Matching for Peer Support: Exploring Algorithmic Matching for Online Mental Health Communities

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Online mental health communities (OMHCs) have emerged in recent years as an effective and accessible way to obtain peer support, filling crucial gaps of traditional mental health resources. However, the mechanisms for users to find relationships that fulfill their needs and capabilities in these communities are highly underdeveloped. Using a mixed-methods approach of user interviews and behavioral log analysis on 7Cups.com, we explore central challenges in finding adequate peer relationships in online support platforms and how algorithmic matching can alleviate many of these issues. We measure the impact of using qualities like gender and age in purposeful matching to improve member experiences, with especially salient results for users belonging to vulnerable populations. Lastly, we note key considerations for designing matching systems in the online mental health context, such as the necessity for better moderation to avoid potential harassment behaviors exacerbated by algorithmic matching. Our findings yield key insights into current user experiences in OMHCs as well as design implications for building matching systems in the future for OMHCs.

CCS Concepts: • **Human-centered computing → Collaborative and social computing**; *Empirical studies in collaborative and social computing*.

Additional Key Words and Phrases: mental health, peer support, online communities, algorithmic matching

ACM Reference Format:
Anna Fang and Haiyi Zhu. 2022. Matching for Peer Support: Exploring Algorithmic Matching for Online Mental Health Communities. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 311 (November 2022), 37 pages. https://doi.org/10.1145/3555202

1 INTRODUCTION

As mental health problems continue to rise in prevalence globally, people are increasingly turning to peers for mental and emotional support [110, 116]. Peer support — defined as interactions between people marked by mutually sharing experiences and practical guidance to promote wellbeing — has long been shown to be critical in maintaining and improving mental wellbeing [24, 42, 65]. Among other benefits, receiving peer support improves self-efficacy, strengthens trust in mental health treatment, and reduces depression [92, 99, 102, 105]. In particular, online mental health communities (OMHCs) have emerged in recent years as one of the most effective and accessible ways for achieving peer support, often relying on either trained or untrained volunteers to provide peer support in one-on-one or group chats [9, 22, 34, 38, 46, 85, 96]. Many OMHCs provide free and live 24/7 support, which circumvents many barriers that prevent help-seeking and allows immediate address of people's mental health needs [10, 114]. This greater accessibility is particularly vital for communities disproportionately impacted by social stigma, such as non-cisgender people and racial minorities [3, 8, 15, 68, 128], as well as youth, who have the highest rates of mental health

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2573-0142/2022/11-ART311
https://doi.org/10.1145/3555202

problems but largely avoid using traditional mental health resources due to issues such as lack of anonymity and preference for speaking about sensitive issues online [19, 47, 48, 63].

Despite the significant evidence that OMHCs are capable of yielding trusting, long-lasting, and meaningful relationships [39, 85], the mechanisms for finding and establishing supportive relationships online are underdeveloped compared to in-person resources. For example, clients of traditional therapy typically engage in an involved process for selecting a therapist given their unique preferences and individuals seek peer support from select individuals depending on the situation [74, 76, 87, 95, 121]. However, the selection process in OMHCs often relies on random or naive matching; users are helped on a first-come-first-serve basis or matched with one another based on simple criteria, such as solely the topic of discussion. For example, support forums such as Facebook's support groups are topic-based and rely on users to find these groups using search, trial-and-error, or word-of-mouth means. Other communities such as Wisdo and TherapyTribe also provide support groups based on topic. The most potential for more advanced matching methods exist on sites that rely on professional therapists online rather than free peer support, such as Betterhelp.com and Talkspace.com that offer intake forms for new users but do not provide details on how the intake form is actually used for matching. OMHCs that provide free and accessible peer support, such as 7cups.com, do not currently consider users' personal characteristics and preferences that have been shown to be vital to decision making in mental health resources [25, 70]. As a result, algorithmic matching may have the potential to resolve these challenges by providing more optimal matches given users' characteristics, including for live chats, with minimal efforts on a user's end. However, it has not been explored in online mental health contexts.

In this paper, we will address this gap by studying how algorithmic matching may improve community member experiences in OMHCs and whether community members are receptive to such a system. As past work has demonstrated, technically sound systems may fail to resolve problems they were designed to tackle if they are inconsistent with — or even harm — important values and needs of the communities who use them [71, 119]. Thus, it is crucial to first conceptualize and understand stakeholders' needs, values, and concerns to guide any algorithm design choices [9, 81, 132]. This may be particularly important for OMHCs due to the vulnerability of their members. As a result, we will use a mixed-method approach to discover the experiences and values of users in OMHCs and, given this information, explore how we can improve the formation of positive online peer relationships through algorithmic matching. We utilized one of the world's largest online peer support platforms called 7 Cups to conduct interviews with 12 users and analyze behavioral log data of nearly 200,000 chats among around 129,000 users. Our study found (1) current first-come-first-serve-based matching systems do not adequately support users' needs and capabilities; (2) users were overwhelmingly supportive of algorithmic matching for OMHCs, including being comfortable disclosing information to support algorithmic matching; (3) algorithmic matching may be especially valuable for vulnerable populations like LGBTQ+ and female members; (4) users suggested algorithmic matching systems be optional in order to alleviate potential concerns, such as connecting with the same group of people repeatedly. Our quantitative analysis also suggests that potentially striking improvement can be made through purposeful matching based on gender, age, and experience levels. This improvement could be especially salient for marginalized groups; for example, our interviews revealed that nonbinary members felt hesitance towards speaking with male listeners and our data analysis showed a remarkable chat rating improvement of 1.18 stars out of 5 when nonbinary members chatted with a nonbinary listener instead of a male listener.

2 RELATED WORK

2.1 Peer Support in Online Communities

Over the past few decades, there has been ample research studying the impact and effectiveness of support in online communities. Peer support through online communities is able to fill gaps in accessing health services for many, helping those whose needs are unmet by traditional resources [49, 83, 96, 107] or individuals who lack adequate peer networks in their daily lives to achieve needed support [64, 67, 106, 117]. Online peer support occurs through general-purpose social networks and their sub-communities, such as Reddit's subreddits or Facebook groups dedicated to specific health issues [11, 51, 53, 124], or on entire social networking platforms aimed solely at providing health support, such as 7Cups.com that provides mental health support through 1-on-1 chats or BabyCenter.com that provides resources for pregnant women [27, 52]; support through both types of communities has been shown to be vital in spreading health information, reducing harmful thoughts, empowering help-seeking for stigmatized populations, reducing suicidal ideation, and fundraising or spreading awareness for health issues [30, 31, 52, 57, 85, 94].

Given the anonymity and accessibility of online communities, past work has often focused on the usefulness of online peer support to particularly vulnerable or stigmatized groups. For example, Gui et al. found that pregnant women are susceptible to lacking offline social support, thus benefiting from mutual exchange of advice and knowledge in online communities [52]. Cipolletta et al. explored how online support aids transgender people suffering from discrimination by enabling them to build close relationships, share relevant information, and reduce prejudice [23]. Using OMHCs to support the health of young people has also been a central interest to researchers, given that 75% of mental illnesses begin by age 24 [66]. Past work has found that adolescents often prefer using OMHCs to engage in help-seeking and peer interaction, and prefer to speak online rather than face-to-face regarding sensitive topics [5, 14, 36, 73, 91]. Ellis et al. explored designing online mental health services to help young men in particular, who historically show reluctance to seek out mental health services [37]. D'Alfonso et al. created a social media-based system using artificial intelligence methods to provide individualized interventions for youth mental health [28]. Online social support has also been shown to be a significant contributor to well-being for LGBT youth [131]. However, OMHCs are also capable of causing adverse health effects. For example, adolescents may also be vulnerable to the same harm in OMHCs as they are there to overcome. Razi et al. found that youth seeking support on sexual experiences through an online peer support platform actually received unwanted sexual advances during that process [97]. OMHCs may also be especially susceptible to the challenge of moderation as Saha et al. explored the unique moderation needs of these communities given their potentially vulnerable populations and the risk of sensitive content impacting the wellbeing of moderators themselves [101].

Assessing the success of OMHCs has posed a significant issue in past work, particularly in regards to examining retention of users to OMHCs. Wang et al. found that receiving emotional support lowered risk of dropout from support groups, while informational support did not have a long-lasting impact on community retention [122]. Yang et al. explored how the dynamics and amount of communication that members receive influence their tenure in OMHCs [129]. However, interpreting success of these communities through retention has been shown to be a complex issue, as Massimi et al. found that lower usage of OMHC platforms may actually be indicative of a positive change due to users' improvement offline [80]. Engagement in general is also affected by important platform features or community norms, such as anonymity through throwaway accounts on Reddit significantly raising users' engagement in self-disclosure and support-seeking behavior [7].

2.2 Matching for Mental Health Purposes

Although past work has not examined the potential of algorithmic matching in OMHCs nor measured the effects of influential factors for matching in this context, some initial exploration has taken place on what users may find valuable in finding connections through online support systems. Andalibi and Flood studied a digital support platform that manually matched users together, and found that users felt compatible with those who had a shared identity and shared interests; however, users felt some concerns with partners who had shared mental health issues in part due to potential comparisons to one another [6]. People's unique goals and needs at the time of sharing health related information online may also affect who they choose to interact with [89, 90]. O'Leary et al.'s work touched on the value of some demographic factors in online peer support as well, such as their finding that women found groups consisting of all women yielded greater safety and comfort for sharing sensitive experiences [90].

There is also extensive research on matching people in traditional mental health services, consistently finding that people often have strong preferences for mental health providers who are similar to themselves although these similarities do not necessarily impact health outcomes. Social psychology research over decades has established the notion that people perceive those similar to themselves to be more trustworthy [18, 88, 104] and likely to share their worldviews [79]. Thus, research over many decades has explored how matching a client and therapists' race, language, gender, and other variables impact therapeutic outcomes [40, 58, 60, 72, 84, 111]. Although our paper addresses online peer support platforms, our work is grounded in the variables explored from past research in traditional therapy contexts.

Racial matching has been a main focus of past literature in matching for mental health. Coleman et al. conducted a meta-analysis of studies from 1970s to early 1990s, concluding that clients have strong preferences for choosing a therapist of the same race [25]; however, Maramba and Hall found that this preference did not yield significant effects on actual wellbeing outcome [77]. The effects of racial matching may differ between racial groups as well, most notably for African-American clients. Although studies do vary, some research has suggested that Black clients not only show significant preference for Black therapists but also may benefit from racial matching due to mistrust towards mental health services and its association with White or European American values [82, 125]. Flaskerud also found that Asian clients showed better therapeutic outcomes if their therapist shared other common languages with them [43].

Gender has been presumed to be an important factor in choosing a therapist [50]. Felton et al. in the 1980s found that clients consistently prefer therapists of the same gender [40], and Jones et al. found that clients found female therapists more effective regardless of their own gender [61, 62]. A study measuring gender effects in treatment plans for adolescent substance abusers found that gender matching resulted in higher likelihood to complete treatment [126]. Wu and Windle found that specifically Asian male clients had higher retention with male therapists, but did not see the same effect among other racial groups or females [127]. Flaskerud and Liu similarly found that the dropout rate significantly decreased with a male client and male therapist, but did not see this same gender effect with females [44].

There has also been peripheral work in matching based on client needs. Yarborough et al. studied how to match mental health service type to clients' goals [130] while Vlahovic et al. found that matching users' expectations of emotional or informational support can have significant differences for their satisfaction [120]. Hartzler et al. studied what factors influence participants' choice on who to reach out to as a potential mentor in an online medical community, finding that sample posts on mentors' profile pages were the only significant predictor rather than their person-generated health data or demographic data [54].

2.3 Matching for Other Purposes

Although algorithmic matching has not been introduced to OMHCs, it has been explored in other social matching contexts. Algorithmic matching has most notably been established successfully in The National Resident Matching Program for matching physicians to residency programs, as well as in the educational context such as matching students to public high schools in New York City and Boston [1, 2, 100]. Further research done in the education space has explored matching students together based on various factors to better academic outcomes. Campbell and Campbell studied how racially matching students to mentors led to better long-term performance like higher GPA, graduation rate, and rate of entering graduate education [20]. Pairing students by gender, however, has had conflicting results; Fenwick and Neal finding that gender matching in group educational settings was predictive of outcomes while Stewart and D'Mello refuted that claim [33, 41, 75, 109]. Researchers have also studied pairing students according to their performance levels [112]. Day et al. found that pairing low performing trainees with high performing partners resulted in little benefit [29], and similarly Fuchs et al. found that pairing people of similar performance ability together resulted in better quality work [45]. Recent work by Robertson et al. studied the disconnect between algorithm designers' aims and the actual real-world impacts of matching algorithms for educational systems, stressing the importance of directly engaging with stakeholders to align values with real-world conditions [48].

Matching based on people's personal characteristics has been explored in online dating and friendships as well. Hitsch et al. found that users often have strong preferences for dating people similar to themselves across numerous dimensions; most notably, racial matching is often highly influential despite often not being self-reported [56]. Similar work has found that other dimensions of similarity, such as profile similarity and history of past relationships, lead to better recommendation success on online dating sites [86, 115]. Researchers have also explored platonic relationships, having developed algorithmic systems to optimize friend finding in online social networks based on matching user qualities like their lifestyles and personalities [13, 123]. Chen et al. found that recommend content matching for friend-finding, such that users who post similar content may be good friends [21].

Our research is at the intersection of this prior work. Although the effects of matching have been studied in traditional mental health resources, the potential for algorithmic matching in the online mental health context and its improvements on member experiences have not been studied. Thus, in this paper we will address the key research question and its subparts:

RQ: How can algorithmic matching form better online peer relationships in OMHCs?

- What are the challenges that users currently face in matching on OMHCs?
- What are users' sentiments towards algorithmic matching systems on OMHCs?
- What characteristics may be useful to optimize matching peers in OMHCs?

3 METHODOLOGY

3.1 Research Site

In order to study matching in OMHCs, we collaborated with one of the largest peer support platforms called 7 Cups. 7 Cups was launched in July 2013 and provides free 24/7 chat support through trained volunteers. The site has grown to support over 2 million users each month, making it the world's largest online emotional support system. Users who sign up on 7 Cups to seek support are called "members"; users who volunteer to provide support can go through active listening training to become "listeners". Users can have both a member and listener account. Although 7Cups has forums and group support chat features, the primary method of support is through 1-on-1 chats between one member and one listener. In total, 7Cups has had around 54 million members and over 400,000 trained listeners, spanning 152 languages.

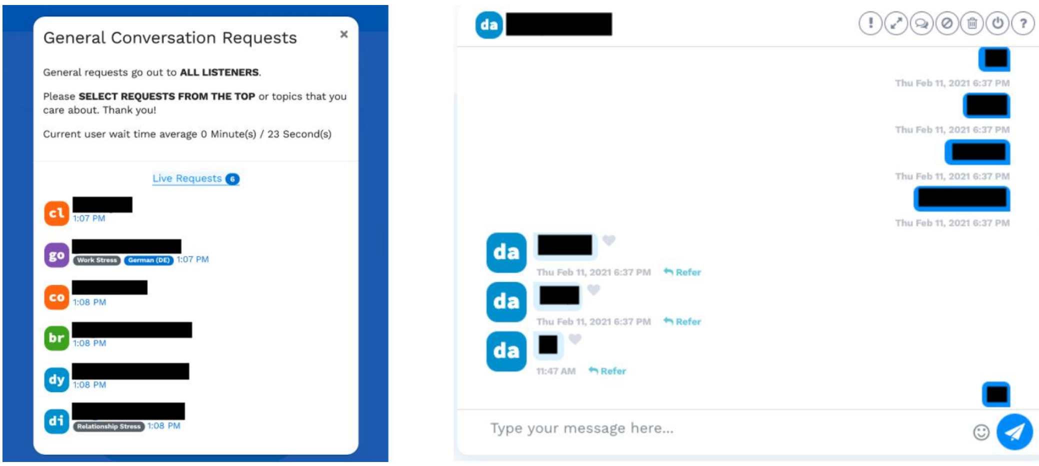


Fig. 1. The 7 Cups general queue (left), which goes out to all listeners, and the chat interface (right) once a listener and member connect.

Members who are seeking a 1-on-1 chat on 7 Cups join a live queue and have the option to select one of many "topic tags" labelling their reason for being on 7 Cups (e.g. 'depression', 'relationship stress', 'anxiety'). The 7 Cups system is a self-selection by listeners where listeners can start a 1-on-1 chat room by manually selecting member(s) off of the queue, which only displays each member's waiting time and possibly the single topic tag if the member chose to select one. Figure 1 shows the 7 Cups queue from a listener's point of view and the chat interface. The few other OMHCs, such as TalkLife and HealthfulChat, that provide free live support like 7 Cups use similar or more trivial matching systems, commonly connecting people solely based on topic.

3.2 Research Methods

We conducted our study through mixed-methods using qualitative and quantitative analyses. To understand users' challenges with current systems and how they perceive algorithmic matching, we conducted interviews with 7 Cups users, followed by analysis of the 7 Cups behavioral log dataset to quantitatively evaluate the potential benefits of algorithmic matching and further explore the findings from our qualitative study.

Privacy, Ethics and Disclosure. This paper used behavioral log data obtained through a collaboration with 7 Cups to conduct our analysis. All data was anonymized before analysis and no personally identifiable information was used in this study. Note that chat messages of 7 Cups were only analyzed to find the gender distribution of 7 Cups' users. This work has been approved by the appropriate Institutional Review Board (IRB). All methodologies and results were discussed and approved with 7 Cups executives, including its founder/CEO and engineering lead. Our research team consists of researchers who identify as female and BIPOC [1]. No authors on this paper are affiliated with 7 Cups nor does this work rely on any funding from 7 Cups.

[1]BIPOC: Black, Indigenous, and People of Color

#	Account Type	Gender	Age	Tenure
1	Listener, Member	Male	18	<1 month
2	Listener, Member	Female	19	4+ years
3	Listener	Male	20	1-3 months
4	Listener	Female	22	1-3 months
5	Listener, Member	Nonbinary	23	1-2 years
6	Listener, Member	Nonbinary	24	1-2 years
7	Listener, Member	Female	25	1-3 months
8	Listener, Member	Female	26	1-2 years
9	Listener	Female	29	3-6 months
10	Listener, Member	Female	36	1-3 months
11	Listener, Member	Female	47	3-6 months
12	Member	Female	53	4+ years

Table 1. Details for each of our interview participants regarding their account type, gender identity, age, and tenure on 7 Cups.

3.2.1 Interviews. To understand how users of OMHCs perceive algorithmic matching, we conducted semi-structured interviews with 12 users of 7Cups. Participants were recruited by 7 Cups staff, who emailed our interview invitation to interested users who were at least 18 years old and based in the U.S. Note that although interviewees were constrained to users in the U.S. due to our study's compensation restraints, our quantitative analysis includes all 7 Cups users regardless of country. All site privacy policies were obeyed during this process [2]. Our participants are sampled across 4 dimensions: (1) account type (member/listener/member and listener), (2) gender, (3) age, (4) tenure on 7Cups. As the 7Cups user population skews female and over three-fourths of users are 25 years old or younger, our participants also reflect a higher proportion of females and young users. Details on the 12 interviewees are in Table 1.

Interviews were semi-structured, guided by a list of questions (see Appendix A) but allowed to deviate depending on topics participants may have introduced. All interviews took place remotely via Zoom or Google Hangouts in December 2020 and January 2021. Interviews lasted approximately 1 hour and participants were compensated with US$20. During the interview, participants were asked their challenges in using the current queue system (e.g., How do you normally connect with a member/listener and what are the challenges, if any, that you have experienced using those methods?). Participants then reflected on what qualities made certain conversations or chat partners a good match for them (e.g., What characteristics do you feel make certain conversations better or worse than others?). We also sought to understand participants' opinions on algorithmic matching, including their willingness to disclose personal information to OMHCs for matching purposes, likelihood to engage with an algorithmic matching system, and their needs for transparency in such a system. Lastly, we probed for our participants' reactions by showing them some preliminary quantitative analysis comparing how different pairings of members and listeners perform. In some cases, this further elicited experiences from our participants that either countered or complemented our results.

All interviews were recorded and transcribed. Analysis was completed by a team of two academic researchers, who both identify as female and BIPOC. Based on Braun and Clarke's method of thematic analysis [16], our analysis involved tagging topics in each transcript including both

[2]https://www.7cups.com/Documents/PrivacyPolicy/

inductive codes and sensitizing codes from past research. Our iterative analytic cycle consisted of: (1) recording and transcribing interviews (2) coding transcripts (3) amalgamating codes (4) discussing codes as a team (5) highlighting themes (6) writing and revising memos. Our analysis continued until saturation, when new interviews gave no new insights. Our analysis ended with 225 codes, organized into 34 axial-codes, and summarized into 10 themes presented. We noted key quotes that illustrate our findings. A summary table of our themes and their axial-codes can be found in Appendix B.

3.2.2 Behavioral Logs. The behavioral log data was obtained through a collaboration with 7 Cups, and followed a data agreement with our university. All data was anonymized before analysis.

The dataset consisted of all chat messages between January 2020 to August 2020, including the message text, timestamp, and user IDs involved. The dataset also includes user information such as all users' signup dates and birth years, as well as logs of users' actions such as every time a user started a new chat and blocked another user. The most vital part of the dataset for our study is the chat ratings; members can rate a chat on an equidistant scale of 1 to 5 stars once the chat has continued for a certain length of time or after the chat ends, while listeners are not able to rate a chat. The distribution of chat ratings and dataset details are shown in Figure 2.

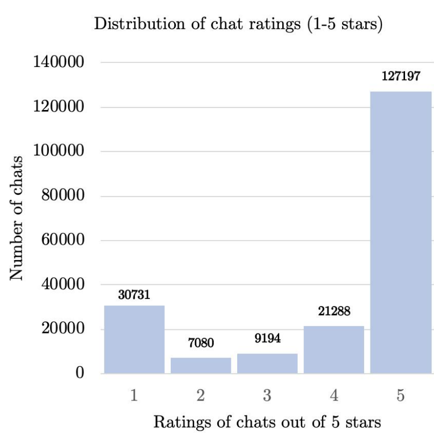
We utilize chat ratings to measure the outcome of a member-listener pairing. Ratings provide us a richer view of a chat's performance given its scale of 1 to 5 stars, as opposed to a binary measurement, and is the most reliable indicator of a member's chat experience. Each rating only pertains to a particular member and listener pairing. It is worth noting that there are three other possible metrics for measuring outcome: (1) "hearts" that members can send listeners on specific messages in chat, (2) retention of a member to 7Cups, and (3) emotional wellness tests that 7Cups sends periodically to members. The metrics of hearts, retention, and chat rating are not highly correlated with one another, indicating that they likely show different definitions of success in accordance with past literature [26, 103]. Compared to chat rating, the number of hearts sent in a chat is a more ambiguous assessment of a member-listener pairing, considering it occurs at a message-level rather than chat session-level, can indicate simple acknowledgements rather than positive interactions, and is highly dependent on the number of messages in a chat [103]. As for retention, it is unfortunately an unclear metric in OMHC contexts as retention has been shown to be an indication of either failure or success of the community [80] and poses issues of truncation [17]. Lastly, the emotional wellness tests (PHQ-9 for depression [69] and GAD-7 for anxiety [108]) are likely a useful indicator of long-term improvement and actual mental health outcome for members on the site. Unfortunately, these tests are scarcely filled out by users and evaluating change in well-being would require users to have filled out the assessments more than once; a total of 4.6k users filled out the PHQ-9 more than once and 1.3k filled it out more than twice over the 8-month period of our dataset, which is not a significant enough population of 7 Cups users to be adequate for our study's analysis.

3.2.3 Labeling missing demographic information. For our behavioral log analysis, we focus on how both personal characteristics (gender, age) and experience (number of previous chats on 7Cups) impact member experiences on 7Cups, as these are characteristics we can identify through people's profile information and chats as opposed to other characteristics such as assessing listeners' expertise in mental health or on specific mental health subjects.

Demographic information such as gender identity can be optionally added by users at a later time while using 7 Cups and thus is a sparsely populated field in our dataset. Because gender is a central element to past research done on matching in traditional mental health resources, we attempted to label users' gender identities using their chat data in order to evaluate gender effects for our study. Using 6 gender groups (female/male/nonbinary identities, transgender female, transgender male, transgender female/male unknown), we automatically labeled users' gender identities in the 7 Cups dataset if a user had stated their own gender identity in their chat messages. We utilized a variety of phrasing and gender terms to capture the variance in how people present their own gender. For example, a user who has stated their gender (e.g. "I'm", "I am") as a female-identifying term (e.g. "female", "woman", "girl") will be labeled as female-identifying. The full term list is included in Appendix C. This process can introduce conflicting labels, such as if users have said they are female and male at different times; in these cases, our labeling system takes a conservative approach by not labeling these users as any gender.

Our labeling process was highly accurate. Among all users on 7 Cups, 34,423 users had both input their gender identity on their 7Cups profile and been gender labeled by our system. Only 0.8% of those users were given a mismatched label from our system. Additionally, we were able to significantly increase the number of users with a labeled gender identity. In our analysis dataset of 129,318 users, originally only 12,845 members (13.9%) and 160 listeners (0.4%) had manually input their gender identity through 7Cups. Our method ended up increasing the number of users with a labeled gender identity to 17,316 members (18.7%) and 8,420 listeners (23%).

Other demographic information like race is rarely given during chats thus, despite it being a central element to matching, we are unable to label users' race or ethnicity for analysis. Basic statistics of the dataset are in Table 2.



# of chats with ratings	195,832
Average chat rating	4.06/5.0
# of users involved in chat ratings	129,655
# of distinct members in chat ratings	92,909
# of distinct listeners in chat ratings	36,746
% of users with gender labels	20%
% of users with age information	100%

Fig. 2. Basic statistics of our 7 Cups dataset. Note that the dataset we use for our analysis is restricted to chats with ratings.

4 QUALITATIVE RESULTS

We first provide an overview of our results from interviews with 12 users of 7Cups.

Firstly, we found that users believed that the current matching mechanisms of the 7 Cups platform are insufficient and ineffective, which leads to both short-term and long-term negative impacts. In particular:

(1) Members already engage in a manual selection process in order to find relevant listeners to meet their mental health needs; however, the manual selection process is both ineffective and inefficient.
(2) The lack of a matching system can lead to listeners feeling incapable of adequately helping certain members.
(3) Ineffective matching can lead to fewer long-term relationships and reduced member commitment.

Secondly, participants shared their insights and opinions about algorithmic matching.

(1) Users were overwhelmingly supportive of algorithmic matching for OMHCs, including being comfortable disclosing information to support algorithmic matching.
(2) Users varied on the degree of transparency they would like in an algorithmic matching system.
(3) Users largely felt that algorithmic matching could be especially valuable for populations who are vulnerable to harassment, such as LGBTQ+ and female members.
(4) Members expressed that matching based on experience level would help appease their frustrations arising from chatting with inexperienced listeners.
(5) Users felt the priority in matching on OMHCs should be to avoid the worst possible outcomes.
(6) Blocking inappropriate behavior in OMHCs was seen as necessary for the success of algorithmic matching

Each of these findings is expanded on below.

4.1 Current challenges

During our interviews, users generally expressed dissatisfaction with the current matching process on 7 Cups. Many challenges that users mentioned regarding the process promote the need for algorithmic matching.

4.1.1 Members already engage in a manual selection process in order to find relevant listeners to meet their mental health needs; however, the manual selection process is both ineffective and inefficient. During our interviews, all participants regardless of their account type stated that members commonly come into 7 Cups with their own personal criteria for the type of listener they want to chat with. Most often, members reported seeking listeners who had demographic qualities similar to themselves. This follows previous work showing that people often associate this similarity to shared worldview and greater feelings of comfort [79].

Because the queue is limited to just displaying members' username and topic tag, information can only be shared between the listener and member once they are already connected in the chat room. Although 7 Cups' current policy states that users should not share personal information, all of our interviewees stated that they ask or have been asked general demographic information at the beginning of the chat in an effort by users to gauge their fit to one another. Participants reported that gender and age are commonly given information and can be barriers to whether a chat will continue.

> "As a member, I like to talk to females more. I just feel more comfortable with females than I do with males...I do ask [the listener's gender]." (P10)

> "We're not supposed to normally reveal [our information], but sometimes people feel more comfortable talking to a certain gender or age. It happens majority of the time, [members] will ask some personal information about you...I don't mind talking about personal experiences, letting them know I'm a female." (P7)

Although anonymity is important to creating safe spaces for vulnerability in OMHCs [7], participants expressed that knowing more about users during the matching process would help people better judge fit up front and gauge how to exchange support during their conversations. Additionally, the uncertainty of the queue disproportionately impacts members more due to the fact that the queue relies on listeners choosing members to chat with and members have no control in the process.

> "I feel like a lot of the times I queue up with someone, no idea anything about them...you kind of have to take cues rather than knowing directly the person's age or gender. That would probably be a little bit more helpful in selecting who to help, because maybe I'm not able to help females as much as males in certain situations, stuff like that." (P3)

> "As a member, it kind of feels awful with the current system, because you never know when you're going to get picked or how long exactly it's going to take for somebody to pick you up. Because you're being chosen at random, basically based on listeners choosing you, you never ever know if you're going to get a good listener or not, you never know what kind of experience you're going to get." (P6)

This system also results in many dropped conversations — if a listener ends up not matching the member's criteria, the member will leave the chat to go back onto the queue and wait for another listener. The trial-and-error process was described by our interview participants as tedious and time wasting, and may cause lowered confidence in participating on 7 Cups for both listeners and members. As P3 states, reflecting on his experiences as a listener:

> "When I message someone, they're like 'if you don't mind me asking, are you a boy or a girl?'. I'm like 'I'm a boy'. And then they say 'Ok, well I want to talk to a girl'...that's fine, but again that kind of wastes their time...it delays their time and my time and then sometimes when they do see I'm a male, they don't respond afterwards. I'm assuming they didn't want me then."

P1 has had similar experiences as a male listener, mentioning, "Usually when I tell them I'm male, they don't want to talk to me, they just disappear."

Furthermore, ineffectiveness is further exacerbated if the topic tag is not utilized by a member. According to our interviews, members sometimes do not list a topic tag if they "just want to have a chat with someone to get to know each other" (P2) or their issue is "not covered by the categories 7 Cups has" (P5). However, all of our participants who were listeners stated they primarily choose members to chat with based on the topic tag listed, if available, and therefore actually avoid taking chats without a topic tag because "you don't know what you're going to get" (P6). P4 avoids tagless chats, reflecting, "I'm definitely a little bit more wary. It's so much more comfortable, especially in an anonymous chatting room, to know what's going to happen." P2 echoed a similar opinion, "If I'm familiar with the topic, then I will click on that member. Sometimes when people don't have a topic...I don't feel like I'm capable." Thus, members who do not choose a topic tag wait longer on the queue. Again, these asymmetries stem from only listeners getting a choice on who to chat with, and may be alleviated by automated matching that gives equal power to both members and listeners, as P12 mentions,

> "I think really for 7Cups [algorithmic matching] is a good idea because there's a lot of listeners that pick and choose, you've got this group of members that nobody will take their chats."

Given the challenges that members shared during the interviews, it is clear that the 7 Cups community shows a core need for more purposeful matching. As we have seen, this need is so widespread that users actually violate community rules about sharing personal information to work around current limitations in order to create a type of selection process amongst themselves. Migrating the matching process to be algorithmic or automatic can help support the community's goal in more systematic and time-efficient ways.

4.1.2 The lack of a matching system can lead to listeners feeling incapable of adequately helping certain members. Although interviewees stated that normally the member is the one to leave a chat from unmet criteria, listeners also have their own criteria for what kinds of members they feel they can support. Given that listeners have sole ability to start chats with members by selecting them off of the queue, most listeners reported choosing a member to chat with primarily based on the listener's experience with the member's topic, while continuing a chat was dependent on demographic factors.Although some participants mentioned that demographic factors such as gender and sexuality were more important to members rather than listeners — as P11 summarizes: "For the listener, it doesn't matter much...everyone needs some help sometimes" — the common consensus among interview participants was that factors such as the age difference between a listener and member was a vital factor to whether a listener was capable of proceeding with a chat. In particular, younger listeners (P1, P2, P3, P4) reported that they found it difficult to help members who were significantly older due to either inexperience with the topics that older people struggle with or from natural generational differences.

> "It's tough to help with someone who's much older...and especially the cultural barrier now with just colloquium and the way people engage with each other. I would understand why it would be better to have someone talk with you who is your age...I've come across marriage problems and managing their life with their spouse and their job. It's like, I'm still in college and I'm not married. That's already two things I don't have in common with this person. It ends up being difficult to even understand what they're going through because I don't have my own experience with it. " (P3)

> "They always ask me my age and sex to see if they are comfortable talking with me. [If not then] they will just find someone else that is close to their age range...there are some older people on there, and I'm only 19. If they want to talk about something more serious, I cannot talk about that with them. So I will just tell them to find someone else with the correct age group because I just don't feel I am capable." (P2)

P4 reflects on her experiences observing conversations among older members and younger listeners in forums and group chats:

> "[Young listeners] are all trying to figure out what life looks like. And we're hearing all these older people being like 'we still have problems'...and even we can't figure out what life is all about. It's harder for younger listeners to listen to older members. I know that I don't have a weight of experience or wisdom that I think is going to be the most useful to an older member."

However, when P4 starts a chat only to find out later that she is speaking with an older member, she finds herself in a difficult position of not wanting to abandon the member:

> "I don't have really any experience with [certain topics]...it doesn't put me in a position where I can be the most active listener...but I'm not backing out of it. They do say you can, you know, tell them to contact another listener, which is really nice. But I do feel a sense of personal responsibility that once you click on that person, you shouldn't just bail."

On the contrary, older listeners (P5, P6, P8, P9, P11) stated that they could adequately handle the issues of both younger and older members. One exception was P7 who expressed that she has faced challenges relating to members much younger than herself:

> "I would say that I can relate to both [older and younger members]. But with teenagers...it's a little bit harder. You have to remember how you were when you were in high school and how you felt because it feels like their problems may be a little bit smaller than other people's problems...you don't want to become negative towards them. You don't want to do that."

4.1.3 Ineffective matching can lead to fewer long-term relationships and reduced member commitment. We have discussed how the lack of purposeful matching on 7 Cups leaves users unable to effectively find suitable chat partners. Importantly, it can also cause longer term consequences on the community as a whole by reducing users' belief of whether they can obtain adequate help on 7 Cups.

As we have mentioned, retention to the community is not necessarily a clear indicator of success in the OMHC context. However, previous work has studied how specifically returning to the same therapist or health provider shows indication of satisfaction with help received, and that these long-term relationships can lead to more self-disclosure and better outcomes for clients [55, 124]. As a result, we asked interviewees whether they were able to form lasting relationships with other 7 Cups users, returning to the same listener or member to chat repeatedly. Overwhelmingly, interviewees stated that they did have up to a few people that they repeatedly chatted with, but these were rare occurrences. Interviewees spoke highly of these relationships, and expressed that they led to more periodic check-ins with one another either during times of need or just to casually chat.

> "I have some long term members that I talk to. We talk about ongoing problems, not necessarily very deep issues. There's this one girl I talked to a lot and we just check in every week. I just kind of help her stay on track...I feel like that's kind of the best, like a light but serious sort of relationship." (P8)

> "I get people messaging me back after we've talked days before, and asking like 'do you mind chatting with me, I'm really struggling with this again'. I'll reach out to them sometimes too if I've had a long chat with them and if I feel like, they still weren't at a resolution or anything, just to check up on them." (P9)

> "There are some that go especially well...and if I see that they're on, I'll go back and message them and see how they're doing. It's awesome." (P10)

Interviewees agreed that there were many benefits of repeated interactions with the same user(s), including greater willingness to open up or engage in self-disclosure:

> "After I've gotten to know someone and had repeated conversations with them, then I would be more comfortable and more open with what I said. And I would say a lot more to someone I've been talking with for 8 or 9 months than someone where this is the first or second time we've chatted." (P12)

However, these relationships were widely reported to be infrequent occurrences and difficult to find. Participants, at most, stated they had only a few of these longterm chat partners even for those who had been on the platform for years. Some have never returned to the same chat partner. P12's experience from over 6 years on the platform reflects this:

> "There were a couple [long lasting relationships]. There was one that we talked for well over a year. I've been through, I don't know, probably 50 different [listeners]."
>
> "I think part of it is, I'm older than a lot of the people on 7cups, so I have a different perspective. So they get on, you know, and they want to talk about how their parents are so demanding. And I'm like, I'm that parent...most of the time, I think it'd be more helpful if it was someone my age...that's usually the way it goes, you know, if I get someone young, it flip flops and I almost become the listener" (P12)

Ineffective matching through the queue may cause not only a lack of lasting relationships, but also long-term consequences on member commitment. P12 stated that she had stopped using the live listener system completely due to not receiving adequate support from repeatedly getting listeners who were too young or irrelevant for her needs:

> "I've gotten to that point over the years that I just gave up using listeners. The one last time I did try to use a listener was on Election Day...this [listener] happened to be a pro Trump-er from Canada. You can imagine I did not cope well....they just lectured me on what my country was doing to the world."

These effects of unmet needs on long term use of OMHCs is consistent with previous work studying why dropout occurs in therapy. Studies have found that people often stop utilizing mental health resources due to lack of improvement, perceiving that the resource could not provide any better help, and mismatching demographic qualities particularly for clients belonging to minority groups [99].

4.2 Users' opinions about algorithmic matching

Given our interviews, we summarize below how users felt regarding algorithmic matching as well as common themes that users expressed were important in such a system.

4.2.1 Users were overwhelmingly supportive of algorithmic matching for OMHCs, including being comfortable disclosing information to support algorithmic matching. All but one interviewee were supportive of algorithmic matching and felt it would improve the limited process in OMHCs currently. Interviewees largely felt that algorithmic matching would most help the inefficiencies of finding helpful partnerships in OMHCs. For example, P1 stated: "If the system knows their gender, age, location, it'd be a lot easier to match them with someone best suited towards them...rather than putting them with someone that they don't necessarily need." P3 expressed that purposeful matching is "what's best for the members, just to decrease the variability and experience with other things."

P11, who was the sole interviewee doubtful about algorithmic matching, felt it may still suffer from similar challenges to the current 7Cups system:

> "I think it would have the same problems. It always depends on what people put in about themselves which can be misleading or random. The improvement should be the listener having higher transparency with the member."

However, it is worth noting that after further discussion, P11 echoed many mechanisms that would be in place with algorithmic matching:

> "It would be helpful for there to just be filters. That would make the listener's job a lot easier. The listener getting more information from the member. One problem is that members look for specific listeners — certain gender, age. It would be better to have that displayed so members and listeners don't waste their time."

In addition to supporting algorithmic matching conceptually, all participants stated they would disclose any reasonable information needed for such a system such as demographics and mental health experiences. In fact, while all participants stated that they already disclose information to their chat partners in the current system, everyone was surprisingly equally or more comfortable disclosing information to 7 Cups for algorithmic matching. No participant had any concerns, including data privacy, with giving this information to the platform.

4.2.2 Users varied on the degree of transparency they would like in an algorithmic matching system. Although participants were very supportive of contributing information to be matched algorithmically, their opinions varied on whether a platform should display users' information and why they were matched with one another.

As we have discussed previously, 7 Cups users actually already engage in self-disclosure to varying degrees so that users may gauge who they are talking to. Only 2 participants expressed during the interviews that they currently feel hesitation towards sharing detailed information to their chat partner. Surprisingly, this caution did not result from privacy or safety concerns — instead, both users stated that they were hesitant to share too much information in case it changed their chat dynamic.

> "Usually if I do get a question [about my age], I will say 'I'm in my 20s'. But I don't say a specific age because I want to try to keep it as vague as possible...It's more for the sake of dynamics, I'm not too concerned about safety...if the member kind of creates their vision of me in their head for them to talk to I feel like that's more effective." (P8)

> "I don't disclose much...I'm not worried anybody's gonna come to my house, none of that information is there. I think people talk to you differently when they can picture more of who you are...I like being just kind of this formless entity that's allowing people to express their emotions." (P4)

We then asked our participants whether they would want an algorithmic matching system to be transparent about their information, displaying why two people were matched in the chatroom and the information used during the matching process. Of our 12 interview participants, 7 people expressed that they would definitely want that information to be available, 3 people were not opposed but expressed they were not particularly interested in knowing why they were matched, and 2 people stated they would be supportive only if users could choose which information could be revealed. No participants were opposed entirely to the algorithmic matching system being transparent about its process and the users' information to their chat partner. P7 is one participant who was supportive of the system being fully transparent, but also mentioned a potential drawback of the chat dynamic being altered if her age is always revealed:

> "Age can make it so that somebody treats you in a different way. So if there's someone who's 50 years old they might not feel comfortable talking to someone who's in their 20s because they don't feel like they can relate on the same level of life...I have a lot of things that I've gone through in my life that most people my age haven't gone through. So my life experience would be more of someone in their 30s or 40s...it's not really going to be an accurate picture just by age."

Notably, both participants who would be conditionally supportive of showing information if they could choose the information shown were nonbinary. Both expressed that having choice over revealing the information individually was important for situations that they did not feel comfortable disclosing their gender identity.

> "I identify as nonbinary and a lot of times, if I'm talking about my stress during a pandemic, for instance...my gender doesn't matter at all to the topic. The way I'm envisioning it, the site would be like 'Do you care about [seeing] the gender of your listener?'...I think [having choice] would be nice. I think a lot of members would probably find that to be acceptable as well. If it was just buttons of like, "Are you okay with us sharing this information? Yes or no?" I feel like a lot of members would think that's a good system." (P5)

> "I don't know that as a member if I would feel comfortable telling a listener [my gender identity] unless I know that their gender was also listed as being nonbinary...if I'm in a bad mental health state, I want to make sure the listener is going to be okay with that sort of thing...I would want to know [why we were matched] if it's information that I personally choose to reveal. I would be okay if somebody is shown my age if I can see theirs, I don't care about that." (P6)

Given these findings, users do not seem to fully agree on the degree of transparency that an algorithmic matching system should have. Thus, these systems may need options for people including selection for which information they are comfortable being shown to their chat partner or used for matching purposes.

4.2.3 Users largely felt that algorithmic matching could be especially valuable for populations who are vulnerable to harassment, such as LGBTQ+ and female members. Many users brought up that algorithmic matching could be particularly useful for populations that have been historically vulnerable to stigmatization that prevents them from seeking support [3, 8, 15, 68]. These populations, including female and gender-variant members, may especially benefit from gender matching in order to avoid harassment or abusive chats.

Participants widely reported that female members often prefer female listeners due to greater comfort. P4, a female listener, commented, "I usually get a little scared when somebody asks [if I'm a girl] but it's usually because the person on the other line is also female and has certain issues that she wants to talk to another female about" while P9 mentioned that since she is a female listener, female members tend to be "more open about whatever the issue might be." Both of our male participants also mentioned that female members typically "aren't looking for a male" (P3) and often "just want to talk to another female because they're more comfortable" (P1).

Our participants reflected on the importance of matching for the LGBTQ+ communities, given that better help can be given if the listener has similar life experiences to the member.

> "Openness to LGBTQ issues is often important. If I'm talking about my boyfriend, [listeners] assume my gender is a girl...if someone is trying to talk about questioning their gender, I would think that most people like that would want someone who either has real life experience with that, or has family members or friends or people around them who have struggled with that, and who are open about it, and who were accepting. And I've known a couple people to be like, hey, I want someone who's in the LGBTQ community who is trans or nonbinary, that just makes them more comfortable" (P5)

> "Most of my friends and my partner as well are transgender. I'm on the cusp of gender topics. With situations like LGBTQ issues, it is very helpful to know if a person is in the LGBTQ community." (P8)

P5 expressed that generational differences can sometimes contribute to negative experiences of the gender-variant community:

> "There was a chat I had with someone who was in his 40s. I had mentioned struggling with my gender and wanting to be nonbinary...I could tell the reaction he had was because of his age, like he just grew up in a generation where nonbinary people weren't open and he wasn't educated. So his reaction to me being nonbinary was basically like, 'Oh, it's fake, you're just being stupid.' Basically he just told me that I'm a stupid kid, I don't know what I'm talking about...I know people who are nonbinary who are in their 40s and 50s, they're fine."

P5, who also struggles with lifelong disability, additionally added that matching can be important for those seeking support on disabilities:

> "I'll mention that I have a lifelong debilitating disability. [Listeners] say, 'Oh yeah, I wear glasses so I can understand.'...they're trying to understand from their perspective, instead of putting themselves in my shoes and having empathy...I have listeners, though, who do struggle with similar things to me, and they tend to relate to me a lot better...I like listeners who actually have some sort of real life experience with issues that are similar to mine"

Interestingly, participants also mentioned that LGBTQ+ members may be wary of male listeners in particular. P5 commented that they are "definitely uncomfortable" with male listeners and "a lot of the bad listeners that I've had are cisgender males". P8 expressed that her experiences with male listeners have been positive, but understood the hesitance for LGBTQ+ people such as her partner and friends:

> "From what I've heard, non binary-identifying people feel apprehensive about talking to cis males off the bat. There's often a barrier there to begin with."

4.2.4 Members expressed that matching based on experience level would help appease their frustrations arising from chatting with inexperienced listeners. Our interviewees who were experienced members on 7 Cups reported difficulty chatting with less experienced listeners. In particular, most participants who had been on 7 Cups as a member for more than a year (P5, P6, P8, P12) expressed that they had become increasingly dissatisfied with the current queue as they became more cognizant of what kind of listeners they wanted. The more experience a member gained on 7 Cups, the pickier they became about their listener matches.

> "As a member, I have definitely gotten more critical. I know what talking to a good listener is like versus a bad listener." (P8)

> "My evaluation of chats has changed as time goes on. At the beginning, it was great to just have somebody to listen. And then I got a little more picky as time went on. I got to the point where I was comfortable saying, you know, this is not right for me. This is not the right listener." (P12)

> "[Over time], I'm very picky. Getting a new listener, I'll give them a chance. But it's kind of like, new listeners have like one strike. Then I'm done with you." (P5)

Several participants expressed that incorporating experience level into algorithmic matching would improve experiences significantly. P1 mentioned that "pairing with a listener that has as much experience as [the member does], that would be better than just putting them with a listener that just started off". P6 felt that shortcomings of the current queue largely were a result of the system not considering tenure time,

> "That's basically what the problem is. The listeners who tend to do the general queue requests tend to be newer listeners and they don't have as much experience...If [members] are just getting a random listener every time they're going to have more negative experiences."

P12, who has been a member for several years, suggested that experienced listeners may be important to pair with members losing faith in the system similar to herself.

> "Put [experienced listeners] with someone like me, that had been around for a long time that you can look and see has, you know, 30 listeners and none of them are repeats. Why is this member not coming back to these listeners? Just to restore their faith in the site, even if it's just one or two chats, but to let them know that there are some decent listeners out there."

Similarly, P7 also expressed that factoring in experience levels alleviates a concern of hers regarding constantly matching with bad or new listeners through algorithmic matching, stating "The only thing is with auto-matching, it feels like a lot of the time you're always getting people who have just started. That's kind of discouraging because a lot of the time it's their first or second chat. . . [matching new listeners with new members] would be one solution, I like that idea."

4.2.5 Users felt the priority in matching on OMHCs should be to avoid the worst possible outcomes. When asked about the primary objectives of algorithmic matching systems, the overwhelming majority of our participants felt that avoiding the worst outcomes was the most vital in OMHCs. Participants expressed that having extremely bad experiences in OMHCs may deter people from seeking help, cause even more distress for members, or change users' behavior on the site from then on.

> "If you're gonna match people that have extreme negative experiences, then they both can walk away [from 7 Cups]...if you can at least get just a normal conversation, it would be a lot better." (P10)

> "I think we should just try to avoid the worst situation...realistically, we cannot guarantee people's experience on 7 Cups, but we can try to do the least harm for everyone." (P2)

> "I would say that it's definitely important to keep people away from the extreme negatives. Because I know, as a listener, if somebody is in distress and they really want to talk to someone...that could put them more in distress. So at least have a level where they wouldn't get more in distress." (P7)

> "It isn't that big of a deal if it isn't, like, the best listener out there." (P1)

Avoiding harmful situations may be especially important in a member's early stages on OMHCs, especially for vulnerable populations. P6, a nonbinary user, discussed how their first chats on 7 Cups were marked by harassment towards their gender identity, which ended their willingness to reveal or discuss their gender from then on:

> "Avoiding the extreme negative would be better...I did experience some transphobic and abusive behavior from members. And that was very upsetting to me as a new listener...that's basically the main reason that I only take requests that are tagged with certain topics, because I don't trust the general queue as it is right now. . . [the

> transphobic experiences] as a new listener put me off basically entirely of talking about my gender identity at all on the website. I can't trust. The one time as a member I did try to talk about my identity, they tried to give me very, very bad and dangerous advice." (P6)

4.2.6 Blocking inappropriate behavior in OMHCs was seen as necessary for the success of algorithmic matching. As Saha et al. [101] describe, OMHCs are susceptible to antisocial behavior like trolling and harassment similarly to other online communities but moderating against this negative behavior can be complex due to the especially vulnerable population of OMHCs. Unfortunately, all of our participants reported experiencing trolling or abusive behavior while chatting, occurring more regularly for our female interviewees. According to participants, the lack of adequate prevention of these inappropriate behaviors is a key challenge to having productive conversations from the queue.

Our participants recall their negative experiences:

> "It goes both ways with listeners and members, there are some that sexualize the chats. I've experienced that quite a lot. They always ask your gender, then they will decide to continue the conversation or not, depending on gender. I told them that I'm not going to engage in those chats, if they don't listen to me I just report them." (P2)

> "There were a lot of guys, they got listener accounts just to try to hook up with female members. They were very sexualized conversations." (P12)

Some users mentioned workarounds they do to avoid these behaviors from the queue, such as avoiding certain topic tags or judging by username.

> "Certain categories are more reliable to have actual people that want to talk about problems. 'Depression', they really want to talk about whatever it is that's going on. But I've noticed that 'Relationship Stress', 'Loneliness', a lot of the time end up having people who want to have conversations that aren't appropriate. I've also noticed there are people that continuously use the general request queue. There's one member specifically that changes their username...the first part is always "noMales"...it was some guy and as soon as you say, this isn't appropriate, then he calls you all sorts of names. For the most part, I try to stick towards certain topics that are less likely to bring out something like that." (P9)

> "There are still people who use [7Cups] as like, a sex chat line. You can usually tell from the username...I've never picked up a chat that I thought was going to be inappropriate, just by telling by the username. So definitely I see the majority of [inappropriate] chats I've seen are put out onto the general queue. They're kind of just sitting there waiting to be picked up." (P4)

As a result, a primary concern of users was how algorithmic matching could impact the prevalence of inappropriate behavior in OMHC. Participants largely felt that the current reporting system on 7 Cups does not adequately deter bad behavior due to users "just logging out and making a new user and doing the exact same thing over again" (P9). As a result of the distrust in the current reporting system, listeners felt worried that they could automatically match with the same abusive users repeatedly and not have sufficient means to avoid these chats.

> "It's kind of concerning like auto-matching that is going to keep [inappropriate] people coming up in my inbox. If you're going to do auto-matching, there has to be some way to improve how people are able to just regenerate new accounts and not have to deal

> with the consequences from their behavior." (P9)

> "I think [algorithmic] matching takes some free will for listeners out of it...like what if I get matched to a person who I know is using it as a sex line? Do I have to pick it up? That'd probably be the biggest problem." (P4)

Thus, an improved system for preventing and blocking inappropriate behaviors may be necessary for migrating to algorithmic matching.

4.2.7 Users preferred if algorithmic matching was an optional system. While we have discussed the concern of users about being automatically matched with users exhibiting inappropriate behavior, another potential issue is how connecting with the same group of people can potentially stifle opportunities to learn new skills on 7 Cups. 4 of our participants brought up this concern, including P2 who expressed "I would like to talk about other things as well besides just talking about the same topic all the time" and P4 who shared,

> "I think auto matching takes the capacity for growth for listeners out of it...To its credit, you want to have people have the most meaningful conversations possible and you don't want anyone to walk away feeling like they haven't been listened to. I just think it can create a pool where you're never going to have different perspectives that could possibly help you."

However, all four users who expressed this sentiment felt that making algorithmic matching be optional in addition to the queue system alleviated this concern. P2, who previously felt concerned about talking about the same topics all the time, felt that the option to still pick off of the queue would help her vary her topic choices adequately, stating, "Yes, it does [alleviate my concern]. I like having two options instead of one, if this was it I actually think I will use both [the queue and algorithmic matching]". Similarly, P4 stated: "I think [making auto-matching optional] helps that concern, that's a really great option." During our interviews, we also asked all participants how they felt about the current manual queue, a mandatory algorithmic matching feature, and a hybrid approach where users could choose between the two. All 12 interviewees preferred the hybrid approach where users have an option between algorithmic matching and the manual queue. Participants reported that algorithmic matching would be useful for getting good quality matches and seeking long-term partnerships on 7 Cups while using the queue system could help give variety to their conversations or find a chat partner quickly. Most commonly, participants cited that giving options in general for users would be positive.

5 QUANTITATIVE RESULTS

Throughout our interviews, it was clear that users perceived matching gender (see 4.2.4), age (see 4.1.2), and experience level (see 4.2.5) as impactful for their chats on 7 Cups. Using behavioral log data, we measured whether these qualities actually do significantly impact chat outcomes.

In this section, we utilized OLS regression with the 7 Cups dataset described in Section 3.2 to show how various factors directly impacted chat rating outcomes, and then presented these results to our 7 Cups stakeholders given the ease of interpretability of OLS. We used the statistical software package Stata [3] to run regressions on member and listener gender, age, and experience level individually as independent variables while utilizing chat rating as our dependent variable; all qualities were organized into categorical variables (i.e. gender groups, age groups, experience level groups).

[3]www.stata.com

	Members N = 92,713	Listeners N = 36,605
Gender		
Female	12.6%	14.1%
Male	5.0%	7.9%
Nonbinary	0.2%	0.3%
Transgender (Female/Male unknown)	0.5%	0.4%
Transgender Female	0.2%	0.1%
Transgender Male	0.3%	0.1%
Unknown	81%	77%
Age (in Years)		
15-18	42.6%	25.2%
19-25	34.8%	48.1%
26-30	11.0%	14.2%
31-35	5.1%	5.6%
36-40	2.6%	3.0%
41+	4.0%	4.0%
Unknown	0.0%	0.0%

Table 2. Distribution of gender and age among all members and listeners.

	Total # of chats = 195,832	
	Members	**Listeners**
Experience Level		
0-1 chats	33.4%	6.5%
2-10 chats	26.1%	14.4%
11-100 chats	23.7%	36.0%
101-1000 chats	14.0%	32.8%
1000+ chats	2.6%	10.3%
Unknown	0.2%	0.0%

Table 3. Distribution of member and listener experience level among all 195k chats. Experience level is measured by a user's number of previous chats on 7 Cups. The 0.2% of members with unknown experience level is due to missing log data and has a negligible effect on our analysis.

For reference, Table 2 shows the general distribution of gender and age groups among members and listeners and Table 3 shows the distribution of experience level for members and listeners among chats. We provide descriptive statistics of the average chat rating and total number of chats by each of these groups in Table 4. We then present our regression results, in which all tables have labels for the control group (baseline) and statistically significant ($p<0.05$) values. Descriptive statistics of the counts for each member-listener group pairing is presented in Appendix D as well.

5.1 Matching based on gender

As mentioned, users felt algorithmic matching could be especially important for vulnerable populations. Our results in Table 5, which show the effect of different genders of listeners with each member group, support this notion. Some groups of listeners, such as nonbinary listeners, are

Gender	Avg. chat rating	# of chats
Female		
Member	4.16	39100
Listener	4.20	46832
Male		
Member	4.20	18658
Listener	3.89	34859
Nonbinary		
Member	4.14	734
Listener	4.46	1002
Trans (F/M Unkn.)		
Member	4.20	1172
Listener	4.24	1644
Trans Female		
Member	4.28	1119
Listener	4.02	1485
Trans Male		
Member	3.06	1479
Listener	4.30	1353

Age	Avg. chat rating	# of chats
≤ 18 yrs.		
Member	4.20	73936
Listener	4.19	52917
19-25 yrs.		
Member	4.02	66948
Listener	4.04	81015
26-30 yrs.		
Member	3.94	24896
Listener	3.93	31687
31-35 yrs.		
Member	4.02	12252
Listener	4.0	12437
36-40 yrs.		
Member	3.87	6608
Listener	4.0	6519
41+ yrs.		
Member	3.83	11165
Listener	4.07	11230

Experience	Avg. chat rating	# of chats
0-1 Chats		
Member	3.99	65243
Listener	3.97	12601
2-10 Chats		
Member	4.19	50997
Listener	4.08	28135
11-100 Chats		
Member	4.1	46298
Listener	4.04	70285
101-1000 Chats		
Member	4.05	27394
Listener	4.07	63910
1001+ Chats		
Member	3.43	5129
Listener	4.12	20130

Table 4. Descriptive statistics broken down by group for each of our analysis features. Note that for gender, the chat rating and number of chats includes those with users of unknown gender (see Section 3.2.3).

overall better than others, such as male listeners. However, we see that even good listeners who receive high ratings from most or all gender groups do perform particularly well given certain matches, such as nonbinary listeners with other nonbinary and transgender members.

Compared to the control group of female members with female listeners, female members on average rate male listeners a moderate 0.36 stars out of 5 lower. This may reflect our female interviewees' experiences of feeling more safe and comfortable speaking with a female listener. Additionally, we see evidence of the reflections of our participants that members of the gender-variant community may be particularly cautious when speaking with male listeners, as well as preferring listeners who are also gender-variant. Nonbinary members rate nonbinary listeners noticeably well, 0.673 stars higher than the baseline group (female listeners). This is a stark contrast compared to when nonbinary members chat with male listeners, which results in ratings of 0.515 stars lower than the baseline. Thus, these results show a potentially striking improvement that can be made — on average, nonbinary members rate chats a remarkable 1.19 stars out of 5 higher if chatting with a nonbinary listener instead of a male listener. Transgender members had an even more extreme effect — compared to speaking with male listeners, on average transgender (female/male unknown) members rated chats 1.33 stars higher with a nonbinary listener and 1.38 stars higher when matched with a transgender male listener. Based on these gender effects, there is evidence that purposeful matching can create especially positive change for LGBTQ+ populations and can take into account the preference of members belonging to vulnerable populations to have listeners similar to themselves.

We also found through our interview study in Section 4.1.1 that users will disclose their gender in chat in order to manually assess whether the match fits their needs. As an additional analysis, we fit an OLS to identify the effects on chat rating when users' genders are known or unknown in our dataset (i.e. has gender labeled through the process described in Section 3.2.3). The results of the OLS predicting chat rating given the two binary independent variables of (1) whether the member's gender is known and (2) whether the listener's gender is known follow our findings from the interviews. Chat rating is significantly affected when users' genders are labeled, showing a

	Member Group					
	Model 1: Female N = 17,719	Model 2: Male N = 8,391	Model 3: Nonbinary N = 320	Model 4: Trans (F/M Unknown) N = 489	Model 5: Trans Female N = 473	Model 6: Trans Male N = 546
	Coeff, Std. Err.	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*
Baseline (Female Listener)	coeff = 4.33	coeff = 4.35	coeff = 4.21	coeff = 4.29	coeff = 4.39	coeff = 3.13
Male Listener vs. Baseline	-0.357*, 0.022	-0.395*, 0.034	-0.515*, 0.178	-0.673*, 0.144	-0.366*, 0.137	0.105, 0.174
Nonbinary Listener vs. Baseline	0.142, 0.098	0.122, 0.159	0.673*, 0.241	0.658*, 0.312	0.393, 0.374	1.874*, 0.852
Trans (F/M Unknown) Listener vs. Baseline	0.031, 0.076	0.051, 0.110	0.253, 0.398	-0.031, 0.293	-0.464, 0.374	0.096, 0.639
Trans Female Listener vs. Baseline	-0.081, 0.086	-0.253*, 0.118	0.192, 0.449	-0.019, 0.415	-0.017, 0.489	1.208, 0.639
Trans Male Listener vs. Baseline	-0.137, 0.082	0.036, 0.134	0.692, 0.449	0.708*, 0.328	0.608, 0.969	0.446, 0.722

* $p < 0.05$

Table 5. Results of OLS regression measuring the effects of gender on chat rating. Each model in the table shows the regression analysis for the given member group. The coefficients reported in the table show the difference compared to the baseline, which is with female listeners (the highest population of listeners on 7 Cups). For example, female-member-male-listener pair on average performed 0.357 points worse (on the 5-point rating scale) compared to the baseline. * $p < 0.05$. Note that this table only shows chats where we know both member and listener genders. All gender groups are mutually exclusive and ~20% of all users have a labeled gender.

coefficient of 0.129 (p < 0.001) when a member's gender is known and a coefficient of 0.028 (p < 0.001) when a listener's gender is known. Given that our gender labeling process relies on users having revealed their gender in their chat messages and users reported disclosing their gender in chats in order to find better matches on 7 Cups, this result follows our expectations as well as our interview study's findings.

5.2 Matching based on age

We conducted a similar analysis on age shown in Table 6. We grouped users into age groups following the World Health Organization's population standardization[4], although adjusted slightly so the youngest age group consists of 7 Cups youth users (18 years or younger); on 7 Cups, youth users are restricted to only speak with other youth or with "verified" adults who have completed extra training modules, which also contributes to a noticeable drop in the number of chats between youth listeners and adult listeners.

[4]https://seer.cancer.gov/stdpopulations/world.who.html

	Member Group					
	Model 1: <= 18 yrs N = 73,936	Model 2: 19-25 yrs N = 66,948	Model 3: 26-30 yrs N = 24,896	Model 4: 31-35 yrs N = 12,252	Model 5: 36-40 yrs N = 6,608	Model 6: 41+ yrs N = 11,165
	Coeff, Std. Err.	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*
Baseline (≤ 18 yrs. Listener)	coef = 4.20	coef = 4.08	coef = 4.11	coef = 4.22	coef = 3.88	coef = 3.89
19-25 yrs. Listener vs. Baseline	0.004, 0.014	-0.062, 0.040	-0.163*, 0.061	-0.235*, 0.087	-0.066, 0.121	-0.138, 0.096
26-30 yrs. Listener vs. Baseline	-0.086*, 0.019	-0.199*, 0.042	-0.216*, 0.063	-0.276*, 0.090	-0.013, 0.124	-0.091, 0.099
31-35 yrs. Listener vs. Baseline	-0.035, 0.031	-0.130*, 0.046	-0.214*, 0.069	-0.093, 0.097	0.007, 0.135	0.005, 0.106
36-40 yrs. Listener vs. Baseline	0.002, 0.043	-0.123*, 0.051	-0.283*, 0.076	-0.164, 0.106	0.120, 0.143	0.111, 0.116
41+ yrs. Listener vs. Baseline	-0.009, 0.032	-0.084, 0.047	-0.080, 0.069	-0.071, 0.098	0.183, 0.133	0.216*, 0.105

* $p < 0.05$

Table 6. Results of OLS regression measuring the effects of age on chat rating. Each model in the table shows the regression analysis for the given member group. The coefficients reported in the table show the difference compared to the baseline, which is with the youngest listener group 18 years or younger. For example, 41+ members with 41+ listeners performed 0.216 points better (on the 5-point rating scale) compared to the baseline of 41+ members with the youngest listeners (* $p < 0.05$).

Our findings reflect the reported struggles of young listeners and older members. In particular, we see evidence of members in their mid-30s and older showing more dissatisfaction with younger listeners; for example, the average ratings from members who are mid-30s and older to listeners who are 18 years or younger is around 3.88 stars out of 5. By contrast, these ratings increase when chatting with listeners who are of similar age.

We also show in Figure 2 how the average chat rating changes with the listener's age difference compared to the member. In general, members in the youngest age groups rate listeners similarly regardless of the age difference. However, chat ratings by older members such as those in the 33-38 and 45+ age groups show significantly more sensitivity depending on listener age. For example, the average chat rating by members who are 33-38 years old increases by a drastic 0.32 when chatting with a listener who is older by 11 years or more as opposed to a listener who is younger by the same amount. Similarly for members who are 45+, there is a detrimental impact when chatting with a listener who is significantly younger; paired with a listener who is older by either 1-10 years or 11 years or more results in high chat ratings of 4.3 and 4.2, respectively, while having a listener who is instead younger by 11 years or more results in a low average rating of only 3.77. We also check on the main effect of listener age on chat rating to analyze whether older listeners are just better overall. The results shown in Table 7 show that the average ratings for older listeners are around average or below average, making us further confident that the age difference between member and listener is indeed the driving force behind these disparities in chat ratings.

Given these results and our interviews, we conclude that age difference is particularly important when members are in their 30s or older. Generally, younger members have a similar experience with listeners of similar age or older, while older members have a significantly better experience when matched with a listener who is older as opposed to a listener who is much younger than themselves.

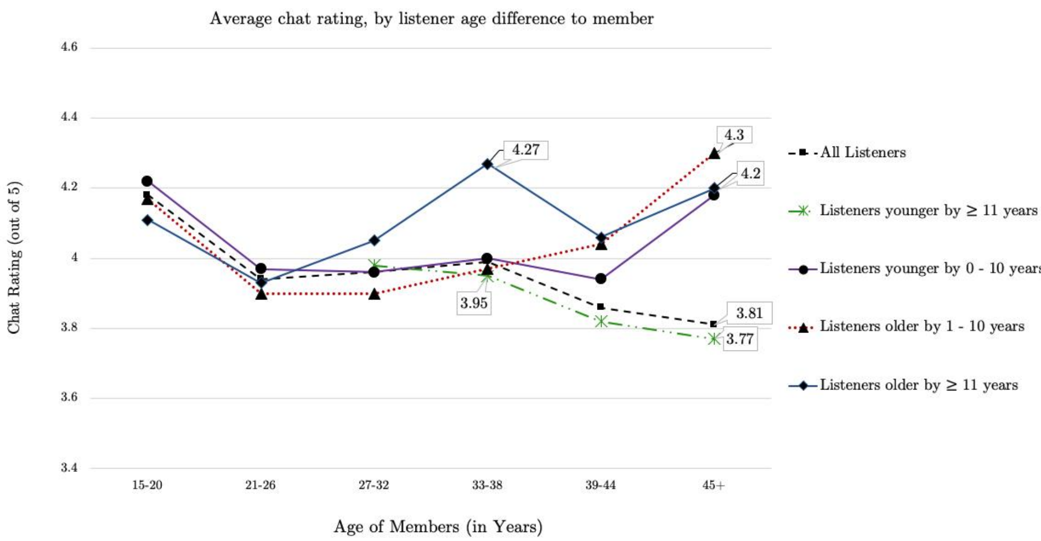


Fig. 3. Comparison of average chat rating given the age difference between member and listener.

5.3 Matching based on experience level

We labeled users' experience levels to investigate the reported challenges of experienced members chatting with inexperienced listeners. Since many users have had a 7 Cups account for a long time but have not used it often, we defined experience level by how many chats a user had at the time of a chat rating rather than their sign-up date for this analysis. Given that the skill and experience gained for a listener is likely most salient near the start of their tenure (i.e. the difference between listeners with 0 versus 100 chats is larger than the difference between a listener with 500 versus 600 chats), we constructed the experience level buckets following the power law distribution often seen in online community behavior [59]. Our results are shown in Table 7.

We found that the largest effects on chat rating occur when very experienced members chat with very experienced listeners versus very inexperienced listeners. Experienced members have extremely negative experiences with inexperienced listeners, as seen in the baseline rating of 2.57 stars out of 5 between members with 1001+ chats and new listeners with 0 or 1 chats. These experienced members give a significantly higher rating with listeners who have more experience chatting, such as 0.774 points higher with listeners between 11 and 100 chats on 7 Cups and a striking 1.289 points higher with listeners having 1001+ chats. Furthermore, members who were the most experienced in general rated chats poorly compared to newer members. These results echo our participants' reflections in the interviews that they became generally more picky over time. On the other hand, less experienced members (2-10 and 11-100 chats) are overall consistent with listeners of varied experience level, although with generally more positive effects with more experienced listeners; this may be a natural result as experienced listeners may be better at chatting in general.

	Member Group				
	Model 1: 0-1 chats N = 65,243	Model 2: 2-10 chats N = 50,997	Model 3: 11-100 chats N = 46,298	Model 4: 101-1000 chats N = 27,394	Model 5: 1001+ chats N = 5,129
	Coeff, Std. Err.	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*	*Coeff, Std. Err.*
Baseline (0-1 Chats Listener)	coef = 4.07	coef = 4.0	coef = 3.87	coef = 3.77	coef = 2.57
2-10 Chats Listener vs. Baseline	-0.051*,0.024	0.242*,0.032	0.238*,0.037	0.284*,0.052	0.699*,0.144
11-100 Chats Listener vs. Baseline	-0.110*, 0.021	0.176*,0.029	0.196*,0.034	0.261*,0.048	0.774*,0.133
101-1000 Chats Listener vs. Baseline	-0.111*,0.021	0.192*,0.029	0.263*,0.034	0.329*,0.048	0.972*,0.133
1001+ Chats Listener vs. Baseline	-0.075*, 0.144	0.248*,0.033	0.288*,0.038	0.347*,0.053	1.289*,0.144

* $p < 0.05$

Table 7. Results of OLS regression measuring the effects of experience level (number of previous chats on 7Cups) on chat rating. Each model in the table shows the regression analysis for the given member group. The coefficients reported in the table show the difference compared to the baseline, which is with the least experienced listeners who have only 0 or 1 chats on 7 Cups (* p < 0.05).

Interestingly, this effect did not appear for the least experienced members (0-1 chats). However, our participants provided us insight that this is likely due to blocked or reported users who often create new accounts constantly to rejoin 7 Cups. These users may rate all chats negatively to troll or may rate a listener badly if they do not engage in the member's harassing behavior.

6 DISCUSSION

This study investigated how users of OMHCs may benefit from algorithmic matching. In particular, we employed a mixed-method approach combining qualitative interviews with quantitative behavioral log analysis to understand users' current challenges, their opinions on algorithmic matching, and the potential benefit that algorithmic matching has for improving community experiences. Our research was guided by previous work regarding matching for in-person therapy resources based on demographic characteristics, which has spanned decades but has had varying conclusions. Our study explored how this past research translates to the online community context as mental health support has increasingly migrated to online means. Our quantitative analyses highly correlated with the perspectives of our interview participants, and our interview participants were largely in agreement with one another on most topics. Users generally felt matching demographic features could have a significant impact on the quality of peer support, although listeners and members differed slightly in how important they perceived certain features to be. Interview participants also echoed one another about core challenges with the current matching system, where listeners choose a member to talk to based on limited information, and the severe barriers it creates for the efficiency of giving or receiving support on 7 Cups. Furthermore, almost all interviewees were supportive of algorithmic matching and felt they would use the system. Interviewees expressed that having both the current queue system and an algorithmic matching system as options would be the most beneficial, such that a variety of chat topics or faster waiting times could still be obtained by using the original system.

Our quantitative results analyzing gender, age, and experience level effects on 7 Cups indicated that matching based on the three levels could have significant impacts on chat outcome. In particular, both our interviews and analyses found that gender has potentially extreme effects for gender-variant populations, and gender identity matching may create a more accepting and relatable environment. Both our interviews and quantitative analysis showed that age has significant effects particularly for older (36+) members with younger listeners. Participants who were either a young listener or an older member indicated a common issue on 7 Cups is that young listeners have a hard time relating to older members, and this can also cause frustration on the member's end. Many of these connections end in abandonment of the conversation or the listener continuing the chat but feeling unhelpful. For a similar reason, our findings also suggest that experience level matters heavily with experienced members and inexperienced listeners. Interview participants who were the most experienced on 7 Cups indicated that they had more specific needs as they spent more time on 7 Cups, and thus felt more picky and critical of listeners as time went on. A few participants expressed that experienced members should thus be matched with experienced listeners to not lose commitment to the community.

Matching to produce better member experiences in OMHCs has not been explored previously, despite the rising popularity of online peer support. OMHCs are particularly important for helping vulnerable or stigmatized populations, which are also populations that may most require purposeful matching to avoid unsafe, uncomfortable, or abusive environments online. Our study is holistic, deriving its findings from a combination of user interviews and behavioral logs. This paper provides grounding for the future of algorithmic matching in OMHCs, including investigation into the unmet needs of users, core values of community members that are vital to the deployment of automated systems, and evaluation of how incorporating user characteristics can benefit member experiences.

7 DESIGN IMPLICATIONS

Our work has demonstrated that users not only have strong preferences for those that provide them aid through OMHCs, but also the quantitatively measurable benefits on member experiences through matching users on these dimensions. Our study also explored users' possibilities of implementing algorithmic matching, concluding that users are overwhelmingly supportive and willing to engage with an algorithmic approach to matching. As a result, we urge for better matching mechanisms in OMHCs, which are quickly growing in size but have currently limited means to optimize support. We detail below various suggestions and design implications of our work for the creators and designers of OMHCs to improve their communities' matching systems. Building matching systems for OMHCs involves many complex considerations and trade-offs. As a result, we organize our recommendations for algorithmic matching into three levels: algorithm-level, interface/process-level, and deployment-level.

7.1 Algorithm-level Considerations

We begin by discussing considerations for designers of algorithmic matching in the OMHC context.

7.1.1 Features. Firstly, we suggest that algorithmic matching for OMHCs consider all three elements of our quantitative study — gender, age, experience level — as possible elements for matching users. We also believe there is valuable future work in modeling the effects of these elements jointly, in addition to our exploratory work on their individual effects.

In addition to all three of these features showing significant effects on chat outcome in our log analysis, all three features emerged as important to users in our interview study to some degree. For example, gender was particularly important to vulnerable populations, including the LGBTQ+ community, who must navigate unique challenges of stigmatization and harassment in these online communities. We have also seen that members generally have a better experience on 7 Cups with listeners of similar age, and that older members have more negative experiences with significantly younger listeners. As a result, algorithmic matching may often match people who are similar to one another together. In the case of experience level, we note that although the most experienced members felt growing frustration over time with chatting with inexperienced listeners, matching inexperienced members with inexperienced listeners could potentially create negative experiences for those just entering the community. As a result, accompanying training modules, chatbot interactions, or greater requirements for live chatting with users are likely good features to add to live OMHCs such as 7 Cups. Requirements such as a set number of forum posts or training modules where beginner listeners chat with more advanced listeners for practice would be good steps in this direction. However, it is vital that training modules are not so extensive such that they deter listeners from engaging with the community at all and quitting the platform. Additionally, although our analysis did not assess the impact of topic on matching, we recommend that topic continues to be a central feature in OMHCs for identifying good chat partners due to our interviewees using this feature often on 7 Cups to find suitable matches in the queue and listener viewpoints that members who do not have a topic tag can be difficult to assess fit for.

7.1.2 Avoiding Worst Outcomes. It is worth noting that, despite many factors being important to matching, platforms are still largely dependent on the available population of users providing aid; there will not always be ideal matches for the members seeking help. As a result, we recommend that algorithm designers prioritize avoiding the most negative pairings of users. Nearly all interviewees in our study stated that mediocre conversations are not problematic nor is always having the best experiences necessary; instead, it is most important to avoid situations that could cause extremely negative consequences on members to avoid worsening their emotional states, deterring them from using 7 Cups again, or impacting their feelings of comfort using the site from then on. As a result, actions such as blocking and reporting on OMHCs should be utilized as indicators of extremely negative experiences for users, and can be potential outcome metrics for assessing algorithmic matching protocols.

7.1.3 Balancing Waiting Times and Accurate Matching. A potential tension with implementing algorithmic matching is the balance between waiting times for members seeking help and finding an optimized match for these members. Several participants expressed that the queue normally moves quickly and one participant mentioned that algorithmic matching could result in longer wait times while the system waits for a relevant listener to come online. As a result, an algorithmic matching system should display the expected waiting time for members (as the 7 Cups system does currently).

During our study's interviews, listeners mentioned their appreciation for how the current system gives listeners autonomy in how many members to chat with and who to chat with. We suggest that OMHC systems such as 7 Cups continue to allow users, whether seeking or providing help, to chat with multiple people at once. Users providing help should be able to set their own capacity for handling multiple chats, which would allow the platform to efficiently intake users seeking help.

7.1.4 Allowing for personalization. Past research has found that users greatly value being able to customize online community tools for their own needs and desires, and personalization of these tools help give users a sense of control as well as showcase an individual's sense of identity [78]. Although our findings indicate that algorithmically matching users has the potential to increase efficiency and member experiences, it is vital that online platforms remain conscious of users' unique needs regardless of their demographic factors or background. Moreover, users' needs may change day-to-day or even chat-to-chat. Thus, any algorithmic matching system should rely first and foremost on users' preferences that they may input.

For example, one of our oldest interview participants who is a member mentioned that an algorithm would likely match her with someone of her same age, but at times she may want a younger perspective regarding issues with her son. As a result, we urge designers of OMHC matching systems to ensure that users can input their own preferences for the listener (for example, members specifying the listener's gender and age) as well as be able to change these preferences easily. However, it is likely that many users will not input all preference options (i.e. a user may prefer a certain age of listener but no preference for gender) or may opt for the system to fully algorithmically match them — in this case, we believe algorithmic matching that is built on historical data analysis is useful for forming a suitable matching to supplement any user input preferences.

7.2 Interface/Process-level Considerations

7.2.1 Making Algorithmic Matching Optional. A sizable portion of listeners stated that they would also be worried about lacking variety in chat partners or chat topics if using an algorithmic system. As a result, we suggest making algorithmic matching optional in addition to the manual current system. All our participants who feared a lack of variety stated that having algorithmic matching be optional would alleviate this concern. Since we envision the system to allow listeners to input which topics they are willing to be matched on, it may be important to allow these settings to be easily reconfigurable such that listeners could choose to talk about different topics at any given time.

7.2.2 Transparency of Algorithmic Matching Systems. At the forefront of building algorithmic matching for OMHCs should be considerations for transparency of users' information. Past work has found that users' participation in online communities is heavily influenced by their trust in the community; platforms with greater transparency over how they are using users' information may benefit from mitigating users' hesitations in engaging with new tools and systems of the platform [12].

When asked about whether 7 Cups should display users' information to one another once they start a chat through an algorithmic matching system, most participants in our study were supportive. This transparency was important to users for gauging who they were speaking to off the bat and avoiding assumptions about their chat partner, as well as simply fulfilling curiosity.

However, some concerns were brought up that we feel should be incorporated into a matching system. A couple of participants had concerns regarding revealing their demographic information, either due to the potential of changing the chat dynamic or opening up opportunities for harassment, but stated that they would be willing to reveal this information if they felt their chat partner would be accepting; for example, our nonbinary participants stated they would want their information to be shown if they knew they were speaking with someone also in the LGBTQ+ community. Our previous suggestion for a system that considers user preferences as a priority for their match may be able to provide this comfort, as users would have the ability to essentially restrict their matches to certain communities for increased feelings of safety and comfort. Systems should also allow for users to engage with a manual selection process, such as 7 Cups' current queue or a profile search system, so users have the option to not disclose any information about themselves to the platform or other users.

We note that our interviewees were open to disclosing their demographic information to the platform but varied more on whether to reveal this information to their chat partner. Thus, we recommend that matching systems also provide a granular level of transparency such that users are be able to decide whether to show their information to their chat partner at all as well as which pieces of information is acceptable to show. It is essential that OMHC platforms deploying matching systems also ensure that users are properly informed on safe boundaries of information disclosure so that their privacy is not at risk of violation, given that users regularly disclose personal information in chat (see section 4.1.1) and none of our interviewees expressed any concerns with disclosing demographic information to the platform (see section 4.2.1). There exists some conflict between users who want to remain anonymous and those who would provide their personal information conditional on their chat partner providing their information as well, and a key benefit of algorithmic matching is its ability to utilize users' information for the purposes of finding a good match without necessarily showing this information to their partner.

Interface-level changes may also incorporate further transparency but in less expensive ways than algorithmic and system-level changes. For example, changes to the interface like displaying users' demographic information at the time of users picking their chat partners may alleviate many pain points brought up in our study. However, we note that interface-level changes may exacerbate challenges around unwanted behaviors by requiring user information to be openly disclosed to the wider population, which algorithmic matching may instead alleviate. Our interview participants also indicated that search methods to find user profiles are inefficient despite greater autonomy over who to chat with, and users need to scour huge numbers of profiles that often lack important information like gender, age, race, or sexuality needed for an effective search [40, 70, 74, 94]. As a result, we suggest that communities using user profiles and search features allow for their users to voluntarily show demographic information (i.e. gender, age, race, sexuality) along with implementing search filters, which is likely to help users more effectively find chat partners if they choose to do so manually.

7.3 Deployment-level Considerations

Given that algorithmic matching is not incorporated into the online mental health context, designers of these communities must experiment with different matching mechanisms and protocols depending on their community's unique goals and users. However, continuous implementation and iteration on these mechanisms in real communities may disrupt the existing community and even pose potential dangers to users' health. As a result, we recommend that builders of matching systems approach experimentation with simulation of different algorithmic matching protocols.

Agent-based modeling, which can yield understanding of agents and their actions under different conditions, has been used in past work to reveal trade-offs in different design decisions for online communities, including to study the effects of social influence and information propagation [4, 32, 35, 93, 113, 118]. Importantly, Ren and Kraut found that agent-based modeling can be used to apply social science theories and understand trade-offs in designing new tools for online communities [98]. Thus, simulation relying on agent-based modeling can navigate the complex effects that different algorithms have on a community's outcome metrics and how these effects work towards the community's unique sets of goals, and allows community stakeholders to iterate on these algorithms before deployment without continuously changing the real-time experiences of their users. For example, communities like 7 Cups may wish to simulate filter-based methods given our findings that vulnerable groups are subject to harassment on the platform and that these groups often wish to chat with those similar to themselves, as well as the trade-offs of these hard filters with impacts on the broader community. Another possibility for OMHCs that allow users to block one another is to simulate matching for optimizing lowering blocking numbers between users, which would align with our finding that avoiding the worst outcomes is most important to OMHC users. We also believe one strong possibility as the basis for algorithmic matching on OMHCs is to rely on the applicant-proposing deferred-acceptance algorithm, which we have previously discussed as having been established in contexts such as school matching and The National Resident Matching Program, which produces a stable matching assignment; the OMHC matching problem similarly consists of two types of agents (in 7 Cups case, members and listeners) who each have preferences and personal features for matching, akin to the stable marriage problem.

8 LIMITATIONS

Our work has several limitations. First, we have only analyzed one online community, 7 Cups, and thus cannot guarantee generalization of these findings to other OMHCs without further investigation. Secondly, our interview participants were restricted to those in the US due to our study's compensation purposes and thus we were not able to get a global perspective in our interviews. However, we note that our quantitative results are not restricted to US-only users and account for 7 Cups users globally. Thirdly, our interview methods and model selection may not account for selection bias among our participants. Our interview participants were users who responded to an announcement by 7 Cups staff, and may be more motivated and engaged with 7 Cups. This study did not include users who had dropped out of using 7 Cups, for example. Our regression analyses also do not take into account the many users who choose not to rate a chat. Alternatives like the Heckman 2-stage regression model may better account for this bias; however, chats without ratings in our 7Cups dataset are not adequately organized for a proper input to the Heckman 2-stage model. We also note the possibility of bias when using OLS with ordinal data, and emphasize our behavioral log analyses as complementary to our interview study and as a starting exploration for this context. Fourthly, our interview population is not representative of the 7 Cups population. Although we attempted to cover many dimensions of users, we still missed out on some users dimensions (such as missing transgender male participants). Despite these limitations, we believe that our quantitative analysis of behavioral logs was able to make up for some shortcomings and provide a more comprehensive view of 7 Cups. The dataset contained thorough coverage of behaviors from January 2020 to August 2020 on 7 Cups, and it confirmed many conclusions drawn from our interviews. Lastly, our measurement of a partnership throughout this study was from chat ratings that members give listeners on 7 Cups. This measurement has some limitations, such as listeners being unable to rate chats and being just a 1 to 5 stars scale that users could interpret differently (i.e. rating the chat versus rating the listener). However, as discussed in section 3.2.2, we view chat rating as the most honest signal on whether a conversation adequately supported a member.

9 CONCLUSION

Our work investigated how users of 7 Cups, an online emotional support platform, are currently connected to one another for peer support and how algorithmic matching may improve upon the current challenges they face. Evaluating data from qualitative interviews and quantitative analysis of behavioral logs, we provide a general view of how members and listeners on 7 Cups utilize current mechanisms for matching, their opinions on algorithmic matching for the future, and what qualities may be used in algorithmic matching for better community member experiences. Our results indicated that users are widely receptive to algorithmic matching and find that it would resolve many of the limitations in current methods. We found that purposeful matching based on gender, age, and experience level can have potentially striking improvement on member experiences.

ACKNOWLEDGMENTS

We thank our colleagues from Social AI Group at Carnegie Mellon University for their feedback, including Dr. Robert Kraut, Milo Fang, and Hao-Fei Cheng. We also thank 7 Cups executives and engineers, including Dr. Glen Moriarty and Cris Firman, as well as our interview participants from 7 Cups for their valuable insights. This work was supported by the National Science Foundation (NSF) under Award No. 1939606, 2001851, 2000782, and 1952085.

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Received: April 2021, Revised: November 2021, Accepted: March 2022