope of a trusted and engaging mental health conversational agent, when collecting the highest possible level of sensitive personal data, and (ii) review whether such a conversational agent can decrease the administrative burden for mental health providers by collecting the level of sensitive personal data required for an initial mental health assessment.

Such collection may be done by using AI to gather all the sensitive personal data needed for a trained professional to immediately identify the right treatment and support for their client, or a more complex system that can identify individuals who require mental health treatment from a trained professional, and those whose needs can be met by existing online applications such as Wysa or Youper.

A third aim of the current research is to explore feature-preference, notions of 'trust' and disclosure of sensitive and personal data in relation to user demographics, such as age, gender identity or continental nationality.

The first stage of the project was designed to understand and establish what human-like features people believe a mental health conversational agent should exhibit to increase trust.

The second stage tested the human-like features, within a simple bespoke conversational agent, for trust, level of data collected and for which demographics.

Both studies are explored in more detail below.

3 Understanding Human-like Requirements

To explore the potential of cultivating trust in mental health conversational agents and identify the human-like features required to facilitate personal data disclosures, an initial study was completed.

The initial study [21] commenced with in-person and online discussions, across twenty industry and health contacts, then expanded to shadowing trained professionals at a local mental health provider, over a period of four weeks.

This resulted in a set of 25 questions that related to different human-like features that are used in existing conversational agents, alongside extra attributes such as compassion and empathy that trained professionals utilise when completing the initial mental health assessment conversation.

One hundred and seventy seven participants (F=53%, Non-binary (NB)=2%, Prefer not to say (PNS)=1%) were recruited from the shadowed mental health service provider and through social media, using Leo Goodman's statistical snowball data sampling [23], to achieve a wide range of global participants.

The study's main aim was for participants to rate the importance of human-like features, from insignificant to essential, when building trust in mental health conversational agents. The higher the percentage rating and participant engagement with each question, the more weight was placed on the feature being essential for cultivating trust. For example one question asked 'How do you expect a human-like chatbot to greet you?', with quantitative answer choices of:

- Friendly: 'Hello, how are you today?'
- Formal standard greeting: 'Hello, what can I do for you today?'
- Depends on the type of chatbot: Different organisations e.g. financial, mental health, security etc.

The participants were asked to rate each answer from 1 to 5, with 1 being insignificant and 5 being essential, then qualitatively explaining their answers via an open text field.

Both the quantitative and qualitative replies were collated and a review completed at demographic levels of age range, gender identification and continental nationality. It identified 12 human-like features that were universal across the participants and a further 7 that diverged based on demographics, see figures 1 and 2.

Feature	Percentage	Universal Data
Patience	99%	Required partially or fully patient conversation
Decisiveness	98%	Required a high level of decisiveness
Focus and Consistency	98%	Required partial or fully focused and consistent questions and answers
Sentence length	95%	Required either medium or full sentences
Empathy and Compassion	95%	Required some empathy and compassion. Could encompass some language shortcuts, such as emoji's
Humour	90%	Required some humour throughout, as this would improve engagement with the system
Text or Voice	86%	Required text rather than voice-based conversation. Evidenced by UK charity - text only preferred
Formal or informal language	80%	Required a mix of formal and informal language, as this would make the system feel more human
Small talk	76%	Required some small talk, especially at start as this is standard for human conversations
Greeting	76%	Required a friendly greeting. Further 10\% dependent on what the agent relating to, e.g. mental health= friendly, but financial = formal
Biography	71%	Stated a biography not required, as most organisations don't offer this feature
End conversation	60%	Required a friendly end to a conversation

Fig. 1. Study 1: Universal human-like requirements across demographics. Source: [21]

Age and gender identification were established to be the two main factors where trust differs, but there were also some divergences across continental nationality.

The analysis resulted in a software engineering MoSCoW (Must have, Should have, Could have, Won't have) [25] feature framework, see figure 3, that was implemented during study 2.

4 Analysing Data Disclosures

Testing the human-like MoSCoW framework was undertaken in the second study, with aims of (i) identify if a bespoke conversational agent could collect more sensitive personal data than via standard online Microsoft forms, sent by social media or a mental health service provider (ii) identify if the data collection differed across demographics, such as age and gender identification (iii) analyse if a simple bespoke conversational agent could establish sufficient trust to potentially decrease the burden of trained professionals when completing initial mental health assessments.

Feature	Percentage	Diverging Data
Static Avatar	99%	Required a static avatar. Divergences for Non-binary and prefer not to say who require zero gender identification. Ages 45-49 and 65-69, and those that prefer not say do not want age or nationality reflected
Language Shortcuts: Phrases	75%	Required phrases such as `I believe'. Divergences for South American and Asian participants. They required zero phrases
Optimism or Pessimism	63%	Required a mix. Divergences for 80+, African and Prefer not to say. These required zero use of either
Language Shortcuts: Colloquialisms	51%	Required some colloquialisms. Divergences for age range 60-69 and African participants. They required zero colloquialisms
Language Shortcuts: Emojis	49%	Required some emojis. Divergences for age range 70+ and African participants. They require zero emoji use
Spelling and grammar	43%	Required zero errors. Divergences for African, Non-binary and Prefer not to say. They required some errors
Language Shortcuts: Pop Culture	43%	equired some pop culture references. Divergences for age ranges 60-64 and African participants. They required zero pop culture references
Language Shortcuts: Abbreviations	37%	Required some abbreviations. Divergences for age range 70+ and South American and African participants. They required zero abbreviations

Fig. 2. Study 1: Diverging human-like requirements across demographics. Source: [21]

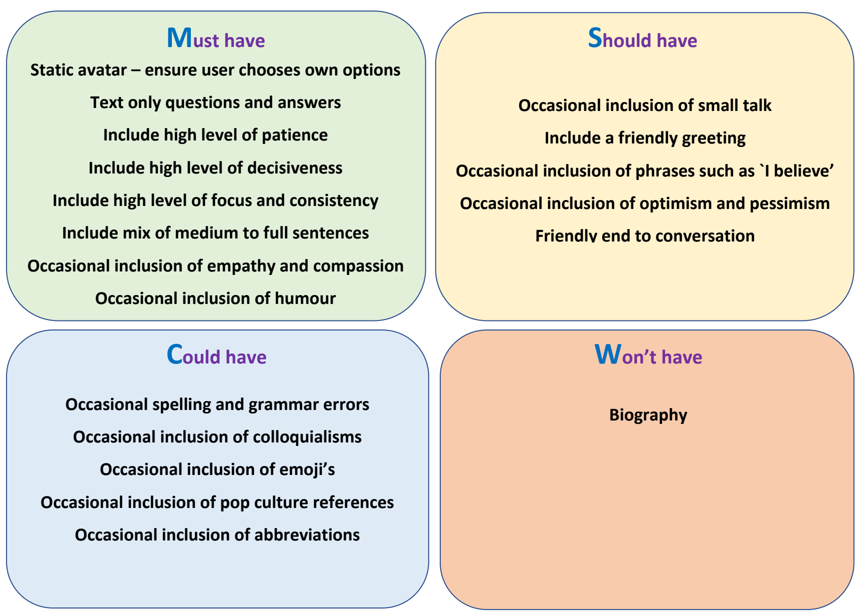

Fig. 3. Study 1: MoSCoW framework for human-like features in conversational agents. Source: [21]

Due to the novelty of this research, consultation with the same study 1 local mental health provider was sought, to ensure both the online social media and mental health provider forms, and the bespoke conversational agent, covered the basic data currently collected, but also include the more sensitive disclosures asked by a trained professional during the initial assessment. Ethics approval was supplied by the University of East Anglia (UEA) School of Computing Science, with input from the mental health provider, and non-disclosure agreements were signed to enable the sensitive data to be collected.

The questions ranged from low-sensitivity such as age, continental nationality, pet ownership, enjoying career, etc. to high-sensitivity and/or controversial subjects such as gender identification, sexuality, religion, health and mental illness, abuse of drugs or drink, family relationships and conflicts, financial debt, etc.

The participants were advised to only complete questions they felt comfortable answering and to choose the collection tool they felt was most trustworthy, online form requested by social media, online form requested by a mental health service provider or a simple bespoke, secure, conversational agent utilising the human-like framework from the first study.

The same questions were asked across all collection tools, so a direct comparison of data collected across the demographics of age (ranges 18-29, 30-39, 40-49, 50-59, 60-69, 70-79 and 80+) and gender identification (male, female, non-binary and prefer not to say) could be analysed. Nationality demographics were discarded for this study, due to the limited sample size of some continents.

4.1 Design and Data Collection Process

Both online forms, social media and mental health provider, were created using a standard Microsoft 365 form template, as per the current request process [26].

The bespoke conversational agent was designed and coded using React and Node js, [27, 28]. It incorporated all but one of the Must have and Should have requirements from the MoSCoW framework (figure 3) for use on mobile devices, laptops and personal computers. The missing requirement was a static avatar, as more data needed collecting about the types of avatar participants prefer, for example picture of themselves, their pets, cartoon character, etc.

The conversational agent was fully secured and protected using a database that linked to a secure University of East Anglia (UEA) computing sciences server, allocated specifically to this study.

As a proof of concept study, the conversational agent was coded without a complex AI, as the application needed to ask the same questions in the same order, to complete a direct comparison during analysis. The single manipulation was the conversational agent displaying the human-like feature requirements from study 1, and providing a low-level 'friendly' conversation, rather than depicting the questions solely in formal text, as with the online forms, see figure 4.

Data collection took place over three months from September 2023, with analysis starting in December.

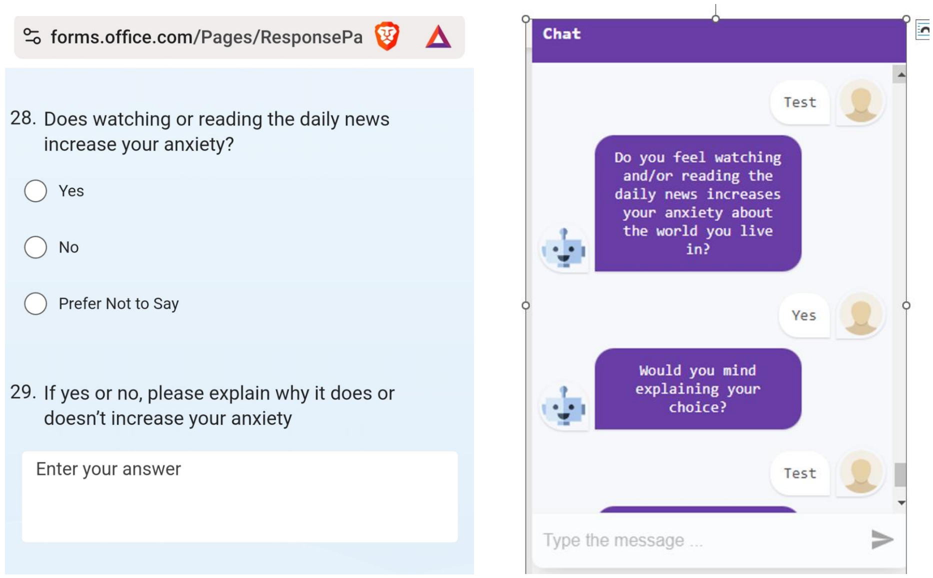

Fig. 4. Differences in language between formal online forms and informal conversational agent

5 Results

Descriptive statistical analysis was conducted to establish any initial patterns relating to the three aims discussed in section 4. A more detailed regression analysis will be completed over the next 3-6 months, as the research is being completed on a part time basis.

Two hundred and fifty three participants (F=58%, Non-binary(NB)=5%, Prefer not to say(PNS)=1%, across age ranges=18-80+yrs and continental nationalities of Africa, Asia, Europe, North American, Oceania, South American, UK and Prefer not to say) were recruited, over a three month period from September 2023.

The recruitment process used social media with the snowball sampling technique [23] and the same UK mental health provider as study 1. The bespoke conversational agent was released alongside the two forms, and participants were asked to choose whichever data collection tool they felt was more trustworthy, and complete the questions via that tool.

The initial findings established that demographics of gender identification, age and source of request are essential considerations for technological data collection processes. Nationalities, used in study 1, was discarded, due to the limited sample size of several continents.

The online form from social media recruited 46 participants (18%), the online form from the mental health provider recruited 81 participants (32%) and the bespoke coded conversational agent recruited 126 (50%) participants.

The gender divisions were comprised of mental health online form (F=54, PNS=1), social media form (F=30, PNS=1) and bespoke conversational agent (F=62, NB=13, PNS=1).

Initial results support the use of conversational agents with these human-like features, as potentially viable alternatives for certain demographics. The findings for gender identification, especially those identifying as non-binary, age and source of request are explored in more depth below.

5.1 Gender Identification

When shadowing mental health professionals for study 1, it was identified that gender identification is often difficult to obtain from the current form process, as people do not feel comfortable raising it until their initial mental health assessment conversation with a trained professional.

The information collected by this study supports this, as data collected from both online forms achieved zero non-binary participants, however, the bespoke conversational agent engaged 13 participants, 10% across conversational agent participant pool and 5% across the overall study, see figure 5.

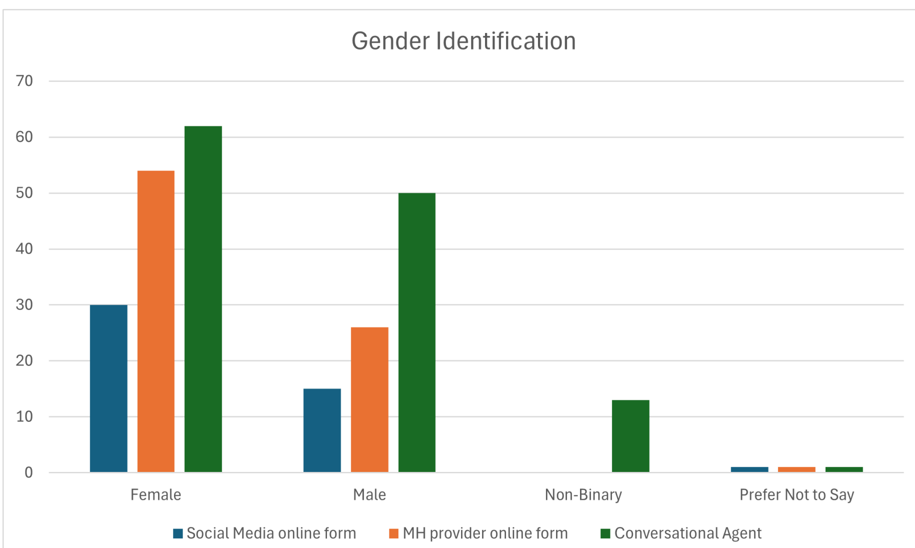

Fig. 5. Gender Identification across collection tools

The non-binary participants, when specifically relating to the conversational agent data, were very open to providing information on the low-sensitivity questions, such as pet ownership (92% yes, n=12 and 8% no, n=1), having siblings (85% yes, n=11 and 15% no, n=2), etc.

When relating to higher-sensitivity questions, such as childhood family conflicts, they also provided more data than male or female participants. For example 8 out of 13 (62%) non-binary participants advised they did experience family conflict, whereas this decreased to 45% (n=28) for female participants and 52% (n=26) for male participants.

When reviewing this question via the online forms, the family conflict data from the mental health provider form collected 37% (n=20) female and 42% (n=11) male, and the social media form collected 46% for both female (n=14) and male (n=7). There were zero non-binary participants for these forms.

Despite the low sample size, collecting this non-binary data from the conversational agent was a significant result. Family conflict is often more prevalent with non-binary people, due to religion, parental disapproval, lack of validation of non-binary gender identities and social intolerance. This conflict and trauma can carry over from childhood into adulthood and often impacts mental health, until patients can get support with reconciling their childhood conflict, verses the person they are today [29, 30].

A study in 2021 by Sapien Labs (participant n=407,959, across 64 countries), published the Mental State of the World Report 2021 states 'on average more than one in two non-binary people (51 per cent) are clinically distressed or struggling' [31]. 13 participants is a low sample size, but the results evidence that non-binary people are potentially more willing to engage with a bespoke conversational agent, with human-like features, rather than online forms.

Gender also impacted the data collected when asked if participants have, or are, taking illegal drugs. This is one of the high-sensitivity questions a mental health professional asks during initial assessments as these substances can be the cause of some mental illnesses, or a way for patients to try to cope before seeking help. The online mental health provider form identified females (n=10 and M=4) were more likely to confirm yes, as did the online social media form (n=5, M=4), but the conversational agent engaged more men (n=9, F=6, NB=2) to admit they were taking these types of substances, see figure 6.

This study has proven that conversational agents can collect a higher percentage of data across different gender identifications, so this could support a decrease in administrative burden, as patients could be referred immediately to counselling sessions, rather than having to first attend an initial face-to-face assessment.

5.2 Age and Source of Request

The findings from the initial descriptive analysis found that age and source of request were also essential elements in collecting sensitive mental health data. For example, 87% (n=110) that chose to complete the conversational agent were aged 18-29 (n=83) and 30-39 (n=27). For the mental health online form the 18-39 age group accounted for a total of 40% (n=32) and the social media online form achieved 83% (n=38), see figure 7.

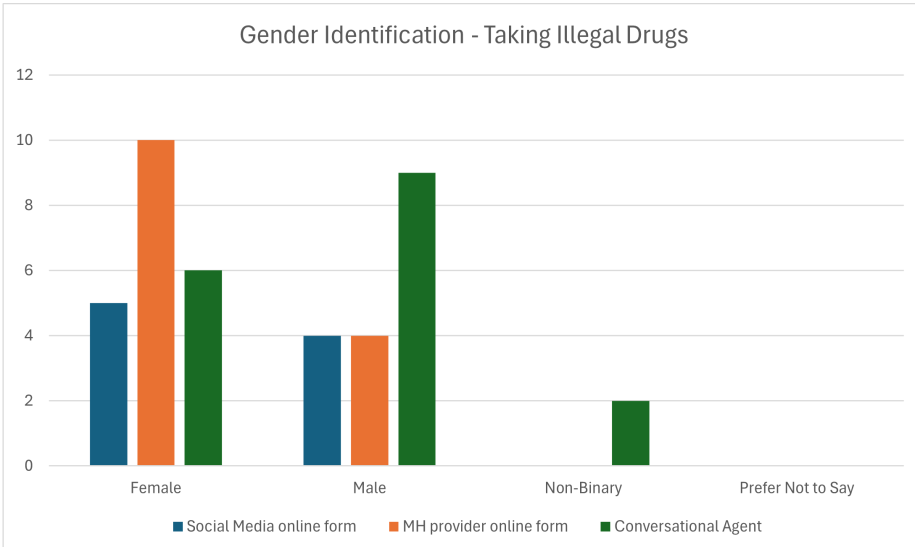

Fig. 6. Illegal drug taking across gender and collection tool

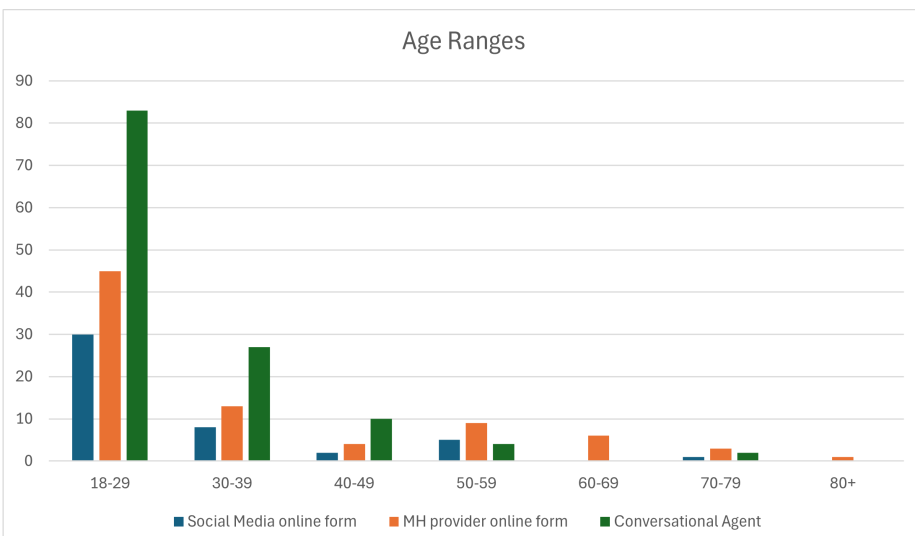

Fig. 7. Age Ranges across collection tools

This supports the findings of Malik et.al [17] and Legaspi et.al [19], that younger age groups are more comfortable and trusting of technology.

This is evidenced when analysing another high-sensitivity question about whether participants easily feel anxious and the impact it has on their mental wellbeing. The UK Mental Health Foundation states that in 2021 people aged 16-29 were 28% more likely to report some form of anxiety, with this decreasing considerably as participants get older, with only 5% reporting this from age 70+ [34].

The research confirms this statement as it found age ranges of 18-39 were more willing to answer with an affirmative when asked this question, verses older age participants. For example, out of all the participants stating yes to this question, the age ranges of 18-39 collected the most data, with 10 out of 11 (90%) from the social media form, 22 out of 26 (85%) from the mental health provider form and 61 out of 64 (95%) were from the conversational agent, see figure 8.

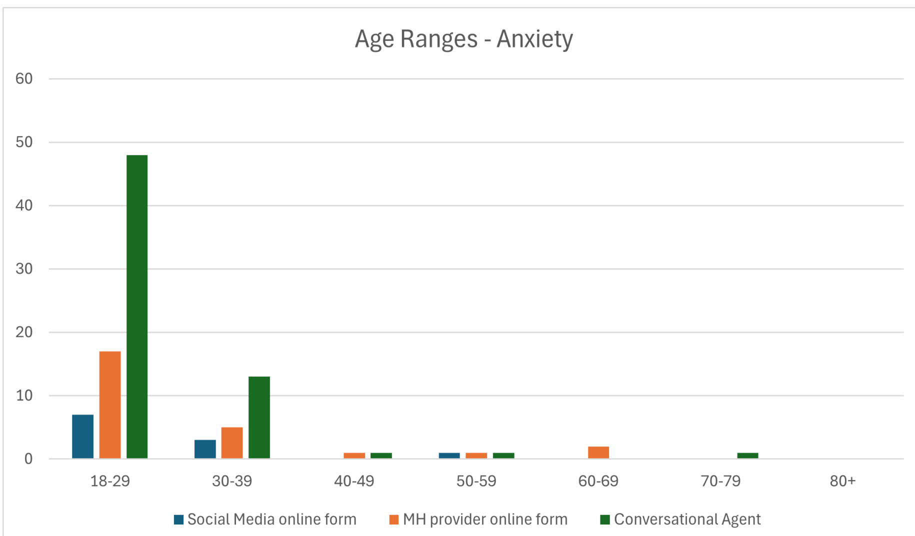

Fig. 8. Age Ranges and anxiety confirmation across collection tools

The importance of both age range and source of data collection was highlighted further, when asked a more controversial question about accepting COVID-19 vaccines. Of the participants confirming yes, the 18-39 age ranges received a much higher confirmation via the conversational agent. 28 out of 36 (70%) completed the social media form, 44 out of 66 (60%) completed the mental health provider form and 92 out of 103 (90%) completed the conversational agent, see figure 9.

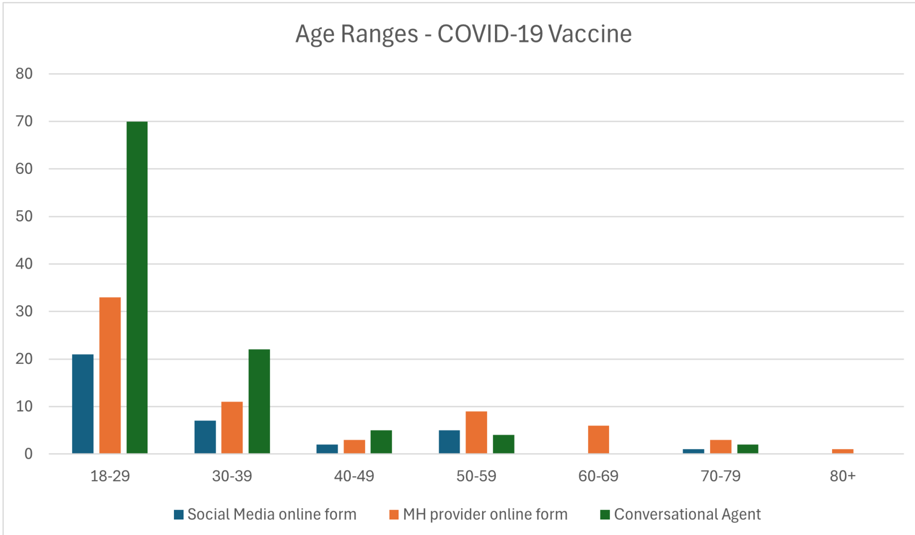

Fig. 9. Age Ranges and COVID-19 Vaccine Confirmation across tools

A similar pattern was identified, across multiple high-sensitive questions, where more data was collected from the conversational agent. This was largely due to the 18-39 year age group being considerably more engaged with the conversational agent, than via the standard online forms, see 7.

The older age ranges achieved a limited with sample size, but these appear to benefit more from traditional data collection tools and sources, such as online forms from mental health providers.

6 Conclusion

There is currently little research on utilisation of conversational agents, with human-like features, for mental health data disclosures. The initial results of this study indicate that conversational agents can be useful when collecting sensitive personal data for initial mental health assessments.

This paper has evidenced the three aims have been achieved, to some extent, as (i) a bespoke conversational agent can collect more sensitive personal data than existing online forms, (ii) level of detail within data collections does differ across demographics and (iii) a bespoke conversational agent, with human-like features can establish sufficient trust to potentially decrease the burden on trained professionals.

Whilst such a tool may not be appropriate for all demographics, a bespoke conversational agent, shows promise for either immediately enabling trained professionals to identify the correct treatment plan for an individual or, potentially, identifying who requires mental health support and from what medium, trained professional, Cognitive Behavioural Therapy (CBT), or online support systems such as Wysa and Youper.

A more detailed regression analysis will be completed on study 2, over the next 3-6 months, in an attempt to scale the information provided. Further research will then be completed on a larger, to test if the regression analysis theories can be proven.

Acknowledgments. We wish to thank Joseph Agagwuncha for his help and support with coding the bespoke conversational agent and Debbie Taylor's previous primary PhD supervisor, Professor Oliver Buckley, for providing feedback on the first study's paper and for discussion on the original concept.

References

1. Baker, Carl.: Mental health statistics for England: prevalence, services and funding. publisher, UK Parliament. (2020)
2. Choi, K. W., Jung, J. H., and Kim, H. H. S.: Political trust, mental health, and the coronavirus pandemic: A cross-national study. In: Research on Aging, 45(2), 133-148. (2023)
3. Haque, M. R., and Rubya, S.: An Overview of Chatbot-Based Mobile Mental Health Apps: Insights From App Description and User Reviews. In: JMIR mHealth and uHealth, 11(1), e44838. (2023)
4. Gaggioli, Andrea., Pioggia, Giovanni.,Tartarisco, Gennaro., Baldus, Giovanni., Corda, Daniele., Cipresso, Pietro., Riva, Giuseppe.: A mobile data collection platform for mental health research In: Personal and Ubiquitous Computing, volume 17 pp. 241-251 Publisher, Springer (2013)
5. Schick, A., Feine, J., Morana, S., Maedche, A., Reininghaus, U.: Validity of chatbot use for mental health assessment: experimental study. JMIR mHealth and uHealth, 10(10), e28082, (2022)
6. Sharma, V., Goyal, M., Malik, D.: An intelligent behaviour shown by chatbot system. International Journal of New Technology and Research. Journal **3**(4), (2017)
7. Shawar, B.A. Atwell, E.: Chatbots: are they really useful? In: Ldv forum, volume 22, pp. 137-140. Publisher, IEEE (2020)
8. Global digital population as of January 2021, https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/key-definitions/what-is-personal-data/. Last accessed 14 April 2023
9. Inkster, Becky. Digital Mental Health Data Insights Group (DMHDIG).: Early warning signs of a mental health tsunami: a coordinated response to gather initial data insights from multiple digital services providers In: Frontiers in Digital Health, volume 2 pp. 64 Publisher, Frontiers (2021)
10. Molodynski, Andrew., McLellan, Angus., Craig, Tom., Bhugra, Dine.: What does COVID mean for UK mental health care In:International Journal of Social Psychiatry, volume 67 [7] pp. 823-825 Publisher, SAGE Publications Sage UK: London, England (2021)
11. Yarrington, Julia S., Lasser, Jana., Garcia, David., Vargas, Jose Hamilton., Couto, Diego Dotta., Marafon, Thiag., Craske, Michelle G., Niles, Andrea.: Impact of the COVID-19 Pandemic on Mental Health among 157,213 Americans. In: Journal of Affective Disorders, volume 286 pp. 64-70 Publisher, Elsevier (2021)

12. Cardno, Samantha., Sahraie, Arash.: The expanding backlog of mental health patients: Time for a major rethink in COVID-19 policy., publisher, PsyArXiv (2021)
13. The wisdom of Wysa-Mental health apps, the (AI) friend who is always there, https://blogs.wysa.io/blog/most-read/best-mental-health-apps-for-employees. Last accessed 28 February 2023
14. How Indian Startup Wysa Built an Empathetic AI Bot to Offer Mental Support to Millions, https://www.news18.com/news/tech/how-indian-startup-wysa-built-an-empathetic-ai-bot-to-offer-mental-support-to-millions-2681669.html. Last accessed 27 February 2023
15. Youper, https://www.crunchbase.com/organization/youper. Last accessed 3 March 2023
16. Youper App Review: What's Offered, Cost, and Who It's Right For, https://www.choosingtherapy.com/youper-app-review/. Last accessed 3 March 2023
17. Malik, Tanya., Ambrose, Adrian Jacques., Sinha, Chaitali.: Evaluating User Feedback for an Artificial Intelligence-Enabled, Cognitive Behavioral Therapy–Based Mental Health App (Wysa): Qualitative Thematic Analysis. In: JMIR Human Factors, volume 9 (2), pp. e35668 Publisher, JMIR Publications Toronto, Canada (2022)
18. Wysa brings mental health digital therapeutic to small to mid-size US employers, https://blogs.wysa.io/blog/b2b-partnerships/wysa-brings-mental-health-digital-therapeutic-to-small-to-mid-size-us-employers. Last accessed 19 January 2023
19. Legaspi Jr, C. M., Pacana, T. R., Loja, K., Sing, C., and Ong, E.: User Perception of Wysa as a Mental Well-being Support Tool during the COVID-19 Pandemic. In Asian HCI Symposium 22 (pp. 52-57), (2022, April)
20. The Startup That Wants to Cure Social Anxiety, https://www.theatlantic.com/health/archive/2015/05/the-startup-that-wants-to-end-social-anxiety/392900/. Last accessed 10 March 2023
21. Taylor, D., Buckley, O., Aung, H.: Understanding User Preferences for Gaining Trust, When Utilising Conversational Agents for Mental Health Data Disclosures. In International Conference on Human-Computer Interaction (pp. 167-174). Cham: Springer Nature Switzerland, (2023, July)
22. Mehta, Ashish., Niles, Andrea Nicole., Vargas, Jose Hamilton., Marafon, Thiago., Couto, Diego Dotta., Gross, James Jonathan.: Acceptability and effectiveness of artificial intelligence therapy for anxiety and depression (Youper): Longitudinal observational study. In: Journal of medical Internet research, volume 23 (6), pp. e26771 Publisher, JMIR Publications Toronto, Canada (2021)
23. Goodman, Leo A.: Snowball sampling. In: The annals of mathematical statistics, pp. 148-170 Publisher, JSTOR (1961)
24. General Data Protection Regulation - GDPR, https://gdpr-info.eu/. Last accessed 23 January 2024
25. Moran, Alan.: Managing agile: Strategy, implementation, organisation and people., publisher, Springer (2015)
26. Microsoft Forms, Microsoft Forms. Last accessed 11 January 2024
27. React: The library for web and native user interfaces, https://react.dev/. Last accessed 11 August 2023
28. Node.js® is an open-source, cross-platform JavaScript runtime environment, https://nodejs.org/en. Last accessed 11 August 2023
29. Reczek, R., and Bosley-Smith, E.: How LGBTQ adults maintain ties with rejecting parents: Theorizing "conflict work" as family work.. In: Journal of Marriage and Family, 83(4), 1134-1153. (2021)

30. Carlile, A.: The experiences of transgender and non-binary children and young people and their parents in healthcare settings in England, UK: Interviews with members of a family support group. In: International Journal of Transgender Health, 21(1), 16-32. (2020)
31. Newson JJ, Sukhoi O, Taylor J, Topalo O, and Thiagarajan TC: Mental State of the World 2022, Sapien Labs, March 2023
32. Rogers, S. A., Malony, H. N., Coleman, E. M., and Tepper, L.: Changes in attitudes toward religion among those with mental illness., In: Journal of Religion and Health, volume 41, 167-178. (2002)
33. Johnson-Kwochka, A. V., Stull, L. G., and Salyers, M. P.: The impact of diagnosis and religious orientation on mental illness stigma., In: Psychology of Religion and Spirituality, 14(4), 462. (2022)
34. Mental health statistics: Anxiety: statistics, https://www.mentalhealth.org.uk/explore-mental-health/statistics/anxiety-statistics. Last accessed 25 January 2024