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Together Apart: Decoding Support Dynamics in Online COVID-19 Communities

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***Abstract*—The COVID-19 pandemic that broke out globally in December 2019 put us all in an unprecedented situation. Social media became a vital source of support and information during the pandemic, as physical interactions were limited by people staying at home. This paper investigates support dynamics and user commitment in an online COVID-19 community of Reddit. We define various support classes and observe them along with user behavior and temporal phases for a coherent in the community. We perform survival analysis using Cox Regression to identify factors influencing a user's commitment to the community. People seeking more emotional and informational support while they are COVID-positive stay longer in the community. Surprisingly, people who give more support in their early phases are less likely to stay. Additionally, contrary to common belief, our findings show that receiving emotional and informational support has little effect on users' longevity in the community. Our results lead to a better understanding of user dynamics related to community support and can directly impact moderators and platform owners in designing community guidelines and incentive structures.**

***Index Terms*—Social support, Support dynamics, COVID-19, Survival analysis**

I. Introduction

As of July 2023, the number of people affected by COVID-19 worldwide stands at 690 million, with the death toll reaching 6.9 million. To tackle the pandemic, authorities imposed travel bans, movement restrictions, and closed public places to reduce the spread. Such drastic changes in the daily routine and uncertainties of the pandemic took a toll on people's mental health. Studies show that COVID-19 has a consistent negative impact on mental health, which has led to an increase in anxiety, depression, and Post-traumatic stress syndrome (PTSS) [1]–[3]. It has also increased the number of people looking for support and mental healthcare [4]. Lack of physical interaction and increased distress resulted in people sitting at home, spending more time on social media to maintain relationships, get information/support during the lockdown [5], [6]. People use social media to share their personal stories [7], look for information on COVID-19 [8], and seek support from others during this challenging time in their lives [9].

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Many people turn to online communities to seek social support [10]. Previous studies have shown that social support in online communities can help people feel better [11]–[14] and positively affect a user's mental health [15]. It has helped users in battling drug addiction [16], dealing with cancer [17], losing weight [18], and curbing depression [19]. Analyzing the kind of support people seek, kind of support they receive, and how it affects a user's behavior can be instrumental for community moderators and platform designers.

Benefits provided by an online community are likely to be more accessible to people who stay longer [17]. To study the extent of online communities' role in providing support, we need to understand what influences a user's decision to participate longer in the community. Analysis of user longevity can give us valuable insights into the dynamics of online social support.

Previous works have analyzed people's sentiments during COVID-19 [20]. Han et al. [21], studied public opinion, while another study [20] used topic modeling techniques to identify discussion topics and analyze emotions. However, more work needs to be done in analyzing dynamics of community support on social media during COVID-19. Moreover, not much work has tried to study user commitment and its effects in a COVID-19 based online community.

We address this gap in our paper by doing a coherent study of the social support community subreddit named *COVID-19positive* on Reddit. We study two popular support categories - emotional and informational support. We examine these support classes in two dimensions - user behavior and temporal phases. Using survival analysis, we then study the support factors that influence a user's longevity in these communities, precisely what compels a user to stay in the community even after recovering.

We discover that (1) In a COVID-19 community, emotional support involves discussing recovery, the status of family and loved ones. Emotions such as gratitude, prayer, and hope are expressed. Informational support involves discussion around research, infections, finance, and tests. (2) People who stay longer seek more informational and emotional support from the community. They also (3) give more support. Surprisingly, (4) the amount of support a user receives from the community is independent of the user's decision to stay. Furthermore, factors like talking about symptoms and recovery and interacting with more users in the community promote a longer stay. Through our work, we make the following contributions:

- Investigate support dynamics in a COVID-19-based online community.
- Characterize the factors influencing a user's longevity in the community.

II. Related Work

Social isolation is associated with increased morbidity and mortality in a host of medical illnesses [22]. Online healthcare communities have extensively studied support for diseases such as cancer and depression. Emotional support in a community can help build relationships, improving their commitment to the group. Wang, Kraut, and Levine [17] conducted a survival analysis to predict how emotional or informational support exposure affects the length of subsequent participation and user commitment. Emotional support was positively associated with how long members remained in the group.

Numerous studies have explored various aspects of social media and COVID-19. For instance, [23] conducted a sentiment analysis of Twitter data to examine changes in public sentiment overtime during the COVID-19 outbreak. The study found a significant increase in negative sentiment during the initial outbreak of COVID-19. Similarly, a study by [24] examined public opinion on COVID-19 in China and found that various factors, including government policies, media coverage, and social media, influenced public opinion. Additionally, studies have shown that social media can be a platform for spreading misinformation about COVID-19 [4].

Despite the importance of social support in health-related communities, the dynamics of support have yet to be explored in detail for COVID-19 communities. Li et al. [25] examined the association between social support and mental health in COVID-19 patients but did not specifically focus on support dynamics in online communities. In contrast, our study aims to fill this gap by examining the support dynamics of users in COVID-19 communities, focusing on emotional and informational support before getting tested positive, during the quarantine, and after recovering.

Existing literature has highlighted the critical role of social support in online health communities. For instance, [26] conducted a study on loneliness in online health communities and found it a prevalent problem. However, social support can help mitigate the adverse effects of loneliness. Similarly, [27] found that social support can buffer the negative impact of COVID-19 related stressors on mental health outcomes. In addition, previous research has shown that understanding users' trajectories in online communities can provide valuable insights into how individuals engage with and benefit from online communities. In their recent research, [35] examined user trajectories in online health communities and found that participation levels can vary significantly. This finding highlights the importance of understanding factors contributing to diverging user trajectories.

In summary, our study aims to contribute to the growing body of literature on social media and COVID-19 by examining the support dynamics of user communities. We build upon existing research on social support in online health communities and aim to provide insights into how online communities can be leveraged to improve mental health outcomes during the pandemic. Additionally, by exploring the trajectories of users in these communities, we hope to understand how seeking/giving/receiving support can affect users longevity in the communities.

III. Dataset

We focus on Reddit as our social media platform. The content on Reddit is organized in communities by topics of interest called subreddits. For our study, we look at the */r/COVID19positive* subreddit[1] where people ask questions and share their stories and experiences around the COVID-19 pandemic. The data used in our analysis were collected using the Pushshift API[2] and PRAW (Python Reddit API Wrapper).[3] Choosing */r/COVID19positive* as the subreddit to study has the following advantages:

- People ask questions, share experiences, and gain information from others on how to cope with the disease, making it a rich source of data for studying support.
- The data is classified using flairs. These flairs allow us to study the data in a structured manner. Each submission can be assigned to a predefined category that the admin of the subreddit has defined. Some popular flairs in */r/COVID19positive* subreddit are Tested Positive - θ where θ can be Me, Family, Friends, etc., Question-to those who tested positive, and Question for medical research.
- The subreddit follows strict guidelines, and the community is well-moderated. Hence there is less possibility of falsely labelled data.

We collected posts, comments, and metadata like usernames, timestamps, and scores. We obtained a total of 93,576 posts and 9,93,030 comments. This data was generated by 104,818 unique active users, of which 37,762 (36.03 %) wrote at least one post and 94,469 (90.13 %) wrote at least one comment. Table I shows basic statistics of */r/COVID19positive* dataset.

IV. Data Classification

Researchers have investigated online social support in a variety of ways. Social support has been conceptualized earlier either in terms of its functional content (the division of support into different categories like emotional and informational), being active (giving), or being passive (receiving) [28]. Some studies also analyze a third behavioral category which is seeking support [29], [30]. Based on these, we study support along

[1]https://www.reddit.com/r/COVID19positive/
[2]https://github.com/pushshift/api
[3]https://pypi.org/project/praw/

the two dimensions, functional content, behavioral aspect and add another dimension, i.e., temporal classification. In the context of COVID-19, a user's timeline can be divided into three phases: before the user tests positive, during the 15 days of quarantine in which a user is positive, and after the quarantine is over. Analyzing support in these three phases can give us more insights into the different support dynamics in each phase. Considering the above points, in the following sections, we classify data on three dimensions as seen in Figure 1 - (1) different categories of support - *emotional and informational support*; (2) the three user behaviors - *seeking, giving, and receiving support*; (3) the three temporal phases in the context of COVID-19 *before, during, and after phase*.

A. Social Support Categories

Many support categories have been identified [31]–[33], but two have been most talked about in online communities:
Emotional Support: Defined as having others sharing care, concern, sympathy, empathy, encouragement, and validation [34]. It can be crucial in the scenario of COVID-19. We define emotional support as posts with flair - Tested positive + θ and the comments received on such posts, where θ can be *Me, Family, Friends*. We define this group as emotional flair set in Table I because posts with these flairs often include people sharing their experiences with COVID-19 drawing other people's interest. People commenting on such posts also show concern, sympathy and offer condolences to those affected.
Informational Support: This is defined as sharing suggestions and information [34], which for COVID-19 includes information about symptoms, treatment, side effects, disease development, preventive measures, etc. This support is vital during COVID-19 because there was a lot of misleading information in the beginning of the pandemic. We define informational support to include posts with flairs - "Verified Research", "Question-to those who tested positive", "Question-for medical research".

B. Behaviour

LaCoursiere [36] presented a holistic theory for online social support in health communities. She defined three main channels by way of which online social support can occur:

- Perceptual: When an individual's need for social support arises due to emotional factors such as stress.

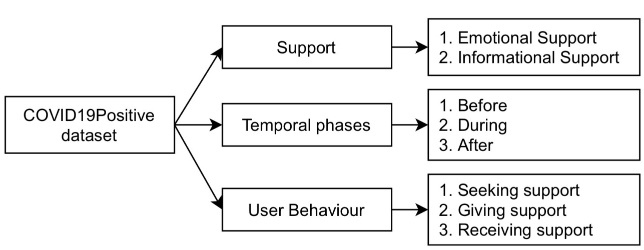

Fig. 1. Data classification of */r/COVID19Positive* dataset.

	Flair	Posts	Comments
Emotional flair	TP	4,219 (4.51%)	46,302 (4.95%)
	TP - Me	26,975 (28.82%)	266,806 (28.53%)
	TP - Family	7,452 (7.96%)	85,243 (9.12%)
	TP - Friends	1,575 (1.68%)	15,588 (1.67%)
	TP - LongHauler	785 (0.84%)	6,860 (0.73%)
	TP - Unvaccinated	269 (0.29%)	3,237 (0.35%)
	TP - Breakthrough	1,034 (1.1%)	10,431 (1.11%)
Informational flair	Verified Research	183 (0.19%)	723 (0.07%)
	Question - to those who tested positive	25,439 (27.18%)	212,748 (22.75%)
	Question - for medical research	4,311 (4.61%)	38,055 (4.07%)

TABLE I
TOTAL POSTS AND COMMENTS FOR DIFFERENT FLAIRS ON THE COVID19POSITIVE DATASET. TP = TESTED POSITIVE.

- Cognitive: When an individual seeks information about particular medical entities like medication, symptoms, procedures, etc.
- Transactional: This is when an individual evaluates the social support they receive from the community.

This theory can be helpful in our social support analysis by defining users' various behaviors in the context of support. We define three kinds of user behavior on the subreddit:
Seeking Behaviour: This behavior can be described as someone asking for support on the subreddit. A user can seek two kinds of support - Emotional support and Informational support, as defined in the previous section. Emotional support seeking is defined as a user uploading a post with a flair from emotional flair set. Informational support seeking is defined as a user uploading a post with a flair from informational flair set. Emotional support seeking is a example of the perceptual channel of online social support, whereas, informational support seeking is an example of the cognitive channel of online social support.
Receiving Behaviour: This behavior can be described as the community's response to someone seeking support. We consider received support to be the comments on the posts seeking that particular kind of support. Therefore, emotional support receiving are the comments on the posts seeking emotional support. Informational support receiving are the comments on the posts seeking informational support. Since we are considering the community's response here, we remove the comments made by a user on their own post. Receiving behavior is a direct consequence of the transactional channel of online social support. In their 2006 study, Moreland and Levine [37] analyzed the antecedents and consequences of individuals' group involvement. The authors put forth a group socialization model, according to which members assess the group's ability to fulfill their needs. They consider the group's past and potential future benefits during this evaluation. Members' level

of commitment to the group is determined by the outcome of this assessment, which in turn influences their inclination to remain in the group and actively work towards collective goals. Primary determinant of whether the user's needs are being met is the support received from the community, which consequently influences the user's persistence in the group. This information can help understand the dynamics of group engagement and its impact on individual behavior.

Giving Behaviour: This behavior can be described as a user supporting others in the community by giving back. Preece and Shneiderman [38] found that people who receive support, start to reciprocate it back to other community members. We consider giving support to be comments made on other people's posts seeking that kind of support. Therefore, emotional support giving is the comments made on the posts seeking emotional support. Informational support giving is the comments made on the posts seeking informational support.

C. Phases

Let the time at which the user tested positive be t. Based on when a user tested positive, we can divide our data into the following three phases:

Before Phase: Any time spent by a user in this community before time t is before phase of the user.

During Phase: Time between t and $t+15$ days is the during phase. This is the period when a user is COVID-19 positive. This period coincides with the quarantine period in most countries before a user gets tested again.

After Phase: This is the time spent by a user in the community after $-t+15$ days.

How to decide when a user tests positive? We assume that a user tested positive the day they uploaded the first post using the indicative flair. We do this because there is no definite indicator in an online community to decide when a user tests positive.

V. Support Analysis

We analyze the differences between defined support classes in two steps. Firstly, we analyze the linguistic differences between support classes across phases using topic modeling and odds of topics. This helps us understand the functional differences between support and behavioral classes. Then, we analyze support in phases this helps us understand how many users move in and out of the community. Next, we analyze which support classes influence a user's decision to stay in the community for longer.

A. Differentiating support classes

Topic Modelling: We use topic modeling to get a high-level overview of the content in support classes and observe the differences between them. This also acts as a validation for flair based classification. Using topic modeling, we represent a document as a collection of topics, giving an idea of what the document is about. We use a dense representation topic modeling framework [4] and a class-based TF-IDF to create dense clusters allowing for easily interpretable topics while keeping essential words in the topic descriptions. This algorithm starts with creating document embeddings from a set of documents useing Doc2Vec [39]. We cluster these embeddings together using HDBSCAN [40]. Since HDBSCAN is prone to the curse of dimensionality, we first reduce the dimensions using UMAP [40], which preserves local structure well, after which we can use HDBSCAN to cluster similar documents. We find cluster descriptors, i.e., words that describe each cluster the best using TF-IDF. We use class-based TF-IDF, which considers each cluster a single document and then applies the standard TF-IDF algorithm.

[4]BERTopic: Neural topic modeling with a class-based TF-IDF procedure - Maarten Grootendorst

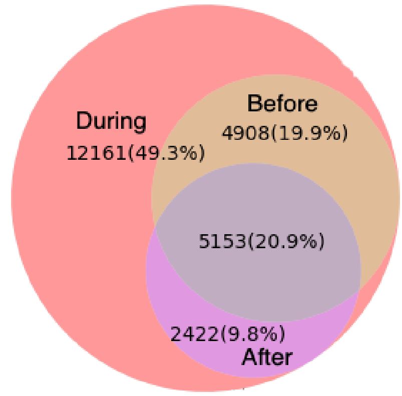

Fig. 2. Distribution of users doing some activity (posting or commenting) in each of the phases. Note that we do not have people just in the before phase or the after phase because we define the phases with respect to the first post of a user made by a user using the flair in emotional flair set which is in the during phase. Any activity before this post lies in the before phase, any activity 15 days after this post is in the after phase

Odds of Topics: For the support classes, we found most frequent topics to be quite similar, which is understandable since all the classes are talking about COVID-19. To find discriminative topics for each class, we use the odds ratio, a statistical metric to measure the association between the presence of one property with another. We define Odds of Topics, where we find a topic for a class that has the least overlap with the topics of the other class. We consider only those topics with a frequency of occurrence greater than 2 to avoid scarce topics. The discriminative topics for each support class are given in Table II. We see a clear distinction between the two support classes in seeking and giving behaviors.

B. Support in Phases

We study the number of users in each phase and intersection of users between phases. Out of all the users who tested positive, 49% of positive users became active on the subreddit in the *during phase*, which means the very first post they did on the subreddit was presumably about their COVID-19 experience. About 41% of people did some activity before they tested positive, and 30% continued to be active in *after phase*, with 21% of users being in all three phases. The Venn diagram in Figure 2 shows the exact distribution of 24,644 users who tested positive in each phase. We observe two subsets of users,

Support seeking				Support giving			
Informational		Emotional		Informational		Emotional	
Topic	**Words**	**Topic**	**Words**	**Topic**	**Words**	**Topic**	**Words**
Symptoms	smell, taste, body, temp, headache, breathe, shortness, asthma, insomnia	Sickness and Family	dad, mom, father, hospital, baby, son, kid, cough, daughter, husband, fever, toddler, family	Infection	swab, allergy, response, nose, itchy, immune, system, fever, breath, shortness, fatigue, headache	Love and Care	love, hug, hugs, sending, virtual, glad, feel, sorry, loss, grief supportive, healthcare
Nutritional and Lifestyle advice	appetite, eat, weight, exercise, take, taking, ivermectin, zinc, quercetin, paxlovid, vitamin, supplement	Recovery	contagious, still, positive, quarantine, resting, test, tested, exercise, run, workout, walk, recovered, longer, isolate, isolation, day	Wellness and Rest	chicken, soup, fruit, immunity, immune, taking, b12, daily, salt, appetite, gargle, honey, electrolyte, hydrated, exercise, workout	Coping Strategies	pfizer, moderna, shot, steroid, antibiotic, netflix, watch, binge, watching, game, podcasts, book, tv, show, green, tea, honey, ginger, lemon, water, cayenne, manuka
Test	test, tested, positive, pulse, levels, oxygen, oximeter, day, vaccinated, antibody, blood	Mental health and Anxiety	anxiety, feel, pain, fear, panic, scared, nausea, anyone, brain, fog, memory, focus	Research and Facts	covid19, science, study, studies, data, evidence, research, scientific, scientist, theory	Gratitude	please, thank, thanks, you, so, much, contribution
Other related topics	menstrual cycle, periods, urination, bladder, alcohol, smoke, smoking, dog, cats, pets	Personal and Health Concerns	fever, cough, taste, fatigue, breath, job, loss, pay, employer, manager, living	COVID19 related topics	pcr, antigen, mask, air, n95, quarantine, omicron, delta, variant, body, response, hair	Pray and Hope	wish, speedy, recovery, better, pray, sending, you, strong, hope, hopeful, crossed, fingers, miracles

TABLE II

TOPIC MODELLING RESULTS. INFORMATIONAL SUPPORT SEEKING HAS TOPICS CONSISTENT WITH ASKING FOR INFORMATION- CURIOSITY, HELP, DETAILS ABOUT INFECTION AND THE TESTING PROCESS. IN CONTRAST, EMOTIONAL SUPPORT SEEKING HAS CONTENT DESCRIBING MILD SYMPTOMS, RECOVERY, SICKNESS IN THE FAMILY AND ANXIETY ABOUT HEALTH OF FAMILY MEMBERS. INFORMATION SUPPORT GIVING PROVIDES INFORMATION RELATED TO FINANCE, INFECTION, RESEARCH AND SEVERE SYMPTOMS. ON THE OTHER HAND, EMOTIONAL SUPPORT GIVING INCLUDES SHOWING GRATITUDE, LOVE AND HOPE, ALONG WITH RECOMMENDING REST. WE SEE A CLEAR DISTINCTION BETWEEN THE TWO SUPPORT CLASSES, IN BOTH THE SEEKING AND GIVING BEHAVIOURS

one in *before and during phase* but never entered *after phase*. They never returned to do any activity (post or comment) in their *after phase*. Other subset is the users who were present in all three phases. This compels us to ask the question *What makes a user stay in the community?*

We analyzed the support types provided by each group and found that those who stayed in the community were likelier to seek and provide information and emotional support than those who did not. In the during phase, users who stayed received significantly more emotional support than those who did not.

Figure 3 illustrates the values for each support class for both subsets. Our analysis revealed that the average number of users who sought information in before phase was 0.18 for the "*Before During After*" group, while it was only 0.012 for the "*Before During NOT After*" group. Additionally, the average number of users who gave emotional and informational support in before phase and during phase were 2.28, 1.43, 3.11, and 1.72, respectively, for the "*Before During After*" group. The corresponding values for the "*Before During NOT After*" group were 0.08, 0.04, 0.1, and 0.05, respectively.

Moreover, the average number of users who received emotional support in the during phase was much higher for the "*Before During After*" group (20.27) compared to the "*Before During NOT After*" group (1.94). Also, emotional support seeking and receiving was not defined for the before phase. In summary, our findings suggest that users who stay in the community are more engaged and active in seeking and providing support to others. We test the validity of this hypotheses by performing causal inference using survival analysis.

VI. Survival analysis: Relationship between support and longevity

Survival analysis [42] is a statistical approach that assesses the likelihood and timing of an event's occurrence, and how various factors influence it. We use survival analysis to find whether there is a causation between how long a tested positive user participates in the group and the amount of support they seek, give, or receive. In our case, the event of interest is whether a user is active in the after phase. Our goal is to understand whether the amount of emotional or informational support a user gives, seeks, or receives has any role in increasing the length of participation. We also try to discover what other factors may be responsible for their behavior to remain active in later phase.

A. Data and Methods

To conduct the analysis, we included only users who contributed more than one post. Failure event is defined as the user's last login date. If a user does not return in the after phase, failure event is true.

Survival time of a user is defined in days as the time between their first activity on the subreddit and their last activity of interest. If a user returns in after phase (failure event is false), survival time is the number of days between the first post in after phase and the first post ever created. If a user does not return in after phase (failure event is true), survival time is the number of days between the last post in during phase and the first post created. Because people who logged in close to the end of data collection might still be participating, we considered those who last logged in within 15 days of data collection as right censored.

Covariate	coef	HR	se(coef)
Before Info Seeking*	0.08	**1.09**	0.02
During Emo Seeking*	-0.07	**0.93**	0.02
During Info Seeking*	-0.07	**0.94**	0.04
Before Emo Giving	0.12	1.13	0.01
Before Info Giving*	0.01	**1.01**	0.01
During Emo Giving	0.14	1.15	0.01
During Info Giving	-0.02	0.98	0.01
Before Info Receiving***	0.0	1.0	0.0
During Info Receiving	0.0	1.0	0.0
During Emo Receiving***	0.0	1.0	0.0
Num Self Comments*	-0.02	**0.98**	0.0
Outdegree	-0.14	0.87	0.01
Degree*	-0.02	**0.98**	0.0
Avg Post Length***	0.0	1.0	0.0
Avg Comment Length***	0.0	1.0	0.0
Avg Post Time Diff***	0.0	1.0	0.0
Topic Post Family*	-0.13	**0.88**	0.02
Topic Post Symptom*	-0.24	**0.79**	0.01
Topic Comment Gratitude*	0.01	**1.01**	0.01
Topic Comment Recovery***	0.0	1.0	0.01

TABLE III
RESULTS FROM SURVIVAL ANALYSIS. THE COVARIATES MARKED $***$ HAVE A SIGNIFICANT POSITIVE EFFECT ($p < 0.005$) ON SURVIVAL.

B. Cox Regression

Cox proportional hazards regression [41] is a method for investigating the effect of covariates on time a specified event takes to happen. In such cases, the conditional survival function is calculated

$$S(t|x) = P(T > t|x) \tag{1}$$

Where x denotes the covariates and t denotes the time till the event of interest occurs. Cox proportional hazard is represented as:

$$h(t) = h_0(t)^{b_1 x_1 + \ldots. + b_k x_k} \tag{2}$$

where,
$h(t)$: hazard at time t
$h_0(t)$: hazard for a person with value of 0 for all independent variables
b: regression coefficient for independent variable x
x_i: independent variables
For our model the survival event is whether a user is active on the community in their after phase. We use Cox Regression to see what are the factors that affect this survival.

C. Covariates

Support seeking/giving/receiving is divided into before and during phases of the user. There is no emotion seeking in the before phase due to our definition: The first post with "Tested positive" (emotional support) flair starts the during phase.

- `Emotional support seeked`: Total emotional seeking posts made in the corresponding phase.
- `Informational support seeked`: Total informational seeking posts made in the corresponding phase.
- `Emotional support given`: Total emotional giving comments made in the corresponding phase.
- `Informational support given`: Total informational giving comments made in the corresponding phase.
- `Emotional support received`: Total emotional comments received in the corresponding phase.
- `Informational support received`: Total informational comments received in the corresponding phase.

Total support received is the summation of all the comments received by that user. We also used covariates found from the topic modeling like number of posts with topic `family`, `symptoms`, `gratitude`, and `recovery`. Other covariates considered were `Num Self comments`, number of unique people a user interacts with (`Degree`), `Avg Post Length`, `Avg Comment Length`, and average time interval between consecutive posts.

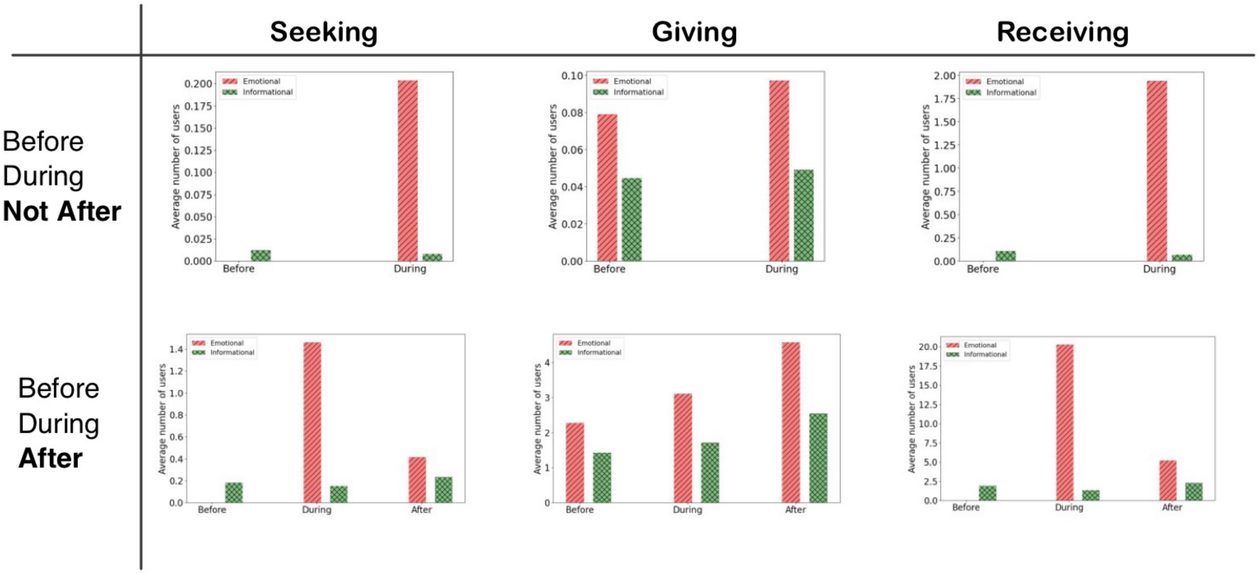

Fig. 3. Support in phases. Users who stay tend to seek double the information support in before and during phases than those who don't. They give three to four times more support, both emotional and informational, in before and during phases. They also receive 1.6 times more emotional support in the during phase.

D. Analysis

Table III shows the results obtained from the Cox Proportional Hazard model. The *coef* column represents the covariate's effect on a user's survival. If the coef is negative, hazard is less; therefore, the particular covariate will positively affect survival. This means that if we increase the value of this parameter, survival will increase and vice-versa.

The Hazard Ratio (HR) is the effect of an explanatory variable on risk or probability of participants' leaving the group. The HR value for Before Info Seeking is 1.09, indicating that users' survival in the group is 9% (100-(100*1.09)) lesser for those seeking information support than those not. Similarly, people seeking other forms of support during emotional seeking (7% more survival) and informational seeking (6% more survival) are more likely to remain in the group. Hence more support-seeking behavior in *during phase* is associated with more probability of staying, and surprisingly, more support-seeking behavior in *before phase* is associated with a lesser probability of staying in the community.

For support-giving behavior, before informational-giving (1% less survival), people are less likely to stay. Hence, people giving more informational support are less likely to stay. Also, before emotional giving, during emotional giving, and informational giving, behavior is not significantly associated with the user's probability of staying in the community. However, contrary to our assumption, support-receiving behavior did not significantly affect the user's stay in the community.

Other factors that promote users staying are if a user posts about their symptoms (21% more survival) or posts about their family (12% more survival). Also, users with more self-comments (2% more survival) and users who interact more with other users (2% more comments) are more likely to stay in the community.

VII. Discussion

Our work aims to analyze online COVID-19 communities for support dynamics and factors affecting the longevity of the users. We collect data from */r/COVID19positive* subreddit. First, we classify all the activities into different types and phases of support like Information or Emotional giving/seeking/receiving. We also divide a user timeline into before being contacted with COVID-19, during, and after the recovery.

We see that higher the support seeking, higher the probability of survival. Contrary to common belief, support receiving volumes did not significantly affect a user's stay in the community. Our results leads to a better understanding of user dynamics related to community support and can directly impact moderators and platform owners in designing community guidelines and incentive structures.

VIII. Limitations

Our work provides direct insights into the support dynamics of COVID-19 communities, which can assist moderators and platform designers in setting guidelines and incentive structures. However, our analysis also has some cavities which should be accounted for while building upon our work. Firstly, our definition of during phase is based on when the users post about it. We can't be sure if the user tested positive the same day or earlier. Further, our analysis does not consider that a user might get tested positive multiple times during their stay on the subreddit since data available for such cases was limited.

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