Peer Support in Online Communities

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To. my mother and father

Abstract

Online peer support groups provide a conducive environment, allowing members to get connected with peers who share similar difficulties. There, members are able to provide informational and emotional support to each other without restrictions of time and geographic location. However, peer support also suffers from a variety of challenges, including members' lack of commitment and expertise in providing support. Failure to address these challenges might lead to unwanted consequences such as volunteer burnout and mistreatment of helpees.

In my work, I started off studying peer support in a health-related context, emphasizing two research questions, 1) how to keep members committed to providing support and 2) how to empower committed members with skills so that they can provide better support. It is not clear, however, the extent to which conclusions obtained from this research can be applied to support groups where members might have conflicts of interest. I then expand my work to peer support groups where members have competition by examining how gig workers provide and receive support online.In a specific case study, I explored how gig workers collectively make sense of algorithms that manage their work in online communities.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

In a forest of a hundred thousand trees, no two leaves are alike. And yet, with tens of thousands of leaves, they form a beautiful forest. People sharing similar experiences naturally offer support to each other, as they can better relate, and thus provide more authentic empathy and practical advice that professionals might not offer [16, 155]. Since the 1970s, offline peer support services such as self-help groups have proven to be tremendously effective in medical contexts; the advancement of the Internet makes peer support even more accessible than ever [134]. Members can participate 24 hours a day, 7 days a week, with the ability to retrieve information posted at any time in the past [175]. Such accessibility also allows members to interact with a large number of unacquainted peers and thus extend their social network far beyond their existing ones. Prior research suggests that learning new information is more likely to happen through connections that are not embedded in one's close network [172]. With the collective power, peer support groups can also serve to help their members brainstorm more solutions and ideas that provide members with a variety of choices for dealing with their problems [132]. Together with similar peers, members might take greater risks in expressing their feelings and have their situations better understood [6].

However, a multitude of challenges undermine the effectiveness of peer support groups. First, the lack of gatekeeping that allow anyone to contribute may also make it easy for members to leave. Without a steady stream of newcomers to replace those who leave, online support groups might struggle with existential sustainability. While high turnover is not uncommon in online communities (e.g., 60% of new Wikipedia editors make no edits after their first day on the site [142]), members' participation in support groups are sometimes contingent on temporary and intermittent needs, such as diagnosis of a disease [64, 126]. To the extent that members view the group as rewarding, they will be motivated to keep participating in the group; otherwise, they may tend to disengage after members' imminent needs are satisfied [128]. In this dissertation, I investigated the following research question:

RQ1 - How can online peer support groups retain their members?

Second, while peers can provide information based on their own experiences [63], they might lack the necessary training and expertise to address some tricky challenges that only professionals can handle. With the large amount of information available in online support groups, the accuracy of information is hard to audit, which can lead to the spread of misinformation. In the context of mental health, for example, poor communication between helper and helpees may lead to unwanted consequences for both parties; the helpees may feel disempowered and devalued [37, 158], and the helpers might suffer from increased anxiety as well as decreased self-efficacy[130, 194]. This leads to the second research question I examine in this dissertation:

> **RQ2** - What are some strategies to equip members with the skills to provide better peer support?

In my dissertation work, I started off studying the two aforementioned challenges of peer support in online health communities (OHCs). Chapter 2 focuses on **RQ1** and examines temporal changes in members' participation in a cancer-oriented OHC, focusing on the changes in members' motivations and behavior as they transition from newcomers to other roles or when they ultimately leave the community. Combining behavioral log analysis, automated content analysis, surveys, and interviews, I found that shifts in members' motivations seemed to be driven by two sources: the internal dynamics common to becoming a member of most online communities and the external needs associated with their cancer journey. When members' disease-driven needs for support decreased, most members quit the sit. The motivations of those who stayed shifted from receiving support to providing it to others in the community. Though oldtimers contributed the vast majority of content, they also encountered challenges that threatened their commitment, including negative emotions related to other members' deaths, which led them to take leaves of absence from the community or to drop out permanently. Chapter 3 focuses on **RQ2** and investigates, using a qualitative interview approach, how volunteer counselors develop their expertise in online mental health support groups. I found that the initial training volunteers received was insufficient, and that volunteer counselors frequently had to independently develop strategies to deal with specific challenges. Furthermore, their strategies generally relied on their personal experiences and lacked systematic feedback from mentors or clients. In addition, volunteer counselors reported having issues with maintaining their professional boundaries with the clients. Even though training and support resources were available, they were under utilized.

While most prior research on peer support has been conducted in medical contexts, the Internet allows people with other interests to gather as well. Such online spaces might be especially useful to marginalized populations who are unable to receive support from offline sources [41]. In addition to patients to chronic diseases [85, 156] and mental health issues [38, 138], recent literature has described how new parents [6], people with bereavement needs[125], adolescents [143], the LGBTQ population [61] and gig workers [160, 190] leverage online spaces and exchange support. There, members can share personal stories, information relevant to their interests and provide each other with support. It is not clear, however, the extent to which conclusions obtained from medical-based contexts can be applied to other types of support groups; the success of these online support groups might be significantly impacted by their context and the nature of the support offered in those groups.

In Chapter 4 and 5, I expand my work to peer support groups among gig workers, in which members may be at competition with one another. In my research, I explore two unique challenges that gig workers might face when they exchange support online, namely, **competition and the need for collective action**. First, gig workers' incentives sometimes conflict with one another, as they are competitors in a highly competitive market. It remains unclear how such competitive tensions affect their conflict resolution processes, and thereafter their support exchange. Second, gig workers count on each other to reach for stronger collective power. Given that collective labor activities have proven to be effective in advocating for better working conditions [98], it is crucial for gig workers to reach some level of common ground. Such need for collective power is different from contexts examined in prior work - in health support groups, for example, each member's personal decision making is unlikely to affect other members' treatments, so usually, a consensus is neither sought out nor deemed necessary.

I began with a high-level exploration of how gig workers provide and receive social support during COVID-19 as documented in Chapter 4. Specifically, I employed a qualitative approach to understand how online social media groups provide informational and emotional support to physical gig workers during the COVID-19 pandemic. I found that social media groups alleviate the atomization effect, as workers use these groups to obtain experiential knowledge from their peers, build connections, and organize collective actions. However, I also noted a reluctance among workers to share strategic information where there was a perceived risk of being competitively disadvantaged. In addition, the diversity among gig workers has also led to limited empathy for one another, which further impedes the provision of emotional support. While social media groups could potentially become platforms where workers organize collective efforts, several factors, including the uncertainty of other workers' activities and the understanding of the independent contractor status, have stymied efforts at collective action.

In Chapter 5, I delved into a case study where I explored how gig workers collectively make sense of algorithms that manage their work in online communities. I conducted a content analysis of 69 posts and 1,198 comments on the r/uberdrivers subreddit to explore the collective sensemaking process of gig workers regarding algorithms within online communities. I found that a negative violation of mental models prompts workers to engage in collective sensemaking efforts. During this process, workers utilize both exploratory and confirmatory research methods. While collective sensemaking can validate workers' experiences and sometimes provide feasible solutions to counteract the algorithms, the power asymmetry between workers and the gig platforms makes it challenging for workers to achieve their desired sensemaking outcomes.

Chapter 2

Engage Peers with Different Tenure

2.1 Introduction

Face-to-face health support groups are places where people come together to exchange social support around health related issues [136]. With the emergence of the Internet, online health communities (OHCs) allow people to gather in a virtual environment without restrictions based on geographic distance or temporal availability, offering them a platform to share experiences, ask questions, and receive and provide social support [115, 126]. OHCs are thus different from face-to-face support groups, in which groups of people gather at a set time and place to discuss problems and get advice. In the latter, professional experts and lay volunteers often help moderate discussions, provide guidance, and evaluate medical content. In contrast, OHCs are typically larger, rely upon asynchronous communication among geographically dispersed people, and rely on members to provide each other with peer support [33]. Since the benefits of OHCs are provided by members, it is crucial that OHCs maintain a critical mass of active members.

Retaining members is a key challenge faced by many types of online communities, including question and answer sites [141], peer production platforms like Wikipedia [23, 142], and OHCs [126]. In an attempt to develop general principles, much of the research on how to retain members in online communities, including Kraut and Resnick's review [104], has been agnostic to community type. It is not clear, however, the extent to which conclusions from this research can be directly applied to OHCs. One feature that might prevent such direct application lies in that, unlike many other types of online communities, including peer production ones, OHC members' participation is often heavily dependent on their users' own health status and is mostly driven by temporary and intermittent needs [64, 85, 114]. Thus, it is reasonable that many newcomers join OHCs mainly for self-centered motivations, in search of actionable information that is specific to current challenges they are facing in their personal lives [76, 114]. In contrast, although there are exceptions (e.g., [96]), most research on participation in online communities does not examine how it is driven by offline events.

Existing work focusing on health communities has investigated factors that influence members' behavior and tenure (e.g., [81, 181, 195]). For example, Wang et al. [181] found that those looking for and receiving informational support were less likely to stick around than those looking for and receiving emotional support. Although a small fraction of members become core contributors in many online communities [149], we know little about the reasons they become valued core members in OHCs.

In this chapter, I seek to explore the following research question: **how do OHC members' motivations and behavior change as they transition from newcomers to other roles or when they ultimately leave the community?** We take into account two dynamic processes holistically: the general, internal processes common to participation in many online communities (e.g., the reader-to-leader framework, [23, 128, 149]), and processes specific to health communities based on members' illness trajectory (e.g., their cancer journey, [48, 81, 86]).

We examine members' life cycle in the context of the American Cancer Society Cancer Survivors Network® (CSN). The research used a mixed-methods approach, which combined interviews, behavioral log analysis, content analysis and surveys. The research found that (1) members joined OHCs for self-oriented goals driven by the uncertainty generated by their disease state, especially their need to get relevant information and conduct social comparisons; (2) when members' disease-specific needs for support decreased or were satisfied, most members quit the site; the motivation of those who stayed became more community-oriented and shifted from obtaining support to helping other members in the community; and (3) old-timers experienced challenges that seemed to undermine their long-term commitment to the community, including strong negative emotions brought on by other members' passing away and other signs of burnout.

2.2 Related work

In this work, we are interested in the process by which individuals become valued core members of OHCs, taking into account the general internal process of participation in many online communities and social groups, and the unique characteristics of OHC participation. In the following section, we first draw on classic theories on online communities to examine how and why community members change their behavior over the course of their participation. We then delve into our context by introducing OHCs. We discuss why members' behavior in OHCs might differ from those in other online communities, and why improved understanding of OHC members' life cycles might be crucial for its organizers.

2.2.1 Members' Life Cycles in Online Communities

Social computing researchers have examined how members change their participation in online communities over time (see [104] for a review). Typical of this genre is the Preece and Shneiderman's reader-to-leader framework, which describes how members of online communities evolve from being a lurker or reader, to a contributor and collaborator, and eventually to a community leader [149]. Bryant et al. [23] uses ideas from legitimate peripheral participation and activity theory to understand participation in the Wikipedia community as an adaptable process that evolves over time.

The changes in participation in online communities described in prior work fit into Levine and Moreland's more general group socialization framework [128], which attempts to explain changes in motivations for participation in most types of social groups. The model differentiates five phases of group membership, three of which are particularly relevant to our present concerns

– (1) investigation, in which prospective members decide whether to join a group and the group decides whether to receive them; (2) socialization, in which new members seek to influence the group to satisfy their needs and the group seeks to influence them to meet its goals; and (3) maintenance, in which full members play specialized roles designed to meet both their needs and the group's goals. In all of these phases, the individuals and the group evaluate the past, present, and potential future benefits of their relationships. To the extent that the individual views the group as rewarding, he or she will be motivated to join during the investigation phase and to remain during the socialization and maintenance phases.

Such research attempts to explain the general dynamics of sustained participation and dropout in online communities and thereby has the potential to help designers and managers of online communities identify ways to better meet members' needs [13, 81, 107]. However, these general principles may not be directly applicable to the context of OHCs due to their unique characteristics and the influence of members' illness trajectories on member participation, which we will review in the following section.

2.2.2 Online Health Communities

OHCs are internet-based platforms where people come together to exchange social support around health related issues [92, 136, 193]. A substantial body of prior research has examined benefits conferred by participation in OHCs. This work [33, 136] suggests that participants in OHCs enjoy convenient access to other people with similar experiences, including those with significant firsthand experience dealing with relevant health problems. Social support is an important resource as patients and caregivers cope with corresponding disease. Through participating in OHCs, members obtain useful information sometimes not available from medical experts [33], such as effective strategies for coping with disease, side effects or family relations [115]. Members also receive emotional support from each other when facing life-threatening crises, which help them deal with emotionally crippling events [166]. These benefits may be due, at least in part, to immediate availability (i.e., 24/7 access without restriction of geographic locations) and the anonymity of OHCs [126].

Given the critical role that social support plays in OHCs, prior research has examined the dynamics of social support and how receiving social support influences members' subsequent participation in OHCs. For example, Introne et al. [81] analyzed data of thirteen disease-specific discussion forums hosted by the WebMD OHC and found that a small group of core senior members generate the majority of support for others. Ploderer et al. [148] found that more senior roles in OHCs are often occupied by those who have successfully managed their own health problems and have the knowledge and experience to support others. Wang et al. [181] found that those looking for and receiving social support stay longer than those looking for and receiving informational support.

2.3 Methodology

2.3.1 Research Site

Our research site was the Cancer Survivors Network (CSN), a collection of online peer support groups organized by the American Cancer Society. Launched in July 2000, CSN was designed to offer cancer patients and their families experienced-based knowledge and social support from other members [52]. According to a report published in 2018, CSN attracts over 3 million unique visitors per year and over 140,00 people register new CSN accounts per year. The majority of the members are cancer patients; other members include families and friends, who have been impacted by cancer [52].

2.3.2 Research Methods

This research used mixed methods incorporating both qualitative and quantitative analyses. We first interviewed 20 long-time CSN participants. The qualitative analysis of the interview transcripts was used to inform a series of targeted quantitative analyses, and the results of the quantitative analyses are presented alongside the qualitatively derived narratives. The quantitative analyses are based on surveys with over 5,000 CSN members and behavioral logs from over 130,000. Table 2.1 summarizes the sample size of each data source and the time period each group of participants stayed on CSN, defined as the number of days between their registration date and the last time they logged into CSN. Our interview sample represents a small group of highly motivated old-timers on CSN. Our behavioral log analysis sample represents the entire population of CSN users, whereas the survey sample is based on a large but selected group of more motivated users.

Interviews

To explore how OHC members' participation change over time, we conducted semi-structured interviews with 20 CSN users. We first identified all users who had logged onto CSN at least once in the six months prior to recruitment, sent email interview invitations to 300 members who had registered over a year ago, of whom 19 responded and were interviewed (6.3%), and to 300

	Sample size	**CSN tenure**
Interviews	20	All participants except 1 stayed more than a year.
Surveys	5,426, answered all or part of the survey questions	Median tenure = 10 days, 1,648 (30.4%) participants stayed more than a year.
Behavioral logs	136,323	Median tenure = 1 day, 9,920 (7.2%) participants stayed more than a year.

Table 2.1: Sample size and characteristics of each data collection method

people who had registered for CSN in the past year, of whom only one (0.3%) responded and was interviewed. Our interviews took place remotely via Skype, Google Hangout or phone call. The average age of the interviewees was 56.3 (sd =10.63), with all but one more than 45 years old. Among the 20 participants, 17 were cancer survivors and three were caregivers to cancer patients. Although we sent out interview invitations to a random sample of recent users, those who responded had been active on the site far longer than average: all but one had registered more than a year before the interview date.

The interview typically lasted around an hour. During the interview, the participants were shown samples of their posts on the site and were asked to describe their experiences when they first joined the site, made their first post, and made their most recent post (e.g., Could you please navigate me to the very first thread that you started/the most recent thread you started? Can you tell me why you posted this message?). They also reflected on their motivations and challenges on CSN both when they first joined and during later stages (e.g., Now that you've been on CSN for X years, what are your current reasons for using CSN?). Finally, they discussed how their experiences of using CSN had changed over their tenure (e.g., How do you think your experience have changed over time?).

All 20 interviews were recorded and transcribed. We started inductive, open-ended qualitative coding by tagging topics in the transcripts. We then tried to build connections between the tags to identify emerging themes from the interview data. Finally, we grouped various themes into different stages of participation and drew key quotes to illustrate our findings. In addition to interviews, we also looked at interviewees' posts and comments to better understand their experiences on CSN. Note, as part of the consent processes, interviewees gave permission to view their posts and discuss their posts with them. Examining the interviewees' profiles and posting history allowed us to better understand the context of their CSN journey and to effectively facilitate the interviews. Some of the discussion posts were used as probes to elicit interviewees' reactions and thoughts at the time of posting; this technique asks participants to recall an actual event, and the probe serves to make up for some of the drawbacks (e.g., inaccurate memories) associated with retrospection [161].

Log data analysis

The behavioral log data consists of the users' posts, comments, profiles and history of login session history on CSN between August 2008 and August 2018. Note all message traffic on CSN can be viewed by the public without registration. The behavioral log data was obtained through a collaboration with the American Cancer Society; the university's IRB and US federal regulations do not consider the analysis of publicly available data to be human-subjects research. All our data were anonymized before analyzing. The sample consisted of 136,323 users who had logged onto CSN during this period. In addition, we leveraged machine learning models to measure features of their posts and comments. The machine learning models were those developed by Yang et al. [195] based on social support definitions in [14], in which linguistic features of the posts predict the extent to which support-relevant constructs appear in them. Specifically, the models predicted **support-seeking actions**–how much thread-starting posts sought **informational support** and **emotional support**, as well as how much **positive and negative self-disclosure** they contained. We also examined **support-provision actions** in replies to posts, including how

Support actions	Definition and examples	Corr.
Seeking informational support	Seek information, advice, referrals or knowledge in the thread starting post. *"I was wondering if anyone who has had whole brain radiation has had hair not grow, back on head?"*	0.73
Providing informational support	Provide informational support to the person starting the thread. *"It was explained to me that microcalcifications look like as if one were to throw rock salt on a blacktop driveway and they would 'cluster and fall' in many locations"*	0.79
Seeking emotional support	Seek understanding, encouragement, sympathy or caring in the thread starting post. *"So, much of the stuff I find on the web is 'doom and gloom'. Would love to hear from some long-term survivors!!!! Mainly cuz I'm scared, out of my wits about all this - any thoughts?"*	0.64
Providing emotional support	Provide emotional support *"I do understand the frustration and anger and sadness of having drugs fail you and then venturing forth on unknown territory yet again. This whole journey is fraught with crappy bumps and turns. wish you the best."*	0.75
Self-disclosing positively	Discuss positive thoughts or emotions, such as gratitude and love. *My family is so supportive and makes me feel like such a loved person."*	0.72
Self-disclosing negatively	Discuss negative thoughts or emotions, such as worry or anger. *"I am freaked out after reading my mammogram report"*	0.71

Table 2.2: Definitions, examples of six support-related actions, and our model accuracy as measured by the Pearson correlations between model predictions and human judgements.

much informational and emotional support a reply contained. Full details regarding the machine learning models used are in [195] and summarized in Table 2.2. Human annotation agreement on a training dataset was high (mean ICC=.84), and the machine learning models were highly correlated with the average of the human judgments (mean Pearson correlation r=.71). We then applied these models to estimate six types of support-related actions in posts from our corpus.

Survey

The data also include responses from a survey sent out at the beginning of 2014, during which we emailed 83,589 CSN users who had logged in at least once between January 1, 2000 and October 30, 2013. The American Cancer Society sent out invitations to CSN members to participate in the survey so that the researchers would not have access to personally identifiable private information. Of the 83,589 emails sent out, at least 11,000 never received the survey based on

Scale	Sample statement used in the survey	Alpha
Get informational support	To get information about the cancer I'm dealing with.	.86
Get emotional support	To be comforted by others in CSN who have been there.	.94
Conduct social comparison	To see how other CSN members like me are doing.	.87
Provide support to others	To help others solve their cancer-related problems.	.96
Interpersonal attachment	I feel very close to some of the people I've met on CSN.	.85

Table 2.3: Self-report scales, sample questions, and scale internal consistency (Cronbach's Alpha)

undelivered and bounce back notifications. 5,426 people completed at least part of the survey (6.5%) and among them 55.81% finished. Because of missing data, there is some variability in the number of participants answering a particular question. Therefore we specify sample size for each analysis presented in later sections. In this paper, we mainly focused on participants' self-reported motivations for participating in CSN and their interpersonal attachment to other CSN members. Members' motivations to join online support groups were measured by four short, but highly reliable scales representing four common reasons why members join online support groups: to get informational support, to get emotional support, to conduct social comparisons, and to provide support to others. These four reasons were based on two in-depth, qualitative analyses of the reasons people participate in online groups in general, including health support groups, and in online cancer support groups [154, 156]. For each of the three statements, CSN members responded to the question "How valuable is participating in CSN for each of the following purposes?" using a 5-point Likert scale, where 1 = not at all and 5 = very much. Confirmatory factor analysis showed that the four factor solution is a good fit to the data (CFI=.971, TLI=.958, RMSEA=.087). In addition, the survey measured participants' attachment to other CSN members on a 5-item scale (alpha = .85). Table 2.3 shows sample survey item for the motivation and attachment scales.

2.4 Results

2.4.1 Initial motivation to participate in OHCs

According to the interviews, new members typically joined CSN shortly after being diagnosed or when they were in active treatment stages of their cancer (i.e., screening diagnosis, information seeking, and acute care treatment) and thus were in need of informational support. The results, however, also indicate that new members are there for more than just information. Members' participation in CSN was aimed at reducing their uncertainty and anxiety about their disease. In addition, to find useful information, participants reported employing strategies such as conducting social comparisons with other members. Quantitative analysis supports the interview findings.

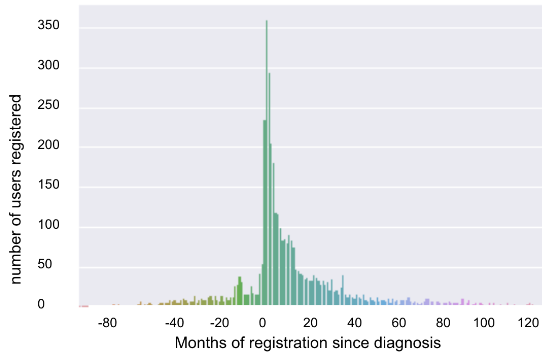


Figure 2.1: Distribution of registration time since diagnosis

Members typically joined OHCs early in treatment when they were especially in need of help.

All 20 interview participants reported joining CSN when they or their loved one were just diagnosed with cancer or were in active treatment of cancer. They described that they felt "shock[ed]," "horrified," "uncertain" or that they "did not know what to do" about their disease at the time. Eighteen of the 20 described a similar scenario about how they found out about the site: in order to know more about their disease, they chose to search online.

> "Because I was there and I didn't know what I was going through. And I wanted answers that, the doctors couldn't... they couldn't tell me, they couldn't have real life experience." (P11)
>
> "So I did ...well I started my research for [my partner's] cancer, I think the American Cancer Society site popped up. And so then I started searching, you know, for his particular type of cancer, I found the American Cancer Society to be actually very, very helpful..." (P5)

Our log data support the qualitative findings that most members joined OHCs in their early stages of treatment. Figure 2.1 shows the distribution of the time interval between CSN members' (or their loved one's) diagnosis time, derived from the survey (N = 2928), and their CSN registration date, derived from the log data. It shows that 44.8% of the users registered within three months of cancer diagnosis. This suggest that many newcomers join OHCs in search of actionable results that are specific to the challenges (i.e., cancer diagnosis in this case) they are facing in their offline life [13, 33].

Furthermore, the majority of users found CSN through informational search engines such as Google. For instance, according to Google Analytics data, a total of 6,305,602 unique users visited CSN via a search engine in 2017, probably searching for cancer information or support, but only 13,231 users created a new account during 2017. Although the data do not allow us to identify the pathways through which particular people joined CSN, this disparity between unique visitors versus registrations suggests that many users got to know about OHCs such as CSN when searching for relevant information on the Internet, and a minority decided that they wanted interaction with other survivors in addition to static information.

Motivations to use CSN	Mean	SD
Get informational support***	3.82^a	1.14
Conduct social comparison	3.33^b	1.23
Get emotional support	3.30^b	1.39
Provide support to others*	3.21^c	1.35

justification=centering

Table 2.4: Motivations to use CSN reported by survey participants.
Mean and SD are shown. Within columns, means with different superscripts were statistically different from each other. Get informational support is significantly higher than other three types of motivations (***: p<0.001); to provide support to other members is significantly lower than other three types of motivations (*: p<0.05).

Self-reported data from our survey show also that informational needs stand out among other reasons for OHC participation. One-way ANOVA showed a statistically significant difference among the four types of motivations reported by survey participants (F(3,11738)=134.99, p<0.0001). Post-hoc Tukey tests indicate that members' needs for informational support were significantly higher than the other three types of motivations examined (mean = 3.82, versus all others, p<0.001). Second most important was the use of CSN to make social comparisons (mean = 3.33) and to get emotional support (mean = 3.30). Participants also reported that they used CSN to provide support to others but the score is significantly lower than those of others (mean = 3.21, all p <0.05). Table 2.4 contains the descriptive statistics for the four types of motivations reported by survey participants.

Members received support from OHCs that was otherwise unavailable via offline sources.

Interview participants reported that obtaining disease-relevant information and conducting social comparisons with other users were two useful strategies to reduce their uncertainty. In particular, they described information from CSN as information "otherwise unavailable via offline sources" that sometimes facilitated their treatment decision-making.

> "There were issues in my treatment that were pretty severe. And I didn't get information from doctors, but the other patients that had similar problems like I had, I read about them...like, when I was debating whether or not to have radiation after the chemo. And I went on CSN and I asked, Does anyone else have the same thing going? Well, I didn't get a whole lot of responses, [but as for] what I did get, that that's basically what I use for this." (P16)

Interviewees have stressed the helpfulness of assessing other members' situations, which could be more personalized than guidelines they received from doctors.

> "The forum itself, I found very helpful... So it was just interesting to read other people, you know, going through the same thing, and, how they were dealing with it. Like, for instance, food was a big issue, you know, how are they eating? What were they eating? The pain was terrible, you know, how are they dealing with the pain?" (P12)

As for social comparisons, OHCs such as CSN allow patients and caregivers from all over the globe to participate and thus view a variety of cases. Specifically for new OHC members, upward social comparison (i.e., comparing one's situation with those who are better off) led to positive feelings about their situations.

> "Doctors tell you, you know, come from a clinical side. CSN tells you, people who have lived it...So to hear from the people who have done it, it makes it okay. You know, when they say chemo is doable, it's, um, you know, it is doable, and yeah, let's do that." (P15)

While the majority of the interviewees reported that they joined CSN mainly to know more about their disease, interviewees also identified obtaining emotional support as an associated benefit brought by participating in CSN. Members got direct encouragement from fellow members regarding their situation, as P2 reflected:

> "When I made my very first post, you know...I got responses immediately. Some are like, just a couple of words, saying that 'you could do it'. It does make me feel a whole lot better, seeing these responses."

Companionship with members in similar situations provides comfort and reduces feelings of isolation. Members expressed "not feeling alone."

> "I think it was just comforting to be in a group of people that were going through the same thing. You know, I don't have my own personal friends [who] have this kind of stuff. I don't really know anybody who had this kind of cancer. Hmm. So I didn't have any personal resources." (P7)

Similar experiences also provide a common ground for better understanding each other, even compared with close family members and friends as P9 noted,

> "Everybody said I looked fine. I didn't even look like I was sick... it made me mad because when you have this I guess there's a part of you that wants a lot of sympathy, empathy whatever you want to call it. [On CSN], you know you get something from these guys, as they are just like you. You know you could only expect hugs sent to others – it's still keystrokes, but was better than nothing. "

Our results are consistent with prior research that OHCs provide members with informational and associated emotional support that are otherwise unavailable to them [151, 174]. The results also echo prior work on cancer journey, which indicates patients tend to spend a lot of time seeking information to get their questions answered and thus informational support is of the most value to them [64].

These findings are consistent with prior work that treat participation in OHCs as primarily driven by the course of members' diseases: social support afforded by OHCs can help members navigate intense and difficult periods in their lives.

2.4.2 To leave or not to leave? A decision for continuous participation at OHCs

Most OHC members dropped out after their initial needs for joining the site were met, because continued participation brought few benefits.

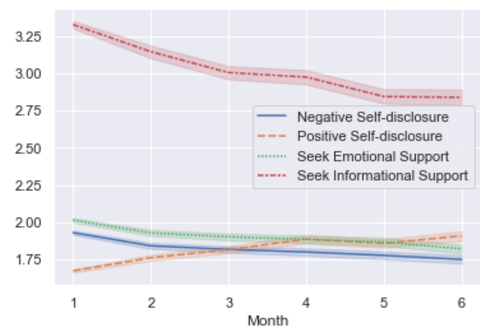
Participation in OHCs was primarily driven by the course of members' diseases: social support afforded by OHCs can help members navigate intense and difficult periods in their lives; over time, however, the amount of support they sought and received declined, as urgent questions got answered, and individuals developed additional mechanisms to cope with their diseases [33]. OHC members dropped out because they no longer found the group valuable. For example, cancer patients who have been declared in remission with "no evidence of disease" after receiving treatment often shifted the focus of their lives away from cancer. P7, who had not logged into CSN for three months before his interview, reported: *"As I stay longer, more that I give input and less that I need input. Probably just a year has gone by and in my life everything has become better."*

Our log data analysis results support the findings from the interview that the majority of users tend to quit quickly after initial use: 62.5% of registered members on CSN never logged in again after the first day of their participation. Among those who logged into CSN at least once after their registration date, the half life of their CSN participation was about 31 days. Together, these figures indicate that less than 20% of the users stayed on CSN for more than a month. Members who did stay sought less support over time. Figure 2.2 shows that the average amount of informational, emotional support seeking and negative self-disclosure per thread-starting post decreased and that positive self-disclosure increases over the first six months of members' participation. Those who never initiated a post sought less informational and emotional support over time. Specifically, the duration of CSN membership was negatively associated with the amount of informational and emotional support the members sought in threads they started (coef = -0.0029, $p<0.001$; coef = -0.0009, $p<0.001$, respectively). Moreover, the longer members stayed on CSN, the more positive self-disclosure (coef = 0.0018, $p <0.001$) and less negative self-disclosure (coef = -0.0009, $p<0.001$) their posts contained. The decline in negative self-disclosure is consistent with the hypothesis that members are seeking less support over time because prior research has shown that negative self-disclosure is the major mechanism through which people seek support, especially emotional support, in online health support communities [181, 196].

As for the provision of support, log data analysis results show that the longer members stayed on CSN, the more emotional support (coef = 0.0010, $p <0.001$), but the less informational support (coef = -0.0008, $p<0.001$) they offered in their replies to other members' threads. Figure 2.2b illustrates that the amount of emotional support provision increased, whereas the amount of informational support provision decreased over the first six months of participation.

Members continue to participate in OHCs because of the obligations of reciprocity and the ties they formed with other community members.

Notably, all but one interviewee showed "no evidence of disease" at the time of their interview, suggesting that they no longer needed or were actively seeking informational or emotional support.

(a) 

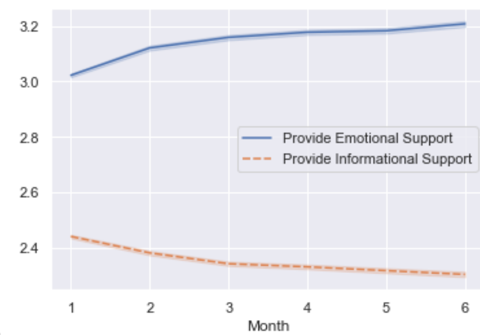
(b) 

Figure 2.2: How members' support seeking behavior change within the first 6 months of their participation. (a) The average amount of informational support seeking, emotional support seeking, negative self-disclosure and positive self-disclosure contained in the thread-starting posts made in the first six months since users' registration time. Y axis reflects the score generated by our machine learning model (range = 1-7). Each line represents the mean in each month. The borders represent standard errors. Only members who stayed $\geq$ 6 months were included. (b) The amount of informational support provision and emotional support provision contained in the comments made in the first six months since users' registration time. Y axis reflects the score generated by our machine learning model (range = 1-7). Each line represents the mean score in each month, and the borders represent standard errors. Only members who stayed $\geq$ 6 months were included.

Although the remaining interviewee (P8) reported that her tumor was "spreading," she "has not been seeking for help recently," for she has gained "more than enough knowledge for her own disease". This is consistent with the cancer journey perspective [85], which predicts that the amount and way that members engage in OHCs depends on their disease state. Although the cancer journey perspective predicts that support-seeking will decline, it does not convincingly provide a rationale for why these members continued to participate even after remission.

Interviewees revealed a variety of reasons to stay and help other members on CSN. Some described a general reciprocity process, in which they wanted to return the favor to a community where they've been offered similar types of support when they were newcomers. P17 shared her experience of being helped when she was a newcomer to CSN and identified reciprocity as her reason of staying:

> "When I was new to the site, I had everybody there who is undergoing chemo. You know, there was one lady who had undergone an IP chemo and she was able to tell me, you know, this is gonna hurt. She didn't lie: this is gonna hurt. You know what, since it is your best chance, here's what's you're gonna feel and she's able to describe it. That helped to take the fear of the unknown away. And because of this type of thing, this type of support I've got, I wanted to give back."

Interviewees also mentioned empathy as another reason for staying; based on their own experiences, participants could relate to other members' anxiety and uncertainty, and therefore wanted to provide support.

> "...at the end of the day, you're by yourself and you know, your mind is going crazy. And that feeling of [being] all by yourself versus having people around you, especially

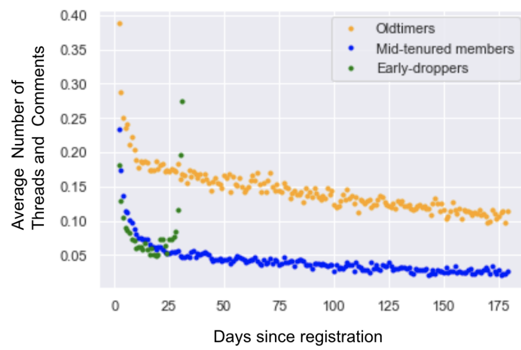


Figure 2.3: The average number of posts and comments users made over the first 6 months of their participation. Early-dropouts stayed up to a month; mid-tenured stayed for a month to a year; old-timers stayed more than a year.

> with an unknown aggressive cancer, you know, never would have guessed it in a million years that you would have that. So if people can find their way to CSN, yeah, I remain. I can be there in a minute. I can remember exactly how I felt. I can remember exactly the things I was thinking." (P15)

In addition to altruism, OHC members' tenure on the site could also be influenced by their connection with other members. Interviewees indicated that they had developed some level of friendship, or at least had become acquainted with other members in the forum. Some expressed the desire to "check up on [their CSN acquaintance]" when on the site. Although five out of the 20 interviewees mentioned they've exchanged contact information with other members outside CSN (e.g., Facebook, email, or in-person meeting), most interviewees indicated that they just knew other members "on the cancer level." P1 described his friendship on CSN as follows:

> "I don't know them very personally but I know them on the cancer level. And I know where they go and what they do and what they like just through the forum and stuff. You know if I have time and I'm sitting around, I'll log in and just see who is online and then ask how's Ann, or how's Ted or how's Matt[1]. We just kind of talk about just stuff. You know, their cat's name, how much wood the guy split intermingled with ... how are you with your disease. "

Besides their online experiences on CSN, interviewees also quoted individual differences or their personality traits as the reason why they continued participating on the site. For example, some mentioned that they tend to do charity and volunteering work even offline.

> "I wanted to help. I've been volunteering for a lot of stuff my entire life. I was a volunteer emergency services model in college [..] I volunteer now with a bunch of charities including this one in Florida." (P18)

Our log data analysis results provide additional insights about how people who choose to stay might be inherently different from those who drop out early - that is, their behavior differs even in initial days of their participation. Based on our analysis, members who stayed in the community for a long time were substantially more active even from the beginning of their CSN participation

[1]Names have been pseudonymised.

	seek emo support		seek info support		negative self-disclosure		positive self-disclosure	
	mean	sd	mean	sd	mean	sd	mean	sd
Early-dropouts	2.14^a	1.03	3.41^a	1.60	2.07^a	1.00	1.56^a	0.65
Mid-tenured members	2.12^a	0.98	3.41^a	1.58	2.30^b	0.96	1.62^b	0.70
Oldtimers	2.00^b	0.91	3.31^b	1.56	1.91^c	0.88	1.69^c	0.74

Table 2.5: Four types of support acts performed by early-dropouts, mid-tenured members and oldtimers in threads started within the first 30 days of their participation. Within columns, means with different superscripts were statistically different from each other.

compared to those who dropped out within a year. Specifically, we compare three groups of CSN members: those who stayed on CSN for different lengths of time: *"early-dropouts"* who stayed up to a month, *"mid-tenured members"* who stayed on CSN for 31 to 365 days, and *"old-timers"* who stayed longer than a year). In this analysis, we only consider those who logged into CSN at least once after registration (N = 51,097). We delineate early-dropouts and mid-tenured members at the thirty-day mark because the median minorlength of time these 51,097 users stayed on CSN was 31 days. We chose one year as the threshold for defining old-timers because cancer patients typically view the one-year mark as a milestone in their cancer treatment and call it their "cancerversary." Figure 2.3 shows the average number of thread-starting posts and responding comments members made over the first six months of their participation for the three tenure groups. One way analysis of variance (ANOVA) analysis showed that old-timers started significantly more threads and commented more even during the first month of their participation ($F(2,87) = 6.82$, $p<0.01$; 0.23 posts per person per day) than did mid-tenured members (0.11 posts per day) and early-dropouts (0.10 posts per person per day).

In addition to the *quantity* of members' posts, we also examined how the *content* of their posts during their first month of CSN participation varied as a function of how long they ultimately stayed on CSN. We found old-timers sought significantly less support (both emotional and informational), disclosed less negative content, but more positive content as compared with the two other groups in the earliest stage of their membership. We leveraged machine learning models to measure the amount of members' support seeking behavior and negative and positive self-disclosure contained in their thread-starting post We then used one-way ANOVA to test the differences between these acts among early-dropouts, mid-tenured members and old-timers. Table 2.5 shows the mean score and the standard deviations for the amount of each of these support-related acts performed for the three tenure groups. The tenure groups differed in terms of emotional support seeking ($F(2, 32837)=73.26$, $p<0.001$). Post-hoc Tukey tests indicated that old-timers sought less emotional support than the other two groups of members (both $p<0.001$) who did not differ from each other. The tenure groups also differed in terms of informational support seeking ($F(2, 32837)=15.90$, $p<0.001$), with the post-hoc Tukey tests revealing that old-timers sought significantly less informational support than the other two groups of members (both $p<0.001$), who did not differ from each other.

The tenure groups also differed in terms of negative self-disclosure ($F(2, 32837)=78.94$, p<0.001), with the post-hoc Tukey tests revealing that old-timers disclosed significantly less negative content than the other two groups of members (both p<0.001); members who stayed beyond a month also disclosed less negative content than members who dropped out within a month (p = 0.009). Finally, the tenure groups differed in terms of positive self-disclosure (F(2, 32837)= 94.89, p<0.001). Unlike the other support-relevant actions, the post-hoc Tukey tests indicated that old-timers disclosed significantly *more* positive content than the other two groups (both p<0.001); members who stayed beyond a month also disclosed more positive content than those who left within a month (p<0.001).

The small group of old-timers in OHCs contributed to the community in multiple ways.

Interviewees reported that old-timers on CSN make important contributions to the community by providing both direct and indirect support. Seven out of 20 interviewees recalled that they were directly supported by other members when they first joined the community, with support coming from those with similar cancer experiences to be especially helpful. For example, P20 said: *"And immediately [after registration] I got a personal message from a person. Her husband was a survivor but 15 years younger than my husband, but identical cancer, identical circumstances. And so that was like a lifeline to me. "*

Interviewees also reported that having experienced cancer treatment themselves enabled them to better help others. P2 described a scenario where she used her own experience to support other members: *"I'll post on the discussion group because somebody will say, 'I'm waiting for my results and I'm not sure how I feel about this or I'm freaking out.' And I'll say well this is what happened to me. Yes it's really tough to wait for results but you just have to do one day at a time and leave ... a little blurb on it."*

Besides offering others knowledge relevant to their disease, experienced members had also learned strategies for how to best respond to others. P6 noted a specific strategy she thought might be useful when trying to help others: *"...You can't throw out all the negative stuff all at once, which would made them even more worried. Rather you need to go bit by bit..."* P10, on the other hand, was sensitive to the type of information members of the community should be providing: *"I don't say specific things as you should do this, do that, for I know I'm no doctor."*

In addition to directly responding to other members to provide support, interviewees indicated that old-timers were also able to help in an indirect manner. First, by contributing the majority of the content on CSN, old-timers effectively made CSN an active group, which in turn attracted prospective members. P2 observed that she joined CSN after deciding it had a critical mass of activity [123]:

> "I found the online forum. So then I clicked on there, and I was pleasantly surprised, maybe pleasant not the right word for cancer, but it was just really nice, because I went in there, and there was like, all the different cancers. And so I found the head and neck cancer and I went in there, and it seemed like, that was actually a pretty active forum. And, you know, people ask lots of questions."

Second, responses old-timers left for a particular thread benefited other members and even unregistered lurkers who browsed the conversations on CSN, as P8 noted:

> "I think there's an awful lot of people, newcomers like me back then, [who] just go

Comments made by:	Reply to threads started by early-dropouts	Reply to threads started by mid-tenured members	Reply to threads started by oldtimers
Early-dropouts	17,942 (24.3%)	7,846 (10.6%)	11,643 (2.0%)
Mid-tenured members	6,030 (4.4%)	40,339 (29.7%)	36,108 (5.9%)
Oldtimers	48,037 (65.0%)	89611 (65.9%)	562,408(92.2%)

Table 2.6: Interactions between early-dropouts, mid-tenured members and oldtimers.

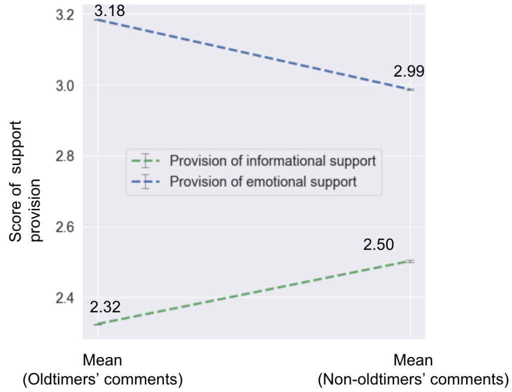
> on there and spend hours on there just reading other people's posts, seeing what their issues were, and reading how other cancer patients got through treatment."

In addition, as previously discussed, newcomers to OHCs often sought upward social comparisons with other members who have shown "no evidence of disease" after treatment to gain optimism and inspiration during their own treatment. Old-timers who have undergone treatment and improved their health conditions served as natural "role models" for this type of comparison. Interview participants also reported feeling hopeful after reading old-timers' positive updates after their treatment was over, as P14 remembers:

> "I read about these, you know, 'don't feel bad. I felt the same way you did, but there is light at the end of the tunnel.' You know, people who are battling don't give up, and life does get better after treatments were over."

Our quantitative analyses provide further evidence of old-timers' contributions to the community. Not only do they generate the majority of the content, but they also disproportionately provide emotional support to others. As is well known from prior research on many types of online groups [141, 142] including OHCs [81], a small group of core contributors on CSN were the heavy contributors. Although only 7.2% of CSN members stayed longer than a year on CSN, they contributed the vast majority of the content on CSN by initializing 66,604 threads (61.6% of the total) and creating 742,396 replies to others (85.1% of the total). Table 2.6 illustrates the pattern of interactions among early-dropouts, mid-tenured members and old-timers, operationalized as the number of comments each group made to thread-starting posts initiated by each group. The overwhelming majority of interactions that old-timers had were with fellow old-timers (i.e., 92% of the comments written by old-timers were replies to threads started by other old-timers). This finding strongly suggests that interpersonal ties and repeated interaction with fellow old-timers were major reasons for their continued participation on the site. However, old-timers were so active on the site, they also provided the most comments regardless of who initiated the thread. For example, they provided 65% of the replies to threads started by both early-dropouts and mid-tenured members. Thus, in a very concrete sense, old-timers were the fuel that kept this OHC running. In addition to posting more content, old-timers' comments contained more emotional support compared to the comments of those who dropped out earlier. Using Welch's t-test, we compared comments posted by those who stay less than a year and old-timers in terms of their average amounts of informational support and emotional support, as illustrated in 2.4a. Old-timers' comments contained significantly more emotional support($t(161747) = 66.33$, $p<0.001$) but less informational support ($t(159364) = -63.96$, $p<0.001$). This latter finding can potentially be explained, in part, by the fact that old-timers primarily communicate with other

(a)



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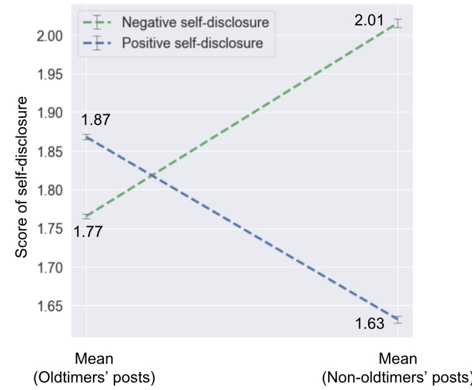
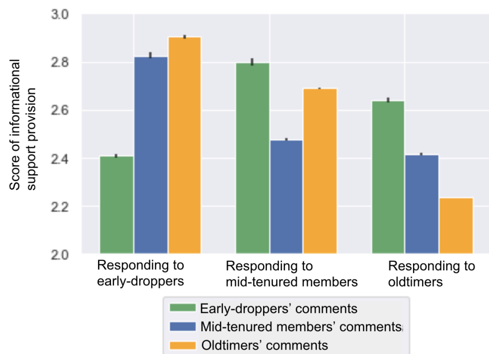


Figure 2.4: The comparison of old-timer and non-old-timers' support provision (a) and self-disclosure (b) based on Welch's t-test.

(a)



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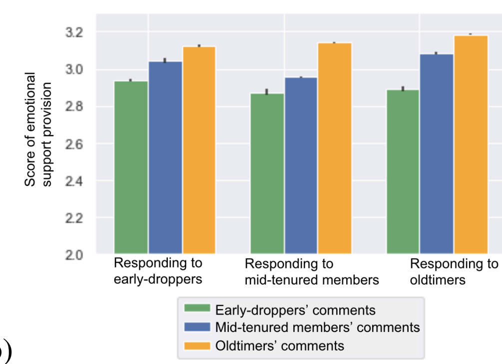

Figure 2.5: The average amount of informational support (a) and emotional support (b) per thread-starting post provided in comments by early-dropouts, mid-tenured members and oldtimers to the threads started by these groups.

old-timers, who no longer need or seek informational support.

We also conducted a set of six ANOVA analyses to examine whether old-timers' support provision varied based on the recipient of the support. We looked at replies to threads started by early-dropouts, mid-tenured members and old-timers separately, and investigated how old-timers' support provision differed from the other two groups of members. Figure 2.5 shows the mean amount of informational and emotional support provided in comments by early-dropouts, mid-tenured members and old-timers to the threads started by these three groups. We could see that, despite providing less informational support overall, old-timers were the most likely to provide informational support to early dropouts (mean = 2.90) and a reasonable amount to mid-tenured members (mean = 2.69). They provided little informational support to fellow old-timers. As for emotional support, old-timers provided more compared with early-dropouts and mid-tenured members regardless of the recipient.

2.4.3 Challenges of long-term participation in OHCs

Old-timers faced some unique challenges brought about by their own health problems and prior experience participating in an OHC. Reflecting theories about non-use of HCI systems [162] and the disease journey perspective [126], disengagement with OHCs is not necessarily a failure of the site's design, but may represent a logical reaction to one's changing life circumstances (e.g., remission or ending of treatment). However, as we have seen, a minority of members stay in the community to offer help to others even though their initial needs and life circumstances have changed. Although these old-timers indicated that they were eager to stay and support others, they also pointed to challenges and risks of continuing their participation, which could lead some of them to drop out of the community in the future.

It is reasonable to draw similarities between the behaviors of old-timers on CSN and the reasons offline volunteers stop their volunteerism, such as a need to return to other commitments in their lives and undesirable interaction with the beneficiaries, which may lead to a decrease in the value they place on their volunteer work and their satisfaction with it [12]. In addition, old-timers in OHCs may be plagued with the stresses similar to the burnout experienced by offline volunteers [28, 129]

Old-timers on CSN did express similar complaints. For instance, P9 explained how "wanting to get over with cancer" could lead to (tentative) dropout:

> "Sometimes I finally want to be done with the whole experience you know, I just don't want...Like my wife, she can't watch an ad for the Cancer Centers of America, she can't watch a movie that has cancer in it because she just can't handle it. She doesn't want anything to do with it. Sometimes I think about that too. People step away from this – they're done they don't want to do this anymore. "

Interviewees also reported unpleasant interactions with other members on CSN, as P13 reflected interacting with "a couple of whiners":

> "For example this one woman, she respond to all of these posts repeating her own experience, yeah, over and over and over and over. But she never answered any of these questions."

Nevertheless, interviewees insisted that, despite "feeling uncomfortable" with these experiences sometimes, these were not what drove them away. They felt capable of "handling it or just ignoring it." However, the old-timers on CSN expressed an additional challenge that seems specific to cancer-oriented OHCs: distress related to hearing of fellow members' deaths. Eleven of the 20 interviews expressed feeling "shocked" or "saddened" when reading about other members' deaths.

> "I know them through the message board, not personally. But yeah, there's been a lot of members that I become feathered by them passing. It was very difficult I would cry. I would be you know... I would feel very hurt I would just...you do become very sad." (P11)

> "But it's got to be depressing after a while reading about people that lost their battle with cancer. I could connect with them, though I never actually met them face to face, we had a bond because of a website. And you end up losing those people to something that you almost died from. So it's got to be depressing." (P13)

While similar scenarios have been described in prior work [10, 151], we found that discovering peers' deaths may have been especially heartbreaking for experienced CSN members because they often felt very connected to fellow OHC members, as P10 expressed:

> "I think probably a couple different things [for me to take a break]. Among them, when one or two of the women have died. It really affects you because you feel like you know some of these women via the posts on there...You know a lot of what they've done through so it's really hard to think that way."

Moreover, reading about other members growing sicker or dying may lead to downward social comparison, that is, comparing one's situation with those who are in a less desirable position. Unlike those who are earlier in the treatment, the direction of members' social comparison may change as a result of these losses. Earlier in their participation, members were able to perform upward social comparison with patients who are better off than they were and to seek for both information and optimism when relatively new to the site. However, as some stayed longer, they started to make downward social comparisons, comparing themselves to fellow users who are in worse off situations than they are. P3 illustrated this point by saying:

> "Seeing them dying...or being very very sick, I feel like I can do very little regarding this. The only thing I could do is to send prayers, which I think seems really weak."

P6 brought up that he can't help "reflecting that same situation to myself. What about it was me who suffered from that recurrence?" Legg et al. [111] suggested that downward comparisons could be threatening when they invoke concerns about another member's possible negative future cancer events, which could increase anxiety about one's own situation.

2.5 Discussion

This research investigated how members of OHCs evolve as they stay longer on the site. We employed a mixed-methods approach combining interviews, surveys, behavioral log analysis and automated content analysis. The research was informed by both a disease-journey perspective, which argues that changes in motivation and participation in OHCs are primarily driven by the members' disease states, and a more general online communities perspective, which argues that the changes are more generic, reflecting internal dynamics common to many types of online communities. Consistent with the disease-journey perspective, results indicate that members seemed to join the OHC because of health crises shortly after they were initially diagnosed or while undergoing active treatment. They were seeking informational support, often to inform disease-relevant decisions, and social comparison, to better cope with the uncertainty associated with their disease. However, most quickly left as their initial informational needs were met. Among the minority who continued to participate over an extended period, motivations for participation often shifted from receiving support to providing it to others. As in many other online communities [142], a small group of old-timers were responsible for the majority of the interactions in the OHCs. They were both capable and willing to provide support to other members. As in other online communities, the heavy contributors behaved differently from those who dropped out quickly after joining the community. But our research also presents several strands of evidence suggesting that the shift from self-centered to other-centered motivations was associated with their greater feelings of connection to and repeated interactions with other long-term members of the community.

The core members left for many of the reasons people might leave any community. However, one of the major contributions of our research was identifying reasons for leaving that are unique to OHCs – the emotional toll of participation, especially from reading about the poor health and even death of fellow members. Old-timers want to help others, but doing so had negative consequences that made continuing participation difficult and seemed to lead them to take a break or indefinitely quit using the site.

A strength of our work is the comprehensiveness of our findings, which were derived from a combination of behavioral logs, surveys and interviews; with all these data available, this paper provides a relatively holistic view of members' experiences in OHCs. Most of the prior work that studied members' journeys in OHCs relied either on quantitative methods, analyzing log data (e.g., [81]), or qualitative ones relying on interviews and surveys (e.g., [126]), and thus were often only able to focus on either changes in OHC members' observable behavior or changes in their self-reported motivations. Our work leverages both self-reported data including surveys and interviews, and behavioral data, which allows us to examine changes in OHC members' motivation (i.e., what they thought) and behavior (i.e., what they did) as they stayed longer in the community. These analyses used retrospective interviews in which participants reflected on their experiences at different times, and one-time surveys to compare old-timers with shorter-tenured members and longitudinal data, including behavioral logs to examine how individual members' motivation and behavior changed over time.

Chapter 3

Empower Peers with Better Skills for Support Provision

3.1 Introduction

People with mental health problems are increasingly turning to their peers for help instead of professional clinicians for reasons of cost and availability [55]. Prior research has shown positive outcomes from the use of non-professionals to deliver mental health interventions, with users judging peer support services to be as helpful as traditional psychotherapy [16]. Online peer counseling services have flourished in recent years[15]. For example, the support service we examine in this work, 7Cups.com, has supported nearly 40 million clients since 2013 and has attracted 320,000 volunteer counselors [1].

Yet the quality of the help people receive from online peer counseling services varies and depends on the skills of the volunteer counselors who staff them. Volunteer counselors typically do not have an academic background in psychology and are not as rigorously trained as their offline counterparts [150]. Prior work has extensively studied the development process that leads to the making of successful professional psychotherapists (e.g. [22], [168]). However, many of the commonly-adopted psychotherapy training methods, such as clinical supervision and role play, are not widely available for online volunteers[184]. There is limited understanding of how online volunteer counselors acquire skills as they evolve from novice to more experienced counselors. This understanding could inform the design of techniques and tools to help volunteer counselors to deliver therapy of higher quality and cope with the stresses associated with psychological counselling.

We conducted an interview study to investigate how volunteer counselors develop their skills in the context of 7 Cups - an peer support community for mental health. We found that although 7 Cups' mostly-text-based training materials and interactive exercises helped volunteer counselors understand relevant therapeutic knowledge, this material was not sufficient either in preparing volunteers to master technical skills for counseling, or in ensuring their own mental well-being. While volunteers reported difficulties in translating declarative knowledge into the conversational behavior they need to use in counseling sessions, they often have to develop strategies on their own.

[1] https://www.7cups.com/about/research-stats

However, their strategies usually come from intuitions based on their experiences as a counselor or client and the occasional and ambiguous feedback they received from the clients. When dealing with especially tricky situations, such as working with clients expressing suicidal intent, the volunteers were aware of site policies, but differed in how they implemented them. Furthermore, volunteer counselors often drew on personal experiences that were similar to the clients' to develop empathy with the clients. Indeed many of the volunteers had been 7 Cups clients seeking support, which provided them a unique strength when dealing with clients who have similar problems. However, this blurring of roles can also caused distress when hearing about clients' problems reminded them of their own. In addition, volunteer counselors reported non-session related problems, including maintaining professional boundaries with clients and having conflicts with other volunteers and the 7 Cups organization. Failure to deal with these challenges could cause negative consequences for the clients and the volunteer counselors themselves. We discuss potential implications from this study on how online peer support communities can provide better support for the volunteer counselors.

3.2 Related Work

3.2.1 Online Peer Support for Mental Health

Online health support groups are characterized by immediate availability (i.e., 24/7 access without geographic restriction) and the anonymity of members [126] for support provision. A number of online health platforms and communities, such as Talklife[2], 7 Cups[3] and SilverCloud Health[4], specialize in dealing with mental health problems [15]. Clients using these platforms can take advantage of group therapy through forums or chat rooms, blogs to create personal journals of daily experiences, and one-to-one therapy sessions with volunteer counselors or professional psychotherapists.

Prior work has provided some evidence for the effectiveness of the one-on-one conversations hosted by peers. For example, a survey study with 2700 7 Cups users indicated that users showed high satisfaction with the support provided by volunteers Baumel[16]. Moreover, the findings also suggest that receiving support from volunteers rather than professionals made users feel that the support was more genuine. Despite these suggestive findings, we know of no rigorous clinical trials showing the effectiveness of these online mental health support services. Since their success is likely to depend on the skill of their volunteer counselors, concerns remain about how to support volunteers' skill development.

In the context of online peer counseling, prior HCI work has focused more on specific strategies that are associated with better outcomes in online peer counseling [4, 32, 138, 150] than the development of individual counselors. For example, successful counselors tend to adapt their linguist style to that of their clients' and manage the progress of the conversation [4]; concrete, positive and supportive messages from volunteers are associated with better outcomes for the clients [32]. HCI researchers have also designed tools to help volunteer counsellors

[2]https://www.talklife.co/

[3]https://www.7cups.com/

[4]https://www.silvercloudhealth.com/

deliver better conversations; techniques such as technological writing assistance [145] and guided chat tools [139] have been explored. While these cross-sectional studies have been useful in suggesting the types of skills that successful volunteer counsellors use, more research is needed to understand which skills are responsible for their success and how competent volunteers acquire them. Similarly, while researchers have stressed the importance of protecting volunteer helpers' psychological well-being[144], we still need a deeper understanding about how volunteer counsellors can learn to cope with the stress associated with psychological counselling.

3.2.2 Skill Development of Volunteer Counselors

Lack of necessary counseling skills could cause negative consequences for both the clients and volunteer counselors themselves. According to prior work, unhelpful therapist behaviors, such as rigidity, over-control or a lack of knowledge, could make clients feel disempowered, silenced, or devalued [37, 158]. Previous studies also suggest that poor communication skills among volunteers providing support can lead them to feel increased anxiety as well as decreased self-efficacy[130]. Even if volunteers are successful in working with clients, they may suffer from volunteer burnout and high turnover [194].

The current research examines how the online volunteers evolve from novice to more experienced and presumably better counselors in the context of 7Cups. Particularly, we focus on two important goals for the success of online volunteer counselors. First, volunteer counselors should be able to acquire various technical skills and thus deliver counseling sessions of high quality. Second, volunteer counselors need to care for their own psychological well-being and cope with potential burnout. In the next two sections, we briefly review literature on how professional counselors achieve these two goals.

Acquiring the technical skills

Prior work identifies three important steps for counselors to acquire the technical skills related to the therapeutic process [17, 19]. First, counselors need to understand "what" the corresponding skills are (e.g., understanding the components of motivation interviewing). Second, they need to know when and how to apply this declarative knowledge in real-world situations (e.g., what to do when a client declines to open up in an active listening session). Counselors progressively accumulate larger and more detailed sets of condition-action rules to guide their problem-solving behavior in therapy sessions. As counselors gain more experience and expand their procedural knowledge repertoire, the application of procedural knowledge becomes more automatized. Third, counselors need to constantly reflect upon and internalize their declarative and procedural knowledge, so that it could be adapted to new, previously unencountered situations, because the therapeutic context continuously changes and simply repeating prior successful strategies might not work [17, 19, 120]. Novice counselors are especially likely to struggle in translating declarative knowledge into procedural skills [120].

There is no consensus on the best ways to teach counseling skills or which training methods produce the best outcome[147]. However, supervision and mentoring are generally widely recognized as key [69]. For example, an increasingly popular form of training professional therapists is to discuss videotaped treatment sessions conducted by a mentor [146]. When novice counselors encounter difficulties in applying procedural knowledge and skills in initial therapy sessions, they tend to fill in the void by imitating their mentors. Thus, their practice is very much influenced by professors and supervisors.

Maintaining helpers' well-being

Counselors can provide a valuable service to their clients, but doing so may be at the cost of their own psychological well-being. Both theory and practical evidence suggest that counselors' core tasks, being involved in others' mental health problems, can evoke considerable discomfort or even feelings of helplessness and fear [29, 65, 100]. For instance, clients' pain and loss or their attitude (e.g., lack of cooperative) could all become potential emotional stressors to counselors and lead to their countertransference, in which a counselor's reactions to a client is influenced by the counselor's personal vulnerabilities and unresolved conflicts[66]. Countertransference can have a detrimental effect on therapy session quality as well as the counselors' psychological well-being[65]. For instance, counselors may face anxiety and intense emotional distress when conducting therapy with suicidal clients [100, 109]. If it becomes a chronic strain, counselors' self-esteem would be lowered when they believe they are not providing effective support [59]. Counselors' inability to work through their emotional reactions could eventually escalate and lead to burnout, contributing to difficulty in managing everyday stress in their personal lives. Thus, it is generally accepted that people working in the helping professions are themselves in need of emotional support from counselors [177].

Although the challenges we described above were mostly drawn from research on professional psychotherapists, it is foreseeable that volunteer counselors could face even more serious difficulties. For professional counselors or graduate school trainees, adequate supervision and debriefing sessions may be the most effective ways either to teach them counselling skills [69, 147] or to help them to manage their own emotions [29]. These techniques are used less in volunteer organizations, especially online platforms. Much of the training and mentoring professional counselors receive is not available for online volunteer counselors and may undermine the goal of insuring an adequate supply of volunteers for any client who needs one. In this paper, we investigate the following research question:

RQ: How do online volunteer counselors learn knowledge, skills and strategies to become competent counselors?

1. How do online volunteer counselors acquire therapeutic skills to deliver high-quality counselling sessions?
2. How do online volunteer counselors learn to cope with the stresses of counselling to protect their own psychological well-being?

3.3 Method

To answer our research questions, we employed a qualitative approach to explore how volunteer counselors improve their session quality and how they maintain commitment to volunteer work. In this section, we first introduce our research platform, followed by a description of the data collection procedure and the analysis methodology.

3.3.1 Research Site

7Cups.com is an online psychological support service, where clients (known as members) with a variety of mental health problems participate in text-based chats with volunteers counselors (known as listeners). As of April 2020, 7 Cups had over 300,000 trained listeners from 189 countries providing support in 140 languages, supporting over a million people a month. Demand for the 7Cups service increased significantly since the COVID19 outbreak in 2020, increasing from approximately 14,000 conversational sessions between members and volunteer counselors per day before March 2020 to 20,000 per day after March 2020.

All listeners at 7 Cups are required to complete an initial training program before they are allowed to connect with clients in listening sessions. The training program consists of 1) a training course teaching active listening and similar skills and a test in which listeners are asked how to apply active listening skills in response to a scenario, 2) a mock chat with a bot and 3) an honorific oath. The content of the training course was based on academic guidance [68] and is presented using texts, images and videos. For example, when listeners were trained about how to conduct reflection, they were taught to “repeat back to the person the facts that they have just shared” with the goal of “drawing out more of the person’s story by showing that you are listening". Volunteers were also given guidance on how to handle emergency situations, including circumstances such as suicidal ideation that require an escalation to a professional. In addition, 7 Cups training informs listeners about the potential risks associated with offering help on the site (e.g., trolls and sexual harassment). The initial online training is meant to take between 45 minutes to 1 hour to complete all required modules, although listeners can go through it more quickly due to the multiple choice format of testing. The original training materials remain accessible to volunteer counselors throughout their participation.

In addition to the initial training, 7 Cups provides opportunities for volunteers to continue developing their listening skills and obtain support when necessary. For example, 7 Cups offers an optional, continuing education program featuring specialized mental health topics (e.g., anxiety, depression, and eating disorders), problems of daily living (e.g., loneliness, bullying, and family stress) and advanced counselling skills such as "Active Listening In-Depth." A badge system provides listeners an incentive to take further training. Besides the training programs, 7 Cups has community-based resources from which listeners can obtain support. Listeners are encouraged to sign up as members and start a one-on-one chat with a peer listener when they were emotionally triggered during counseling chats. A real-time, listener-only chat room is also available to all volunteers, where listeners can seek and provide peer support to each other when necessary. In addition, 7 Cups has forums that allow asynchronous communication and subforums dedicated to specific mental health issues such as depression and eating disorders. On these forums, volunteer counselors can learn about listening techniques and socialize with one another. Finally, listeners can be matched to more senior listeners and mentors who have had additional training to guide others in improving their session-specific skills and tackling more general problems of being a volunteer.

3.3.2 Data collection and analysis

To capture the richness and depth of volunteer counselors' experiences, we employed a qualitative interview method and conducted 20 semi-structured interviews with 7 Cups listeners to understand their learning experience. This study has been reviewed and approved by the university's Institutional Review Board. All participants have provided their informed consent to participate in the interviews, to have their voice recorded, and to have the conversation analyzed.

With permission from 7 Cups administrators. we recruited volunteer counselors who were over 18 years old to share their experience as listeners by making a post in 7 Cups' forum. A site-wide announcement was also pushed to increase the visibility of our recruitment message. Twenty listeners (5 male, 15 female) responded to our recruitment message and signed up for an interview. All of them had been a 7 Cups listener for at least three months. They were relatively active listeners; their self-reported frequency of 7 Cups participation as listeners was well above average, ranging from once a week to multiple times every day.

Interviews, between 60 and 120 minutes, took place remotely via video conferencing calls or audio-only phone calls. Inspired by [69], we interviewed the 20 participants using a combination of critical incident techniques and more open-ended approaches. Using the critical incident approach, we asked participants to think about counseling strategies they learned in their listener experiences and specific incidents that helped them come up with these strategies. Specifically, we asked the participants to explain why and how these incidents facilitated their improvement as listeners. Prior work shows that volunteers mostly develop skills through what has been described as "largely invisible" informal learning[47], and thus they are likely to have difficulties making connections between learning outcomes and the experiences that lead to them. With this in mind, we also asked participants to describe in an open-ended manner how they changed over their tenure (e.g., compared with your first couple of sessions you've just described, do you think you are a better listener now? Why or why not?). Participants also described positive and negative experiences they had (e.g., have you considered quitting 7 Cups? Why or why not?), in an effort to collect a wide range of experiences that may have influenced their counseling skill.

All interviews were recorded and transcribed. Guided by grounded theory [31], the first author started the inductive, open-ended qualitative coding by tagging topics in the transcripts. We then tried to build connections between the tags to identify themes in the interview data. After multiple iteration of thematic analysis, we grouped various themes and extracted key quotes to illustrate our findings.

3.4 Results

None of the 20 interviewees was a professional psychotherapist, and only two were attending academic programs related to psychology or social work (and both started their degree program after becoming a volunteer counselor at 7 Cups). The other 18 interviewees had no formal psychotherapy-related training. Twelve of the 20 interviewees had a "client account" as well as a ”listener account", meaning they had used 7 Cups to obtain support for themselves as well as to provide support to others. These nonprofessional listeners, however, reported being be able to provide valuable support to those clients who are in need of help.

In general, listeners reported having a positive experience at 7 Cups. In most cases, they are able to leverage the active listening skills taught in 7 Cup's initial training program to chat with clients who came in with problems. In the chatting sessions, volunteer listeners used techniques such as reflection, paraphrasing, and asking open ended questions to demonstrate they understood the client's problems and to draw clients out. They reported being able to promote a sense of empathy and support to the clients. Interviewees felt that they were able to provide support to those in need and make the clients feel more positive after the session; successful chatting sessions in turn bought listeners a sense of satisfaction. Positive feedback and returning clients led listeners to believe their chatting sessions were effective. For example. P12 recalled:

> "What's most impactful is when I have a member who comes back to me later and tells me about where they're at now and the impact that it had. And so I have had several members, whether it's a one off conversation, or I've talked to them for quite a while [. . .] For example this one guy, who ultimately decided to come out of the closet to his family, came back six months after we chatted and said, 'I don't know if you remember, but we talked about this. And I just wanted to let you know like, here's what happened'. "

However, volunteer counselors also faced challenges and negative experiences when providing support to others. Some challenges resulted from their abbreviated training and minimal experience, such as their lack of listening skills when they first started out, and were ones they expected; others, such as emotional turmoils or boundary management issues, are not. In fact, even the good counseling experience described above took time and struggle to achieve. In the sections below, we examine how volunteer counselors develop and become more competent over time. Specifically, we examine how they improved their therapeutic skills, grew a sense of empathy, and developed strategies to cope with the emotional distress associated with their experience as listeners.

3.4.1 Skill development as a psychotherapist

Development of therapeutic skills

Interviewees reported they encountered communication challenges during chatting sessions, often due to their inexperience and lack of related skills as a counselor. The volunteer counselors reported feeling confused and dismayed when conversations were not heading in a direction they desired, especially when the clients did not conform to their expectations of how they should behave in the sessions. For example, a client might not respond to interviewees' prompts, leading to unproductive conversations (e.g., "no matter what I said, the only thing he [the client] would reply, was 'I don't know'"). Clients might even critically challenge or confront the volunteers (e.g., "he [the client] was basically accusing me, like questioning my intention, doubting if I really tried to help"). An experienced professional therapist might be able to handle challenges like these, either because they were trained or they had successfully resolved similar issues before. Interviewees, on the other hand, reported they often needed to devise solutions to conversational problems "on the fly" especially when the problem was new or they wee inexperienced. When an existing solutions didn't work, interviewees reported not knowing how to hand unanticipated situations. For example, P11 described a typical situation where she struggled when facing a client who was very emotional entering the chat:

> "I had one member who was really angry at women, I guess... And he just... kept asking me ‘are you a woman? are you a woman’. Then he said ‘you’re a woman. you are a bitch’. It’s hard to know what to say to him at that moment really. It doesn’t seem that anything you say will be helpful. "

Although volunteer counselors at 7 Cups were required to take the hour-long training session before they could start taking clients, the theoretical knowledge they gained from this initial training provided only general guidance, but did not prepare them for translating the guidance into the specifics they needed to carry on a conversation with a real client. "After all, no one would prepare a script for me.” said P5, “You know when I was doing the [training] modules, I thought those were just straightforward, easy stuff. Like you need to show your understanding, you need to behave friendly, that kind of thing. But then I find that I have to express that with my words. Finding the exact words is much harder to grind. ”

To deal with challenges they encountered and to develop their counseling skills, volunteers counselors sometimes turn to peer listeners or even mentors for support, especially when they were unable to improvise a solution themselves. The interviewees described such external support as most valuable when it was very specific and tightly tied to the problem that they faced. Sometimes they even received precise instructions about what to do. i.e., the exact words they should say to the client. For example, P15 described how she received real-time support from peer counselors when she encountered a deadlock in a counseling session:

> "When she [the client] stopped messaging me back, I was in the listener chatroom. Like, I think it was something wrong. What do I do? I was freaking out. The people were like, if she wants you to be back, she’ll message you back. They told me to say, you know, "I’m sorry if what I said offended you. If you ever want to talk, I’m free. "And then I sent that message to her. This was probably why she messaged me back. "

Prior literature has highlighted the importance of mentors and supervisors providing timely feedback and modeling. Similar to psychotherapy trainees, volunteer counselors could occasionally get support from fellow volunteers and showed appreciation of the support that they were able to obtain. However, this kind of support was not always available to volunteer counselors on 7 Cups. Although 7 Cups had a variety of volunteer and paid roles to support listeners, such as mentors, ambassadors and community managers, the mentorship support at 7 Cups relied almost completely on other volunteers and is loosely organized (e.g., "I talked to my mentor only once after I was assigned. Just greetings. I don’t know where I could start with her...and she did not reach out to me either.") Interviewees reported that there was no guaranteed real-time solutions from the peer group chat rooms or from mentors, because volunteers in these settings were not obligated to show up and provide support. In fact, interviewees indicated that it took them a substantial amount of time and counseling sessions before they figured out potential resources they could draw upon for support. P10 talked about his situation when he was new to 7 Cups.

> "In the beginning it was all chats [with the clients]. I did one after another without knowing I could get connected with other listeners. I tried to explore some options available. I saw the forums. But it was after, I think, a couple of weeks after that till I found the group chat rooms. Later I found that really helpful."

Besides learning strategies from others, volunteer counselors also reflect on the situation and develop counseling strategies on their own, usually after they solved problems in particular sessions with clients. These strategies could be about technical knowledge (e.g., gaining more knowledge about bipolar by chatting with a client suffering from bipolar), perceptual skills (e.g., how to see beneath the surface of thoughts and actions of the client) or interpersonal skills (e.g., how to facilitate a conversation forward when in deadlock). An accumulation of such experiences often led to strategies to deal with similar challenges in the future. The integration of these if-then strategies to a therapist's procedural knowledge is often regarded as a key to the success of a psychotherapist [17]. Consistent with an informal learning process, such reflections and strategy development often took place incrementally and often outside of conscious awareness. Although some interviewees reported a specific incident that "clicked" and led them to think deeply, the majority of them could not recall a single significant incident that directly led to a strategy. Instead, they stressed the importance of accumulating experience. For example, P8 described how talking to similar clients many times helped her find an underlying pattern in the sessions:

> "I found over the years of doing this that most of the time, the first question people ask is not the question they really want to ask. Or the problem they think they're having turns out to be a completely different thing when they look at it again. For example, like one of these kids, coming to me, be like 'the society is getting me down'. After talking to so many of them, I now know that they would not come here because of the society, but because of specific things in life. "

Refinement and evaluation of therapeutic strategies

Interviewees also mentioned they progressively elaborated and refined their strategies, often using a "trial and error" strategy to see what techniques worked. With repeated use, evaluation and feedback, volunteer counselors were able to refine these strategies until they become relatively automatic and fluent. In addition,reflections also enabled the volunteers to discern in what context, under what conditions, and with what types of people particular strategies were useful. For example, P2 described how she developed her standardized way of closing conversations with clients:

> "It was about different things I did, trying to figure out what worked in terms of how to close out a conversation. Whether it it was helpful to say right away that 'I only have this amount of time versus to let things go and then give the heads up that I'd only have that amount of time'. What was helpful in terms of reassurances that we could talk again, as well as trial and error to figure out what I was personally comfortable with, in terms of how long a chat I was comfortable taking, and how the person I talked to felt. Over time, I've got pretty standardized language that I use in most cases, or then I'll flex based on who I'm talking to like in terms of age, in terms of what their style is, what they're struggling with [or] that sort of thing."

The trial and error learning mode described by P2 is typical among the interviewees. While clients' feedback can be good standards for volunteer counselors to validate or to refute the strategies they used, such feedback does not seem to be common. Unlike psychotherapy trainees, who often have mentors and supervisors providing feedback, volunteer counselors typically did not have these advising resources either. While a few interviewees mentioned direct, verbal feedback (e.g., ”Wow, that really that makes a difference”, “Thank you. That is something I would have never thought about”), many others noted that they needed to interpret indirect signals or rely on their intuition to decide whether a chatting session was successful or not. P6 mentioned that she considered recurring sessions as a positive signal: “I have tons of repeat people who are like, hey, I need to talk about something else with you.” Nevertheless, he also noted that these signals were sometimes ambiguous. “For someone who does not come back, it’s hard to tell. Personally I don’t take that as a negative really, but I won’t know exactly how they feel. ”

Note that these strategies are heavily based on volunteer counselors’ own experience and thus could be highly subjective and idiosyncratic. Participants, especially experienced ones, seem to be confident and have their own rationale for their strategies. Their insights usually came from their subjective feelings (e.g., "do I feel comfortable with this?") based on their experience as a counselor, the occasional and ambiguous feedback they received from clients, their own experience as a member-client when they actually talked to listeners, imaging themselves as a client, or even subjective judgements without a source of evidence.

Listeners did not act consistently when dealing with tricky situations (or the so-called gray areas), even though 7 Cups had explicit policies that they should follow. Instead, they frequently developed their strategies. Consider the case of clients mentioning the possibility of suicide. 7 Cups has clear policies when dealing with suicidal clients. The 7 Cups platform includes filters that automatically inform users using suicide-related language that 7 Cups volunteers are not trained to handle crisis situations and instead point them toward telephone suicide hot-lines staffed by people with extensive training. If a client expresses suicidal ideation in a conversation with a volunteer, 7 Cups policy is for the volunteer to immediately direct the client to a suicide prevention hot-line or www.suicide.org and disconnect from the chat using the script below.

> “I can tell you are going through a very hard time right now. I encourage you to reach out to the resources I have provided for extra support. As a listener, I am able to show you empathy and compassion, but 7 Cups of Tea is not a crisis referral center and I am not trained to help you through this difficult situation. In a few moments, I am going to leave the chat to provide you the space to reach out to the crisis centers. I am still more than willing to support you as your listener and will check in with you shortly.”

Despite the clear prescriptions about how they *should* behave during these counseling sessions, interviewees reported substantial variation on how they *actually* behaved. Of the eleven interviewees who reported they had dealt with suicidal cases, five reported that they followed the rules strictly, four mentioned they tweaked the rules based on their own understanding, and two expressed strong objection to the rule. For example, P15 indicated that she found the suicide rule legitimate, because she thought she was not qualified to intervene in suicidal situations. She explained:

> “I don’t think there’s anything wrong with the rule. Even I myself I don’t think I could be in a situation like that and I know I’m not very helpful with those kind of things so I didn’t have any problems. ”

Others tried to follow the 7 Cup’s guidelines in spirit while making modifications that allowed them to be more empathetic. For example P7 followed 7 Cups’ disengagement and referral guidelines but did not use the exact wording when disengaging because she tried to place herself in client's situation and felt the default script was not sufficient. P7 explained her rationale:

> "There was the protocol for that [suicidal] situation where you give them the number for suicide helpline in the chat. I would find if I was at their place, and I was saying all these things and then a person just set messaging me a phone number and then ended the chat. That would be so damaging. And there has to be a better protocol, whether it's, you know, notifying the website of this person's ID or something, I don't know, but it just seems woefully inadequate. It would just be more alienating for the person than he probably was. So I didn't use these sentences word by word. I said things like "I'm very sorry. You're going through this. I just said that you call this number. But there was nothing I could do because honestly, I think in that situation, that's like a liability."

Similarly, P6 also redirected suicidal clients to other resources, but she did not choose to immediately disconnect; instead, P6 chose to accompany the client when redirecting him. P6 discussed her approach below:

> I usually try to get them to go to the [suicidal hotline] website. But I don't want to just end the chat with somebody who's feeling like that... So I make sure that they go, like ask them questions about the site and stuff and they're gonna call somebody before I leave them. Yeah, I did redirect them but I don't, I can't just like, leave somebody like that. You know, and I know I'm supposed to, I probably should, but it's been successful because people do get back to me and told me that they called on the site or whatever.

Although most participants described small modifications to 7 Cups' rules, two expressed strong objections to the rules. For example P13 indicated that he did not feel comfortable following 7 Cups rules.

> "I don't think that [the suicidal] rule was making too much sense. I mean, at least I felt like, if I were the person I'd feel totally abandoned. Like, having that kind of thought made me even ineligible for a chat. I think it's not about theories, guidelines or whatsoever, it's more about my feelings as a person. ... I got it [a suicidal case] only once. The lady I talked to...I guess she did not come in and say she had those thoughts up front but she mentioned it when we were chatting. I think it was slightly different too. I just talked her through it, like I explained things like we all had that kind of moment, it's all gonna be fine. "

Another interviewee was even more explicit in objecting to the 7 Cups rules.

> "Okay, well, I can either talk to this person, like I would any other human being who's having a problem. Or I can ... hang up on them, right. I can say, 'No, I'm sorry. I can't talk to you. Go talk to this [hotline]. Bye.' ... I can't do that. I mean, it breaks my heart when somebody blocks me from a suicidal person,

In general, the interviewees were in agreement that accumulating listening experience is the key to developing counseling skills. Compared with trainees in psychotherapy, volunteer counselors on 7 Cups relied primarily on informal, experiential learning. Of the twenty interviewees, only one reported that they had referred to formalized psychological knowledge, such as training materials on motivational interviewing techniques, to hone their skills as a counselor. Another two mentioned they turned to Google to search psychological terms that they do not understand. Four interviewees mentioned they completed additional training modules on 7 Cups to acquire more information about counseling. Even though informal learning is known to be beneficial in acquiring procedural knowledge, participants demonstrated that they were able to obtain declarative knowledge from their experience as well. For example, instead of referring to psychological terms such as “defensive mechanism”, a number of interviewees were able to identity the common issue of clients unwilling to open up. P7 compared learning from training versus learning from accumulating counselling experiences:

> "I guess, since they [the 7 Cups training modules] are really information oriented, maybe make them a little more empathy oriented. You could include things like, snippets from things that people have to say about their own experiences with listening. But of course, I guess chatting with members is where you get those stories."

Empathetic skills

Empathy is key to the success of both clinical psychotherapy and peer support volunteers [16, 46]. According to prior research, peers are sometimes able to show more empathy than a professional counselor because they have had personal experiences similar to the clients’ [16]. Consistent with this research, our interviewees also reported that they are able to be more empathetic when they and their clients had similar experiences. For example, P17 thought that she was especially strong at counseling clients with eating disorders because she had experienced it herself but poor at counselling clients with grief because she didn’t have personal experience with it:

> “I came in knowing my strengths. I think I got a lot better at the other stuff. So when I started, I focused on eating disorders because I had actually done that. I have personal experience there. And I’ve done some peer type counseling in that space already. ... But I struggled if I was talking to somebody where it was an issue that I have less familiarity with. For instance ... grief was always a really hard one for me to discuss, even on 7 cups where you have a moment to think in a moment to type back.“

In addition, since 7 Cups is a global service where the assignment of volunteer counselors to clients is based on a first-come-first-serve basis algorithm[5], volunteers can work with clients from a different cultural background than their own. Cross-cultural empathy has been widely recognized as an acute challenge for professional counselors[43], interviewees also reported facing similar difficulties. As P9 noted:

> "[In a conversation] with a guy earlier today. He’s telling me about how school is tough. So, I’m like, you know, here’s a, here’s a thing you can go look at. And he kept telling me that I don’t understand how things are in India. So I can’t relate to him ... and I’m like, Okay, well, you can probably find somebody from India, who can relate to you better."

When interviewees felt they were inadequate for a topic, they sometimes used search engines to learn more (e.g., looking up bipolar disorders using Google) or take the corresponding training

[5] 7 Cups also allows clients to search specific listeners by the issues they have, they countries they are from and the languages they speak

modules available at 7 Cup (e.g., the bipolar training module). Others picked up the knowledge through conversations with clients (e.g., learn about resources available for people with alcohol use disorder after client disclosing his experience). Still others, recognizing limitations, would selectively refrain from working with clients with whom they could not be empathetic. As P1 noted:

> "I had a woman who came to me and she was a brand new mom. And she was going through postpartum and stuff like that. So I'm 42. When I was 26, I had the ability for me to ever have kids taken away from me. I don't know what it's like to be a mom. Do I have maternal instincts? Yes. But I have no clue what she was going through. And I told her that right away and I said, may I help you find a listener? "

Volunteer counselors were also able to leverage their own experiences as clients on 7 Cups to take the clients' perspective and act towards them as they would have wanted to be treated. This is a unique strength for peer counselors, who often assumed both roles as a volunteer counselor offering support and a client-member seeking it. For instance P5 disapproves of multitasking by talking to multiple clients at the same time. "That's extremely noticeable and it hurts. It hurts my feelings. So and I think it hurts other people too. "

In summary, volunteer counselors reported relying upon what is known as "person empathy" in therapeutic literature–near understanding of the client's world or a sense of what it is like to be that person [45]. To gain person empathy, volunteer counselors heavily relied on their personal experiences. They were successful when they shared personal experiences, but struggled when they did not. When the volunteers were unfamiliar problems their clients presented them, they either tried to learn relevant factual information or acknowledged their limitations and refrained from dealing with those problems.

3.4.2 Learning to protect volunteers' psychological well being

Boundary Management

Interviewees reported having issues with maintaining their professional boundaries with the clients. While prior literature has highlighted how boundary violations could potentially harm the clients [9, 153], our participants emphasized how boundary violations posed risks to volunteers themselves.

One typical example of boundary violation occurs when clients request volunteer counselors' personal information (e.g., age, gender, marital status, and contact information outside 7 Cups). Although 7 Cups has implemented a number of filters to prevent such requests from going into the chat, interviewees still reported encountering these requests. This posed a conflict for volunteer counselors who wanted to express friendliness and warmth to support the client while at the same time maintaining their privacy and adhering to 7 Cup's policies to abstain from off-platform contact with clients. P4 describes this conflict when a long-term client asked to connect on Facebook.

> "I was helping that guy who had an issue with his teachers in high school. At the point when he asked [for my information], we had chatted...I think at least five times, all on 7 Cups. I thought it was kind of natural for him to ask because we were just talking

about things like Facebook. Then he asked me if he could add me [as a Facebook friend]. I don't think he meant anything else but I was aware of 7 Cup's rule [of no offsite contact]. I think it's quite possible that he may not know it but I did not know an appropriate way to bring the rule up. So I thought, like I was helping him anyway. I don't use Facebook a lot anyway so it's probably gonna be OK."

An related boundary management problem involved volunteers devoting more time to a client than they wanted to. This was not a common type of boundary violation for professional counselor, mostly because their counseling service was remunerated with an hourly fee, whereas volunteer counselors provide a free service. Nine of the 20 interviewees mentioned that they had struggled handling chat sessions that went too long, especially when they were new to 7 Cups. Five of them admitted that they had considered leaving the site because of the problem. P2 described the problem this way:

> "When I first started 7 cups, I was literally letting someone talk with me for like four hours at one time. You know, we would resolve their issue they originally came for, and they would just go on and on and on. And I didn't know how to set my own boundaries to say, hey, I need to pull away and do my own life, you know what I mean? And I need to eat or use the restroom."

In both cases described above, participants described difficulties turning down clients' requests and thus failed to protect their own boundaries, even though these requests were against their own wishes. Interviewees felt they were not taught appropriate ways to deliver their message, and thus often feel awkward when rejecting the client. They expressed lack of confidence in their communication skills, fearing inappropriate ways of expressing rejection might end up hurting the client, which was inconsistent with their altruistic goals.

> "When I first started, I was in high school. I was on 7 Cups all time during class. Oh. And there were chats I would have like going all day. I later realized that, you know, probably shouldn't have even had. But at the time, I was...maybe very engaged in the conversation. There might be a part of me who wanted to call it a day but I really did not know how to deal with it, like how to properly say it out without causing harm. "

The boundary managment challenge is especially difficult when the it came from a long-term client with whom they have had repeated sessions. Because of the nature of therapists' involvement as support providers, clients often become very attached to and sometimes develop close relationships with their therapist [54]. At 7 Cups, clients and counselors could reach out to each other directly after they chatted at least once. Thus, in addition to requesting extension for an existing chat session, long-term clients could "keep nagging" the volunteer counselors whenever they were displayed as online at 7 Cups until the counselors got back to them. Participants also reported difficulties turning down a client they considered a friend; they experienced role conflict when trying to be a friendly peer to their clients and a counselor. Twelve of our twenty participants indicated that they felt they were friends with the clients to some extent, four of whom believed that the friend relationship was stronger than the counselor one. Participants described a sense of awkwardness and embarrassment as if they were turning down a friend: "You know, it's [refusing to disclose Facebook information] almost like say 'No' to your buddy. I just felt really bad." (P7)

Maintaining a professional boundary is not an easy task even for professional counselors. 7 Cups' initial training provided volunteers guidance about internet safety and self protection. They informed volunteers about 7 Cups rules to protect their boundaries (e.g., no-offsite communication) and identified support channels available if they needed to report clients actively violating community rules. In subsequent training modules, 7 Cups also provided a specialized module called “Boundary”, which covered the theoretical definition of boundary and potential risks when boundaries were violated. Several tips for how volunteer counselors could manage their boundary with clients were also presented, but were rather vague. A sample strategy in the training module is presented below:

> “Identify the Symptom. Look at your own life situation and see where boundary problems exist in your relationships. Ask yourself, “Where have I lost control of my property?” Identify those areas and see their connection with the family you grew up in.”

Among the 20 interviewees, only one (P8) mentioned that she referred to this training module, and she noted that such written materials were insufficient for complicated issues like this and mentorship was preferred.

> “If you don’t put these boundaries, you will continue having this go on, and then we have these amazing ambassadors who actually took time and taught you. They didn’t throw a link out and be like ‘you read this’. They actually taught you and had practice tests and stuff like that. So that was very helpful. The downside is, you know, we don’t have a lot of folks around to take the time to teach.”

Other participants did not recall getting help with boundary management and insisted that they had to figure out corresponding strategies themselves. They indicated that they were in a sink or swim mode before they figured out how to manage boundaries themselves. For example, P3 reflected: “If I did not learn them [the coping strategies] myself, I probably was gonna get burnt out. People would keep taking advantage of me all the time. So luckily I was able to handle that eventually.”

Participants described their learning experience as mostly informal, for they felt the knowledge "was there" after they had accumulated sufficient counselling experience. This view is consistent with informal learning processes, which are largely implicit; unless they are explicitly probed, learners who engaged in informal learning tend not to make connections between their learning outcomes and the learning acquired through experience [124].

> "So, sometimes it was like, okay, I would start typing to say, hey, listen, I gotta go. And then they would start typing a whole another paragraph. And I’d have to read that and respond. You know what I mean? So it was like a never ending cycle. So finally, I just realized, I’ve got to just say no, when I need to do something and just go. " (P18)

Emotional triggers

Interviewees described that it was sometimes hard for them to manage their own negative emotions when helping others. Such negative emotion could be either triggered by hearing a client’s traumatic story or by interacting with an uncooperative client.

Professional therapists and social workers often suffer from secondary trauma; working with clients who have suffered from trauma can cause therapists to become traumatized themselves

[67]. Our participants reported similar experiences. Long time participation at 7 Cups could also lead to a sense of chronic, accumulating negative experiences. P19 for example indicated that the first suicidal case she faced three years ago at 7 Cups still haunted her.

> "The first [suicidal] one I did not take well because I had messaged her and we kept talking for a little while. She told me that she really wanted to kill herself and I told her to come and chat with me again at her leisure when she wanted to. And she has never answered me to this day and I… Yeah, it really freaks me out. "

Although sessions involving possible death are general emotional triggers, many interviewees also reported that they had personal triggers, which would cause distress when certain topics were mentioned in the counselling sessions. Such triggers are often related to volunteer counselors' past personal histories, including sexual assault, alcoholism, or suffering from an eating disorder. While sharing similar experience could facilitate empathy, it could also stimulate negative emotion for the counselors. Volunteer counselors could be particularly vulnerable to this, as many rely on their personal experience and a strong shared identification with the clients to provide emotional support. P20 recalled her experience chatting about sexual assault as a victim to it.

> "I was sexually assaulted in the past. So when the member came to me to chat about that, my own feelings came up too strongly. I was hoping that I could help her but I realized that I simply could not. Even thinking about it made me...you know, go back to that scene. Later I figured that this topic might be one of my triggers and I have avoided it ever since."

Participants expressed frustration with guarded clients whom they perceived to be reluctant to become deeply involved in the conversation. These conversations could lead to frustration and loss of self-efficacy. On one hand, volunteers blamed the client for "refusing to collaborate". On the other hand, they tended to question their own therapeutic skills, feeling incompetent. P3 described an experience when she was providing support to a woman who was filing for divorce:

> "It seemed that everything that I either said, she either didn't want to do or was very hopeless and within a very negative state of mind. Like I was trying to provide her support, or refer her to resources… She wouldn't listen. So I was questioning, like it was me or it was her. I could totally be inexperienced but I just felt frustrated when she did not seem to engage. "

7 Cups has a section in their initial training that teaches volunteers how to cope with potential triggers. The training says that such triggers are normal and introduces ways to cope with, it such as seeking support from another peer listener. However, many participants were not aware of their own triggers until they occurred in the course of a conversation, after the damage had already taken place (see the P20 quote above).

Conflicts with other stakeholders

In addition to the stresses emerging from counselor-client interactions, volunteers also occasionally had problems when interacting with other peer listeners or 7 Cups as an organization. Social relationships on the platform are not limited to dyadic ones with clients, and interactions with peer listeners and paid 7 Cups staff were inevitable and important for governance and training.

Interpersonal hassles with peer volunteers and volunteer organizations also occur in many off-line volunteer organizations [140, 194]. Participants in 7 Cups reported disappointment when they had direct conflicts with peers or when peers were not acting as expected. These types of negative interactions can reduce volunteers commitment to the community. For example, P20, who feared that a client would discover her real, off-line identity, was disappointed when peer listeners dismissed her desire to change her username:

> "I told them [the other listeners] about the issue. And I think I got a reaction that I found to be dismissive especially when I shared the experience and I asked them for suggestions whether I should have changed my nickname. And they were saying that as long as they [the clients] didn't try to approach me or text me, it was OK. But still they said that if I wanted to change anything, I could, but I should have mentioned something like more serious, more solid, not that just some kind of, you know, a paranoia that someone might follow you. They didn't say paranoia, but it's almost like, 'hey, you're paranoid, No one is going to follow you' like the way they were talking to me. "

Similarly, P16, a male listener, reported disappointment when seeking support from a fellow listener after being trolled by a client using sexual language:

> "I needed to talk about it. And I started like telling her [the peer listener], you know, I'm struggling with this because it just kind of really bothered me. And her response was nothing, nothing else. She said 'but I'm a woman and we get 10 times that.' That was it. "

Some interviewees also reported negative experiences when interacting with peer moderators. Moderators at 7 Cups are listeners promoted to more advanced roles in the community, where they have the right to apply community rules and potentially ban others. To obtain the moderator role, one needs to file an application and get approved by the official 7 Cups community. P13 expressed disappointment with a peer moderator who blocked him without listening to his case and showed a lack of empathy:

> "I personally was reported by a mod here. I won't name that specific mod but the thing is that I tried to explain to him what happened. But he took sides fairly quickly. He did not even bother to scroll the chat upwards or to see what was going on in that either. They just saw that last snippet of the chat and be like 'Okay, this person [the participant] was wrong]. He [the moderator] would not listen and be able to empathize in the manner which they should be empathizing. They were just enforcing... I feel they're just imposing, like 'you did this, okay, you are blocked, you're muted or whatever you do'."

Five participants mentioned the conflicts with peer listeners or moderators led them to reduce their participation in 7 Cups. Of the five, three mentioned that they were prioritizing the counselling tasks over other non-counselling ones. Specifically, they tried to support clients while minimizing the interactions with other stakeholders in the community. P11 described her rationale for continuing to volunteer with 7 Cups despite her disappointment some peers:

> "Briefly [considered leaving 7 Cups], yes, but never seriously because I can't leave my members. I have left all roles besides listener, but I wouldn't abandon my members.

> There's some of them that I think that would be more destructive to and my intent the entire time and big aside is to serve members. "

While quitting is one way for volunteers to cope with the stresses associated with volunteer work [194], when they quit the volunteer organization is losing a valuable resource. In the case of 7 Cups, clients who seek support might not receive it. In addition, interviewees also reported that witnessing other listeners leaving made them feel sad and loose confidence in 7 Cups. 7 Cups did have one module (out of 65 available) in their added training program named "Listener Community Guide" which presented guidelines for interacting with fellow listeners. However, only four participants mentioned that they completed any of these advanced modules, and none of them mentioned the guide for interacting with listeners or how it had been helpful to them.

3.5 Discussion

In summary, listeners reported a positive experience at 7 Cups. They thought the training they received combined with their cumulative experience working with clients equipped them to help the clients. Yet our findings also indicate the introductory training modules provided by 7 Cups were themselves not sufficient in preparing volunteer to deliver high quality counseling sessions or protecting their own mental well-being.

Volunteer counselors often faced ambiguous situations and had to develop counselling strategies on their own. Real-time support from experienced listeners was not always available. The strategies developed by the volunteers, moreover, often heavily rely on their personal experience, with little feedback from fellow listeners or clients or evidence-based, best practices. Volunteers also struggled in non-session-related challenges and were often in sink or swim mode; that is, if volunteer counselors were unable to tackle these challenges themselves, they might choose to quit 7 Cups.

Although it might be possible for mental health support platforms to increase the length and rigor of the formal training sessions their volunteer have to complete, this will increase the burden on the volunteers and decrease their supply. In the next sections, we propose ways for online peer counseling platforms to improve volunteers' skill development without overwhelming the volunteer counselors.

3.5.1 Developing a collective knowledge repertoire for therapeutic guidelines

Participants reported that they occasionally encountered challenging, unexpected sessions when their past experiences could not be applied. Volunteers often had to develop strategies on the fly when they confronted these challenges. However, it was often difficult for volunteers to figure out the best approach in the little time available during a counseling session while simultaneously conversing with a client. Even though 7 Cups has a listener-support chatroom where volunteers could ask questions and more experienced peer listeners could provide them support, this type of resource for volunteers is loosely organized. When a volunteer needed help, too few experienced listeners were typically available or the ones available not might have had relevant experience.

To help volunteer counselors deal with these difficult situations, platform designers might consider developing a collective knowledge base that documents widely-accepted community practices for different counseling scenarios. Prior research demonstrated the professional therapists are effective when they develop their own procedural knowledge repertoire [19]. However, given the limited number of cases each volunteer counselor might encounter, it might be more useful to pool the collective knowledge of individual volunteers rather than having a central body set the agenda. For example, one could imagine a question and answer site similar to StackOverflow, which would allow volunteer counselors to get answers on very detailed and practical questions (e.g., How do I get a client to open up when she keeps saying “I don’t know” to my open-ended questions?). Volunteer counselors could search this database when they were not sure about how to proceed within a session and are not able to rely on the availability of other peers to obtain support.

3.5.2 Improving mentorship through systematic program design and novel AI technologies

Our study found that volunteers needed more than the current training to prepare them for some of the challenges they encountered as counselors. Although the existing 7 Cups training modules covered topics such as boundary management and Internet safety, our participants did not perceive these modules as particularly helpful. In professional psychotherapist training, senior psychotherapists often provide "psychotherapy supervision" [184] to junior ones, by monitoring the quality of the therapy they offer to the clients, providing feedback, and serving as a gatekeeper for those who want to enter the profession. Although 7 Cups developed a variety of specialized roles, including the peer mentor role, to support listeners, interviewees reported difficulties in developing a meaningful relationship with a mentor. For reasons of confidentiality, under supply of senior counselors serving as mentors, and difficulties maintaining long-lived relationships between trainers and trainees in a volunteer labor market, volunteer counselors rarely had opportunities to practice their counseling skills with real-time feedback from senior mentors.

A direct design implication for platform designers is to implement a more systematic mentoring program than the ad hoc type that 7 Cups offered. In addition to matching mentors with mentees, the organization needs to provide detailed guidelines for how such mentorship programs could be the most effective. For instance, mentors and mentees could hold regular debriefing sessions to discuss counseling techniques in addition to mentors answering specific questions brought up by mentees. Regular mock chats could also be arranged to help mentees practice and obtain valuable feedback from experienced mentors.

Alternatively, AI-based tools could also be incorporated to play the role of a mentor when human mentors are not available. For example, one can develop a "mentorbot" that automatically analyzes and evaluates volunteer counselors’ performance in counseling sessions, detect problems in real-time or after a session is completed, and provide them with hints to help them interact with clients. Volunteer counselors can learn what they did well or poorly and how they can improve. Furthermore, this "mentorbot" approaches could be enhanced if the AI mentorbot could incorporate the collective knowledge base that documents widely-accepted useful strategies for different counseling scenarios (described in section 5.1).

3.5.3 Improving volunteer counselors' psychological well-being

The organizations hosting online volunteer counselors should better prepare volunteers for the challenges they might encounter, including both session-related ones and and more general ones. For example, when initially signing up to be a volunteer counselor, many volunteers were not aware that their personal boundaries might be compromised and that they might struggle to reject boundary-violating requests from clients they intended to help. Such mismatches between expectation and reality, if not handled properly, could lead to negative consequences such as additional stress. Training for volunteer counselors needs to teach them how to care for the clients without becoming overly emotionally involved themselves.

In addition, these organizations could also incorporate more support channels for non-session related challenges. On the one hand, they could provide informational support, such as training modules about time management skills. On the other hand, emotional support might ease the psychological burden brought by feelings of burnout.

Chapter 4

Friends and Competitors: Peer Support among Gig Workers

4.1 Introduction: Atomized Gig Workers

A 2015 World Bank report showed that around 25 million people in Europe and the U.S. were participating in some gig work [105]. And the number is growing. And yet, the more than 25 million gig workers are atomized. Workers are rarely in the same physical space, and the interaction between companies and workers is principally conducted via digital interfaces [185]. Workers interact almost exclusively with the app, which allocates the work and not with a human supervisor or with co-workers[84]. Due to the nature of the smaller gigs involving more straightforward tasks, workers typically complete their tasks independently and rarely collaborate with each other as they usually do in traditional companies. After all, these gig economy platforms' goal is said to increase efficiency[2], and therefore, the redundant, often unnecessary communication between colleagues is discarded.

Such atomization might exacerbate a number of problems gig workers already faced. First, atomization limits workers' opportunities to obtain task-related information from their peers, makes it harder for workers to understand how their individual activities fit within the broader picture, and hence worsens the information asymmetry and power imbalance between workers and platforms [84, 185]. Second, prior literature suggests that meaningful social and collegial relationships in the workplace can buffer the effects of work-related stress[91]. The lack of meaningful social interaction with colleagues might lead to feelings of loneliness and cut off the channel where workers could support each other [191]. Third, although workers' diverse background and motivations have already made it difficult for them to identify targets for collective action, atomization would only make this issue more irreconcilable, as it again hinders the communication between peer workers [135]. To sum up, atomization is not just a lack of fixed physical workplaces, but the absence of viable worker networks [176]. Without an effective social network, gig workers have difficulty accessing the social capital (i.e., resources available from their social ties) from their supervisors and coworkers [73]. The resources can range from useful information to emotional or tangible support.

Despite the atomized working conditions imposed by gig work platforms, workers were still able to meet each other in both online and offline spaces [83, 190]. For example, a rideshare driver could know another driver simply because they were friends before starting their gig career. She could also bump into a stranger driver when queuing up in the airport. Besides, she could participate in online forums and social media platforms to communicate with her peer drivers. A variety of topics could be covered, ranging from a rant about drunk passengers to best practices to boost their income.

Indeed, social media groups such as Facebook groups and Reddit are known to facilitate access to social support and broaden the resources that the members have access to [38, 179]. They are as particularly well suited to the maintenance of weak ties[56] and knowledge sharing[172], thus seems promising in alleviating the 'atomization' problem gig workers are facing. Recent evidence from a study of gig workers also suggested that social media groups had the potential to facilitate the information and emotional support exchange, coordination, and collective action for gig workers, and helped them form new kinds of group social identities [84, 112].

However, these gig workers' groups also suffer from challenges experienced by OHC groups. The temporal nature of gig work might result in a high turnover rate in these groups as well, for members typically drop the group after their short-term gig career was over. Gig workers similarly lack the expertise in crucial issues in the on-demand economy, especially how the algorithm that manipulates their job works. In addition, unlike the members of health support groups, gig workers have conflicts of interest, as they are competitors in a highly competitive market. Hence, it is not clear the extent to which conclusions from prior peer support research can be applied to groups of this type.

In the dissertation, I study the peer support exchange among gig workers in online spaces, whom the on-demand platforms often assumed isolated. In Chapter 4, I present a qualitative study aiming to understand how online social media groups provide informational and emotional support to physical gig workers. Combining interviews and content analysis of social media posts, I found that social media groups can serve as platforms where gig workers exchange information, build connections, and organize collective actions. While workers can obtain concrete experiential knowledge from peer workers, we found that they are less likely to share difficult to obtain information or to share with people who might compete with them. In addition, because of the competitive nature of gig work and the diversity among workers, the workers sometimes have limited empathy with each other, which impedes the exchange of emotional support. While social media groups could potentially serve as platforms where workers organize collective efforts, several factors, including the obscurity of the overall picture and other workers' activities, prevent that from happening.

4.2 Related Work

In this section, I first introduce the definition of physical gig workers and explain why we focus on this specific group of gig workers. We then examine atomization and the informational and emotional challenges it brings. Lastly, we draw on the prior success of social media groups in other contexts and discuss how social media groups could potentially help resolve some of the challenges we discussed.

Depending on how the gig service is fulfilled, gig workers can be roughly divided into two categories: physical gig workers whose work is conducted offline and locally, and virtual workers whose work is performed online [39, 173]. Physical gig work consists of transportation services (e.g., Uber and Lyft), delivery services (e.g., Instacart, Doordash, Grubhub), as well as household and personal services (e.g., Taskrabbit, care.com)[94]. Because the COVID-19 pandemic presented unique challenges to physical gig workers, whose work required them to risk exposure to the virus, we try to understand how gig workers dealt with these new challenges and what resources they leveraged. We also explore how CSCW systems could help in this case.

4.2.1 Challenges faced by gig workers and atomization

Prior research has found that being a physical gig worker can often lead to challenging and frustrating experiences. First and foremost, physical gig workers are often poorly compensated [18]. A 2019 U.S. study shows that delivery gig workers earn an average hourly wage of $17.10, handyman gig workers $16.71, and driver gig workers $14.31, which all pale in comparison to online freelancers' average hourly wage of $25.33 [53]. Moreover, gig workers typically do not receive employee benefits, such as health insurance, and they are expected to cover their own expenses, such as gas expenses and vehicle depreciation as well [97]. In addition to low pay and little to no benefits, physical gig workers also deal with income uncertainty [94]. The nature of working as on-demand, contracted workers is that there is not much job security - workers are usually not earning when they are not working [1]. Workers are at the whim of the market; if there is no market demand, they may end up wasting time and gas driving empty cars for some unpredictable period of the day or waiting in lines.

The working conditions of physical gig workers are also far from ideal. Rideshare drivers, for example, suffer from abuse at different levels of severity ranging from verbal abuse to physical assaults [3] and sexual harassment [75], partially because their work often involves dealing with the public in isolation. Moreover, physical gig workers are often the victim of racial discrimination, as reflected in fewer working opportunities, lower ratings [62], and lower market prices for underrepresented populations [44]. Furthermore, unlike, say, flight attendants who are trained in the management of their own emotions and in emotional appeasement of customers, physical gig workers, who are untrained in this area, are nonetheless expected to exert such emotional labor in appeasing the needs of their customers. This expectation is reinforced through the rating system initiated by the gig platforms, in which customers are encouraged rate their experiences with the worker [152]. Such poor working conditions are associated with negative psychological outcomes such as anxiety and decreased psychological resilience [11, 97, 119, 167].

Information asymmetry is another core challenge faced by gig workers [99, 117]. Algorithmic management allows gig platforms to automatically organize and coordinate large groups of workers in a highly effective manner, but they are usually secretive about the algorithms that determine how jobs are allocated [88]. Because of the lack of transparency, workers find it difficult to interpret the decisions made by the algorithms. Such information asymmetry clearly favors the gig platforms' interest because it undermines workers' ability to make rational decisions and develop corresponding strategies [110]. For example, because rideshare drivers might have little insight into how passengers are assigned, they cannot consciously strategize about which trips are more profitable to take and which should be avoided [157]. A strike in May of 2019 organized by rideshare drivers explicitly targeted information asymmetry and demanded data transparency.

Collective labor activities, such as negotiations, work actions, strikes, and corporate campaigns, are effective ways for workers to advocate for better working conditions [57, 98]. However, geographical dispersal of gig workers (i.e., *atomization*) poses obstacles to collective activities because it limits the communication among workers [35, 42, 178, 185]. Indeed, most gig platforms, perhaps intentionally, do not facilitate in-app communication among workers. This separation is further exacerbated by the typically simple, individualistic nature of physical gig tasks, which hinders collaboration and interaction among workers and reduces opportunities for collective action. Although prior literature noted that 'spatial proximity and temporal synchronicity' could alleviate the atomization effect for physical gig workers [192], COVID-19 has further isolated gig workers from one another.

Atomization (i.e., the isolated and individualized nature of gig work) seems to exacerbate a number of problems faced by gig workers. First, atomization limits workers' opportunities to obtain task-related information from their peers, makes it harder for workers to understand how their individual activities fit within the broader picture, and thus worsens the information asymmetry and power imbalance between workers and platforms [84, 185]. Second, prior literature suggests that meaningful social and collegial relationships in the workplace can buffer the effects of work-related stress [91]. The lack of meaningful social interaction with supervisors and colleagues might lead to feelings of loneliness and cut off the potential avenues through which workers could provide support for one another [191]. Third, although the diversity of worker background and motivations have already made it difficult for workers to identify targets for collective action, atomization would only make this issue more irreconcilable, as it again hinders communication among peer workers [135]. To sum up, atomization is not just a lack of fixed physical workplaces, but the absence of viable worker networks [176]. Without an effective social network, gig workers have difficulty accessing resources (e.g., useful information or emotional support) available from their social ties, such as supervisors and coworkers [73].

4.2.2 Social media groups as a supporting infrastructure for gig workers

As independent contractors, physical gig workers can only obtain limited support and resources from their gig platforms. Structurally, gig platforms are typical examples of risk transference [119], where they displace the risk and responsibility from the corporation to the independent contractors themselves. Thus, gig workers are unlikely to receive benefits like health insurance and paid sick leave like their counterparts in traditional companies, though a number of platforms including Uber, Lyft, Instacart, and Doordash have issued new policies that offer some of the aforementioned benefits in limited circumstances in response to COVID-19 (see [77, 79, 80]). Moreover, informational support is provided to workers typically in the forms of textual FAQ (available in the help menu of the applications), manual hotlines, and local service hubs [117]. However, most of these local offices, such as Uber's Green Hubs, were temporarily closed during the COVID-19 pandemic [78].

The Internet has the potential to help gig workers overcome some of the problems of atomization. Given the limited external support available, we expect online social support, especially peer support, to be particularly important for physical gig workers. Social media groups such as Facebook groups and Reddit threads are known to facilitate access to social support and to broaden the resources that the members have access to [38, 179]. These social media groups are particularly well suited for maintaining a loosely tied community [56], and thus seem promising in alleviating the 'atomization' problem gig workers are facing.

Indeed, a number of prior studies have identified social media groups as useful platforms for providing social support to independent workers, including Amazon Mechanical Turk(mTurk) workers [160], Airbnb hosts [72], rideshare drivers [3, 95, 106, 152], and online freelancers [190]. First, gig workers can leverage these groups for their informational needs. For instance, rideshare drivers are known to communicate via these groups to share experiences, gain insights, and discuss their workarounds for common challenges they face. Important topics such as the surging price mechanism, safety measures, and Uber rules and regulations are also covered [3, 95]. Social media groups also provide emotional support to gig workers [3, 72, 106]. As gig work is often regarded as low-status, social media offers workers a safety net where they are less likely to be judged as some might fear stigmatization by their strong tie networks such as family and friends [112]. By listening to one another's experiences, members in social media groups can provide emotional support to one another by allowing their peers to vent their frustrations and potentially devise workarounds [3, 72, 106]. Limiting platform access to individuals who share similar experiences also brings in a sense of community and social inclusion, which might help workers cope with the social isolation they face [164].

However, we also identified a few gaps in the prior research. First, existing research has largely focused on the potential benefits of social media groups in facilitating peer support. Little is known about how gig workers actually perceive peer support, and the limitations of social media groups in helping gig workers cope with their challenges. Second, it is generally acknowledged that the atomization of gig workers makes it difficult to coordinate collective activity across dispersed, individual workers, and social media groups could be a potential solution [178, 189]. Lastly, while social media groups have been recognized as playing a central role in structuring and organizing labor activities among virtual gig workers (e.g., mTurk workers [160] and online freelancers [190]), it is unclear whether and how the physical gig workers (e.g., Uber/Lyft drivers and Instacart workers) would use social media groups to organize offline strikes.

4.3 Method

In this study, we conducted semi-structured interviews with 20 physical gig workers from the United States. We also performed a content analysis on 162 posts on subreddit r/Uberdrivers and 173 posts extracted from a semi-public Facebook group for rideshare drivers in New York City. In addition, we analyzed 100 replies from r/InstacartShoppers related to the Instacart March 2020 strike (see [163]) in order to take a close look at how online group members reacted to the strike. Below, we present the details of our method.

4.3.1 Interview

The interview study was initially planned in November 2019 with the goal of understanding how social media groups provide informational and emotional support to rideshare drivers. The first author joined multiple local and nation-wide Facebook groups for rideshare drivers to observe the interactions within these groups. Four in-person formative interviews were carried out in February 2020 with drivers from the authors' local regions. With the unexpected COVID-19 crisis, we decided to restructure the study and expand the scope of our study to include other physical gig workers (i.e., delivery people and handymen) in addition to rideshare drivers. Another three formative interviews were conducted in April 2020 with local rideshare drivers to understand how COVID-19 has affected their work and life. The near year-long observation of gig worker communities, along with seven formative interviews, have greatly informed our interview protocols. We used COVID-19 as a probe to unfold the process of how workers obtain informational and emotional support to cope with the new challenge. The interview protocol included questions about how interviewees typically acquired general support acquisition (e.g., "if you need to obtain information about your work, where do you go?"), as well as how social media groups play a role in supporting their work (e.g.,"Can you describe to me how you would typically participate in these groups? Can you describe to me one post that you found the most helpful in these groups?"). All twenty interviews reported in this work were conducted via Zoom audio call in July 2020, the month when the U.S. reached a monthly record of 1.9 million new COVID-19 cases [30].

We aim to cover three types of physical gig workers in this study: rideshare drivers, food delivery workers, and handymen. We recruited participants using both online and offline methods. For online recruitment, we posted open recruitment messages in relevant Facebook groups. Groups on Reddit tended to be more restrictive about recruitment of this type, so we took a different approach with Reddit recruitment by sending direct messages to members of relevant gig work subreddits (e.g., r/uberdrivers and r/instacartshoppers). For offline recruitment, we employed snowball sampling (similar to [106]). Thus, these participants did not necessarily belong to the same online groups as the interviewee who referred them. Other offline participants, in particular, Taskrabbit workers, were recruited when we reached out to the participants directly using the application. This approach was useful especially because the social media groups for the handyman type of workers were not as active as the other two (e.g., r/Taskrabbit has about 1800 members as of Oct 15, 2020 while r/InstacartShoppers has 36.8k). In addition to these two primary methods, one participant was recruited directly as a friend of a member of our research group. Although the goal of the study is to study how online social media groups provide support to gig workers, we found it important to talk to those who did not participate in online groups as well, for they might provide a different perspective on why these groups are not particularly helpful to them. The combination of online and offline recruitment thus yields a more diverse participant pool with differing amounts of experience in using work-related online groups.

We present the demographic information of our interviewees in Table 4.1. The participant pool consisted of 20 gig workers from across the United States, with five working for at least one rideshare company, and six working for a gig platform like Taskrabbit that favors handyman-type work. Of the 13 participants that worked in food delivery, five worked for Doordash, and four worked for Instacart, and four worked for both, making them the two most popular gig platforms among our pool. Most were currently working for at least one gig platform at the time of the interviews as of July 2020. Thirteen participants did gig work part-time alongside another, typically more traditional job, while only five considered their gig work to be full-time jobs. Two participants described themselves as "mixed", meaning they did gig work part-time during the school year and full-time over school breaks. Thirteen participants engaged in gig work before the COVID-19 pandemic hit the country, while seven began doing gig work after the pandemic

ID	Companies	Company Type	Full / Part Time	B/A Mar 20’	State	Recruitment
P1	Uber, UberEats	Rideshare, Food Delivery	P	Before	ME	Offline
P2	Lyft, VIA	Rideshare	F	Before	NY	Online
P3	Uber, Lyft	Rideshare	F	Before	CA	Online
P4	Taskrabbit, Rover	Handyman	P	After	PA	Offline
P5	Taskrabbit	Handyman	P	After	PA	Offline
P6	Taskrabbit	Handyman	P	After	PA	Offline
P7	Taskrabbit, Rover	Handyman	P	Before	PA	Offline
P8	Taskrabbit, Postmates, Airbnb	Handyman	P	After	PA	Offline
P9	Uber, Doordash, Postmates, Taskrabbit	Rideshare Food Delivery, Handyman	P	Before	PA	Offline
P10	Instacart, UberEats, Doordash, Postmates	Food Delivery	P	After	NY	Online
P11	Instacart	Food Delivery	F	Before	NY	Online
P12	Instacart, Doordash, Postmates, Shipt	Food Delivery	P	Before	NY	Online
P13	Instacart	Food Delivery	P	After	NY	Online
P14	Instacart, Doordash, Grubhub	Food Delivery	P	Before	MI	Online
P15	Instacart, Grubhub, Doordash, UberEats	Food Delivery	Mixed	Before	GA	Online
P16	Ubereats, Doordash	Food Delivery	Mixed	Before	SC	Online
P17	Doordash	Food Delivery	P	Before	IN	Offline
P18	Doordash	Food Delivery	P	After	MI	Offline
P19	Instacart, Postmates, UberEats, Doordash	Food Delivery	F	Before	AZ	Online
P20	Uber, Instacart, Grubhub	Rideshare, Food Delivery	F	Before	CA	Online

Table 4.1: Recruitment demographic for Interviewees

	Informational support				
Code	Seek experience	Seek solution		Share external info	Share experience
Facebook	62 (35.8%)	63 (36.4%)		8 (4.6%)	13 (7.5%)
Uber Reddit	29 (21.5%)	37 (27.4%)		21 (15.6%)	37 (27.4%)
	Emotional Support			Tangible support and commercial	
Code	Humor	Rant	Offer emotionalsupport	Offer tangiblesupport	Commercial
Facebook	8 (4.6%)	7 (4.0%)	3 (1.7%)	6 (3.5%)	14 (8.1%)
Uber Reddit	19 (14.1%)	26 (19.3%)	2 (1.5%)	1 (0.7%)	2 (1.5%)

Table 4.2: Content Analysis Codes for the Uber NYC group and r/uberdrivers

took hold. We defined "before" COVID-19 as before March 1, 2020. Any participant who did not start gig work until after that date was designated as starting "after" COVID-19.

To kick off the data analysis, the research team held brief discussion sessions following every interview. More in-depth weekly meetings were organized starting the first week of data collection. During the meetings, the research team gathered virtually to discuss emerging codes and themes from the interview. All interviews were audio-recorded and transcribed after the data collection was wrapped up. Guided by grounded theory [31], the three independent, trained coders started the inductive, open-ended qualitative coding by tagging topics in the transcripts. We then developed a codebook iteratively, starting with topics of interest based on prior discussions and existing literature. After multiple iterations of thematic analysis, we grouped various themes and extracted key quotes to illustrate our findings.

4.3.2 Content Analysis

To examine gig workers' interactions in social media groups, we collected posts from both relevant Facebook groups and subreddits. Our data sources include a Facebook group organized by rideshare drivers from New York City, called UBER,VIA,LYFT, DRIVERS IN NEW YORK CITY (about 11,000 members, referred to as the Uber NYC group in the rest of the paper), and the Reddit community r/uberdrivers (about 76,000 members). These groups were chosen mainly because they have a large, active community and thus might reflect a diverse pool of members. In addition, the aforementioned platforms are both grassroots-based, meaning they are not associated with any of the gig work platforms.

We first looked at the Uber NYC group. Posts were collected between April 20, 2020, and May 15, 2020, resulting in a total of 173 posts in the coding. Two independent coders then started to develop codebooks with the first 85 Facebook posts, using a combination of provisional coding and open-coding [95]. Afterward, the coders discussed the codes, resolved the conflicts, collectively developed a new codebook with consolidated codes, definitions, and examples, and applied the new codebook to the remaining 88 Facebook posts. The group performed another check-up after finishing coding the entire Uber NYC group dataset to resolve conflicts and refine the codebook.

We then examined data from r/uberdrivers. Because r/uberdrivers has much higher traffic (averaging 39.1 posts per day in 2020), we picked a starting date (March 15, when the U.S. hit 1000 COVID-19 cases) and collected all posts that were submitted after that day. We applied our codebook to this new dataset and ended up collecting 162 posts up until the end of March 18, for we reached data saturation with the 335 posts we collected. Table **??** presents an overview and counts of our codes. We grouped the posts into actions based on the type of social support they provided, namely informational support, emotional support, and tangible support. Note that the total of the percentages does not add to 100%, for some code could belong to more than one category. We will explain and delve deeper into these codes in the results section.

To understand the impact of social media on collective labor rights activities, we collected posts related to the recent, nation-wide Instacart strike. In late March 2020, Instacart workers led a strike to demand expanded sick pay, more company-provided personal protective equipment, hazard pay, and an increase in the default tip percentage on orders [163]. We identified ten relevant posts on the subreddit r/InstacartShoppers by searching for the keyword "strike" in posts and selecting those that were posted around the strike time and with over 30 comments. Among these ten posts, six expressed positive opinions towards the strike, and four were negative. For each of the ten posts, we picked ten up-voted comments for further analysis. For the strike-relevant posts, two independent coders followed an open coding procedure to identify themes focusing on members' attitudes towards the strike. In addition, we coded each message to determine whether the commenter participated in the strike and whether they held a positive opinion towards it.

4.4 Results

In general, the results show that social media groups like Reddit and Facebook groups help connect workers and expand individual workers' "professional" social networks. Given the solitary nature of gig work, gig workers typically work in isolation. The interviewees reported having small social networks of other gig workers they know personally, ranging from 0 to 10 people. For interviewees who did know other gig workers personally, many mentioned that they did not meet their "gig friends" through gig jobs, but simply happened to have other friends or family members who did gig work. For example, P1 said: *"I have a pretty significant network of friends that do similar work. And we're not friends necessarily because we do the same work. We just happen to know each other."*

Although social media groups connect gig workers with one another and potentially facilitate support exchange among peer workers, only a small portion of gig workers are a part of these groups. For example, the subreddit r/uberdrivers has approximately 68,000 users, and one of the major nationwide U.S. Facebook groups for rideshare drivers, UBER DRIVERS, has approximately 28,000 members, while Uber is said to have had 750,000 drivers total in the U.S. in 2017. Most interviewees stated that they discovered these social media groups accidentally, either while searching for information via search engines or upon being referred by a gig friend. Other interviewees relied on their prior experience with social media to locate useful resources. For example, P15 said: *"So I was like, I'm sure there's going to be channels in here for these gig jobs. I use Twitter and Reddit the most, from a social media standpoint. I assumed that I would be able to find a channel on Reddit for it."* Noticeably, the gig platforms often do not provide direct links to grassroots support groups, and none of our participants stated that they located these groups through the platforms' official channels.

In the following sections, we report how gig workers exchanged informational and emotional support on social media groups. We then discuss the effectiveness and constraints of social media groups as platforms for organizing collective labor action.

4.4.1 Informational Support

Workers exchange various types of information in social media groups, which supplement the information they receive through official channels

Interviewees mentioned a number of channels where they were able to obtain task-related information, including personal observation and reflection, government authoritative information, and gig platforms' official QA and support hotlines. Most of them believed these official channels were sufficient for both beginning the job (i.e., onboarding) and routine operation but were not as helpful when gig workers encountered unusual problems. Interviewees complained that the platform-provided information consisted of written instructions and other resources that were difficult to comprehend. They also noted that platforms took too long to reply to questions, and any help that they did receive was not satisfactory as the hotline operators were unable to resolve their issues. For example, P13 described how Instacart's official support failed to assist her when she was unable to deliver an order to a client: *"And [Instacart's support] is outsourced somewhere in the world and 99% of the time, they are no help. Or if they are [able] to help, they take a long time to help. So, that's time you're wasting, when you could be doing another order."*

These evaluations of the official support help set the stage and provide a rationale for how social media groups supplement the information already available to workers. Our qualitative coding of social media groups shows that the majority of posts were for informational purposes, as 82.7% of Facebook posts and 76.31% of the Reddit posts are either seeking or providing informational support. Specifically, there are four major types of posts that lead to information sharing behavior, as illustrated by Table 4.3.

- **Seeking solutions**. Workers often directly ask questions in social media groups. Most questions are close-ended, soliciting either a simple Yes/No answer or specific responses. The replies (comments) would benefit not only the worker who posted the questions, but also others who have similar issues or concerns due to the transparency of the conversations.
- **Seeking experiences**. Workers also elicit opinions from peers who have similar experiences in an effort either to initiate a discussion about certain topics or simply to find companions. Such posts typically start with language such as "Are there any other people...," or "Did anybody else...". Based on our observations and coding, this is a major category of posts in these social media groups, as it accounts for 35.8% of the Facebook group posts and 21.4% of the Reddit posts (both social media platforms are among the highest among information provision activities). The accumulation of various data points provides workers with a good reference by allowing them to compare their own experiences with the experiences of a large number of peer workers.
- **Sharing experiences**. Members make new posts to share their personal experiences and observations about their gig work, often accompanied by photos or screenshots. The shared information is often time and location sensitive. Frequent topics include personal income, local traffic, business hours, or warnings about bad clients. During the initial outbreak of

Code	Definition	Example
Seeking solutions	Ask for answers and solutions to specific issues directly	Do anyone know if it is possible to drive for uber or Lyft in the state of New York with seattle Washington plates just wondering
Seeking experiences	Ask for similar experiences from other members, often accompanied with self-disclosure	Mitsubishi Outlander for UberXL? Anyone drive a Mitsubishi Outlander for UberXL? I've seen some people talking about how it's the best since it's cheap and gets good mpg, but then it know others say they drive an Outlander but don't even do XL because the third row is too small. Thoughts?
Sharing experiences	Share personal experience releated to gig work	As I was leaving the LAXit with passenger, I saw 3 black and white airport police cars parked in the LAXit entrance driveway and pulling over random uber drivers. They use to harras uber drivers on the waiting lot for all kind of bullshit things and tickets were $1000 flat plus 30-day impound. Uber covered those tickets in the beginning, but after some time, they declared, that tickets and impound fees are on you
Sharing external resources	Share pointers to external sources	"IRS issues warning as Bay Area workers receive 1099s from Uber, even though they've never driven a rideshare" (https://abc7news.com/5964785/)

Table 4.3: Code book for information sharing behavior on social media groups. Example 1 and 3 are Facebook posts; example 2 and 4 are from Reddit.

COVID-19, many workers posted observations about their local gig market.

- **Sharing external resources**. Besides subjective experiences and feelings, members of these groups also share external resources. The posts within this category are primarily just links to task-relevant information. During COVID-19, crucial information such as changes in government policies or important press releases from gig platforms is often shared in social media groups.

Concrete and experiential knowledge is valuable for workers

The analysis of the social media posts illustrates that many workers share their own experiences or ask for similar experiences from other workers in social media groups, which highlighted the importance of concrete, experiential knowledge. Experiential knowledge refers to truth based on personal experience with a phenomenon [21]. While experiential knowledge can be unique and idiosyncratic, they can also be more or less representative of how others experience the same problem, especially when there are common circumstances. An example of this is the discussion surrounding the application for unemployment insurance (UI), which was first introduced on March 27 and allowed qualified applicants to receive an additional $600 per week. A significant number of relevant posts (34 out of 72, 19.8%) were made between April 20 and May 15 in the Uber NYC group, as the community members were collectively making sense of this new policy. In order to gain understanding of their own situations, members inquired about others' experiences with their UI applications (e.g., "Guys, anyone got this message after applying for unemployment? I called the number, an automated message says "do not call us, we will call you"), and also sought out solutions by directly asking about specific challenges they encountered in their application process (e.g., "Question. Does anyone know about if get a call from Labor department to say your claim weekly payment is ready now you can claim it by going to labor department website .",but when I go to the link of it it doesn't go ahead. .Please can anyone tell me how to claim it ?") Although it might be difficult for individual workers to personally get to know many of the other peer workers and accumulate a large number of data points, social media groups allow workers to obtain information otherwise unavailable and compare their own situations with other workers' experiences.

The interviewees also mentioned that reading about other members' experiences was especially beneficial in preparing themselves for unexpected situations. For example, P3 described how reading about another driver being deactivated by Uber helped him prepare for similar situations in the future.

> "I read about, like, how some of these drivers got deactivated and there's no proof, you know, just because some crazy rider said something and... I find that very disturbing, how Uber can just deactivate you with absolutely no proof. So, I'd like to be prepared if something like this happens. I put myself in his situation, what would I do in case something like that happens? So, if I got deactivated for nothing I've done wrong, then I would have a problem with that. "

Similarly, P12, an Instacart shopper, noted that reading posts about others' shopping experiences was beneficial because she was able to call on common solutions when she encountered a problem.

> "One time someone posted about Instacart, ..., sometimes the picture of an item won't match ... the description of the item or how it's named. So that happened today. [According to the post], usually what people do in that instance is they just try to follow what the picture is, and then just double check with a screenshot. I entered the app to that customer today, and I was like, 'do you want ... this fruit bar thing that says or do you want ... this cereal, that's ... what the picture is'. They clarified that it was ... the cereal in the picture. So I was like, 'Okay, great'."

In sum, social media groups are particularly helpful in sourcing experiences from peers with whom workers are otherwise unable to connect and thus help alleviate the atomization effect inherent to physical gig work. Both location-specific groups and nation-wide groups have different strengths for members sharing and seeking experiences. Nation-wide groups such as r/uberdrivers could help workers overcome geographic differences and collect valuable information from across the country. Location-specific groups, on the other hand, seem to be useful in collecting experiential knowledge that is highly relevant to their local context.

“Reddit people talk about how their areas are doing. Like how the Uber drivers can set their rates in California now. Discussing the PUL, unemployment insurance, how people do in different states, how like the riots affected some areas.

(P19, commenting on nation-wide r/uberdrivers)

I find that, like, the New York one, it's more helpful because someone will say something about like Tops [Friendly Market], or like Dechicos [& sons] so it's a lot more.. Like, I recognize them a lot more.

(P10, commenting on local Facebook group for New York State)

In addition to sourcing a wide range of information, any member of these groups can retrieve this information with the search function on these social media platforms. Even though an answer is dedicated to a question initiated by one particular member, it can still benefit a wider audience. A number of interviewees described that they would utilize the search function to check if 'someone has a similar situation to me' before asking a question in the group. In this sense, the social media groups serve as knowledge bases where the best answers are collectively sourced and preserved.

Some information carries emotional costs.

Some information, often the ones about personal experiences, shared in the groups make some members uncomfortable even if they are perceived as providing useful information. For example, four out of twenty interviewees specifically pointed to the so-called "boasting posts", or posts where members share their earnings either by verbal description (e.g., "So Saturday night I did $XXX in Y hours and Z minutes. How am I doing?") or by attaching a screenshot of their earnings. Interviewees used negative words to describe such posts but still noted the benefits in reading them. P15, for instance, described the trade-offs in reading "gloating posts. "

"I'm not one of the people that ... are posting their earnings like 'look I got this really big batch with this unicorn that tipped me $50.' It happened once but, you know, I'm not gonna gloat about it. Though, it has been useful to get an idea of what it's like in their areas around me. Because when people gloat, they also give a lot of information about particular areas, cause they have no shame about showing pictures with addresses and stuff. So, that gives you an idea of which areas are doing good, which ones are doing bad, which ones have the good tippers and which ones have bad customers. If it's worth my effort to drive halfway across [location] or not. "

Another example of trade-offs was "ranting" posts intended to share negative experiences, especially those written with profanity and in an extremely harsh tone. Interviewees described them as "very annoying," especially when they judged the poster to be at fault. P10 recalled her reactions to a post that she did not feel good about:

"When people post about a bad customer experience...I remember one person, they're like, "oh, like, I had to refund all these items, they didn't want any replacements." And it's like, okay, yeah, that's annoying, but at the end of the day, what the customer wants is what the customer wants, so just, like, do it. Many times it just turns out that, like, it's the shopper that was in the wrong."

Fear of competition prevents workers from sharing information in social media groups

As for information sharing, while some interviewees described their experiences of responding to others' questions and expressed willingness to help out, thirteen out of the twenty interviewees described themselves as "lurkers" in these groups. These users were in the browse-only mode most of the time and would only post if they themselves had a question. For those who posted, interviewees reported sharing information mainly via answering questions in passing.

Although lurkers are widely recognized in all types of online communities [133, 137], four interviewees explicitly identified the fear of competition as the main reason they did not share information, which is not a common reason in other types of online peer support groups. Specifically, they prefer not to disclose information believed to be difficult to obtain, such as their "secrets for success." P14 explained his rationale for why he would not share his secret strategies for working for Uber in the local Facebook group he participated in: *"I mean, these are based on my experiences. I took several months to figure them out. It cannot just be there for free. I paid for it. [The other members] gotta pay for their lessons too."* P16 explained that he resists sharing information with peer drivers because every driver is "taking business away from me":

> "Because for me, honestly, every new driver is taking away business from me. You know, every new driver that joins is taking a piece of the pie. And there's only going to be so many customers, and there's basically an unlimited amount of drivers."

P13 added his observation about how the nation-wide Reddit and the local Facebook group differ, speculating that the former is more informative because it involves less direct competition.

> "Typically, Reddit people, when you ask a question, are more honest and forthcoming because it won't directly affect them. So, if you say, 'what's a good area?' or 'What's the best thing to do for this particular gig?' Or like, for Instacart, 'how to be a good shopper?' They're going to honestly tell you the truth. You know, Facebook is basically, especially with the Instacart Facebook groups, they don't want another person to compete with them."

In addition, interviewees with more experience mentioned that the groups are not as helpful as they were when they were new to gig work. Thus, they are not as active as they were previously, lowering their chance of sharing. For example, P7 described how his level of activity decreased on Facebook groups: *"I used to reach out for help [on Facebook] when I was starting out because sometimes I wasn't sure know what I was doing. I don't really post nowadays."* P20 further adds to this line of thought, noting how new workers' questions tend to be repetitive:

> "Every single day, people were asking the same stuff, like, hey, this is my first time driving. I'm not really sure what do, any advice? You know, what's, how much money do y'all make? And it's the same stuff every day. It's like, alright, dude, chill, like, please, we get it. It got annoying, it was basically the same stuff every single day, consistently."

Code	Definition	Example
Humor	Post memes, share humorous images, or discuss experience in a joking manner.	If a fart can get through underwear and a pair of jeans, how can a mask made of cloth save you from covid? Asking for a friend..
Rant	Strongly express negative emotion	Title: Getting Reported By Someone I really hate how UBER never tells me which customer had a problem with something I did during a ride. I'm not asking for names or anything, I get the privacy angle. But at least give me specifics instead of vague sentences. Cause when you give me vague statements I won't learn anything event if I said/did something minor to offend a customer. I wanna give the platform the benefit of the doubt. But all it tells me is that people take advantage to scare the shit out of their drivers. How do I know this isn't a person a canceled (like a recent drunk I kicked out) getting revenge on me? It's ridiculous.
Offering emotional support	Express empathy compassion, or send prayers to other members.	TAKE advatage of all the time we all have#pray and seek forgivness#indeed this is the month filled with blessing, happiness, and forgivness#everything is temporary and we all have to return to ALLAH# ALMIGHTY ALLAH MAYALWAYS BLESS US ALL IN GOOD AND BAD TIMES#AMEEN

Table 4.4: Code book for emotion sharing behavior on social media groups. Example 1 and 3 are Facebook posts; example 2 are from Reddit.

4.4.2 Emotional support and social ties

Workers tend to exchange less emotional support compared to informational support in social media groups

Compared with informational support, emotional support accounts for a smaller portion of all the posts shared in these social media groups for physical gig workers (14.82% in Facebook, 34.8% on Reddit). Among them, two major categories stand out (as illustrated in Table 4.4). First, members often post humorous content such as memes or jokes to uplift the morale of the group or to relieve any work-related stress. Second, consistent with prior work, social media groups provide gig workers with a place to vent and complain about their work-related frustrations [3, 106]. Additionally, there were members initiating prayer or religious posts, but they only account for a minor portion (2 posts in the Uber NYC group, 1 post in r/uberdrivers).

Interviewees' reactions to emotional support in social media groups were mixed. Some participants mentioned that they received emotional support from peer workers in online groups and felt they were not "some outsiders". Learning that they were not alone in dealing with these difficulties gave them a sense of comfort, as well as a sense of community. For example, P17 discussed his experience as he checked the Facebook group when the application crashed.

> "Every now and then the app would crash. And so I pull it up on there [Reddit]. And sure enough, about three or four other people are talking about the same issue. So that was nice. Because it made me feel like I wasn't the only guy- I was having the same problems as everyone else. So it made for a little bit better experience. So things like that helped out."

Disclosing negative experience (e.g., rants and complaints) are often implicit requests for emotional support in other online peer support groups [182]. However, workers' reactions to these negative posts in the gig work groups range from indifference (e.g., *"I ignore them generally. Generally, anybody who's been negative, I just don't bother with them. They're not worth my time."*) to strong opposition. One possible reason for the negative perception of negative posts is that the expression of negative experiences undermines the informational function as the main purpose for these groups. P5 reflects the trade-off between being able to share emotions and being able to see more information.

> "When people post about a bad customer experience. [...] And it's like, okay, so you're just complaining and ranting when all [the] people who need help or have questions about something they're like, 'posts are getting like, buried under that'. So yeah, those are ... not the weird things that people post but just some of the things in life I don't think we need to be sharing that." (edited for clarity)

When prompted about people they would talk to or share feelings with when they felt down during COVID-19, all twenty interviewees mentioned that they primarily relied on strong offline ties such as family and friends to support their emotional needs (e.g., *"Yeah, reach out to like family, friends, relatives, relatives, and friends just to talk call but sometimes FaceTime them or I'll call them and stuff I did. That's what I did during the pandemic."*) None of the interviewees reported having built new friendships through social media groups. At most, they exchanged contact information, for example, by adding each other as Facebook contacts. Two interviewees mentioned instances when the prior contact in the social media groups allowed them to recognize each other offline, for instance, when waiting for a fare at the airport or grabbing food together; however, the pandemic has apparently limited socializing opportunities of this type.

Structure of social media groups, language barriers, and competition might lead to less emotional support among workers

There are a couple of reasons that explain the lack of strong ties or deep emotional support in these social media groups. First, the structure of these social media groups might not be the most ideal for exchanging emotional support and building strong personal connections. P8 mentioned the large number of members on social media groups to be an issue. *" I'm sure you know, Facebook groups there's hundreds people and you can't, you can't be friends with a hundred people."* Besides, gig workers might prefer more intimate or more convenient ways of communication such as phone calls or WhatsApp. For example, P5 mentioned that she typically chats with her "Taskrabbit friend" on the phone: "Oh, I talked to him on the phone. Like I called him. Or he called me or, you know, we chat every once in a while."

Language and cultural barriers are other potential factors that prevent workers from exchanging emotional support. Within our interviewee pool, we had two participants explicitly mention that they were immigrants to the country. Both admitted language was a challenge in interacting with peer workers in social media groups. P20 discussed why he would be more talkative in a Brazillian driver WhatsApp group than on Reddit: "For example, I feel much easier to talk with a Brazilian, you know, it's much easier to start a conversation. I speak Portuguese very well. So, you know, it's much better than my English. And sometimes I don't feel confident to speak English with someone, and sometimes I get stuck in some words."

Lastly, but perhaps most importantly, the competitive nature of local gig work prevents workers from building close and supportive relationships with one another and keeps them from showing empathy, compassion, and genuine concern for each other. As P12 mentioned:

> "I'm not one who talks to other drivers. I joined a group to see if there was any reasonable information. I'm not a fan of being friendly with other drivers. As far as I'm concerned, we're all self employed. There's nothing we can do to compete but, you know, we're both sitting on the same corner waiting for an order. You're gonna take things from my own pocket. Why would I be friends with other drivers? I'm not interested in being friendly."

4.4.3 Social media group as a platform for collective activity

Social media groups are not widely used to organize collective actions among gig workers

Social media groups have been useful for contingent workers when they were organizing union labor activities [178]. For gig workers, who are geographically dispersed, digitally mediated, and thus highly fragmented, social media groups have the potential to help them organize.

However, our study, despite the limited sample size, seems to suggest that social media groups are not widely used as a tool to organize collective actions among gig workers. According to our interviews, none of the interviewees used these groups for labor campaigns or digital activism, and only one of the twenty interviewees had personally participated in a strike.

We collected 100 posts from r/InstacartShoppers regarding the March 2020 Instacart strike using a keyword search. We found that none of the posts were about the organization of the strike, where members asked questions about or comment on the arrangement and logistics of the strike [127]. Instead, in these posts, people expressed their opinions about strikes, explained their personal reasons and perspectives for striking or not, and revealed whether they would strike.

Specifically, among the 100 posts we analyzed, 9 members explicitly stated they were striking or were going to strike, while 26 explicitly stated they would not. More people expressed their opinions rather than directly stating whether they actually planned on participating in the strike. Among these, 22 comments explicitly expressed positive opinions towards the strike by, for instance, highlighting the importance of a strike and persuading or even arguing with opponents. On the other hand, 35 comments indicated the opposite, with many using strong language to argue against it.

Reasons for and against striking

Based on the interviews and analysis of the Reddit posts, we can identify a few common reasons for supporting the strikes. Interestingly, none of the 22 posts that express positive opinions towards strikes tried to sell the potential benefits of broader unionization, despite this being a theme frequently adopted by labor activists in organizing other strike activities [24]. Rather, supporters attempted to explain their rationale for participating from a personal perspective. For example, they mentioned that they stopped working and went on strike because there were insufficient earnings from working or because continuing to work placed them at a high health risk. Many supporters believed that the pay from Instacart was too low, that it was not worthwhile to accept the orders anymore (e.g., *"With all the doubles and triples and $10 orders they're offering, it's pretty easy for me to Strike today!"*). Others pointed out the trade-off between earning money and potentially contracting COVID-19 (e.g., *"All of that [income] will be gone, and much more, if you have to go to the hospital for COVID-19. Conditions ARE poor in stores: inventory is uneven, customers are wandering the stores sick and thoughtless of others... it's a mess at times, especially at places like ALDI."*).

Among the posts that argued against strikes, some workers cited personal obstacles to participation, saying that they "had bills to pay" and hence valued the income they would gain from doing gig work more than participating in a strike. However, the vast majority of comments opposing the strike questioned its effectiveness, writing that the strike would not bring about the desired benefits. Their doubts were based on failures of past Instacart strikes, their distrust of the organizers of the strike, as well as the unclear timeline for the strike. More importantly, they reported being unsure about how other workers would react to the strike, hence doubting if the strike would reach a threshold number of participants for it to have any effect. Unlike traditional strikes, which are typically organized by labor unions and not called without approval from the membership, many Instacart workers couldn't determine the percentage of workers who were going to participate in the strike. Also, in contrast to a non-pandemic-time strike, concerns about infection and lock-down regulations prevented workers from physically gathering together, making it even more difficult to gauge the popularity and likely success of the strike. Commenters did mention the difficulties in monitoring other virtual peers, and creative ways of observation were later introduced.

Posters mentioned that they used "how quickly the batches were taken from Instacart App" as an indicator of how popular the strike was locally, only to find "I actually was too slow for a $78 Bjs batch for 44 items 57 units". Another comment expressed the view that the strike would be unsuccessful because Instacart could keep recruiting workers during the pandemic and reach market saturation: *"Dude, get money while you can. Instacart is hiring 300000 more shoppers and has seen more groceries ordered over the last 72 hours than in its history. This strike will only hurt you."* Workers were aware that the gig platforms could increase their workforce and promote inter-worker competition but felt they could do very little about it. Posters mentioned that new workers were rushing in, because when the unemployment rate was "estimated to be near 30%", people would be "willing" or even "grateful" for the delivery work. While social media groups potentially provided strike supporters an opportunity to use their own behavior as a model for peer workers, only nine out of 100 comments explicitly stated they were going to strike. It seemed that the limited number of individual data points did not convince the majority of the discussion participants.

The interviewees had raised similar concerns about the success of the strike. As P9 argued: *"Unless they can get 90% or, or probably 50 to 60% or better of the people that actually strike, I don't think it's going to make any kind of difference. "* The interviewees explained that, because their jobs were highly replaceable, the gig platforms would easily hire new workers if a strike were to happen. As P16 explained,

> "So I think also, these people [advocating for a strike] don't realize how replaceable that we are, you know, it's, there's always going to be the demand for someone to take our position, and there's always going to be someone that's gonna come that can easily do our job. Because it's not that hard. Can you drive a car? Yes or No, boom, you're good. You have every qualification you need. "

The interviewees also raised an additional complication for why it might be difficult to have most gig workers join the strike–many workers were simply unaware of the strike. Of the twenty interviewees, only five claimed that they knew of a labor campaign related to physical gig work where they could have taken part in, and only one actually reported participating. Even though social media groups serve as information hubs for many gig workers, they are still limited in spreading awareness about labor activism. Since only a small fraction of gig workers join these social media groups, the majority of gig workers who are not members are even less likely to be aware of these labor campaigns, especially because other channels such as in-person gatherings were largely unfeasible during the COVID-19 pandemic.

Besides the perceived ineffectiveness of going on strike, many strike opponents on Reddit also emphasized the discrepancy between collective action and their identification as independent contractors. Those who commented expressed a sense of autonomy they had in decision making, where they had flexibility in selecting work or hours. Gig workers value this autonomy. Their view of themselves as independent contractors places the onus on them to decide whether to take or decline an order, as illustrated by the following Reddit comment:

> "Guess the term 'Independent Contractor' is lost on people. If you are an IC to a snow plowing company, do you expect them to keep your trucks running, blades sharpened, provided cold weather attire? An independent contractor is a person or entity contracted to perform work for—or provide services to—another entity as a non-employee."

The interviewees also stressed that gig work was highly independent work, believing that instead of going on strike, one could individually "choose to do it" or "go and try to find another job" if they were not satisfied with the current conditions for performing their gig jobs. For example, P8 shared his thoughts about the strike: *"I mean, yes, there are particular safety measures that I would like to have been provided earlier. But it was still my choice to go out and work. It's not like if I didn't go to work, I would get fired."*

In addition, atomization, or a combination of working isolation over geographically expansive areas and direct competition with one other, makes it more difficult for workers to be empathetic about the problems experienced by other workers. For instance, a number of Reddit replies posted information about their earnings to prove that their own rate was satisfactory. They could not relate to people who got bad rates and were striking. The following comment, for example, draws evidence from the poster and from their in-person social network:

> “Sorry but I’m going to keep shopping. I made $1000 last week for 37 hours. I had one tip for $60 and have gotten multiple cash tips and handmade thank you cards. It’s your choice to do this job. I lost my usual jobs so I picked this up last week. I got a friend last week and she made $1000 too. Also got my boyfriend’s on it, who’s in the off season for football, and he’s all about it. I’ll take the batches you don’t wanna run.”

The quote above illustrates how fragmented physical gig workers can be, which makes it difficult for them to identify their shared interests and thus build a cohesive voice. Even though gig workers shared earnings data on social media platforms, the dispersed nature of the sharing prevented them from seeing the big picture of how other workers were doing.

Additionally, a number of interviewees mentioned that they did not intend to do gig work permanently, considering such work to be a leisure activity or a source of additional income. These interviewees tended to be less committed and concerned about work conditions than those who relied more on the income from the gig work. For example, P9 explained why he did not pay much attention to the strike: *“I’m thankful that I have an education and other skills as backup, so doing Instacart was just not my thing. So maybe that’s why I don’t care as much.”* P17 took a similar stance, despite believing that a strike "would certainly have an impact". He stated: *"I mean, Doordash is just like a side job for me, a bit like side income from this. I mean, I don’t know how serious I’d take the strike. Now, if it was at my current job I might take it serious. "* This line of thought is consistent with prior literature [116], which indicated the segmentation between full-time and part-time workers could impede the consolidation of shared identities and collective actions.

While social media groups allow gig workers to share their experiences and opinions regarding collective action freely, the decentralized infrastructure of social media groups is highly aligned with the decentralized nature of the gig economy itself, and thus makes it difficult to organize a cohesive voice.

4.5 Discussion

In this paper, we examined how online social media groups provide informational and emotional support to physical gig workers during the COVID-19 pandemic through a qualitative approach. We found gig workers were able to virtually gather in these social media groups and thus alleviate the atomization effect. Workers could obtain experiential information, share positive vibes and frustrations, and discuss labor rights activities with one another in social media groups. However, we also identified a number of factors, such as the fear of competition and the uncertainty about peer workers’ activities, that prevented social media groups from being highly effective platforms for informational and emotional support. In the following section, we discuss these factors and propose directions for future research.

First, we recognized the fear of competition as a recurring, central theme that plays a part in the three dimensions we studied. Our result shows that the fear of competition impedes knowledge sharing, the building of emotional rapport, and the emergence of a collective voice in social media groups. While social media groups might not necessarily aggravate the fear, their functionality in facilitating communication between workers is certainly undermined. What lies behind the fear of competition is the power imbalance between individual gig workers and the mighty gig work platforms [108]. With relatively low entry barriers to the gig economy, the platforms are almost guaranteed with a continuous influx of new workers and thus have the full power to keep recruiting until they reach market saturation [178]. Our study shows that the power imbalance, which caused the fear of competition among workers, could atomize the workers even further as it weakens the emotional rapport within these groups, thus possibly perpetuating a negative feedback loop that enlarges the power gap between workers and platforms. As HCI researchers, we need to recognize these fundamental problems faced by gig workers and take them into account in our design solutions.

Second, our results demonstrate that the vast majority of the information shared in social media groups is the experiential knowledge contributed by individual gig workers. While the concrete experiential knowledge affords several unique strengths, it is worth noting that such information tends to offer specific snippets about one's task-relevant experiences. Prior work on social media groups organized by Airbnb hosts [72], entrepreneurs [74], and digital nomads [169] all noted that their groups provide information on long-term professional development. However, neither the interviewees' recounts nor the content analysis in our study shows that. As gig work is infamous for its lack of career development, future researchers might consider leveraging social media groups to provide more long-term informational support in addition to the experiential knowledge currently shared in the groups.

Finally, our work examines gig workers' current practices in adopting pre-existing groupware infrastructures (i.e., social media groups like Facebook and Reddit) and found that some affordances of these social media groups, such as the decentralized structure, do not facilitate collective activities among workers. Meanwhile, HCI researchers have designed groupware systems that cater to gig workers' characteristics and needs. For example, prior work on mTurk workers designed the online community 'Dynamo' which supported the mTurk community in forming collective efforts and was deemed as a huge success [160]. Similarly, we encourage future research to leverage the findings presented in this work to design groupware systems that better fit gig workers' needs. For example, we found that workers lack confidence in the effectiveness of labor rights activities because they feel uncertain about how many other workers would participate. System design for physical gig workers could thus increase the visibility of individual workers' actions and provide workers with a more comprehensive view of the labor activity.

Chapter 5

Gig workers' Collective Sensemaking in Online Communities

5.1 Introduction

Algorithms have changed the way work is performed. Defined as a set of instructions that take input and generate output [71], computational algorithms offer organizations the ability to manage human workers on a massive scale without the need for human supervision. Millions of drivers globally use a rideshare app powered by an algorithm, overseen by just a small group of human managers. Algorithms play a critical role in every aspect of a driver's job; from job assignment, optimization, and evaluation through algorithms and tracked data [110]. Drivers are automatically matched with passengers, and the fares they earn dynamically reflect the demand for rides and the supply of drivers, all managed through an app on their mobile devices. Drivers also receive automated evaluations based on passengers' ratings of their service quality and their level of compliance with algorithmic assignments (e.g. acceptance rate).

Although organizations view algorithms as a means for efficient large-scale management, researchers are raising concerns that the users of these algorithm-powered apps may not always understanding their functioning [49].For example, prior studies on Facebook newsfeeds showed that the majority of users were unaware of the algorithms that filter their news feeds [60]. Similarly, in the case of gig workers, their comprehension of algorithms is often limited to high-level concepts, such as the notion that rides are generally assigned to drivers located closest to the passenger [110].

Even upon realizing the existence of algorithms, most end-users continue to struggle with comprehending the intricate, non-linear interactions and outcomes generated by these algorithms. Although limited, users' understanding of algorithms is crucial to their corresponding strategies for dealing with the algorithms. Previous studies have investigated how users of Facebook newsfeeds[49], website owners[82], and gig workers[110] have strategically adjusted their strategies based on their understanding of the algorithms to achieve desired outcomes.

The understanding of algorithms might even hold greater importance for gig workers, as their financial well-being is largely contingent on their comprehension of these algorithms. Prior research has shown that workers' reactions to platform instructions are influenced by their understanding of the underlying algorithms[110]. In some cases, workers may comply with instructions if they believe the algorithm is favorable towards them, such as in the case of a surge boost (i.e., a temporary increase in the earnings for drivers in specific high-demand areas). They may also adjust their behavior if they perceive the algorithm to be working against them; for example, if a worker thinks algorithms assign rides based on driver ratings, they may work harder to improve their rating and get more rides. [170]. However, it is still unclear how gig workers come to understand the workings of these algorithms and how varying levels of understanding shape their strategies differently."

Recent evidence suggests that gig workers utilize online groups to gather and exchange information; in particular, they seem to highly value personal and experiential information shared by other workers [197]. Gig workers can collectively organize their individual first-hand experiences into patterns through virtual discussions. This process, known as collective sensemaking [186], has the potential to enable workers to develop a shared understanding of the algorithms that impact their future choices. The resulting shared understanding, which is developed by non-experts and shared informally, can be thought of as folk theories [58]. Collective sensemaking is a common practice in online communities and has been extensively researched in various contexts, including Wikipedia and online health communities [121, 122, 198]. However, gig workers may face two unique challenges in their sensemaking efforts. First, gig workers may encounter a degree of tension in their sensemaking process. While collective sensemaking provides the advantage of generating diverse opinions and perspectives, this diversity can also result in significant disagreements [121]. For gig workers, such disagreements can have even more negative consequences, as they are competitors in a highly competitive market, and their incentives may sometimes conflict with one another [183, 197]. It remains unclear how competitive tensions impact gig workers' conflict resolution processes and their subsequent collective sensemaking efforts. For instance, if workers start using unfriendly language in their discussions due to perceived tension, it could hinder the construction of common ground. Second, despite the conflicts of interests described earlier, gig workers demonstrated an even stronger need for collective power. Since collective labor activities can be effective in improving working conditions, it is crucial for at least a significant number of gig workers to reach some level of common ground to increase their bargaining power [93, 171]. This need for collective power differs from the contexts of collective sensemaking that researchers have examined in prior work in other contexts. For example, in health support groups, each member's personal decision-making is unlikely to affect the treatment of other members, and as such, members typically do not seek a consensus or deem it necessary. Therefore, understanding gig workers' collective sensemaking mechanisms and developing techniques to facilitate the consensus-reaching process becomes an even more critical research question.

This chapter examines how gig workers collectively make sense of the algorithms that impact their work, including their motivation, process, and outcomes of their sensemaking. To this end, we conducted a content analysis of 69 posts and 1,198 comments on algorithm sensemaking on the r/uberdrivers subreddit. We found that workers were primarily motivated to understand the algorithms when they thought the algorithms were harming them (e.g., having difficulties in getting rides or not receiving increased surge fares). The collective sensemaking process they used included both exploratory research (starting with observations to unveil reasons behind expectation violations) and confirmatory research (testing one or several hypotheses to determine if they are supported). Workers made a significant effort to document their experiences, provide context, develop hypotheses based on evidence, and even conduct experiments to verify their hypotheses. This effortful collective sensemaking process can lead to the validation of each other's experiences, interpretation of the anomalies they experienced, and the development of feasible action items to cope with the algorithms. However, we also identified factors that can impede workers' collective sensemaking process, such as insufficient data points, platform control, and conflicts of interest among workers.

5.2 Related work

In this section, we first introduce the definition of algorithms and how they are applied in an algorithmic management economy. We then review studies that investigate users efforts in understanding the algorithms, specifically folk theory and reverse-engineering approaches. We finally present a collective sensemaking framework and set up our research questions.

5.2.1 Understanding algorithm mediated work

An algorithm is a defined set of instructions that takes input data, performs computations or operations on it, and produces an output or result [70]. Algorithms are increasingly prevalent in shaping many aspects of daily human experiences, including social media feeds [49], online advertising [51], and dating apps [165], triggering discussions on their significant and invisible impact on people's daily lives. Gig workers, who are both clients and technically managed by algorithms [90], may face even more profound consequences. Prior research on rideshare drivers documented how algorithms impact their daily working experience in three ways: work assignment, informational guidance, and revenue calculation [110], which mirror the decisional, informational, and evaluative roles of human managers. Consequently, algorithms play a pivotal role in gig workers' complete work cycles.

Prior research demonstrated the importance for users of understanding the algorithms, as the understanding would shape users' expectations towards the algorithms and affect their behavior. For example, Facebook users were found to strategically manipulate their friend lists to see certain feeds more frequently [49]. On freelance platforms, workers would adjust their strategies in response to algorithmic setbacks; for example, they exercise extra caution when communicating with clients to avoid triggering account reviews that could potentially lead to account cancellation [25]. For gig workers, similarly, understanding algorithm can help them make better decisions about when and where to drive, and how to optimize their earnings.

Even though understanding the algorithms is important to gig workers, obtaining this understanding is not necessarily an easy task. While the term "algorithm" has gained increased prominence in mainstream media, the understanding of algorithms remains predominantly confined to computer scientists and engineers; even when some information was provided, there still exists a mismatch between the mathematical level of understanding and the human-scale reasoning and interpretation [26]. Therefore, communicating the intricacies of algorithms can be difficult. This can make algorithms appear like a "black box". This lack of transparency is sometimes intentional, for reasons such as protecting intellectual property and ensuring a seamless user experience[49, 51].

5.2.2 Folk theories for understanding algorithms

Knowing the importance of understanding the algorithms, users themselves also start to develop theories about how these algorithms work, also known as the folk theory approach or reverse engineering [40]. These user-developed theories tend to be intuitive and informal; they do not match the institutionalized, professionally legitimated understandings held by engineers who designed the algorithms. Although the folk understanding can be inaccurate and incomplete, it would still guide users' actions. Much prior work has examined the process and how people perceive and react to the algorithms. For example, Motaharie et al., uncovered various ways users adapted their behavior in response to perceptions of algorithmic curation in their newsfeeds [50]. DeVioto et al., found that most of the information was obtained from within the platform, suggesting that many folk theories arise from participants' experience with the platform itself[40]. Prior work also uncovers challenges faced in the folk theory approach. These collective attempts to determine the specifics of the algorithm by comparing users' experiences are nearly impossible because each user has a different network of friends who serve as the sources of content, which makes comparison difficult [51].

Most of the work described above examines users' efforts in demystifying algorithms in social media or advertising contexts. However, understanding algorithms in the context of algorithmic management has received less attention. Existing work on this topic mostly involves freelancers and influencers. Cameron & Rahman studied how freelance workers contend with an opaque third-party evaluation-algorithm [27]. They found that platform-provided evaluations typically do not explain why workers' scores increased or decreased, nor do they help workers to understand how they could improve their work performance with clients. Workers' reactions depend not only on their general success on the platform, but also on how much they depended on the platform for work, and whether or not they experienced setbacks in the form of decreased evaluation scores [20, 89]

5.2.3 Collective sensemaking

Sensemaking refers to the cognitive process through which individuals or groups attempt to make sense of and understand the world around them [187]. This is especially true when individuals are confronted with situations that are unexpected and do not fall into their existing set of action scripts [186]. The process of sensemaking often includes the following steps: *ecological change*, where the current state of the world deviates from what was expected; *enactment*, which includes noticing and bracketing, meaning the thought process by which people notice discrepancies and the filtering of cues on which sensemaking initially happens; *selection*, where individuals build a schema that can reduce the ambiguity of the situation and discard elements that add to the equivocality; and finally *retention*, which refers to the iterative enactment and selection based on the plausibility of sensemaking narrative [36]. Although these steps were presented here in a sequential manner, the steps in the sensemaking process are rarely distinct. More often, they overlap and interact, rendering sensemaking as an ongoing and improvisational activity where new data are continuously collected and operational mental models are iteratively revised. As the ultimate goal of sensemaking is to build meaning, the outcomes of sensemaking are roughly categorized into different levels of conceptual change: *accretion*, no structural change but with additional data; *tuning*, with adaptive structural change; and *restructuring*, with radical structural change [180]. The key differences between these levels are the extent to which a structural change was involved; a radical change of the structure often take places when prior knowledge conflicts with new information, or when completely new information is presented [199].

While sensemaking typically refers to individual efforts to comprehend and interpret information, when unexpectedness and uncertainties strike communities, communities members may also try to perform sensemaking collaboratively. This is especially when individual members do not have a full picture of a situation [188]. Because online communities and social media are used for connecting individuals around the globe and hence providing vast amounts of information, they have been used and studied as critical venues for their members to understand complicated issues, such in the health domain (diabetes [121, 122], chronic pain [198], pregnancy loss [8],) and crisis contexts [102, 103]. Past studies have demonstrated the effectiveness of online platforms in facilitating collective sensemaking efforts but also found that the loosely-organized nature of these platforms make sensemaking less effective [121]. Previous studies also discussed potential challenges that might impede the process of collective sensemaking. Dawson [113] and Russell et al. [159] highlight the cognitive burden of navigating vast amounts of data which causes cognitive load for sensemaking participants. Janis [87], poses a significant threat in group settings, where the desire for consensus can override critical evaluation of information. Maitlis et al, [118] delved deeper into the emotional aspects, emphasizing the impact of emotions and trust on reasoning and fostering open communication.

Finally, this chapter aims to describe the collective sensemaking of algorithms within the context of the gig economy. A group of gig workers engages in discussions within online communities, where they seek to decipher the inner algorithmic mechanisms behind the transformation of inputs in their working lives into corresponding outputs, such as ride assignments, surging area displays, and performance evaluations. Throughout this process, workers document their own experiences, challenge each other's observations, develop hypotheses, reason about existing theories, and provide actionable advice to their peers.

5.3 Method

To understand gig workers' collective sensemaking process, we conducted a content analysis of posts from the r/uberdrivers subreddit. We chose Reddit as our research platform due to its active community of workers who have demonstrated effective communication outcomes [5, 197]. As one of the earliest pioneers of gig platforms, Uber has made substantial changes to its algorithms throughout the years, providing us with the opportunity to capture workers' perspectives on these updates. For the content analysis, we crawled all posts from the r/uberdrivers subreddit from its founding time (November 2013) to November 2021, resulting in an 8-year dataset. We used keyword search to identify threads containing the term "algorithm" in the theme post, which yielded 100 posts. The precise keyword matching approach can be biased and may result in a smaller sample size, as workers may not always use the specific word "algorithm" even when

Code name	Code definition	Example
Trigger of the sensemaking process	The event that triggered the gig worker to initiate a thread in r/uberdrivers to gain a better understanding of the underlying algorithm	Tell me how 100% five star ratings result in a negative overall rating.
Documentation of workers' observation	The nitty-gritty details provided by the workers to illustrate the triggering events include specific timing, locations, vehicle types, and more.	I received 5 new ratings TODAY after 5 trips. [...] I started today with a 4.77, it bumped to 4.78, and then all the way down to 4.75. All from five 5 star ratings.
(In)validation of the phenomenon	Users in r/uberdrivers contribute additional data points to confirm/disconfirm the expectation-violation phenomenon	Yea, I did the math myself from the information I gathered when I was still driving. It never added up to the score it shows. It doesn't make any sense.
Hypothesis development	Extract patterns and formulate hypotheses from worker experiences to explain the behavior of the triggering event	100% Uber manipulates drivers ratings as well as passenger ratings.
Hypothesis interpretation	Reason and interpret the hypothesis related to algorithms by leveraging existing data, observations, prior knowledge, or occasionally through conducting experiments.	(disagree with the hypothesis) This (alogorithm anomaly) is a known UBER technical issue from the last 3 weeks.
Actionable items	Provide feasible action items for workers to fight against the often undesirable consequences caused by algorithms.	Whatever.. as long as your rating doesn't start to nosedive, don't worry.
Offense to other workers	Use offensive language towards workers who try to understand the algorithm	Either you're an idiot or a troll. No idea how to explain it any more clearly.

Table 5.1: Codebook of gig workers' sensemaking

discussing the underlying algorithm. However, since our study is qualitative and not primarily concerned with statistical significance, we have decided to to use this approach. The first author manually reviewed all posts and identified 69 that involved active sensemaking, where workers observed, interpreted, identified patterns, and shared reflections about algorithms in gig work. For instance, in one post, a worker complained about Uber's high commission using the sentence: *"It's just GPS software combined with a few algorithms."* In this case, the poster only expressed negativity towards the algorithm and did not attempt to interpret it, so we excluded the post from our dataset. We ended up with a dataset that consists of these 69 posts and 1,198 accompanying comments.

With the dataset, the first author initially conducted a thematic analysis of the 69 threads to understand the aspects of algorithms that workers were discussing. Next, the first author developed a codebook based on both existing theoretical framework of sensemaking and the data from r/uberdrivers to understand the concrete sensemaking steps workers engaged in [7, 199]. The codebook (see Table 5.1) and its supporting examples were adapted to better fit the context of gig workers and iterated with the regular input of two other authors. For example, in the sensemaking theoretical framework, the code 'hypothesis development' aligns with the concept of 'selection'; the code 'actionable item' represents a distinct outcome specific to gig workers, as it is not a mandatory step within the sensemaking process. Finally, the first author performed a third round of coding, focusing on how gig workers' interactions with other stakeholders in the gig economy impacted their sensemaking process.

	Definition	Example	Count
Work assignment	Workers discuss how algorithms impact the way they receive pings of rides via gig platforms	I use to drive a bunch back in the day and stopped for about 6 months. Since i returned, I haven't gotten any pings while on freeways. I used to mob out to SFO and take 380-280 back towards state. I used to almost never make it all the way back without getting a ping that usually took me back into the city. Did uber change their ping process/algorithm to stop getting pings on freeways?	33
The display of dynamic surge pricing	Workers discuss how algorithms impact the way dynamic surge pricing is executed.	Anyone figure out if there is an exact algorithm applied to when the rider requests a ride within the surge zone? I thought it started after 10 miles, but I did a 7 mile 8 minute ride last night with a 4.50 sticky that multiplied to 13.40 or something. Idk what caused it but I'down! Maybe the time and miles being so similar ?	15
Performance evaluation	Workers discuss how algorithms impact how their ratings was calculated, and how ratings would affect other aspects (e.g., ride assignment) of their work	I mean, I really don't give too much of a shit, but I am more or less just wondering what is going on here. I've been 1-starred twice over the past few months (both without any feedback), and both times the 1-star will disappear after about a week or two. I never complain or ask Uber about them either. Does anyone know what Uber is doing here? Are these people who Uber has banned? Maybe Uber has some algorithm that ignores ratings from passengers who 1-star everyone? I believe my first 1-star was from an idiot who left a Taco Bell mess in my backseat, but the 2nd I really have no idea.	12
Fare calculation	Workers discuss how algorithms impact how their fare was calculated.	Uber (and lyft) treat us EACH differently by market if not by individual personal algorithms. We should know that, what it is, how it works, who gets what. We should be posting the rates and bonuses we see in the city we are based in. I think that they are different because of more than just the market/city we are in. We have this tool (social media) to defeat them keeping us separate from each other and powerless. Lets use it to help ourselves.	9

Table 5.2: Algorithmic-sensemaking discussion thread themes

5.4 Results

In the following sections, we identify the triggers that motivated gig workers to initiate sensemaking around algorithms in an online space. We found that workers were motivated to make sense of the algorithms when algorithms unfolded in ways that violated their expectations? and had negative consequences for them. We then describe the processes workers used for sensemaking, including conducting exploratory research and confirmatory research. Finally, we present the outcomes of gig workers' sensemaking efforts and analyze the challenges these workers face in the collective sensemaking process. edit this paragraph to reflect change

5.4.1 Background

This section provides an overview of rideshare drivers' workflow and how algorithms affect their work. In rideshare applications, drivers typically await ride requests, often referred to as a 'ping,' which are assigned to them by the platform. Upon receiving a request, drivers are provided with essential details such as the passenger's location, intended destination, and the fare they would earn from the trip. Many rideshare platforms, including Uber, employ a dynamic pricing system, also known as surge pricing, which adjusts fares based on real-time supply and demand conditions in a given area. When the demand for rides surpasses the available supply of drivers in a specific area, fares are increased to incentivize more drivers to come online and cater to the heightened demand. Once the driver picks up the passenger and transports them to their intended destination, the ride is considered complete. At the end of each ride, both drivers and passengers have the opportunity to rate each other using a rating scale that typically ranges from 1 to 5 stars, with 5 representing the highest rating. Over time, all these ratings will be accumulated over time and displayed on the driver's profile.

In the Reddit discussion we examined, we found that drivers focused on four specifci aspects of their work: the assignment of their rides, the presentation of dynamic pricing (i.e., surge), the calculation of the fare they receive, and the evaluation of their performance. Table 5.2 presented a count of algorithmic-sensemaking discussion threads related to each of these themes. Among the four, three of them were in line with what Lee et al., [110] reported, as workers discussed how their rider assignment, surge pricing, and performance evaluation were affected by algorithms; in addition to that, workers discussed on how the app should calculate their fares.

5.4.2 The triggers of collective sensemaking: Negative violation of mental models prompts workers to initiate a collective sensemaking process.

We found that workers were motivated to initiate sensemaking efforts around algorithms when they found that the results generated by the algorithms differed from the results they had anticipated; those that had triggered discussion often had negative consequences for the thread initiators personally. Because workers naturally wanted more shorter waits for passengers, more profitable rides, higher surge pricing, or better ratings, they reacted when algorithms delivered outcomes that went contradicted their goals. These negative outcomes included receiving fewer than usual pings, failing to secure specific surge prices, or learning of unexpected drops in their rating. P42 noted an instance in which a trend of decreased earning violated their expectations of wages:

"Has anyone else noticed a decreased earnings since the call off shutdown of Uber [meaning the Prop 22 act]? I feel the algorithm is working towards reducing wages we are getting paid. I'm intrigued on the opinion of others in this community."

This finding aligns with Weick's theory of sensemaking through expectation violation. According to Weick, the gap between expectations and actual experiences triggers the sensemaking process. Individuals quickly evaluate new information and experiences, and when they do not match their existing mental models, they engage in more conscious processing to reconcile the discrepancy and make sense of the situation. In other words, the unexpected outcome prompts a more active and deliberate sensemaking effort. [186].

With an understanding of the sensemaking trigger, we begin our analysis by posing the following question: What are the workers' expectations of the algorithms? How did they form their norms and standards for the algorithms in the first place? We found that workers are able to establish norms for algorithms that fall into two categories: descriptive norms and injunctive norms [101]. According to Caldini et al., injunctive norms are norms that are subject to the approval of others [34]. In the context of gig workers, this refers to norms that are set by gig economy platforms like Uber and Lyft (i.e., the norms of "ought"). These platforms usually provide basic information on the algorithms used in gig work through generic FAQs and debriefing documents. For instance, Uber defines its ride assignment algorithm as being optimized to "reduce waiting time for all parties". [1] As demonstrated by the previous example, the information regarding the algorithms that is available to workers is often straightforward and easily understandable, such as how ride assignment is linked to proximity and surge pricing to local driver supply and customer demand. As a result, we found that workers generally possess a good understanding of these fundamental principles.

Despite having a generic understanding of algorithms, many workers still experienced confusion and misunderstandings when trying to apply this knowledge to real-world situations. Quantifying algorithmic inputs can be a challenge in the first place. During one evening shift, P-7 observed a shortage of drivers, with no car being available for 'more than 10 seconds between 11 PM and 3 AM'. This observation, combined with a high demand from passengers (some reported 'tapping their phones for 10-15 minutes to secure a ride'), led P-7 to expect a surge in pricing. In this case, the worker understood that the inputs to the surging price algorithm were driver supply and passenger demand. Despite being able to understand the general direction of the algorithm (e.g., a high demand from passengers results in a surge in pricing), they were unable to determine the precise number of available drivers or the level of passenger demand required to trigger a surge. The vagueness of algorithmic inputs presents difficulties for workers in translating such connections into quantifiable numbers that can meaningfully guide their daily work. As a result, they are limited to making rough guesses based on their own perception of the algorithmic inputs, which eventually lead to ill-informed judgements and expectation violation when no surge took place

Additionally, workers had difficulties comprehending the impact that each input has on the output of the algorithm. For example, workers expected that drivers and riders were matched on the basis of proximity and described surprising experiences in which the app would not assign them passengers who were standing in very close proximity to them. For example, p-55 described

[1] https://www.uber.com/us/en/marketplace/matching/

how they did not receive pings from a family member who was already seated in their vehicle. They felt that the outcome of the matching algorithm violated their expectation that ride matching ought to be based on proximity:

> *"[...] but it's now near impossible to match, even with Lyft. In fact, on Lyft I don't even appear as an 'available' car. I've tried everything, being in the immediate vicinity, driving around for a bit, but it always matches with another driver. Is there anything I can do or is this just an algorithm that prevents pax [passengers] from matching with the same driver too many times?"*

In the examples above, workers all agreed that proximity is a crucial input for ride matching algorithms, but workers' experiences demonstrated that proximity alone did not always determine the output of the algorithm. However, it is unlikely that individual workers know other input factors that might impact the outcome, or how important proximity alone is in the ride assignment algorithm. Hence, workers posted their experiences online and sought to elicit discussion around these unknown questions.

Take ride assignment as an example. There was plenty of discussion on how the app unexpectedly routed workers to passengers that were miles away from them and only needed short rides. They argued that such assignment mechanisms 'did not make sense', as the money they earned sometimes didn't even cover the cost of their gas.

While injunctive norms reflect workers' perceived rules of how algorithms should work, descriptive norms refer to the perception of how algorithms took place in their day-to-day work (the norms of "is"), and are based largely on observations of how they or others' work are affected by the algorithms [34]. For example, workers often had a rough idea of the number of rides they'd likely to get per day even while accounting for potential fluctuations (e.g., they'd expect fewer rides on snowy days, or more rides on a holiday). Many only reported their experiences online and began to participate in the sensemaking process when these expectation violations became part of a longer and more stable pattern of violation. For example, p-21 started a thread at r/uberdrivers after not getting an expected bonus for four consecutive weeks. They wrote: *"I've met goals 4 weeks in a row , I can now say... I HAVE SCREENSHOTS, HISTORY...... 1000% the uber algorithm has you work for the first day... then you will NOT, 100% WILLL NOT, GET long rides to match your bonus."* Similarly, p-40 described how the rideshare platform might deliberately prevent them from getting consecutive ride bonuses: *"EVERY first ride I get during these bonus hours is a 45 minute plus ride [so that I was unable to get that bonus]. EVERY MORNING."* By including these descriptions of their experiences, the poster likely added to their own credibility among other users, hence facilitating further sensemaking efforts from others.

In the online sensemaking process, workers attempted to draw a line between randomness, bad luck, and systematic manipulation of algorithms. Despite their best efforts to make sense of the process, individual workers' knowledge about the algorithm was limited, so they were only able to document their personal experiences online and ask other community members for explanations and validation when the experiences violated the descriptive norms they built. In the previous example, p-40 concluded the sensemaking process by trying to confirm whether or not their unexpected experiences were one-off or were systematic issues in the app affecting other colleagues, saying: *"Anyone else experience the same? Just getting frustrated"*.

It is worth noting that the violation of expectation is directional: as expectations can predict

	Definition	Examples of negative expectation violation
Work assignment	Workers discuss how algorithms impact the way they receive pings for rides via gig platforms	Workers receive fewer pings than expected. Workers received pings for rides that are unexpectedly far away from their current location, which made the cost higher.
The display of dynamic surge pricing	Workers discuss how algorithms impact when dynamic surge pricing occurs.	Lack of surge pricing despite having a high customer demand and few available drivers.
Performance evaluation	Workers discuss how algorithms impact how their ratings was calculated, and how ratings would affect other aspects (e.g., ride assignment) of their work	Workers' rating unexpectedly went down.
Fare calculation	Workers discuss how algorithms impact how their fare was calculated.	Workers received less fare than expected.

Table 5.3: Negativity contextualized in workers' discussion topics

desirable or undesirable events, disconfirming these events can be better or worse than expected [101]. Negative expectation violations take place when the situation is worse than expected, whereas its positive counterpart is what people often all 'pleasant surprises'[131]. We found that, in the 69 instances of gig workers' collective sensemaking we identified, all of their expectation violations are negative, meaning the reality is undesirable for themselves or other driver groups, and hence negatively-valenced. In Table 5.3, we present examples of how the negativity was contextualized in workers' discussion topics.

To sum up, gig workers formed their expectations of the algorithms through their intuitive understanding, written guidelines in platform materials, and their own lived experiences. They initiated online sensemaking after identifying occasions when their expectations were violated in ways that led to worse outcomes.

5.4.3 The process of collective sensemaking: exploratory research and confirmatory research

In this section, we present how gig workers engage in collective sensemaking efforts to understand the algorithms involved in their work. Their research efforts can roughly fall into two categories: **exploratory research**, where workers start with observations and aim to discover the reason why expectation violation occurred, and **confirmatory research**, where workers have one or several hypotheses at hand and aim to determine whether or not the hypotheses are supported by facts. Among the two types of research, the exploratory research is mostly started by thread initiators, where they typically reported their observations, and then developed, found evidence for, and presented their hypotheses on gig-work-related algorithms. Confirmatory research, on the other hand, is typically done by commenters who contribute data that is consistent or inconsistent with the existing hypotheses.

Exploratory research

In exploratory research, workers often begin by observing their own experiences and then seek to harness the collective expertise of the community to uncover underlying reasons or patterns. When presenting their observations, many workers paid meticulous attention to their experiences, documenting the timing and location of their expectation violations, their vehicle type, as well as their work routine. When making these self-disclosures, workers did not necessarily make it clear if they felt this information would be helpful in understanding algorithmic patterns; they nevertheless still carefully contextualized their experiences, presumably in an effort to add credibility to their description or, in some cases, to elicit further discussion from other workers. For example, p-7 reported an instance in which they believed that their rideshare platform manipulated the ride assignment algorithm. In their account, they noted in detail about how a surge took place within their city and how the surge pricing changed at each critical time point:

> *"Starting at 4pm, all areas of the city went to 1.5. ALL areas. Simultaneously. Pretty odd as the only other time I had seen that was at the stroke of midnight on NYE. Then at 4:45 pm, I received a text from Uber touting the surge was happening. I checked in about every half hour and saw 8 out of the 13 areas in my city at surge from 1.5 to 3.5. Checked the rider app and saw loads of available cars and watched for a while to see how quickly they received a ping. Didn't see much action and the large number of available cars didn't seem to me to justify any surge. Surge was steady (1.5 to 3.5) until around 8pm."*

In the example above, the poster mentions that they used the rider's app to learn about the driver availability. In fact, it is quite common for workers to go out of their way to collect data from additional sources. For instance, workers quoted passengers' verbal accounts as evidence of a high demand within the market (e.g., *"Some passengers told me that they had not seen a single available car in the past 20 minutes."*). Other workers used third party applications, such as airport apps, to determine whether there was indeed a high demand for drivers. By triangulating the data, workers were able to provide quantitative and qualitative data as evidence for observations based on their subjective experiences and feelings.

As discussed in the previous section, workers often record multiple work experiences that emerge as pieces of a pattern rather than reporting one-off negative experiences; For example, p-23 recorded how their Uber ratings dropped after they completed additional 5-star trips. By documenting real-time ratings after each trip, the worker was able to identify and provide evidence for an error in the calculation of ratings. By putting extra effort into data collection, they were able to provide other workers with critical trend information that was otherwise unavailable from the platform:

> *"I haven't driven in the past 5 days, and in these 5 days I haven't received any late ratings, so my score hasn't changed at all. **I started today with a 4.77, 122 Rated Trips, and 102 5 stars.** After a trip or two, I checked my earnings/rating (as I always do after 1-2 trips) and it bumped up to a **4.78, 124 Rated Trips and 104 5 stars.** Now, after a few more trips, I checked my rating and it was a **4.75 125 Rated Trips and 105 5 stars.** I LOST 0.3 POINTS AFTER GETTING ALL 5 STARS."*

After presenting their observations, the workers who replied , especially those with a more advanced understanding of the algorithms, were sometimes able to propose plausible hypotheses to explain their experiences. This transition to proposing hypotheses leads them to embark on the subsequent phase of the sensemaking process: confirmatory research.

Confirmatory research

As per its definition, confirmatory research is typically conducted when a hypothesis is already lined up and thus conducts additional research to confirm or reject the hypothesis. In gig worker's case, such confirmatory research is typically filled in by workers who comment underneath a thread (where a hypothesis has often been proposed). The community as a whole would attempt to build meaning together and create a shared knowledge structure about the algorithms involved in gig work.

In the collective sensemaking process, workers most commonly contributed to the process by describing their individual experiences and using them as additional data points to validate, enrich, or refute the original posters' experiences and hypotheses. By providing these additional descriptions of personal experiences, participants offered valuable informational support in the discussion. For example, p2 described their experience of not having an expected surge given the lack of drivers and excessive passenger demand. According to their description, they were able to determine the anomaly of the surge algorithm and conclude that "something was wrong."

p2-c1 expressed agreement with p2's point and added their own experiences as proof. They wrote: *"I think so as well. The last few days have been wildly inconsistent. All last night (Saturday Night) there as no surge while there being no cars available. Before that it would show a 2.7x surge, then I'd get a ping with a 1.4x surge or no surge at all. Also, the driver and passenger app will show different surges. Something is screwed up."*

The original poster provided detailed time points and location information, as well as detailed accounts from the passengers as proof of their hypothesis. Data points in the comment provided additional details, such as the precise amount of surge, a comparison of surge situations before and after, as well as information from passengers' apps. By aggregating data from various channels, the group provided additional information to support, triangulate, and ultimately bolster hypotheses.

Workers often engaged in back and forth discussions to carefully examine these personal data points and evaluate whether they could be used as evidence to support each original hypothesis.. In this process, they were likely to collect more information that added to the credibility of their hypotheses. In the same thread, workers asked the original poster whether or not the shortage of cars was stable for a long period of time. The OP responded to the workers by clarifying that: *"Every rider I asked said they had trouble getting a ride. Cars were popping on the screen and off constantly. Every time I dropped off, I immediately got another request. There was very high demand."* In the clarification comment, the OP emphasized how frequently they received complaints from the passengers about the car shortage and how popular the rideshare service was. As the market faced conditions that should presumably have triggered a surge—that is, both an excess of passengers and a shortage of cars—this information was powerful in proving to workers that the surge algorithm was not performing as expected.

5.4.4 The outcomes of collective sensemaking

What collective senseamking can do: validation, interpretation, and action

As discussed in the literature review section, the goal of the collective sensemaking process is to build a shared understanding of a complicated phenomenon, in this case, the algorithms of the gig work platforms. Three outcomes are likely to emerge after the sensemaking activity: accretion, with added data and instantiated structure; tuning, with adaptive structure; and restructuring, with a new structure. For gig workers, most of their collective sensemaking ended up with accretion, where they didn't come up with a new structure of the knowledge, but were able to confirm their observations and hypothesis, as well as to enrich their original argument with additional data points.

As described before, individual workers would contribute their own data after an observation or a hypothesis was presented. Typically, workers would acknowledge others' experiences by using statements such as *"I've seen similar stuff"* or *"yeah I've been having that problem too"*. For example, when reacting to a post on an unexpected rating drop, p23-c5 started with *"I posted about a month ago now this is happening to me too"* to acknowledge the posters' experiences. With such explicit acknowledgment, workers were able to recognize each others' experiences, validate anomalies shared by workers from different locations under different circumstances, and hence reach a consensus that the 'unexpected' algorithmic phenomenon was not one-off or coincidental but rather prevalent.

Because of the diversity of the information sources cited, the collective repertoire of personal experiences might not necessarily converge. Often, they conflicted with one another, making it difficult to prove or disprove a hypothesis. In p25, workers discussed whether or not being the closest driver would always lead to a ping. The original poster started off by leveraging the "proof by counterexample" approach, saying, *"I have seen people saying the closest driver will be selected. I did a test today, by selecting a uberx first and uberselect next from my rider app. Both ride requests didnt come to me but went to 2 different drivers who was like 5 mins away. I am like 0 minutes away. They sure have a different algorithm to pick driver, it is not closest rider."* (p25) The OP deliberately conducted an experiment with multiple phones–covering conditions for both UberX and Uber Select–in order to demonstrate that the algorithm did not ping the closest driver and to conclude that distance did not determine ride assignment. While several commenters echoed OP's hypothesis and provided their own anecdotes, a substantial number of workers also expressed disagreement and cited their own experiences. For instance, P25-c13 wrote: *"False, I did a ride the other night and immediately got a ping from literally across street."* The same is p25-c28, who wrote: *"Today i was at a friends house with some people, someone said they were gonna call an Uber so i turned on my driver app and instantly got the ping."* In both cases, the commenters were able to provide anecdotal examples in which they received the ping as the closet driver. Their personal experiences were indeed concrete and contextualized. Even with such rich information, however, workers were not able to reach a consensus on whether or not the original hypothesis was true based on these conflicting data points.

In addition to validation, workers were also able to come up with sensible interpretations to the hypothesis they came up with (i.e., why did the algorithmic anomaly happen). When it comes to research conducted by an individual researcher, it typically follows a linear research workflow where a researcher analyzes and interprets the data collected, and comes up with a theory based on that. When it comes to collective sensemaking, however, these steps can be jumpy, meaning that the occurrence of a certain step is not dependent on its previous step. While gathering confirmatory data might make the interpretation process smoother (meaning people wouldn't spend additional time arguing the legitimacy of the observation), it is not necessarily a premise for interpretations to happen in the collective sensemaking process. Rather, such interpretations are more dependent on individual respondents' knowledge and expertise on the subject matter.

For example, workers gathered in a heated discussion about how the distance between a driver's current location and the passenger's pick-up point should be calculated in p3. After various rounds of discussion on how rideshare platforms made calculations and whether or not the 'straight-line model'(meaning rideshare platforms calculate the distance based on the straight line distance between two points) is universally applicable to all drivers, discussant c12 attempted to explain why platforms opted for calculation despite such calculations not making sense to the drivers, by saying: *Computing a full route for each nearby driver before pinging them is massively more computationally expensive than just calculating straight-line distance.* This explanation touches technical knowledge from the platform's end, as the discussant reasoned from the computing resource perspective. To construct such an explanation, workers' experience simply from driving might not be sufficient; they often need to draw deep domain knowledge to interpret what was happening.

While validation and interpretation can help workers better understand the algorithms, workers sometimes also provide direct, feasible action items for their colleagues to fight against the consequences caused by algorithms. These proposed actions ranged from technical operations on the app (e.g., when the OP described issues where they were unable to properly see surge pricing, p36-c6 suggested that he "double click the home button, swipe up on partner app to close and reopen the partner app"), to profitable driving routines (e.g., p42-c4 described their 'no chasing surge' strategy as 'I ignore surge and go to where I know I can get a fare unless I anticipated the surge and sat where I needed to be'), and to ways of claiming back their deactivated accounts (e.g., p26- c5 proposed to 'delete old account, make a new account with new email' facing account deactivation, further citing this is 'what my buddy did and got his new account approved'.) Note that all these proposed actions were not based on an accurate understanding of the algorithm but rather on past successful experiences.

When the collective sensemaking leads to positive outcomes such as validation, interpretation, and action proposals, workers might express positive feelings towards it, as they found such discussion helpful. For example, c8-p22 commented on a post where discussants were making sense of Lyft's powerzone algorithm: *"This is a quality post and I hope it isn't the last we see of this kind. If we don't understand the data collection techniques and defend our right to privacy we will (are) set terrible precedents for the future."*

Barriers to successful collective sense-making

Despite some occasional positive results, collective sensemaking frequently fails to deliver the desired outcome of a comprehensive understanding of the workings of algorithms. One obstacle to successful sensemaking is within the nature of the collective sensemaking process itself: even though workers may have gathered some data, the information is frequently not enough to comprehend the algorithmic mechanism. With too scattered (and often conflicting) data, workers are typically unable to reach a convincing conclusion. In a discussion where workers were sharing experiences of observing fewer surges recently, c8-p49 started with "I was seeing this in Salt Lake city too" as a confirmation of others' experiences, only to conclude with the regretful remark of "I wish there was a way to prove it." In another scenario where workers tried to make sense of why their rating unexpectedly went down, they also concluded rather passively: *"I've also seen my 5-star go up without rated trips going up too. idkwtf that would happen but OK."* Because they often didn't have accurate interpretations, workers' proposed actions were often based on experiential outcomes. They could choose to either follow or act against the interpretations and actions proposed in the process of collective sensemaking, without knowing for sure if that's the right way to go. As c30-p15 put: *"Uber has a ton of algorithms going to manipulate drivers. Drivers are rats in the maze."*

The second challenge to collective sensemaking is the strong control exerted by gig platforms over information disclosure. The gig economy platforms hold the information that is crucial to their algorithms and have the power to determine the extent of detail they will reveal to the workers. Unfortunately, what is often provided is vague, generic "explanations" instead of more specific, quantifiable ones. Previously we've discussed how the platform-provided materials only cover the barebones of the algorithms (e.g., the ride assignment algorithm is supposed to 'optimize all parties' waiting time'). In addition to the vagueness of pre-written documentation, workers also got vague responses when they reached out to gig platforms' support staff. p24 described their experience of contacting support and asking why their ratings changed unexpectedly. The person-staffed support line, similar to the platform's documentation, provided only vague explanations about the algorithms. As c8 noted, *"I asked Uber Support, and they gave me some canned response that my ratings can go up or down based on the last 500 trips. My question had nothing to do with ratings but the no. of riders who Rated me. How could that go down?? Go figure!"* Sometimes, the platforms' reluctance in providing explanation to their algorithms can even be quite explicit. In p-49, the poster shared their experience of being deactivated by Uber and Uber's letter excerpt they posted reads as the follows: *"We are not able to go into great details but the examples of improper use include using your rider and driver account at the same time, creating duplicate accounts, accepting trips without the intention of completing them, claiming false fees or charges, the installation, and use of software which has the intention or effect of manipulating the Driver App and trip details"* In this case, the gig work platform explicitly refused to provide the details behind their decision-makings. Even the platform effectively accused the workers of fraudulence, they wouldn't even provide evidence to support their claim and the workers also were left with no channels to voice for them. The platforms were not just vague when it came to the explanations of the algorithm. In their app-designs, They also use unclear language when describing the outcomes of the algorithms. For example, one user complained that after driving to an area the algorithm had recommended, they discovered that there were no passengers in need of drivers. The worker expressed their frustration as they assumed that the in-app alerts would lead them to rides with passengers. They wrote, *"If I drive through an area that shows me, 'expect trips soon, I stop and sit for 30 minutes. It said, "Expect trips soon for thirty minutes." This is a huge waste of time that I could be going to different locations. Why does the algorithm do this?"* Based on the workers' accounts, the in-app alert language of 'soon' was inaccurate and open to multiple interpretations.

As the collective sensemaking process involves lots of personal experiences and feelings, it is inevitable that some narratives could be emotion heavy. Consistent with prior literature, workers also showed empathy towards each other when engaging in collective sensesamking. For example, p8 complained about their experience of being assigned to rides that were unreasonable, as they wouldn't be able to make a profit due to the long pickup distance. P8-c2 echoed their experience by saying that *"I know the feeling, i get call to places across the bay because I'm the closest........despite the fact that i cant drive through the f**king water"*. However, workers also showed a degree of hostility towards colleagues who are not familiar with the algorithm. This is especially true for gig workers who have invested time and effort in mastering the algorithm; some of them may feel a sense of superiority or expertise compared to colleagues who are not familiar with it. For example, p58-10 wrote: *"Because you haven't done your homework to anticipate the surge and all the other drivers let that non-surge ping roll to you."*

5.5 Discussion and Design Implications

In this chapter, we found that workers initiated the online collective sensemaking process when their mental models are negatively violated. We also found workers' research efforts can be divided into two categories: exploratory (starting with observations to understand violations) and confirmatory (testing hypotheses with evidence). While online collective sensemaking can aid workers in validating their thoughts, offering insightful interpretations of what they have observed, and providing actionable plans, it results in uncertain conclusions most of the time.

Throughout the sensemaking process, workers consistently reported feeling frustrated and powerless, regardless of the sensemaking outcome. This frustration may stem from the power asymmetry between workers and gig platforms, particularly for those who heavily depend on gig work for their financial livelihood. Workers frequently felt that the algorithms were designed to work against them and would penalize them when their actions deviated from what the gig platform preferred. For example, a common trigger for collective sensemaking among workers was a decrease in the number of ride requests they received or a decline in the profitability of the requests they did receive. Workers often attributed this to their own behavior, such as declining low-paying rides, having a low ride acceptance rate, or receiving low ratings, which they perceived as unfavorable to the platform. Workers unconsciously believed that deviating from the platform's expectations could result in negative outcomes, limiting their ability to game with the algorithms. While this work shows collective solutions are not common for workers, the power asymmertary can result in backfiring when workers do resist. When reacting to workers' hacks, gig platforms often demand even more precarious conditions, leading to worsened situations for the workers. For instance, in 2019, a group of drivers in Washington D.C. attempted to increase surge pricing at an airport by coordinating their efforts, only to face deactivation from the platform. Platforms then publicly stated that they have implemented technical measures to prevent similar occurrences from happening in the future. [2]

This study highlights several design implications. Firstly, it demonstrates that collective sensemaking among workers can effectively address some of the challenges posed by algorithms. However, the current platforms for such discussions, such as online communities like Reddit

[2] https://wjla.com/news/local/uber-and-lyft-drivers-fares-at-reagan-national

and Facebook groups, are not optimized for this purpose. Similar to other online collective sensemaking platforms, discussions on gig work also tend to be buried in lengthy, unstructured threads, making it difficult to synthesize information. To improve the situation, it is essential to facilitate the collection, organization, and visualization of data to support collective sensemaking. Tools like automated bots armed with advanced language models can assist in extracting key factors in workers' rich descriptions, utilizing them to either confirm or refute the hypothesis. These tools could also play a crucial role in synthesizing evolving hypotheses within the discussion. In addition to the challenges faced by common online sensemkaing platforms, gig workers also faced the challenge that their goals were not as aligned and they faced more emotional tensions...

Designing for the gig economy should consider not only workers and platforms, but also other stakeholders such as policymakers. Our findings revealed that the root cause of the challenges faced by gig workers is the significant power imbalance between the workers and the gig platforms. The platforms' control over the disclosure of information, deciding what information can be revealed and to what extent, greatly hinders workers' efforts in comprehending the algorithms. Due to such power imbalance, third parties such as policymakers should take steps to ensure transparency by requiring gig platforms to disclose necessary information. Efforts like the GDPR have already granted individuals the right to an explanation for automated decisions that significantly affect them. We propose the implementation of more specific regulations for gig work platforms, given the significant impact their decision-making can have on workers' livelihoods. Online sensemaking platforms can be a valuble source for policy activists to actively listen to workers and understand their information needs. For instance, there should be concrete regulations on algorithmic operations that are properly documented. In cases of critical decision-making, such as account deactivation, workers should have the right to understand how the decision was reached and be granted the opportunity to appeal.

5.6 Limitation and Conclusion

This chapter has several limitations. Firstly, the content analysis was conducted on a limited sample size, as our selection process relied on identifying posts explicitly mentioning the term 'algorithm.' Consequently, the 69 posts analyzed represent only a small fraction of gig workers' collective attempts to comprehend the algorithms employed by the company. It is worth noting that workers may describe algorithmic management experiences using different terminologies, such as 'surge,' even if the underlying phenomenon is algorithmically driven. Hence, our sampling approach may introduce bias by favoring workers with a higher understanding and awareness of algorithms. Secondly, this study solely examined discussion posts from online communities dedicated to Uber drivers. This sampling approach could bias the results towards gig workers who are tech-savvy and those who are more motivated to engage online work discussions. Future research would benefit from conducting a more comprehensive analysis encompassing various types of gig workers. By incorporating a broader range of platforms and worker perspectives, a more holistic understanding of algorithmic management in the gig economy can be achieved.

To sum up, this chapter explores how gig workers collectively make sense of the algorithms that impact their work, examining their motivations, process, and outcomes of sensemaking. The study involved a content analysis of 69 posts and 1,198 comments from the r/uberdrivers subreddit.

The findings indicate that workers were primarily driven to understand the algorithms when they perceived negative effects, like difficulties in obtaining rides or not receiving expected surge fares. The collective sensemaking process involved both exploratory and confirmatory research, with workers documenting experiences, developing hypotheses, and conducting experiments to validate their understanding. This effortful process helped validate each other's experiences, interpret anomalies, and develop actionable strategies. However, challenges to the collective sensemaking process were identified, including limited data, platform control, and conflicts of interest among workers.

Chapter 6

Conclusion

Online communities foster connections between people with shared experiences. This shared understanding allows for authentic empathy and practical advice, often exceeding what professionals can offer. Peer support benefits greatly from the internet's accessibility, with 24/7 availability and the ability to retrieve past information. Participation in online communities offers a wealth of benefits, both in terms of information and emotional support. The collective wisdom of their members allows individuals to explore a broader range of solutions for their problems. Meanwhile, the shared experiences within these groups can create a safe space for members to express their feelings more openly.

However, online peer support faces challenges. The lack of commitment due to temporary needs and ease of leaving can threaten a group's sustainability. Additionally, the absence of professional expertise and the potential for misinformation necessitate strategies to improve peer support skills (e.g., communication). This dissertation investigates strategies to address the challenges faced by online peer support groups by focusing on improving member retention and empowering members to provide more effective support. Specifically, in this dissertation, I examined peer support in two types of online communities: online health communities (OHCs) and communities for gig workers.

Chapter 2 focuses on member retention in OHCs. It explores how motivations and behaviors change as members transition from newcomers to other roles or leave the community entirely. The research found motivations shift based on both internal community dynamics and external needs related to a member's health journey. While oldtimers provided most content, they also faced challenges like emotional strain from other members' deaths. Chapter 3 investigates volunteer counselor expertise in online mental health groups. It found initial training to be insufficient, with counselors relying heavily on personal experience and lacking systematic feedback. Maintaining professional boundaries with clients was also reported as an issue; despite available resources, training and support were underutilized.

Chapters 4 and 5 explore peer support among gig workers, where competition can exist. Chapter 4 delves into how social media supports gig workers during COVID-19. It found social media groups alleviate isolation, provide experiential knowledge, and offer platforms for organizing (with limitations due to the challenges mentioned above). Chapter 5 explores how gig workers collectively understand algorithms that manage their work using content analysis. The research found negative experiences with algorithms prompted collective sensemaking efforts.

However, the power asymmetry between workers and platforms makes achieving desired outcomes difficult.

As this dissertation has shown, peer support benefits greatly from the internet's accessibility, offering 24/7 availability and the ability to retrieve past information. However, many challenges for online peer communities stem from the limitations of existing platforms (e.g., thread-based forums, social media groups). For example, Chapter 2 highlighted the lack of personalization in most OHCs, making it difficult for help seekers to find people with relevant expertise. Similarly, Chapter 5 discussed how the decentralized nature of Reddit hinders workers' organization of collective activities. With the emergence of new technologies like AI, peer support has the potential to become even more helpful. By personalizing content recommendations, suggesting relevant subreddits, and even translating languages, AI can make online communities more user-friendly and accessible for a wider audience. Additionally, AI-powered chatbots could summarize complex topics, fact-check information, and ultimately facilitate collective sensemaking within online communities, leading to more informed discussions.

Bibliography

[1] Syed Ishtiaque Ahmed, Nicola J Bidwell, Himanshu Zade, Srihari H Muralidhar, Anupama Dhareshwar, Baneen Karachiwala, Cedrick N Tandong, and Jacki O'Neill. Peer-to-peer in the workplace: A view from the road. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 5063–5075, 2016. 4.2.1

[2] Andrea Alarcon and Mary L Gray. *Future of Work Global Labor. Literature Review.* Learning, Evaluation and Research Activity II (LER II). 4.1

[3] Mashael Yousef Almoqbel and Donghee Yvette Wohn. Individual and collaborative behaviors of rideshare drivers in protecting their safety. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW):1–21, 2019. 4.2.1, 4.2.2, 4.4.2

[4] Tim Althoff, Kevin Clark, and Jure Leskovec. Large-scale analysis of counseling conversations: An application of natural language processing to mental health. *Transactions of the Association for Computational Linguistics*, 4:463–476, 2016. 3.2.1

[5] Juan Alvarez De La Vega, Marta Cecchinato, and John Rooksby. "why lose control?" a study of freelancers' experiences with gig economy platforms. 2021. 5.3

[6] Tawfiq Ammari and Sarita Schoenebeck. "thanks for your interest in our facebook group, but it's only for dads" social roles of stay-at-home dads. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, pages 1363–1375, 2016. 1

[7] Deborah Ancona. Framing and acting in the unknown. *S. Snook, N. Nohria, & R. Khurana, the handbook for teaching leadership*, 3(19):198–217, 2012. 5.3

[8] Nazanin Andalibi and Patricia Garcia. Sensemaking and coping after pregnancy loss: the seeking and disruption of emotional validation online. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1):1–32, 2021. 5.2.3

[9] Samuel B Bacharach, Peter Bamberger, and Valerie McKinney. Boundary management tactics and logics of action: The case of peer-support providers. *Administrative Science Quarterly*, 45(4):704–736, 2000. 3.4.2

[10] Anna N Baglione, Maxine M Girard, Meagan Price, James Clawson, and Patrick C Shih. Modern bereavement: a model for complicated grief in the digital age. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–12, 2018. 2.4.3

[11] Uttam Bajwa, Denise Gastaldo, Erica Di Ruggiero, and Lilian Knorr. The health of workers

in the global gig economy. *Globalization and health*, 14(1):1–4, 2018. 4.2.1

[12] Arnold B Bakker, Karen I Van Der Zee, Kerry A Lewig, and Maureen F Dollard. The relationship between the big five personality factors and burnout: A study among volunteer counselors. *The Journal of social psychology*, 146(1):31–50, 2006. 2.4.3

[13] Martina Balestra, Coye Cheshire, Ofer Arazy, and Oded Nov. Investigating the motivational paths of peer production newcomers. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 6381–6385. ACM, 2017. 2.2.1, 2.4.1

[14] Antonina Bambina. *Online social support: the interplay of social networks and computer-mediated communication*. Cambria press, 2007. 2.3.2

[15] Azy Barak and Nili Bloch. Factors related to perceived helpfulness in supporting highly distressed individuals through an online support chat. *CyberPsychology & Behavior*, 9(1): 60–68, 2006. 3.1, 3.2.1

[16] Amit Baumel. Online emotional support delivered by trained volunteers: users' satisfaction and their perception of the service compared to psychotherapy. *Journal of Mental Health*, 24(5):313–320, 2015. 1, 3.1, 3.2.1, 3.4.1

[17] James Bennett-Levy. Therapist skills: A cognitive model of their acquisition and refinement. *Behavioural and Cognitive Psychotherapy*, 34(1):57–78, 2006. 3.2.2, 3.4.1

[18] Thor Berger, Carl Benedikt Frey, Guy Levin, and Santosh Rao Danda. Uber happy? work and well-being in the 'gig economy'. *Economic Policy*, 34(99):429–477, 2019. 4.2.1

[19] Jeffrey L Binder. Issues in teaching and learning time-limited psychodynamic psychotherapy. *Clinical Psychology Review*, 19(6):705–719, 1999. 3.2.2, 3.5.1

[20] Sophie Bishop. Anxiety, panic and self-optimization: Inequalities and the youtube algorithm. *Convergence*, 24(1):69–84, 2018. 5.2.2

[21] Thomasina Borkman. Experiential knowledge: A new concept for the analysis of self-help groups. *Social service review*, 50(3):445–456, 1976. 4.4.1

[22] David A Brent and David J Kolko. Psychotherapy: Definitions, mechanisms of action, and relationship to etiological models. *Journal of Abnormal Child Psychology*, 26(1):17–25, 1998. 3.1

[23] Susan L. Bryant, Andrea Forte, and Amy Bruckman. *Becoming Wikipedian: transformation of participation in a collaborative online encyclopedia*, pages 1–10. ACM Press, New York, 2005. 2.1, 2.2.1

[24] Alex Bryson, Rafael Gomez, and Paul Willman. Online social networking and trade union membership: What the facebook phenomenon truly means for labor organizers. *Labor History*, 51(1):41–53, 2010. 4.4.3

[25] Eliane Léontine Bucher, Peter Kalum Schou, and Matthias Waldkirch. Pacifying the algorithm–anticipatory compliance in the face of algorithmic management in the gig economy. *Organization*, 28(1):44–67, 2021. 5.2.1

[26] Jenna Burrell. How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big data & society*, 3(1):2053951715622512, 2016. 5.2.1

[27] Lindsey D Cameron and Hatim Rahman. Expanding the locus of resistance: Understanding the co-constitution of control and resistance in the gig economy. *Organization Science*, 33 (1):38–58, 2022. 5.2.2

[28] Maxine Capner and Marie Louise Caltabiano. Factors affecting the progression towards burnout: A comparison of professional and volunteer counsellors. *Psychological Reports*, 73(2):555–561, 1993. 2.4.3

[29] Maxine Capner and Marie Louise Caltabiano. Factors affecting the progression towards burnout: A comparison of professional and volunteer counsellors. *Psychological Reports*, 73(2):555–561, 1993. 3.2.2

[30] Ben Chapman and Valerie Bauerlein. U.s. coronavirus cases rose to monthly record in july, Aug 2020. URL `https://www.wsj.com/articles/coronavirus-latest-news-080220-11596361041`. 4.3.1

[31] Kathy Charmaz and Linda Liska Belgrave. Grounded theory. *The Blackwell encyclopedia of sociology*, 2007. 3.3.2, 4.3.1

[32] Prerna Chikersal, Danielle Belgrave, Gavin Doherty, Angel Enrique, Jorge E Palacios, Derek Richards, and Anja Thieme. Understanding client support strategies to improve clinical outcomes in an online mental health intervention. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–16, 2020. 3.2.1

[33] Katherine Y Chuang and Christopher C Yang. Helping you to help me: exploring supportive interaction in online health community. In *Proceedings of the 73rd ASIS&T Annual Meeting on Navigating Streams in an Information Ecosystem-Volume 47*, page 9. American Society for Information Science, 2010. 2.1, 2.2.2, 2.4.1, 2.4.2

[34] Robert B Cialdini, Carl A Kallgren, and Raymond R Reno. A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In *Advances in experimental social psychology*, volume 24, pages 201–234. Elsevier, 1991. 5.4.2

[35] Ruth Berins Collier, VB Dubal, and Christopher Carter. Labor platforms and gig work: the failure to regulate. 2017. 4.2.1

[36] Matteo Cristofaro. Organizational sensemaking: A systematic review and a co-evolutionary model. *European Management Journal*, 40(3):393–405, 2022. 5.2.3

[37] Joe Curran, Glenys Dean Parry, Gillian Hardy, Jennifer Darling, Ann-Marie Mason, and Eleni Chambers. How does therapy harm? a model of adverse process using task analysis in the synthesis of service users' experience. *Frontiers in Psychology*, 10:347, 2019. 1, 3.2.2

[38] Munmun De Choudhury and Sushovan De. Mental health discourse on reddit: Self-disclosure, social support, and anonymity. In *Eighth international AAAI conference on weblogs and social media*, 2014. 1, 4.1, 4.2.2

[39] Willem De Groen, Ilaria Maselli, and Brian Fabo. The digital market for local services: A one-night stand for workers? an example from the on-demand economy. *An Example from the On-Demand Economy (April 4, 2016). CEPS Special Report*, (133), 2016. 4.2

[40] Michael A DeVito, Darren Gergle, and Jeremy Birnholtz. " algorithms ruin everything" # riptwitter, folk theories, and resistance to algorithmic change in social media. In *Proceedings of the 2017 CHI conference on human factors in computing systems*, pages 3163–3174, 2017. 5.2.2

[41] Michael A Devito, Ashley Marie Walker, Jeremy Birnholtz, Kathryn Ringland, Kathryn Macapagal, Ashley Kraus, Sean Munson, Calvin Liang, and Herman Saksono. Social technologies for digital wellbeing among marginalized communities. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing*, pages 449–454, 2019. 1

[42] Veena B Dubal. The drive to precarity: A political history of work, regulation, & labor advocacy in san francisco's taxi & uber economics. *Berkeley J. Emp. & Lab. L.*, 38:73, 2017. 4.2.1

[43] Lawrence Dyche and Luis H Zayas. Cross-cultural empathy and training the contemporary psychotherapist. *Clinical social work journal*, 29(3):245–258, 2001. 3.4.1

[44] Benjamin G Edelman and Michael Luca. Digital discrimination: The case of airbnb. com. *Harvard Business School NOM Unit Working Paper*, (14-054), 2014. 4.2.1

[45] Robert Elliott, Jeanne C Watson, Rhonda N Goldman, and Leslie S Greenberg. *Learning emotion-focused therapy: The process-experiential approach to change*. American Psychological Association Washington, DC, 2003. 3.4.1

[46] Robert Elliott, Arthur C Bohart, Jeanne C Watson, and Leslie S Greenberg. Empathy. *Psychotherapy*, 48(1):43, 2011. 3.4.1

[47] Michael Eraut*. Informal learning in the workplace. *Studies in continuing education*, 26 (2):247–273, 2004. 3.3.2

[48] Jordan Eschler, Zakariya Dehlawi, and Wanda Pratt. Self-characterized illness phase and information needs of participants in an online cancer forum. In *Ninth International AAAI Conference on Web and Social Media*. 2.1

[49] Motahhare Eslami, Aimee Rickman, Kristen Vaccaro, Amirhossein Aleyasen, Andy Vuong, Karrie Karahalios, Kevin Hamilton, and Christian Sandvig. " i always assumed that i wasn't really that close to [her]" reasoning about invisible algorithms in news feeds. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 153–162, 2015. 5.1, 5.2.1

[50] Motahhare Eslami, Karrie Karahalios, Christian Sandvig, Kristen Vaccaro, Aimee Rickman, Kevin Hamilton, and Alex Kirlik. First i" like" it, then i hide it: Folk theories of social feeds. In *Proceedings of the 2016 cHI conference on human factors in computing systems*, pages 2371–2382, 2016. 5.2.2

[51] Motahhare Eslami, Sneha R Krishna Kumaran, Christian Sandvig, and Karrie Karahalios. Communicating algorithmic process in online behavioral advertising. In *Proceedings of the 2018 CHI conference on human factors in computing systems*, pages 1–13, 2018. 5.2.1, 5.2.2

[52] E. A. Fallon, D. Driscoll, T.S. Smith, K. Richardson, and K. Portier. Description,

characterization, and evaluation of an online social networking community: the american cancer society's cancer survivors network®. *Journal of Cancer Survivorship*, 12 (5):691–701, Oct 2018. ISSN 1932-2267. doi: 10.1007/s11764-018-0706-8. URL `https://doi.org/10.1007/s11764-018-0706-8`. 2.3.1

[53] Sarah Feldman. Infographic: What is the top paying gig job?, Sep 2019. URL `https://www.statista.com/chart/19411/gig-work-pay/`. 4.2.1

[54] Neil Foster. "why can't we be friends?" an exploration of the concept of 'friendship'within client—music therapist relationships. *British Journal of Music Therapy*, 21(1):12–22, 2007. 3.4.2

[55] Ruben Fukkink. Peer counseling in an online chat service: A content analysis of social support. *Cyberpsychology, behavior, and social networking*, 14(4):247–251, 2011. 3.1

[56] Eric Gilbert and Karrie Karahalios. Predicting tie strength with social media. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 211–220, 2009. 4.1, 4.2.2

[57] John Godard. Strikes as collective voice: A behavioral analysis of strike activity. *ILR Review*, 46(1):161–175, 1992. 4.2.1

[58] Robert M Gordon. Folk psychology as simulation. *Mind & language*, 1(2):158–171, 1986. 5.1

[59] James J Guinan, LW McCallum, L Painter, J Dykes, and J Gold. Stressors and rewards of being an aids emotional-support volunteer: a scale for use by care-givers for people with aids. *AIDS care*, 3(2):137–150, 1991. 3.2.2

[60] Kevin Hamilton, Karrie Karahalios, Christian Sandvig, and Motahhare Eslami. A path to understanding the effects of algorithm awareness. In *CHI'14 extended abstracts on human factors in computing systems*, pages 631–642. 2014. 5.1

[61] Benjamin Hanckel, Son Vivienne, Paul Byron, Brady Robards, and Brendan Churchill. 'that's not necessarily for them': Lgbtiq+ young people, social media platform affordances and identity curation. *Media, Culture & Society*, 41(8):1261–1278, 2019. 1

[62] Anikó Hannák, Claudia Wagner, David Garcia, Alan Mislove, Markus Strohmaier, and Christo Wilson. Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*, pages 1914–1933, 2017. 4.2.1

[63] Andrea Hartzler and Wanda Pratt. Managing the personal side of health: how patient expertise differs from the expertise of clinicians. *Journal of medical Internet research*, 13 (3):e62, 2011. 1

[64] Gillian R Hayes, Gregory D Abowd, John S Davis, Marion L Blount, Maria Ebling, and Elizabeth D Mynatt. Opportunities for pervasive computing in chronic cancer care. In *International Conference on Pervasive Computing*, pages 262–279. Springer, 2008. 1, 2.1, 2.4.1

[65] Jeffrey A Hayes, Janet E McCracken, Mary K McClanahan, Clara E Hill, Jennifer S Harp, and Paul Carozzoni. Therapist perspectives on countertransference: Qualitative data in

search of a theory. *Journal of Counseling Psychology*, 45(4):468, 1998. 3.2.2

[66] Jeffrey A Hayes, Charles J Gelso, and Ann M Hummel. Managing countertransference. *Psychotherapy*, 48(1):88, 2011. 3.2.2

[67] Amy R Hesse. Secondary trauma: How working with trauma survivors affects therapists. *Clinical social work journal*, 30(3):293–309, 2002. 3.4.2

[68] Clara E Hill. *Helping skills: Facilitating, exploration, insight, and action*. American Psychological Association, 2009. 3.3.1

[69] Clara E Hill, Catherine Sullivan, Sarah Knox, and Lewis Z Schlosser. Becoming psychotherapists: Experiences of novice trainees in a beginning graduate class. *Psychotherapy: Theory, Research, Practice, Training*, 44(4):434, 2007. 3.2.2, 3.2.2, 3.3.2

[70] Robin K Hill. What an algorithm is. *Philosophy & Technology*, 29:35–59, 2016. 5.2.1

[71] Bernie Hogan. From invisible algorithms to interactive affordances: Data after the ideology of machine learning. In *Roles, trust, and reputation in social media knowledge markets*, pages 103–117. Springer, 2015. 5.1

[72] Maya Holikatti, Shagun Jhaver, and Neha Kumar. Learning to airbnb by engaging in online communities of practice. *Proceedings of the ACM on Human-Computer Interaction*, 3 (CSCW):1–19, 2019. 4.2.2, 4.5

[73] Lei Vincent Huang and Piper Liping Liu. Ties that work: Investigating the relationships among coworker connections, work-related facebook utility, online social capital, and employee outcomes. *Computers in Human Behavior*, 72:512–524, 2017. 4.1, 4.2.1

[74] Julie Hui, Nefer Ra Barber, Wendy Casey, Suzanne Cleage, Danny C Dolley, Frances Worthy, Kentaro Toyama, and Tawanna R Dillahunt. Community collectives: Low-tech social support for digitally-engaged entrepreneurship. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–15, 2020. 4.5

[75] Abigail Hunt, Emma Samman, Sherry Tapfuma, Grace Mwaura, Rhoda Omenya, Kay Kim, Sara Stevano, and Aida Roumer. Women in the gig economy: paid work, care and flexibility in kenya and south africa. 2019. 4.2.1

[76] Kevin O Hwang, Allison J Ottenbacher, Angela P Green, M Roseann Cannon-Diehl, Oneka Richardson, Elmer V Bernstam, and Eric J Thomas. Social support in an internet weight loss community. *International journal of medical informatics*, 79(1):5–13, 2010. 2.1

[77] Lyft Inc. Helping lyft's driver community - covid-19, . URL `https://www.lyft.com/safety/coronavirus/driver`. 4.2.2

[78] Uber Inc. Why is my local glh closed?, . URL `https://help.uber.com/driving-and-delivering/article/why-is-my-local-glh-closed?nodeId=e882c6fc-465c-498b-ad48-b9216020fa9c`. 4.2.2

[79] Uber Technologies Inc. An update on covid-19 financial assistance, Mar 2020. URL `https://www.nytimes.com/2020/03/30/business/economy/coronavirus-instacart-amazon.html`. 4.2.2

[80] Instacart. URL `https://covidresponse.instacart.com/shopper-resources/`.

4.2.2

[81] Joshua Introne, Bryan Semaan, and Sean Goggins. A sociotechnical mechanism for online support provision. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 3559–3571. ACM, 2016. 2.1, 2.2.1, 2.2.2, 2.4.2, 2.5

[82] Muhammad Iqbal, Muhammad Noman Khalid, Amir Manzoor, Malik Munib Abid, and Nazir Ahmed Shaikh. Search engine optimization (seo): A study of important key factors in achieving a better search engine result page (serp) position. *Sukkur IBA Journal of Computing and Mathematical Sciences*, 6(1):1–15, 2022. 5.1

[83] Lilly C Irani and M Six Silberman. Turkopticon: Interrupting worker invisibility in amazon mechanical turk. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 611–620, 2013. 4.1

[84] Nura Jabagi, Anne-Marie Croteau, Luc K Audebrand, and Josianne Marsan. Gig-workers' motivation: thinking beyond carrots and sticks. *Journal of Managerial Psychology*, 2019. 4.1, 4.2.1

[85] Maia Jacobs, James Clawson, and Elizabeth D Mynatt. A cancer journey framework: guiding the design of holistic health technology. In *Proceedings of the 10th EAI International Conference on Pervasive Computing Technologies for Healthcare*, pages 114–121. ICST (Institute for Computer Sciences, Social Informatics and Telecommunications Engineering), 2016. 1, 2.1, 2.4.2

[86] Maia L Jacobs, James Clawson, and Elizabeth D Mynatt. My journey compass: a preliminary investigation of a mobile tool for cancer patients. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 663–672. ACM, 2014. 2.1

[87] Irving L Janis. Groupthink. *IEEE Engineering Management Review*, 36(1):36, 2008. 5.2.3

[88] Mohammad Hossein Jarrahi and Will Sutherland. Algorithmic management and algorithmic competencies: Understanding and appropriating algorithms in gig work. In *International Conference on Information*, pages 578–589. Springer, 2019. 4.2.1

[89] Mohammad Hossein Jarrahi, Will Sutherland, Sarah Beth Nelson, and Steve Sawyer. Platformic management, boundary resources for gig work, and worker autonomy. *Computer Supported Cooperative Work (CSCW)*, 29(1):153–189, 2020. 5.2.2

[90] Mohammad Hossein Jarrahi, Gemma Newlands, Min Kyung Lee, Christine T Wolf, Eliscia Kinder, and Will Sutherland. Algorithmic management in a work context. *Big Data & Society*, 8(2):20539517211020332, 2021. 5.2.1

[91] Zhou Jiang and Xiaowen Hu. Knowledge sharing and life satisfaction: The roles of colleague relationships and gender. *Social Indicators Research*, 126(1):379–394, 2016. 4.1, 4.2.1

[92] Allen C Johnston, James L Worrell, Paul M Di Gangi, and Molly Wasko. Online health communities. *Information Technology & People*, 2013. 2.2.2

[93] Hannah Johnston, Chris Land-Kazlauskas, et al. Organizing on-demand: Representation, voice, and collective bargaining in the gig economy. 2018. 5.1

[94] Arne L Kalleberg and Michael Dunn. Good jobs, bad jobs in the gig economy. *LERA for*

Libraries, 20(1-2), 2016. 4.2, 4.2.1

[95] Vaishnav Kameswaran, Lindsey Cameron, and Tawanna R Dillahunt. Support for social and cultural capital development in real-time ridesharing services. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–12, 2018. 4.2.2, 4.3.2

[96] Brian Keegan, Darren Gergle, and Noshir Contractor. Hot off the wiki: dynamics, practices, and structures in wikipedia's coverage of the tōhoku catastrophes. In *Proceedings of the 7th international symposium on Wikis and open collaboration*, pages 105–113. ACM, 2011. 2.1

[97] Melissa G Keith, Peter D Harms, and Alexander C Long. Worker health and well-being in the gig economy: A proposed framework and research agenda. In *Entrepreneurial and Small Business Stressors, Experienced Stress, and Well-Being*. Emerald Publishing Limited, 2020. 4.2.1

[98] Vera Khovanskaya, Phoebe Sengers, and Lynn Dombrowski. Bottom-up organizing with tools from on high: Understanding the data practices of labor organizers. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13, 2020. 1, 4.2.1

[99] Eliscia Kinder, Mohammad Hossein Jarrahi, and Will Sutherland. Gig platforms, tensions, alliances and ecosystems: An actor-network perspective. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW):1–26, 2019. 4.2.1

[100] Thomas M Kirchberg and Robert A Neimeyer. Reactions of beginning counselors to situations involving death and dying. *Death Studies*, 15(6):603–610, 1991. 3.2.2

[101] Felix Kölle and Simone Quercia. The influence of empirical and normative expectations on cooperation. *Journal of Economic Behavior & Organization*, 190:691–703, 2021. 5.4.2

[102] Yubo Kou, Xinning Gui, Yunan Chen, and Kathleen Pine. Conspiracy talk on social media: collective sensemaking during a public health crisis. *Proceedings of the ACM on Human-Computer Interaction*, 1(CSCW):1–21, 2017. 5.2.3

[103] Peter Krafft, Kaitlyn Zhou, Isabelle Edwards, Kate Starbird, and Emma S Spiro. Centralized, parallel, and distributed information processing during collective sensemaking. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 2976–2987, 2017. 5.2.3

[104] Robert E Kraut and Paul Resnick. *Building successful online communities: Evidence-based social design*. Mit Press, 2012. 2.1, 2.2.1

[105] Siou Chew Kuek, Cecilia Paradi-Guilford, Toks Fayomi, Saori Imaizumi, Panos Ipeirotis, Patricia Pina, and Manpreet Singh. The global opportunity in online outsourcing. 2015. 4.1

[106] Neha Kumar, Nassim Jafarinaimi, and Mehrab Bin Morshed. Uber in bangladesh: The tangled web of mobility and justice. *Proceedings of the ACM on Human-Computer Interaction*, 2(CSCW):1–21, 2018. 4.2.2, 4.3.1, 4.4.2

[107] Cliff Lampe, Nicole B Ellison, and Charles Steinfield. Changes in use and perception of facebook. In *Proceedings of the 2008 ACM conference on Computer supported cooperative*

work, pages 721–730. ACM, 2008. 2.2.1

[108] Airi Lampinen, Christoph Lutz, Gemma Newlands, Ann Light, and Nicole Immorlica. Power struggles in the digital economy: platforms, workers, and markets. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*, pages 417–423, 2018. 4.5

[109] Jayoung Lee, Nayoung Lim, Eunjoo Yang, and Sang Min Lee. Antecedents and consequences of three dimensions of burnout in psychotherapists: A meta-analysis. *Professional Psychology: Research and Practice*, 42(3):252, 2011. 3.2.2

[110] Min Kyung Lee, Daniel Kusbit, Evan Metsky, and Laura Dabbish. Working with machines: The impact of algorithmic and data-driven management on human workers. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 1603–1612, 2015. 4.2.1, 5.1, 5.2.1, 5.4.1

[111] Melissa Legg, S Occhipinti, M Ferguson, J Dunn, and SK Chambers. When peer support may be most beneficial: The relationship between upward comparison and perceived threat. *Psycho-Oncology*, 20(12):1358–1362, 2011. 2.4.3

[112] Vili Lehdonvirta. Algorithms that divide and unite: Delocalisation, identity and collective action in 'microwork'. In *Space, place and global digital work*, pages 53–80. Springer, 2016. 4.1, 4.2.2

[113] Qiujie Li, Yeonji Jung, and Alyssa Friend Wise. Beyond first encounters with analytics: Questions, techniques and challenges in instructors' sensemaking. In *LAK21: 11th international learning analytics and knowledge conference*, pages 344–353, 2021. 5.2.3

[114] Louise Locock and Janice B Brown. 'all in the same boat'? patient and carer attitudes to peer support and social comparison in motor neurone disease (mnd). *Social science & medicine*, 71(8):1498–1505, 2010. 2.1

[115] Haiwei Ma, C Smith, Lu He, Saumik Narayanan, Robert A Giaquinto, Roni Evans, Linda Hanson, and Svetlana Yarosh. Write for life: Persisting in online health communities through expressive writing and social support. *Proceedings of the ACM on Human-Computer Interaction*, 1(CSCW):73, 2017. 2.1, 2.2.2

[116] Ning F Ma and Benjamin V Hanrahan. Part-time ride-sharing: Recognizing the context in which drivers ride-share and its impact on platform use. *Proceedings of the ACM on Human-Computer Interaction*, 3(GROUP):1–17, 2019. 4.4.3

[117] Ning F Ma, Chien Wen Yuan, Moojan Ghafurian, and Benjamin V Hanrahan. Using stakeholder theory to examine drivers' stake in uber. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–12, 2018. 4.2.1, 4.2.2

[118] Sally Maitlis, Timothy J Vogus, and Thomas B Lawrence. Sensemaking and emotion in organizations. *Organizational Psychology Review*, 3(3):222–247, 2013. 5.2.3

[119] Brenton J Malin and Curry Chandler. Free to work anxiously: Splintering precarity among drivers for uber and lyft. *Communication, Culture & Critique*, 10(2):382–400, 2017. 4.2.1, 4.2.2

[120] Brent Mallinckrodt. The psychotherapy relationship as attachment: Evidence and implica-

tions. *Journal of Social and Personal Relationships*, 27(2):262–270, 2010. 3.2.2

[121] Lena Mamykina, Drashko Nakikj, and Noemie Elhadad. Collective sensemaking in online health forums. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 3217–3226, 2015. 5.1, 5.2.3

[122] Lena Mamykina, Arlene M Smaldone, and Suzanne R Bakken. Adopting the sensemaking perspective for chronic disease self-management. *Journal of biomedical informatics*, 56: 406–417, 2015. 5.1, 5.2.3

[123] L. Markus. Towards a "critical mass" theory of interactive media: Universal access, interdependence, and diffusion. *Communication Research*, 14:491–511, 1987. 2.4.2

[124] Victoria J Marsick and Karen E Watkins. Informal and incidental learning. *New directions for adult and continuing education*, 2001(89):25–34, 2001. 3.4.2

[125] Michael Massimi. Exploring remembrance and social support behavior in an online bereavement support group. In *Proceedings of the 2013 conference on Computer supported cooperative work*, pages 1169–1180, 2013. 1

[126] Michael Massimi, Jackie L Bender, Holly O Witteman, and Osman H Ahmed. Life transitions and online health communities: reflecting on adoption, use, and disengagement. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, pages 1491–1501. ACM, 2014. 1, 2.1, 2.2.2, 2.4.3, 2.5, 3.2.1

[127] Dan Mercea. Probing the implications of facebook use for the organizational form of social movement organizations. *Information, Communication & Society*, 16(8):1306–1327, 2013. 4.4.3

[128] Richard L Moreland and John M Levine. Socialization in small groups: Temporal changes in individual-group relations1. In *Advances in experimental social psychology*, volume 15, pages 137–192. Elsevier, 1982. 1, 2.1, 2.2.1

[129] M Pilar Moreno-Jiménez and M Carmen Hidalgo Villodres. Prediction of burnout in volunteers. *Journal of Applied Social Psychology*, 40(7):1798–1818, 2010. 2.4.3

[130] Robert R Morris, Stephen M Schueller, and Rosalind W Picard. Efficacy of a web-based, crowdsourced peer-to-peer cognitive reappraisal platform for depression: randomized controlled trial. *Journal of medical Internet research*, 17(3):e72, 2015. 1, 3.2.2

[131] Jason S Moser and Hans S Schroder. Making sense of it all? cognitive and behavioral mechanisms needing clarification in the meaning maintenance model. *Psychological Inquiry*, 23(4):367–373, 2012. 5.4.2

[132] Clementine M Msengi, Helena Arthur-Okor, Lorraine Killion, and Jennifer Schoer. Educating immigrant women through social support. *SAGE Open*, 5(4):2158244015611935, 2015. 1

[133] Michael Muller, N Sadat Shami, David R Millen, and Jonathan Feinberg. We are all lurkers: consuming behaviors among authors and readers in an enterprise file-sharing service. In *Proceedings of the 16th ACM international conference on Supporting group work*, pages 201–210, 2010. 4.4.1

[134] Keris Myrick and Paolo Del Vecchio. Peer support services in the behavioral healthcare

workforce: State of the field. *Psychiatric rehabilitation journal*, 39(3):197, 2016. 1

[135] Gemma Newlands, Christoph Lutz, and Christian Fieseler. Collective action and provider classification in the sharing economy. *New Technology, Work and Employment*, 33(3): 250–267, 2018. 4.1, 4.2.1

[136] Mark W Newman, Debra Lauterbach, Sean A Munson, Paul Resnick, and Margaret E Morris. It's not that i don't have problems, i'm just not putting them on facebook: challenges and opportunities in using online social networks for health. In *Proceedings of the ACM 2011 conference on Computer supported cooperative work*, pages 341–350. ACM, 2011. 2.1, 2.2.2

[137] Blair Nonnecke and Jenny Preece. Lurker demographics: Counting the silent. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, pages 73–80, 2000. 4.4.1

[138] Kathleen O'Leary, Arpita Bhattacharya, Sean A Munson, Jacob O Wobbrock, and Wanda Pratt. Design opportunities for mental health peer support technologies. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*, pages 1470–1484, 2017. 1, 3.2.1

[139] Kathleen O'Leary, Stephen M Schueller, Jacob O Wobbrock, and Wanda Pratt. "suddenly, we got to become therapists for each other" designing peer support chats for mental health. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–14, 2018. 3.2.1

[140] Allen M Omoto and Mark Snyder. Sustained helping without obligation: motivation, longevity of service, and perceived attitude change among aids volunteers. *Journal of personality and social psychology*, 68(4):671, 1995. 3.4.2

[141] Aditya Pal, Rosta Farzan, Joseph A Konstan, and Robert E Kraut. Early detection of potential experts in question answering communities. In *International Conference on User Modeling, Adaptation, and Personalization*, pages 231–242. Springer, 2011. 2.1, 2.4.2

[142] Katherine Panciera, Aaron Halfaker, and Loren Terveen. Wikipedians are born, not made: a study of power editors on wikipedia. In *Proceedings of the ACM 2009 international conference on Supporting group work*, pages 51–60. ACM, 2009. 1, 2.1, 2.4.2, 2.5

[143] Sungkyu Park, Inyeop Kim, Sang Won Lee, Jaehyun Yoo, Bumseok Jeong, and Meeyoung Cha. Manifestation of depression and loneliness on social networks: a case study of young adults on facebook. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*, pages 557–570, 2015. 1

[144] Sachin R Pendse, Faisal M Lalani, Munmun De Choudhury, Amit Sharma, and Neha Kumar. " like shock absorbers": Understanding the human infrastructures of technology-mediated mental health support. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–14, 2020. 3.2.1

[145] Zhenhui Peng, Qingyu Guo, Ka Wing Tsang, and Xiaojuan Ma. Exploring the effects of technological writing assistance for support providers in online mental health community. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*,

pages 1–15, 2020. 3.2.1

[146] Michael Pica. The ambiguous nature of clinical training and its impact on the development of student clinicians. *Psychotherapy: Theory, Research, Practice, Training*, 35(3):361, 1998. 3.2.2

[147] William E Piper. Implications of psychotherapy research for psychotherapy training. *The Canadian Journal of Psychiatry*, 49(4):221–229, 2004. 3.2.2, 3.2.2

[148] Bernd Ploderer, Wally Smith, Steve Howard, Jon Pearce, and Ron Borland. Patterns of support in an online community for smoking cessation. In *Proceedings of the 6th International Conference on Communities and Technologies*, pages 26–35. ACM, 2013. 2.2.2

[149] Jennifer Preece and Ben Shneiderman. The reader-to-leader framework: Motivating technology-mediated social participation. *AIS transactions on human-computer interaction*, 1(1):13–32, 2009. 2.1, 2.2.1

[150] Yada Pruksachatkun, Sachin R Pendse, and Amit Sharma. Moments of change: Analyzing peer-based cognitive support in online mental health forums. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–13, 2019. 3.1, 3.2.1

[151] Stephen A Rains. *Coping with illness digitally*. MIT Press, 2018. 2.4.1, 2.4.3

[152] Noopur Raval and Paul Dourish. Standing out from the crowd: Emotional labor, body labor, and temporal labor in ridesharing. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, pages 97–107, 2016. 4.2.1, 4.2.2

[153] Frederic G Reamer. Boundary issues in social work: Managing dual relationships. *Social work*, 48(1):121–133, 2003. 3.4.2

[154] Catherine M Ridings and David Gefen. Virtual community attraction: Why people hang out online. *Journal of Computer-mediated communication*, 10(1):JCMC10110, 2004. 2.3.2

[155] Kathryn E Ringland. “autsome”: Fostering an autistic identity in an online minecraft community for youth with autism. In *International Conference on Information*, pages 132–143. Springer, 2019. 1

[156] Shelly Rodgers and Qimei Chen. Internet community group participation: Psychosocial benefits for women with breast cancer. *Journal of Computer-Mediated Communication*, 10 (4):JCMC1047, 2005. 1, 2.3.2

[157] Alex Rosenblat and Luke Stark. Algorithmic labor and information asymmetries: A case study of uber’s drivers. *International Journal of Communication*, 10:27, 2016. 4.2.1

[158] Alexander Rozental. *Negative effects of Internet-based cognitive behavior therapy: Monitoring and reporting deterioration and adverse and unwanted events*. PhD thesis, Department of Psychology, Stockholm University, 2016. 1, 3.2.2

[159] Daniel M Russell, Mark J Stefik, Peter Pirolli, and Stuart K Card. The cost structure of sensemaking. In *Proceedings of the INTERACT’93 and CHI’93 conference on Human factors in computing systems*, pages 269–276, 1993. 5.2.3

[160] Niloufar Salehi, Lilly C Irani, Michael S Bernstein, Ali Alkhatib, Eva Ogbe, and Kristy Milland. We are dynamo: Overcoming stalling and friction in collective action for crowd workers. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 1621–1630, 2015. 1, 4.2.2, 4.5

[161] Neil J Salkind. *Encyclopedia of research design*, volume 1. Sage, 2010. 2.3.2

[162] Christine Satchell and Paul Dourish. Beyond the user: use and non-use in hci. In *Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7*, pages 9–16, 2009. 2.4.3

[163] Noam Scheiber and Kate Conger. Strikes at instacart and amazon over coronavirus health concerns, Mar 2020. URL `https://www.nytimes.com/2020/03/30/business/economy/coronavirus-instacart-amazon.html`. 4.3, 4.3.2

[164] Joseph Seering, Felicia Ng, Zheng Yao, and Geoff Kaufman. Applications of social identity theory to research and design in computer-supported cooperative work. *Proceedings of the ACM on Human-Computer Interaction*, 2(CSCW):1–34, 2018. 4.2.2

[165] Liesel L Sharabi. Exploring how beliefs about algorithms shape (offline) success in online dating: A two-wave longitudinal investigation. *Communication Research*, 48(7):931–952, 2021. 5.2.1

[166] Eva Sharma and Munmun De Choudhury. Mental health support and its relationship to linguistic accommodation in online communities. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, page 641. ACM, 2018. 2.2.2

[167] Daniel Spurk and Caroline Straub. Flexible employment relationships and careers in times of the covid-19 pandemic, 2020. 4.2.1

[168] Hans H Strupp. The psychotherapist's skills revisited. *Clinical Psychology: Science and Practice*, 2(1):70–74, 1995. 3.1

[169] Will Sutherland and Mohammad Hossein Jarrahi. The gig economy and information infrastructure: The case of the digital nomad community. *Proceedings of the ACM on Human-Computer Interaction*, 1(CSCW):1–24, 2017. 4.5

[170] Monideepa Tarafdar, Xinru Page, and Marco Marabelli. Algorithms as co-workers: Human algorithm role interactions in algorithmic work. *Information Systems Journal*, 2022. 5.1

[171] Arianna Tassinari and Vincenzo Maccarrone. Riders on the storm: Workplace solidarity among gig economy couriers in italy and the uk. *Work, Employment and Society*, 34(1): 35–54, 2020. 5.1

[172] Yla Tausczik and Xiaoyun Huang. Knowledge generation and sharing in online communities: Current trends and future directions. *Current Opinion in Psychology*, 2020. 1, 4.1

[173] Rannie Teodoro, Pinar Ozturk, Mor Naaman, Winter Mason, and Janne Lindqvist. The motivations and experiences of the on-demand mobile workforce. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, pages 236–247, 2014. 4.2

[174] Peggy A Thoits. Mechanisms linking social ties and support to physical and mental health.

Journal of health and social behavior, 52(2):145–161, 2011. 2.4.1

[175] Jeanine Warisse Turner, Jean A Grube, and Jennifer Meyers. Developing an optimal match within online communities: An exploration of cmc support communities and traditional support. *Journal of cOmmunication*, 51(2):231–251, 2001. 1

[176] Steven Vallas and Juliet B Schor. What do platforms do? understanding the gig economy. *Annual Review of Sociology*, 46, 2020. 4.1, 4.2.1

[177] Louise Van Aswegen. *The effect the experiences of volunteer HIV counsellors have on their own well–being: a case study*. PhD thesis, North-West University, 2009. 3.2.2

[178] Kurt Vandaele. Collective resistance and organizational creativity amongst europe's platform workers: A new power in the labour movement? *Work and Labour Relations in Global Platform Capitalism, Forthcoming*, 2020. 4.2.1, 4.2.2, 4.4.3, 4.5

[179] Jessica Vitak and Nicole B Ellison. 'there'sa network out there you might as well tap': Exploring the benefits of and barriers to exchanging informational and support-based resources on facebook. *New media & society*, 15(2):243–259, 2013. 4.1, 4.2.2

[180] Stella Vosniadou and William F Brewer. Theories of knowledge restructuring in development. *Review of educational research*, 57(1):51–67, 1987. 5.2.3

[181] Yi-Chia Wang, Robert Kraut, and John M Levine. To stay or leave?: the relationship of emotional and informational support to commitment in online health support groups. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work*, pages 833–842. ACM, 2012. 2.1, 2.2.2, 2.4.2

[182] Yi-Chia Wang, Robert E. Kraut, and John. M. Levine. Eliciting and receiving online support: Using computer-aided content analysis to examine the dynamics of online social support. *Journal of Medical Internet Research*, 17(4):e99, 2015. 4.4.2

[183] Elizabeth Anne Watkins. "have you learned your lesson?" communities of practice under algorithmic competition. *New Media & Society*, 24(7):1567–1590, 2022. 5.1

[184] C Edward Watkins Jr and Douglas J Scaturo. Toward an integrative, learning-based model of psychotherapy supervision: Supervisory alliance, educational interventions, and supervisee learning/relearning. *Journal of Psychotherapy Integration*, 23(1):75, 2013. 3.1, 3.5.2

[185] Juliet Webster. Microworkers of the gig economy: separate and precarious. In *New Labor Forum*, volume 25, pages 56–64. SAGE Publications Sage CA: Los Angeles, CA, 2016. 4.1, 4.2.1

[186] Karl E Weick. *Sensemaking in organizations*, volume 3. Sage, 1995. 5.1, 5.2.3, 5.4.2

[187] Karl E Weick, Kathleen M Sutcliffe, and David Obstfeld. Organizing and the process of sensemaking. *Organization science*, 16(4):409–421, 2005. 5.2.3

[188] Jeroen Wolbers and Kees Boersma. The common operational picture as collective sensemaking. *Journal of Contingencies and Crisis management*, 21(4):186–199, 2013. 5.2.3

[189] Alex Wood and Vili Lehdonvirta. Platform labour and structured antagonism: Understanding the origins of protest in the gig economy. *Available at SSRN 3357804*, 2019.

4.2.2

[190] Alex J Wood, Vili Lehdonvirta, and Mark Graham. Workers of the internet unite? online freelancer organisation among remote gig economy workers in six asian and african countries. *New Technology, Work and Employment*, 33(2):95–112, 2018. 1, 4.1, 4.2.2

[191] Alex J Wood, Mark Graham, Vili Lehdonvirta, and Isis Hjorth. Good gig, bad gig: autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, 33(1):56–75, 2019. 4.1, 4.2.1

[192] Jamie Woodcock and Mark Graham. *The gig economy: a critical introduction*. Polity, 2019. 4.2.1

[193] Zhijun Yan, Tianmei Wang, Yi Chen, and Han Zhang. Knowledge sharing in online health communities: A social exchange theory perspective. *Information & Management*, 53(5): 643–653, 2016. 2.2.2

[194] Galit Ventura Yanay and Niza Yanay. The decline of motivation?: From commitment to dropping out of volunteering. *Nonprofit management and Leadership*, 19(1):65–78, 2008. 1, 3.2.2, 3.4.2

[195] Diyi Yang, Robert Kraut, Tenbroeck Smith, Elijah Mayfield, and Dan Jurafsky. Seekers, providers, welcomers, and storytellers: Modeling social roles in online health communities. 2019. 2.1, 2.3.2

[196] Diyi Yang, Zheng Yao, Joseph Seering, and Robert E. Kraut. The channel matters: Self-disclosure, reciprocity and social support in online cancer support groups. In *CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2019)*. ACM, 2019. 2.4.2

[197] Zheng Yao, Silas Weden, Lea Emerlyn, Haiyi Zhu, and Robert E Kraut. Together but alone: Atomization and peer support among gig workers. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2):1–29, 2021. 5.1, 5.3

[198] Alyson L Young and Andrew D Miller. " this girl is on fire" sensemaking in an online health community for vulvodynia. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–13, 2019. 5.1, 5.2.3

[199] Pengyi Zhang and Dagobert Soergel. Towards a comprehensive model of the cognitive process and mechanisms of individual sensemaking. *Journal of the Association for Information Science and Technology*, 65(9):1733–1756, 2014. 5.2.3, 5.3