Identifying Human Needs through Social Media: 
A study on Indian cities during COVID-19

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Abstract

In this paper, we present a minimally-supervised approach to identify human needs expressed in tweets. Taking inspiration from Frustration-Aggression theory, we trained RoBERTa model to classify tweets expressing frustration which serves as an indicator of unmet needs. Although the notion of frustration is highly subjective and complex, the findings support the use of pretrained language model in identifying tweets with unmet needs. Our study reveals the major causes behind feeling frustrated during the lockdown and the second wave of the COVID-19 pandemic in India. Our proposed approach can be useful in timely identification and prioritization of emerging human needs in the event of a crisis.

1 Introduction

India reported its first case of COVID-19 from Kerala in the month of Jan, 2020 (Andrews et al., 2020). Several control measures including restrictions on international travel, screening of flight passengers, and institutional quarantine were undertaken shortly after to combat the transmission. The Government of India (GoI) imposed a nationwide lockdown¹ on Mar 25, 2020 as a preventive measure to curb the spread of COVID-19. Lockdown is an emergency protocol that restricts non-essential movement of people as well as goods. This lockdown was eventually extended till May 31, 2020, making it one of the longest lockdowns imposed during the pandemic. This resulted in a huge gap in demand and supply of goods (Mahajan and Tomar, 2021), increased stress (Rehman et al., 2021) and mass exodus of migrant workers from cities due to lack of earning opportunities in the informal economy (Das and Kumar, 2020).

Amidst the growing panic, Twitter emerged as the go to platform to express one’s feelings and needs such as travel, food, hospital beds, oxygen, cremation and funds². An overwhelming number of tweets seeking support, lack of timely response and inadequate after-care are a few motivating factors behind this study. We particularly study the tweets from metropolitan Indian cities posted during the COVID-19 pandemic. The main contributions are as follows:

• Using topic modeling and minimal supervision, we create a dataset of tweets labelled with needs as described in Maslow’s Theory of Motivation (Maslow and Lewis, 1987). This dataset with tagged needs is available for public research³.

• Taking inspiration from Frustration-Aggression theory (Dollard et al., 1939), we finetuned a state of the art neural language model, RoBERTa (Liu et al., 2019) to detect the unmet needs.

The rest of the paper is organized as follows. Section 2 describes the prior work pertinent to the research presented here. We present our approach to gather the needs from Twitter in Section 3. We introduce a RoBERTa based classifier to detect unmet needs in Section 4. We discuss the social impact of the proposed work in Section 5 and list down the limitations in Section 6. We conclude our work in Section 7.

2 Background

Understanding human needs is a widely researched domain by state agencies as well as commercial organizations (Costanza et al., 2007). Prior research has shown that fulfilled needs have a positive impact on a person’s feelings of well-being.

¹Coronavirus in India: 21-day lockdown begins; key highlights of PM Modi’s speech’, Business Today (Mar 25, 2020). Available at Link

²Reuters: https://graphics.reuters.com/HEALTH-Coronavirus/India-Twitter/oakpekqlrpr/

³https://github.com/AxleBlaze3/Covid_19_Tweets_with_Tagged_Needs
(Ryff and Keyes, 1995). From stockpiling basic household items during the initial phase of the pandemic to embracing digital technologies such as zoom, the market witnessed quite a shift in consumer needs since the outbreak of COVID-19 (Becdach et al., 2020; Mehta et al., 2020). Identifying one’s true needs, however, is a challenging task. Yang and Li (2013) took inspiration from Maslow’s theory of motivation to predict consumer’s needs and purchasing behavior using social media. Ko et al. (2020) used Korean twitter and blogs to discover customer’s unmet needs through Hierarchical Concept Search Space algorithm. Their approach aimed to facilitate idea generation for home appliances.

More recently, Yang et al. (2021) advocated the use of Weibo⁴ to identify unmet non-COVID-19 healthcare needs. Suh et al. (2021) studied the transition in needs during COVID-19 through the search queries on Bing. The product type in search queries were manually marked with the needs as described in Maslow’s theory of motivation to automate the task of need identification. Their results affirmed a human tendency to first satisfy basic needs such as food and shelter before exploring advanced needs such as creativity and love. Jolly et al. (2020) performed a psychometric analysis of tweets posted in response to official bulletins on COVID-19 by state agencies, revealing the causality between bulletins and the feeling of medical emergency on Twitter.

Prior studies (Saha et al., 2020; Guntuku et al., 2020; Mendoza et al., 2010) have consistently demonstrated the efficacy of social media platforms such as Twitter in capturing the feelings of society at scale. However, this unfurls the challenge of annotating the posts with their expressed needs. In this paper, we propose an approach to automate labeling of tweets with their expressed needs. We also build a model to detect unmet needs from tweets. To the best of our knowledge, this is the first study on the needs expressed through tweets from Indian cities during the pandemic.

3 Identifying Human needs from Tweets

We illustrate the different components of the proposed model in Fig. 1. The block diagram represents the steps of the proposed approach that are, (a) extracting key topics from Twitter discourse, (b) manual mapping of the topics to the expressed human needs, (c) mapping tweets to needs assigned to their dominant topics and (d) detection of unmet needs from tweets. The components in green represent the use case of detecting unmet needs and categorization when given a live stream of tweets.

3.1 Tweets Collection

The GoI officially declared the nationwide lockdown on Mar 25, 2020. The second wave of COVID-19 peaked in the mid of May, 2021. Taking into account the baseline considered by Suh et al. (2021) and the number of COVID-19 cases in India, we set the duration of study from Dec 1, 2019 to Jun 30, 2021, comprising a total of nineteen months. The first three months that is from Dec 1, 2019 to Feb 28, 2020 is the baseline period that serves as an indicator of pre-COVID-19 needs pattern. We here assume that a tweet does not need to be marked with hashtags related to COVID-19 to have a need affected or emerged due to ongoing COVID-19 pandemic.

Using snscrape⁶, we extract Indian tweets posted between Dec, 2019 and June, 2021. We set the

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⁴Weibo.com

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⁵WHO, Coronavirus disease 2019 (COVID-19) Situation Report – 39. Feb 28, 2020. LINK

⁶https://pypi.org/project/snscrape/
parameter “geocode” of the form \([\text{latitude}, \text{longitude}, \text{radius}]\) to the (latitude, longitude) of cities namely Nagpur, Bangalore, Jaipur, Kolkata and Patna with the radii as 500km, 400km, 350km, 50km and 100km respectively in an attempt to encompass representative metropolitan cities situated in different parts of India. The covered region is depicted in Fig. 2.

As a pre-processing step, we removed duplicate and non-English tweets. We also filtered out tweets having less than twelve words. The word limit threshold was decided empirically after analysing the content of tweets. These tweets were either related to marketing/greetings such as good morning, happy birthday or comments on the original tweets without substantial semantic content of its own. We have a total of 1.4M unique tweets for further study.

3.2 Mapping Tweets to Human Needs

In this research, we study only expressed needs in tweets. Bradshaw (1972) defined expressed need as “the felt need turned into action”. To identify the different types of expressed need, we take inspiration from Maslow’s Hierarchy of Needs (MHoN) (Maslow and Lewis, 1987) which categorizes the human needs into five distinct levels namely physiological\(L_1\), Safety \(L_2\), Love and Belonging \(L_3\), Esteem \(L_4\) and Self-Actualization \(L_5\). Physiological and safety needs are considered basic needs that need to be satisfied first before one begins to explore the advanced needs related to esteem and self-actualization.

3.2.1 Topic Extraction

Manual annotation of over 1.4M tweets with their expressed need is time consuming as well as prohibitively expensive. We therefore employ topic modeling\(^7\) (Blei et al., 2003) to identify the major topics of discourse for monthwise set of tweets which we then manually label to a level as described in Maslow’s Theory of Motivation.
The number of topic words is set to 20 and the rest of the parameters were set to default values. The number of topics is decided empirically after analysing the coherence score and execution time for a randomly picked sample of three months. We set the \#topics to 30 after analysing different number of topics, \#topics = \{10, 15, 20, ...45, 50\}. We thus obtain a set \(T\) having 570 topics (30 topics *19 months).

3.2.2 Manual Labeling of Topics

We asked a team of three human annotators to map the extracted topics \(t \in T\) to the levels \(\{L_1, L_2, L_3, L_4, L_5\} \in \text{MHoN}\). Each annotator is an undergraduate student, aged 19-21 years and highly proficient in the English language. Two were male and one was female. Given a topic \(t\) and few tweets elaborating its context of usage, the task is to map the topic \(t\) to either \(L_i \in \text{MHoN}\) or as ‘unclear’. Annotators were encouraged to choose unclear if they find a topic ambiguous. A topic is assigned a need level from MHoN only if all annotators choose the same level.

Out of 570 topics, 59 topics were assigned to \(L_1\), 150 topics mapped to \(L_2\), 84 topics to \(L_3\), 66 topics to \(L_4\) and 95 topics to the level \(L_5\). Rest were unclear.

The key categories emerged after mapping topics with needs are provided in Table 1. The physiological need majorly comprised food staples and beverages, hygiene concerns, mobility. Clearly, the meaning of safety has evolved and included topics such as housing, infection, unemployment, domestic violence, market and financial liabilities. Relationships and concern for loved one’s are discussed under love and belonging. Esteem covers online learning, ideologies, postponed examinations, lack of internet and smart devices. Self-actualization comprises recreational tasks such as DIY, sports, entertainment and skill acquisition.

\(^7\)Gensim LDA: https://radimrehurek.com/gensim_3.8.3/models/wrappers/ldamallet.html
### Table 1: Mapped topics and Need Level in Maslow’s Theory of Motivation

| Need                     | #Tweets | #Topics | Key Topics                                                                 |
|--------------------------|---------|---------|-----------------------------------------------------------------------------|
| Physiological            | 165114  | 59      | staples such as food, beverages, apparel, household products, Hygiene        |
|                          |         |         | such as toilet paper, basic daily services such as grocery delivery, milk,    |
|                          |         |         | bread, rest, medicine, transport                                            |
| Safety                   | 367774  | 150     | Housing such as rental/mortgages, evictions, COVID-19 Safety such as masks, |
|                          |         |         | quarantine or sanitizers. Domestic violence, justice. Financial              |
|                          |         |         | liabilities such as tax, loans, or bankruptcy, stock market, business Job   |
|                          |         |         | posts/application & unemployment                                           |
| Love & Belonging         | 192843  | 84      | Expression of or resources for mental health or emotional issues such        |
|                          |         |         | as anxiety, depression, loneliness, isolation, suicide, nervousness,         |
|                          |         |         | rejection, fear or sadness; Social media, Search for relationships          |
|                          |         |         | with significant others, dating, issues such as divorce or breakup        |
| Esteem                   | 151873  | 66      | Education or learning materials, University/Schools; Online classroom       |
|                          |         |         | learning, Examinations; Educational degrees or programs; Knowledge/Skill    |
|                          |         |         | zoom meetings, Ideologies/religions                                        |
| Self-Actualization       | 258287  | 95      | Recreational tasks such as self-care, home decor, music etc., parenting,    |
|                          |         |         | Talent/Skill acquisition, Life goals, Charity/Donation, volunteering,      |
|                          |         |         | Entertainment such as Netflix, Prime, TV shows, movie, sports (IPL), News   |

#### 3.2.3 Mapping Tweets to MHoN

At this step, we have a list of topics mapped with the need levels as described in MHoN. We also have the probability distribution of topics for each tweet. The dominant topic of a tweet is the topic with the highest probability. A tweet $t$ is thus marked to a need level $L_t \in$ MHoN on the basis of the mapping assigned to its dominant topic. We illustrate this process in Fig. 1 where the topic distribution along with mapped topics are used to infer the expressed need in tweets. If the tweet has multiple topics with same probability, we only assign a need level if all dominant topics are marked to the same need level else it is marked as unclear.

#### 3.3 Analysis

After excluding unclear tweets, we have over 1.1M tweets marked as expressing a need. Below are a few examples\(^8\) that were mapped to their relevant level and those that were unclear:

- "Nobody staying at hotels, So why not convert them into covid centers" – Physiological
- "When I see some people attacking doctors, i get scared about the corona situation" – Safety
- "Not everyone can work from home. Feeling kinda unsafe or its just fear of getting sucked up in situation and putting life of my family friends in danger." – Love and Belonging
- "As a teacher I thank pm for cancelling the Std. 12th board examination." – Esteem
- "xxx movie are a big hit, an average human would have to watch his movies multiple times to understand."

\(^8\)Tweets are rephrased to protect user’s privacy however, the message remains the same.

Figure 3: Volume of tweets expressing needs from Dec, 2019 to Jun, 2021.

"Met her while traveling she was selling fruits adding on to the income of her parents, with her impressive salesman skills."

Unclear

It may be noted that we have not considered tweets on political topics such as Citizen Amendment Act (Wikipedia contributors, 2021b), National Register of Citizens (Wikipedia contributors, 2021c) and Farm laws (Wikipedia contributors, 2021a) which were part of public discourse during the time of study.

We illustrate the time-wise distribution of tweets tagged with different need levels in Fig. 3. We have considered two weeks moving average to nullify noisy fluctuations in the data. For the baseline, we consider the tweets posted in the first twelve weeks that is, between week-48’2019 to week-7’2020, to understand the pre-COVID pattern of needs. Lockdown phase is the period between week-13’2020 to week-23’2020. The first wave ranges from week-31’2020 to week-41’2021.
The second wave started from week-14’2021 and ended in week-23’2021. The phases namely baseline, lockdown, first wave and second wave are annotated with boxes in Fig. 3. The first peak is placed in the lockdown period and the second peak occurred during the second wave of the pandemic. The volume of needs were slightly higher than pre-COVID levels during the first wave. There is also a huge surge in self-actualization and safety needs starting week-24’2021.

Indian Twitter users voiced the safety need most often followed by physiological need during the lockdown. Both needs peak at the same time. A total of 45% more tweets expressing basic needs were posted during lockdown compared to the second wave of the pandemic. Over twice the number of physiological tweets was expressed during the lockdown when compared to the second wave. The relatively advanced needs namely love and Belonging and esteem display a delay during the lockdown and peak almost 3-4 weeks after the basic needs. Soon after the lockdown was lifted, the needs started to return to pre-COVID pattern of needs.

During the second phase of the pandemic, safety turned out to be the foremost concern and physiological needs peaked only after a delay of two weeks. There is no clear precedence for physiological needs over advanced needs during the second wave. Moreover, love and belonging needs stayed at pre-COVID levels during the second wave unlike lockdown phase where concern for loved ones was expressed in large volumes.

Safety has indeed emerged as the dominant concern in the both phases of the pandemic. Lockdown was a special scenario where essential commodities were in shortage due to lack of production as well as black marketing. It is thus not conclusive from our data if physiological needs always take precedence over the advanced needs in the event of a crisis in today’s world.

The most advanced need, self-actualization surged and ebbed through out the months of our study without any clear correlation with the different phases of pandemic. The huge surge in self-actualization and safety needs starting week-24’2021 is due to large volume of tweets discussing Indian Premier League 2021 (Wikipedia contributors, 2022) and mass gatherings.

### 4 Detecting unmet Needs

Unmet needs are widely characterized by frustration (Dollard et al., 1939; Killgore et al., 2021). Through Frustration-Aggression theory, Dollard et al. (1939) defined frustration as an impediment or blockage in achieving one’s needs or goals. An impediment to a goal is considered frustration if and only if the person is actively striving to reach this goal. We thus hypothesize that an unmet need can be detected by identifying whether a tweet with expressed need has frustration or not.

#### 4.1 Approach

Our task is to classify whether a given tweet tagged with need is expressing frustration or not. We fine tuned the RoBERTa pretrained model (Wolf et al., 2020) with a learning rate of $2 \times 10^{-5}$ and dropout of 0.3 for this classification task. For training, we collected tweets containing the hashtag #frustrated. For negative class that is, Not frustrated, we extracted tweets with hashtags that symbolise satisfaction (ex: #satisfied, #FeelingContent). This dataset has a total of 13970 tweets with equal number of instances for positive and negative class. We provide a representative tweet from each class below:

“HOW fast does one have to be to book a slot on COWIN? I saw slots available at a hospital; I selected the time slot; entered the CAPTCHA in not more than 15 seconds... and still it didn’t book the slot. And then when I refreshed, all the slots were gone” - Frustrated

“-----------I did it! ... I officially completed my undergraduate program and received my bachelors degree. may the glory be to God for blessing me with the gifts to achieve this great milestone” - Not Frustrated

As a preprocessing step, we remove hashtags and mentions from the tweet text. We consider 80% of tweets for training and the rest 20% is equally divided for validation and test set. We achieved an accuracy of 93.4% on the validation set. We obtained an accuracy of 92.2% with a precision of 91% and recall of 93% on the test set.

#### 4.2 Performance Evaluation

Out of 1.1M tweets, our model predicted a total of 792533 tweets as frustrated. 77.36% of physiological needs and 77.5% of safety needs expressed frustration. Under advanced needs, 54.13% of love and

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9The Hindu “Coronavirus lockdown: Invoke Essential Commodities Act to curb black marketing, Home Secretary tells States” (Apr 8, 2020). Available at Link
belonging, 70.43% of esteem needs and 62.91% of self-actualization needs were marked frustrated.

To evaluate the quality of predictions, we randomly sampled 100 tweets which were annotated as frustrated or not frustrated by three undergrad students proficient in English. The majority vote was considered as the final label. A total of 45 samples were labelled as frustrated out of 100. The inter-annotator agreement (fleiss kappa) obtained for this task was 0.638 indicating its subjective nature. The trained model achieved an accuracy of 76% with a weighted precision of 78% and weighted recall of 76% on this set of annotated tweets. Below are two example tweets which were classified as frustrated:

- “Please complete the pending projects in Telangana state. Sir please do the needful. There is no direct train from Karimnagar to Hyderabad”
- “Need of hour Free Education Free/Affordable health care No freebies, let people work”

We observe that the above tweets clearly express frustration as described in Dollard et al. (1939). Another point worth noting is the subjectivity when labelling frustration. Consider the below tweets predicted as frustrated but annotated as not frustrated by human annotators.

- “She lost her life in line of duty. She had been performing her duty in adverse circumstances amid lockdown. She should be declared ‘Corona Warrior’ and all benefits and compensation should be given to her family by the govt.”
- “Finally, I am buying an Iphone, twelfth edition but next year. As I also thought about Iphone last year.”

Whether the above tweets express frustration or not, is quite debatable. Therefore, the performance metrics need to be interpreted accordingly.

4.2.1 Decoding frustration through RoBERTa

On a random sample of 30 tweets predicted as frustrated, we used integrated gradients method (Sundararajan et al., 2017) to identify the type of input features that attribute to the prediction to the class frustrated.

We provide few example tweets from this set in Fig. 4. Here, the shade of red signifies the importance of input features in prediction. The greater the significance, the deeper the hue of red. For instance, the words highlighted with deeper red such as shortage, oxygen, where, loose, ridicule, and all led to the classification into frustrated class for the first tweet in Fig. 4. Likewise for other tweets, the words namely have, transport, electricity, delay, infected, ventilators, expensive, treatment are input features that derived the prediction to the class frustrated. Since these terms intrinsically reflect constraints or impediments in leading a purposeful life, we may conclude that the model correctly learned to detect tweets expressing frustration.

4.3 Discussion

We illustrate the week wise percentage of tweets predicted as frustrated in Fig. 5. At first glance, Twitter appears to be a land of frustration with dissatisfaction rate of around 62% even before COVID-19. The jump in frustration rate in the fourth week of December’19 is due to the mulling over the passing year and eventually settled down in the next two months of Jan, 2020 and Feb, 2020.

The percentage of frustrated tweets hovered between 71 – 74% during the lockdown, the first wave and the second wave of COVID-19. Clearly, there is an increment of over 4% in frustration rate when compared to non-stressful phases of the pandemic.

We illustrate the week wise transition for the volume of frustrated tweets expressing basic and advanced needs in Fig. 6. There is a huge jump
in the volume of both categories of tweets. More tweets expressing frustration due to basic needs were posted during the lockdown in comparison to the second wave. The volume of basic tweets during the first wave remained slightly above the pre-COVID level. 

The proportion of frustrated tweets across basic and advanced level of needs is illustrated in Fig. 7. We observe that almost 80% of tweets expressing basic needs are unmet irrespective of the time of the year. Despite the fact that a large number of basic needs were posted throughout the lockdown, the dissatisfaction rate remained constant. It is thus safe to assume that users discuss basic needs only when these needs are unfulfilled. The general rate of frustration for advanced needs is 60%. We also note that as soon as the frustration due to basic needs reduces, the frustration due to advanced needs increased by over 10%. There are three such peaks in Fig. 7. This does support the belief that once the basic needs are secured, one quickly moves to the advanced needs. On analysis, education with key terms such as board exams, national level entrance exams, graduation degree was found to be the dominant concern across each peak. Another common concern was consumer-centric services with worries revolving around delayed refunds, cancelled travel plans, delayed delivery of online orders etc.

Moreover, time specific events such as call against products made in China, Bollywood scandals, football, entertainment were found during the second peak (week-36’2020 - week-44’2020). In contrast, the third peak (week-18’2021 - week-22’2021 discussed the lack of availability of vaccines and further called for inclusivity and transparency in distribution.

4.3.1 Key Themes behind frustration

To discover the themes behind the increased volume of frustrated tweets during lockdown and the second wave of COVID-19, we used a computer program called VOSviewer (van Eck and Waltman, 2011) to create a term co-occurrence map for the tweets labelled as frustrated. Fig. 8 and Fig. 9 illustrate the oft-discussed terms in frustrated tweets posted during the lockdown and the second wave respectively.

Lockdown: Travel concerns due to the imposed nationwide lockdown are evident from the terms in cluster blue in Fig. 8. Major Indian cities namely bengaluru, bihar, pune coupled with transportation choices such as bus, train, vehicle can be seen. We also note terms such as quarantine, doctor, patient, office in the same cluster indicating the traveling problems faced during daily life activities. The nodes in green reveal the challenges faced by logistics and travel industry. Terms such as refund, ticket, airline, flight, credit reflect the chief complaints by customers along with bill and other payments.

The nodes in cluster red highlight the discussion on digital media and news channels. Growing concern due to increasing toll of infections in the USA and a sense of anger towards China were expressed through tweets. Fake news, channel, minority and economy were also a few topics of online discussion. The nodes in cluster yellow depict the
concerns revolving around closed educational institutions, payment of fees, online classes and exams. Second Wave: The usual customer care complaints are depicted in cluster green. The nodes in cluster red particularly reveal the frustration against political parties and elections. There are also terms such as player, season, ball, game due to upcoming IPL cricket matches. The anxiety due to shortage of ventilator, patient, hospital, icu bed and oxygen cylinder is captured through nodes in cluster blue. Words such as refer, friend, help reveal anxious attempts to locate healthcare through contacts on Twitter. Availability of vaccine and booking of slots were also a cause of frustration amongst Indians. Education remained a concern during the second wave as evident from nodes marked in purple.

5 Social Impact

Tsao et al. (2021) highlighted the paucity of action driven research on the COVID-19 data. Early detection of human needs will enable public agencies and independent organizations to provide prompt support including food supplies, medical care, transport and timely awareness about the crisis amongst masses. Our approach can facilitate timely identification and prioritization of emerging human needs in the event of a crisis. When coupled with geo-location tag, the proposed approach can be customized to retrieve closest support available. Unmet needs scoping can help in designing public policies to cater to emerging needs of a society. During the COVID-19 pandemic in India, people expressed distinct needs at different stages of each wave. Public needs on social media can thus serve as an immediate feedback mechanism for public agencies to improvise their relief efforts and policies. Our model to detect unmet needs leverages a pre-trained neural language model that generalises well and is capable of transfer learning from previously labelled data at the start of a crisis. It is thus easy to extend our approach for other languages using publicly available pre-trained multilingual language models.

6 Limitations

Due to our focus on understanding the pattern of needs emerged in India during the COVID-19 pandemic, we performed rigorous filtering to retain only those tweets geo-tagged with locations within India. This significantly reduced the quantity of tweets gathered for our study. Human needs are inherently complex and ever evolving concept. As we transition from basic to advanced needs, the needs become more obscure and implicit. To optimize the time and effort for human annotation, we assumed that the dominant topic of a tweet would reflect its need type as discussed in Section 3. This had an impact on the quality of tweet-need mapping and resulted in incorrect labeling in some cases.

7 Conclusion

In this paper, we examined the human needs expressed in Indian cities during the COVID-19 pandemic. We described a minimally supervised approach to annotate tweets with their need level as in Maslow’s Hierarchy of Needs. This greatly reduced the time and human effort without much impact on the quality of annotation. We observed a recurring pattern in the needs, indicating predictability in the emerging needs in the event of a crisis. The results support the use of pretrained language model for the task of unmet needs detection. In future, we will extend the proposed model to detect needs in regional languages. We will further work upon incorporating theories better suited to capture advanced psychological needs.

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