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Nomophobia before and after the COVID-19 Pandemic - Can Social Media be Used to Understand Mobile Phone Dependency?

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ABSTRACT

Nomophobia is a growing epidemic related to overuse or addiction to technology, and it has become a popular topic of research through surveys. However, research on nomophobia through social media had been limited. Twitter being the most widely used platform in various public health studies, we use tweets collected throughout February (Pre-COVID 2020) and May (COVID-era 2020) to study nomophobia. We built a relevancy classifier to classify tweets as nomophobia relevant or irrelevant and explored the most discussed topics during these periods. We used three machine learning (ML) classifiers which were comparable in their performance. Logistic Regression with chi-squared feature selection has the best performance with 0.77 in precision, recall, and F1-score as relevancy classifier. Topic modeling done on nomophobia-relevant tweets using the Latent Dirichlet Allocation (LDA) algorithm revealed that during pre-COVID the two dominant themes are (I) Addiction to Digital Entertainment (II) Annoyed/Impatient for bad internet service and in COVID-era, the technology overuse manifested in two new contexts (I) Work from home difficulties during pandemic (II) Extreme attachment to digital technology during the quarantine.

KEYWORDS

Nomophobia; Tweet classification; Topic modeling; Natural language processing; Pre-COVID & COVID-19 analysis

INTRODUCTION

Nomophobia or NO MObile PHone PhoBIA is a psychological condition where people have a fear of losing mobile phone connectivity. Nomophobia can be defined as a disorder or anxiety caused by being out of contact or access to any smart device or services provided by phone/computer like the internet. Since their arrival on the market, the excessive use of smartphones has led to the questioning of whether society has developed an addiction to these devices. Some suggest that it should be recognized in the diagnostic and statistical manual of mental disorders, Fifth Edition (DSM-5) as a behavioral addiction [1].

To date, survey methodologies have been the primary method for measuring smartphone addiction [2-4]. However, our relationship with mobile technology is complex and continually changing. Most dramatically, the recent COVID-19 pandemic has caused a sharp shift in how we depend on our smartphones. The need to work http://www.tridhascholars.org | March-2021 © 2021 The Authors. Published by TRIDHA Scholars. 2 remotely has

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only increased our dependence on smartphones. Similarly, physical distancing policies have heightened our reliance on smartphones to connect us with our social networks and loved ones. Stay-at-home mandates have additionally led to a dramatic increase in internet use, including excessive online gaming [5]. Problematic smartphone use has been shown to be correlated with COVID-19 anxiety [6]. Although current self-report methodologies, such as surveys, have shown promise for diagnosing behavioral and cognitive aspects of nomophobia, these methodologies are not naturalistic, meaning that they do not capture behavior in the context of a person's natural interaction with technology. Further, these methodologies are not sensitive enough to help us understand how our relationship with our smartphones has changed over time due to social restructuring events like pandemics. In this study, we use text data from Twitter to better understand key aspects of nomophobia expressed as we interact with our technologies, and how these have changed before and after the COVID-19 pandemic. We explore three research questions: (I) To what extent are we able to distinguish between tweets that are relevant to nomophobia and those which are irrelevant; (II) what do relevant tweets tell us about how we relate to our smartphones; and (III) how has this relationship changed due to the COVID-19 pandemic? Related work diagnostic criteria for nomophobia are not fixed; however, research has supported multiple elements which may comprise smartphone addiction, which has been measured using self-report survey methodologies. Yildrim et al. [7] were able to validate four different dimensions of nomophobia, including fear of (I) not being able to communicate, (II) losing connectedness, (III) not being able to access information, and (IV) giving up convenience. A measure developed by Walsh, White, and Young [2] defined nomophobia in terms of relapse, cognitive salience, behavioral salience, conflict with others, interpersonal conflict, withdrawal, and euphoria/relief. Trub and Barbot [4] developed instrumentation which parametrizes nomophobia in terms of feelings of safety, uncomfortableness, or relief when put into a perspective of separation and unification with one's mobile device. Other work discusses nomophobia in terms of craving as opposed to dependency; for example, De-Sola, Talledo, Rubio, and Rodriguez de Fonseca [3] developed instrumentation to measure the cravings that partner with addiction with regards to smartphones. The authors argue that this craving dimension is important in that exists with other general addictions, and in particular, gambling and drug addictions [3]. The cognitive concept of cravings has demonstrated even more need for smartphone addiction to be placed among other behavioral addictions within the DSM-5. Available surveys support the measurement of nomophobia from both behavioral and cognitive perspectives. However, there is no literature to our knowledge that explores how nomophobia is expressed and discussed online. We believe mining of comments about smartphone use online will offer a unique perspective on nomophobia in that the information is unsolicited, thereby giving a naturalistic perspective on challenges we face as we negotiate the use of mobile technologies and how this has changed in response to the dramatic lifestyle changes imposed by the current COVID-19 pandemic. Most significantly, smartphones have been used as a way to bridge social distance during the pandemic [8-10]. However, the pandemic has furthered our perceived necessity for smartphones in other ways, too, including providing entertainment [5,10], keeping informed [8], accessing healthcare [11], and staying engaged in the workplace [12]. The increased dependency on smartphones during the pandemic has inspired efforts to use mobile phone data to track behaviors that influence the spread of the disease [13]. Although there is no previous work with Twitter to understand how nomophobia manifests, use of Twitter for understanding public reactions to disease is not new. Research using Twitter data to understand specific diseases has generally followed epidemics or pandemics of current concern, including Ebola [14], Zika [15,16], vaccination [17], and COVID-19 [18,19]. Twitter data have also been used to understand chronic diseases such as diabetes and obesity [20], heart disease [21], and cancer [22]. Finally, Twitter has shown promise for characterizing how mental health problems such as depression and anxiety [23,24] and addiction [25-27] manifest in social contexts. Leveraging the previous work with Twitter that has been done with multiple types of diseases, this paper is an attempt to take advantage of Twitter's diverse user base and naturalistic setting to better understand how we relate to our smartphone technologies, and the influence the COVID-19 pandemic has had on our relationship with these technologies. Using natural language processing and machine learning techniques for tweets, we hope to better understand how nomophobia manifests, and how this has changed in response to COVID-19. We organize the paper into four sections (I) Data collection with criteria for annotating the tweets. (II) Feature Engineering technique with term frequency-inverse document frequency (TFIDF) vectorizer for feature extraction and chi-square as a feature selection method. (III) Selecting best performance classifier, building relevancy classification model, and making a prediction on entire tweets corpus with relevancy classifier. (IV) Topic Modeling using LDA on nomophobia-relevant tweets to understand latent information. DATA COLLECTION Tweets were mined using Twitter's REST API with search query keywords like phoneless, no-phone, lost communication, no-communication, no internet, no signal, nomophobia, mobile addiction, no wifi, Ringxiety, textaphrenia, Phantom Ringing, Phantom Vibration, Communifaking. During the mining process, we filtered retweets out and we collected approximately 50000 tweets during each of pre-COVID (February 1st, 2020 to February 29th, 2020) and COVID-era (May 1st, 2020 to May 31st,2020) times. In the next stage, 1583 tweets (pre-COVID) have been annotated, and the final standard data set we got is highly imbalanced with a relevant to an irrelevant ratio of 481:1102 (30% - 70%) as shown (Figure 1). We labeled each tweet as either relevant (tweets being either Nomophobia or Anti-nomophobia) or irrelevant. Criteria considered to annotate tweets as relevant and irrelevant are shown (Table 1), and emoji has been a key factor during annotation as they convey various feeling of frustration, sadness, grief, and disappointment.

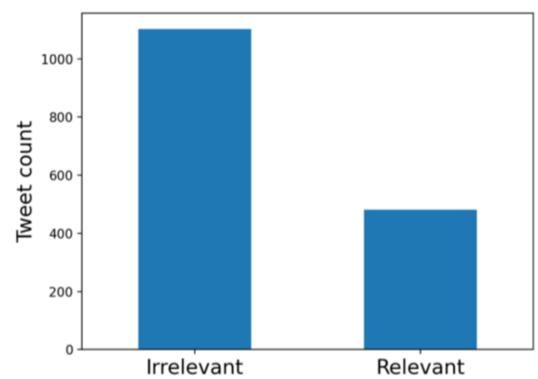

Figure 1: Distribution of tweets in the dataset into the groups 'Relevant' and 'Irrelevant' to nomophobia.

To measure Inter rate reliability (IRR), a sample of 600 tweets were annotated with two annotators and evaluated with statistical measures: percentage agreement 90.55% and Cohen's kappa 0.79. Both show substantial agreement between annotators. http://www.tridhascholars.org | March-2021 © 2021 The Authors. Published by TRIDHA Scholars. 4 feature engineering first, we pre-processed our tweet text as they are unstructured data containing a lot of noisy features like special characters, URLs, mentions (@), internet slang, and incorrect grammar. Since these features did not add any relevant context to our prediction, they were preprocessed for stop words, @mentions, punctuations, contractions (hasn't, won't), slang words (LOL!, LMAO), and elongated words. Contractions and slang were replaced with their true meaning through Urban Dictionary. We removed stop words, punctuations, mentions (@), URLs, non-English words using the "tweet-preprocessor" library in Python. We corrected elongated words like Coooool and lemmatized tokens. Next, we performed feature engineering to deal with extracting features from preprocessed raw text and generate a numerical representation for each feature that can be fed to downstream machine learning models. Our feature engineering includes a twostep process: (I) Feature eExtraction and, (II) Feature selection. Feature extraction In natural language processing, machine learning algorithms cannot work with the raw text directly. So, we used TF-IDF (Term Frequency Inverse Document Frequency) vectorizer to represent text into a matrix of features using the "sklearn" library TfidfVectorizer class. We set three parameters during feature extraction. First, we set Min_df (minimum document frequency) to 0.08. Provided a corpus of 1582 tweets, 15837 features occurred, with minimum document frequency condition the number of features reduced to 182. Few examples of ignored features are week internet, phubbing, wifi problem, cellphone 😩, fear anxiety, people vibin. Second, we set Max_df (maximum document frequency) to 0.98 (ignore terms that have document frequency strictly higher than the threshold i.e., corpus specific stop words) the words that have appeared in 98% of the documents as the word that appeared in most documents have lower (nearly zero) TF-IDF score. Third, to increase the quality of text analysis, along with unigrams, we also included bigrams by setting the Ngram_range to [1,2].

Category	Criteria	Sample Tweets
Relevant	Tweets like "no internet, no phone with some explicit emotion as relevant.	I have no internet for like a week 😩.
		This no phone life is killing me.
	Tweets that express context of High dependency on technology. (Nomophobia)	Having no Wi-Fi is killing me already, can't do any work at home, can't watch anything decent on tv and can't use my phone for anything 😕.
		Make it an Equity issue for the tech need in the classroom. Next PL: Hand Each Teacher a newspaper and assign them to research their next vacation. No Phone, no internet. Analogy: Now you know how students are hindered when they are asked to research in class w/o technology!
	Feeling lost/boring due to no phone/internet/signal (dependency for digital entertainment) (Nomophobia).	I cannot even watch anime rn 😟 no Wi-Fi.
		Well life with no internet is boring, I have literally cleaned all morning and now we just chilling bored.
	Happiness/Vibing without phone/Internet/Wi-Fi (Anti-Nomophobia).	I love being phoneless...Nobody annoying me!! Unreachable.
		The no phone rule while hanging out is a must.
Irrelevant	Tweets like no internet, no phone without explicit emotion or sentiment or talk about other topics.	No internet, no network connection, my phone was still on silent mode 🙂.
		7 days no internet and signal.

Table 1: Criteria used to annotate tweets with respective sample tweets.

Feature Selection

Feature selection is the process of selecting a subset of prominent features for the model-building to improve its performance. We applied the chi-squared feature selection technique and selected the best number of features. Before we proceed to the feature selection experiment process, we performed the linguistic analysis to infer salient features from the tweet dataset. Linguistic analysis is an interpretation of language written by humans.

It uncovers and describes text spoken. We analyzed tweets literature spoken in the context of nomophobia by generating unigrams, bigrams for both classes (relevant, irrelevant) using the chi-squared approach. (Table 2) shows the top unigrams that are exclusive for each category (relevant, irrelevant). These salient features were used in the model building process.

Nomophobia Relevant (Exclusive)	Irrelevant Features (Exclusive)	Both Relevant & Irrelevant
‘😫’, ‘😭’, ’hell’, ‘sight’, ’kill’, ‘suck’, ’damn’,’dead’, ’love’, hope’, ’life’	‘Kashmir’,’app’, ’India’, ’ballot’, ’army’, ‘medicine’, ’curfew’,’paper’, ’standwithkashmir’, ’kashmirisolidarityday	‘😭’,’f**k’, ’😫’,’hell’, ’sight’, ‘bad’, ‘Kashmir’, ’kill’,’shit’,’week ’, ’suck’,’app’, ’watch’,’damn’

Table 2: Top exclusive unique n-grams based on classes of interest.

The number of top features that can be fed into the model for training is identified in a three-step process: (I) Initially considered k (number of best features to be selected) in a range of 10 to 160 with an interval of 10 (II) Calculated f1-scores by applying chi-square feature selection for different values of k (III) Selected k values such that beyond k there is no improvement in baseline logistic regression algorithm performance. The result of this process is shown (Figure 2). With a ’k’ value beyond 60, the baseline algorithm showed deprecated performance. Overall, for 1500 cases, the estimated feature size needs to be around 40 [Error! Reference source not found.]. However, at 40 the difference between train, test scores observed to be high, as compared to k value 60. Hence, k was selected to be 60 with a higher train and test score as the best number of features.

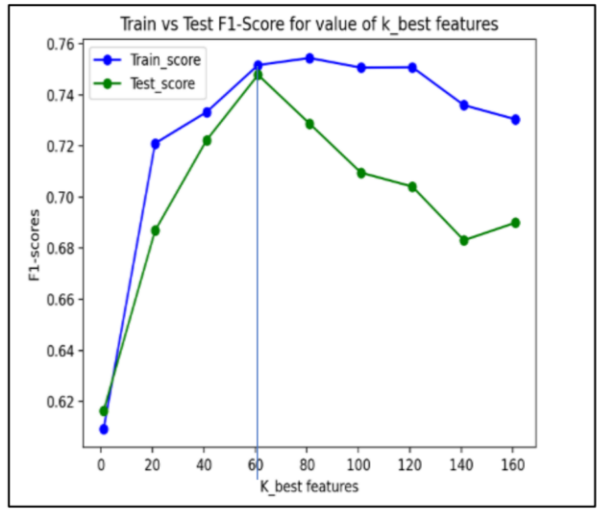

Figure 2: Comparison of train, test f1-scores for top k-features with Logistic Regression.

CLASSIFICATION

Classification of tweets into nomophobia-relevant and irrelevant were explored using multiple machines learning approaches, including logistic regression, naïve bayes and support vector machine. We ultimately used the best performing model to make our final classifications.

Model Building and Prediction

The final relevancy model was built by training 1583 preCOVID tweets on a logistic regression algorithm using a chi-square feature selection method with the best number of features k as 60. The model built was evaluated on a new set of 550 tweets annotated by a single annotator. The classification report of the confusion matrix, weighted precision, recall, and f1-score are shown (Table 4 and Table 5). The final model has improved performance from 0.666 (without feature selection) to 0.77 (feature selection) showing that the data set used for model training is generalized. We can also observe that F1-score for predicting irrelevant and relevant are 0.85 and 0.56 shown (Table 5), which tells the logistic regression model predicts irrelevant tweets better than relevant tweets.

	Train result			Test result		
Model	Precision	Recall	F1- Score	Precision	Recall	F1- Score
Naive Bayes	0.757	0.687	0.699	0.688	0.619	0.634
Logistic Regression	0.77	0.741	0.749	0.676	0.658	0.666
SVC-RBF	0.799	0.692	0.701	0.678	0.549	0.556

Table 3: Performance for relevancy classification without feature selection.

Actual | Predicted	0 (irrelevant)	1 (relevant)	Total
0 (Irrelevant)	349 True Negative	55 False Positive	404
1 (Relevant)	68 False Negative	78 True Positive	146
Total	417 (Predicted Negative)	133 (Predicted Positive)	550

Table 4: Confusion matrix of predicted new/unseen data.

We predicted 55395 pre-COVID and 59735 COVID-era tweets. (Figure 3(A) and Figure 3(B)) show the data distribution, which is similar to manually annotated tweets proportion i.e. 70:30 (Irrelevant to Relevant) shown (Figure 1), indicating that the model is reliable in predicting unseen nomophobia-relevant tweets.

	Precision	Recall	F1-score	Support
0	0.84	0.86	0.85	404
1	0.59	0.53	0.56	146
Weighted avg.	0.77	0.78	0.77	550

Table 5: Final model: label level and overall, precision, recall, and f1-score.

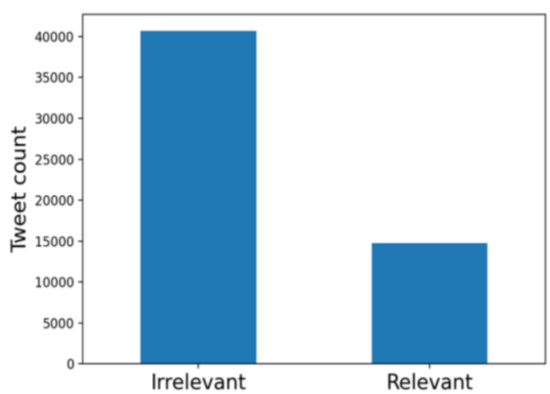

Figure 3 (A): Model predicted data distribution ratio 73:27 of pre-COVID (February 1st, 2020 to February 29th, 2020) tweets.

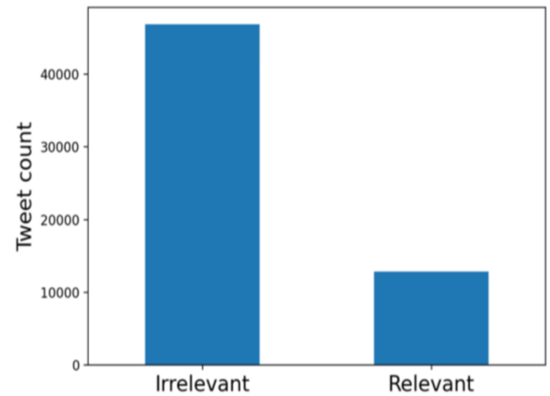

Figure 3 (B): Model predicted data distribution ratio 78:22 of COVID-era (May 1st, 2020 to May 31st, 2020) tweets.

TOPIC MODELING AND ANALYSIS

A topic model is a probabilistic model used for discovering the latent semantics of the text, and it provides a simple way to analyze the large volumes of text without labels. Of many algorithms, Latent Dirichlet Allocation (LDA) is the most commonly used topic model even for a short text like tweets [28,29], and performance evaluation was done with a coherence score. LDA algorithm has two main parameters alpha and beta where alpha dictates how many topics a document potentially has, and the beta parameter dictates the number of words per topic. The lower the alpha, the lower the number of topics per document. Similar to the alpha, the lower the beta, the lower the number of words per topic. In LDA, each text/document is viewed as a mixture of a various numbers of topics with corresponding probabilities. In this paper, we considered the dominant probability value as the topic for a corresponding tweet, and 14700 pre-COVID and 12800 COVID-era nomophobia-relevant tweets were used for topic modeling. Using the default genism LDA algorithm as the baseline model, a possible range of an optimal number of topics 'K' is shown (Figure 4 (A) and Figure 4 (B)) which is a plateau region of coherence scores for topics 10 to 14 (preCOVID) and 9 to 14 (COVID-era).

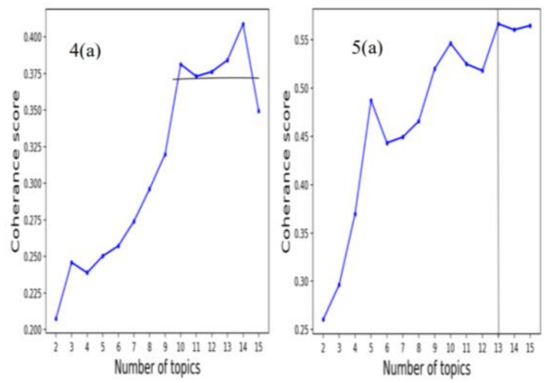

Figure 4 (A): Pre-COVID graph of optimal topics range10 to 14 with default LDA using coherence score. **Figure 5 (A):** Pre-COVID optimal LDA model with best alpha and beta, coherence scores for topics in range 2-15.

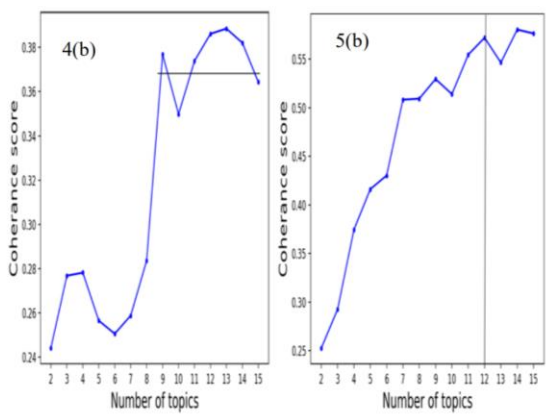

Figure 4 (B): COVID-era graph of optimal topics range 9 to 14 with default LDA using coherence score. **Figure 5 (B):** COVID-era optimal LDA model with best alpha and beta, coherence scores for topics in range 2-15.

We performed a series of sensitivity tests to help determine the model hyperparameters for a given range of an optimal number of topics ('K'). A total of 150 and 180 combinations of the hyper-parameter with alpha and beta values in the range 0.01 to 1 with a step count of 0.03 were experimented with, which resulted in "asymmetric alpha" and "0.31 beta" as the best parameters. Using the graph of coherence (Figure 5 (A) and Figure 5 (B)) we observed that the optimal number of topics is 13 and 12 for both respective data sets.

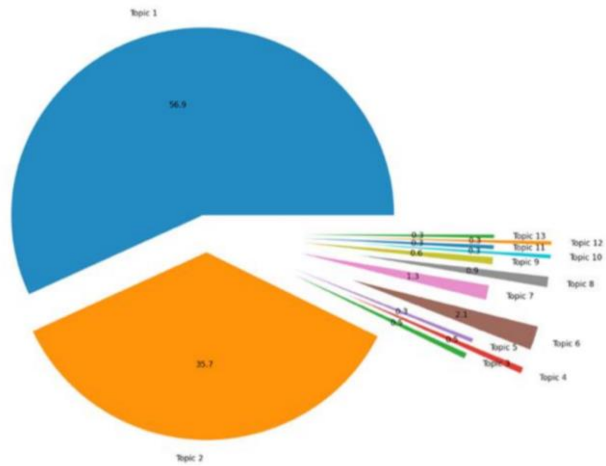

Figure 6 (A): Pre-COVID percentage distribution of topics.

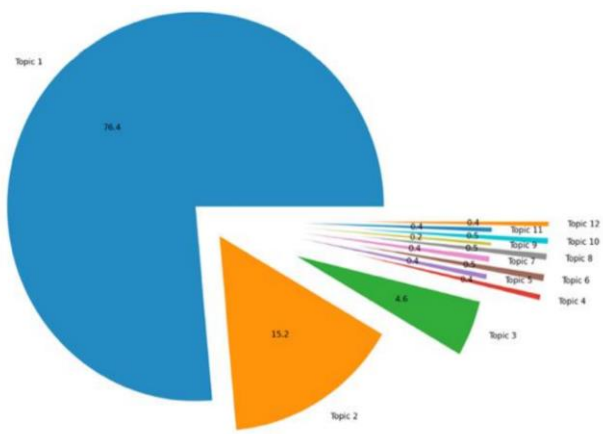

Figure 6 (B): COVID-era percentage distribution of topics.

Post building the LDA model, we visualized the distribution of topics (Figure 6 (A) and Figure 6 (B)) to understand how widely a topic is discussed on social media. We observed that Topic 1 and Topic 2 are the most prevalent topics in both sets of corpora (pre-COVID and COVID-era). Topics were inferred by reading the most contributed tweets, because sometimes just topic keywords may not be enough to make sense of the topics. Since topics 1 and 2 collectively make up about 90% of the dataset, we explained these two topics further in the paper. If any topic has the keyword phone, internet, Wi-Fi means it is talking about no phone, no internet, and no Wi-Fi, and these are considered as corpus-specific stop words as all the tweets speak about opinion/reaction when there is no phone, internet, and Wi-Fi.

Figure 7 (A): Pre-Covid Topic 1 word cloud-addition to digital entertainment/streaming.

Figure 7 (B): Pre-Covid topic 2 words cloud annoyed/ Impatient customers for bad service.

The term (Figure 7 (A)) of Topic 1 focus on digital entertainment ('phone', 'internet', 'Wi-Fi', 'week', 'watch', 'f**k', 'life', 'shit') and (Figure 7 (B)) of Topic 2 focus on "No internet and Customer service issue" ('Internet', 'Wi-Fi', 'signal', 'week', 'phone', 'service', 'bad', 'work'). Unique terms of Topic 1 ('watch', 'f**k', 'life', 'shit'), sample tweets from (Table 6) confirmed Topic 1 speaks about "Addiction to Digital Entertainment/ streaming" and unique terms of the Topic 2 ('signal', 'service', 'bad', 'problem'), sample tweets from (Table 7) confirmed Topic 2 speak about "Annoyed/Impatient customers for bad service".

Topic 1, about "Addiction to Digital Entertainment/ Streaming" provided insights that people concern about the unavailability of streaming entertainment services like Netflix and, YouTube because of no internet/phone and looking for offline downloaded video or DVD or television as a substitute when they cannot use these streaming platforms. The tweets in Topic 1 reflect various elements of internet dependency, but primarily related to the need to use the internet for entertainment purposes. Topic 2, about "Annoyed/Impatient customer" provided insights that people express their dissatisfaction when they could not get customer service instantly for complaints on the internet/cell signal issues and frustration for paying without getting proper service from respective mobile carriers and broadband service providers.

S. No.	Tweets
1	Today is already starting off real shitty No Wi-Fi until Wi-Fi man comes and now the power is off so I'm sitting in the dark for who knows how long I just wanted to enjoy my day off of work and watch the new Gorillaz music video 😭.
2	Welll no internet and unsure when it will be paid so no streaming till then 😢😢.
3	I watched all your videos the best possible way I can when I was very young. Bought your CDs, posters and even performed at school with your greatest hits! With no internet and all, I managed to be updated with your upcoming albums and tours.
4	@bt_uk little to no Wi-Fi since Friday, is it due to the bad weather ...? Kinda wanna watch netflix again 😢😢😢 storm dennis is not welcome.
5	@Tearastar It's true though! I feel bad cause I've been missing streams from everyone as of late lol. Work instituted a "no phone use on call floor" policy so it kinda nerfed my stream watching time.
6	fuuuuck, i have no Wi-Fi, i wonder if it's the snow, but now how am i supposed to watch random YouTube shit.
7	no internet for 2 days can't even stream f**king Netflix ok tv I gotta watch on phone, throwback to when I watched entire GoT on my phone x).
8	this is fucken bullshit man how am i supposed to watch the new star trek with no internet?
9	F**k sake I cba playing anything now I want to watch Netflix or amazon prime on my ps4 but there's no WiFi and can't hotspot
10	Hour 4 with no internet. This shit is miserable. Had to put a movie in my xbox to watch like some kind of CAVEPERSON😭.

Table 6: Pre-COVID Topic 1 sample tweets: Addiction to digital entertainment/streaming.

S. No.	Tweets

1	@virginmedia 3 weeks no internet. Fix date changes, call centre worse than useless. Costing me money. Nobody at virgin seems to be bothered about the customers. Terrible customer service I want to cancel account so can use a company that will supply a proper service to me
2	@ACTFibernet Its been more than a week since there is no internet in my premise no one from ACT has take an initiative call and check what is the issue, very bad customer service 👎👎👎 I will rate the service only 2/10 very poor.
3	@ThreeUKSupport Trouble is I barely use my phone, I have a dual SIM phone and have a work SIM for data so my personal sim with you is only for receiving calls so I can't justify the high price. @SMARTYMobileUK offer suitable plan but no Wi-Fi calls/home signal which is a deal-breaker :(.
4	Appalling service from @WeAreOpenreach. My father (70, health issues) has been left with no phone line or internet for over a week in area with no phone reception. Answer me this: what happens if he has an emergency? Once again rural areas are left forgotten about! 😟 #badservice.
5	Really disappointing service @SkyHelpTeam - unable 2 report fault on my in laws phone - tonight as weather deteriorates they have no phone (no mobile signal) - older, isolated (rural/remote). They cannot report fault as they have no phone / internet to do so #badservice #notgood.
6	@Ask_Spectrum worst customer service experience of my life. Talk about a “pass the buck” culture. No one takes responsibility for terrible service. My internet speeds suck, technician replaces with “new” router...now no internet!!! And no one will fix it!!! #cutthecord.
7	My biggest mistake was to choose @airtelindia. Very worst network, zero tower, no internet, no network, call drop issues...these are daily problems. Worst network. Searching best network to port from airtel.
8	@TikonaTIL it's very bad response from you for a new connection u guys come to home within 10 min but after paying 6 months advance payment and today facing "no internet connection issues" after complaining no one till now even try to contact… feeling like just pick the router
9	From last 4 days, there is no response from customer care as well no internet connection for last 5 days. Not responding any one after multiple complaints. Very bad service in Gurgaon. Fuck you Ben**** @youbroadband. !Triple play inter service is far better than @youbroadband.
10	@virginmedia Your customer service is just as bad as your broadband signal. I’d rather no Wi-Fi than Wi-Fi that hardly works.

Table 7: Pre-COVID Topic 2 sample tweets: Annoyed/Impatient customers due to bad internet service.

The terms (Figure 8 (A)) of Covid-era Topic 1 focus on "work-from-home difficulties" (’internet’, ’phone’, ’Wi-Fi’, ’week’, ’watch’, ’bad’, ’work’, ’service’) and (Figure 8 (B)) of COVID-era Topic 2 focus on "Extreme attachment to Digital Technology" (’phone’, ’phoneless’, ’😆’, ’😟’, ’shit’ , ’life’, ’laugh’, ’louder’). Unique terms of Topic 1 (’bad’, ’work’, ’service’, ’online’), sample tweets from (Table 8) confirmed that topic 1 speaks about people being unhappy about no internet/Wi-Fi and poor service response from carrier which affects their daily professional work and academics during pandemic and, unique terms of the Topic 2 (’phoneless’, ’😆’,’😟’, ’shit’), sample tweets from (Table 9) confirmed Topic 2 addressed "Extreme attachment to digital technology like phone".

Figure 8 (A): COVID-era Topic 1 word cloud-Work-from-home difficulties.

Figure 8 (B): COVID-era Topic 2 word cloud-extreme attachment to digital technology.

COVID-era Topic 1, "Difficulties working from Hhome" provided insights about people expressing concerns and annoyance during COVID times when they cannot have internet connectivity and poor customer service. The primary concern is from IT professionals, teachers who work remotely online, or students taking online classes and COVID-era Topic 2, "Extreme attachment to digital technology" provided insights about people feeling lost and disconnected when they have no phone. We observed people having restlessness and irritability when they are phoneless during the quarantine, and the Topic 2 is different from other topics. Pre- COVID Topic 1, Pre- COVID Topic 2, COVID-era Topic1 addresses about no internet/phone/Wi-Fi in variable proportions, but COVIDera Topic 2 have context about being phoneless and their fear of being without phone during the pandemic.

CONCLUSIONS AND FUTURE WORK

In this study, we sought to utilize posts on Twitter to understand how people express signs of nomophobia online, and how this has changed in response to the unique lifestyle constraints imposed by the COVID-19 pandemic. The adequate performance of the relevancy classifier (F1-score = 0.77) demonstrates that it is feasible to filter out tweets about nomophobia using an automated process. The logistic regression models showed that the presence of emojis is a strong indicator of a tweet reflecting traits associated with nomophobia. Given that phobias involve an association with strong negative emotions, it makes sense that emojis could potentially serve as a strong indicator for many phobias in addition to nomophobia. Although we acknowledge that the scope of future Twitter studies on nomophobia may vary, the relevancy classifier proposed here could provide a useful starting point for a system to locate and classify social media posts related to nomophobia. This would set the stage for larger-scale efforts to compile posts over time, which would make way for studies focused on understanding the impacts of social interventions on how we relate to our mobile technology.

S. No.	Tweets
1	Hey @NESpower - not happy. Power out to wherever the @googlefiber hub is that feeds 37208, so no internet since 2:10 PM. That makes working from home during a pandemic pretty damned difficult.
2	Working from home sucks when the Wi-Fi is pants ☹. I could have gone directly to the office to do my work, but no, I succumbed to the temptations of WFH and now I have no internet, a moody Eldest, a cross (no PS4) Youngest and a grumpy other half.
3	@OrtelComm I am getting very bad service in Cuttack. From two days internet is not working. Time like this having no internet is a very sad thing. I am having daily online classes. So please help regarding this.
4	this is the same teacher who doesn’t understand i live in a dead zone basically for my service provider so when i explained that i needed Wi-Fi he said “well zoom for phone works too” OKAY but how to am I supposed to access zoom for phone if I have no Wi-Fi or LTE/4G.
5	Pretty fucking tired of paying more money for NO internet service, @Xfinity. Are y'all gonna be the ones to tell my clients that I can't provide crisis management consulting services to them during a pandemic because my internet service provider can't provide internet service?
6	@SuddenlinkHelp I’m a teacher working from home with a college student in the middle of finals & middle schooler trying to complete work. No internet service for 24+ hours. Sitting in campus pkng lot using their Wi-Fi was not productive today. We need our internet. #help.
7	@CoxHelp Still poor service from 6 pm Monday to 4 pm Tuesday without notice. Cannot accomplish anything online if service is slower than slow, or off completely. Have no issue with overnight work, but 22 hours with basically no internet not good for people stuck at home.
8	@OpenreachHelp engineers turned up yesterday no advance warning. Turned internet/phone off to replace pole. Job done got no service at all now. Any ideas please. No phone/internet for 24 hours now. No hotspots to connect to. Working from home so need connection
9	@airtelindia your internet service sucks. I have 2 mobile and 1 dongle and on all devices your internet is not working. I am using this dongle for work from home. And suddenly net stops working. so how reliable is your network. @jio is better as it never has no internet issue.
10	@ViasatInc @azcommerce @LocalFirstAZ Help families? Help them what? Sign a 2 years contract for no internet? @ViasatInternet is the worst internet company on the planet!!! My kids can’t do their online schooling nor can I work from home. We did find a broadband provider locally and switching this week.

Table 8: COVID-era Topic 1 sample tweets: Work from home issues due to no internet/Wi-Fi.

S.no.	Tweets
1	I can use my laptop for 2 more hours and then on my break but the other time I have to be phoneless this is so weird to me I always have my phone what if someone tries to kill me & I can’t call 911 LMAO.
2	Have you ever walked out of the taxi and immediately touch your pockets with no phone, 😭...Well you don’t know what a heart race is, a heart attack ,you don’t know what Adrenaline rushing is, you know nothing 😂😂.
3	ohmygod this is a dark moment in history 😭😭😭😭I can’t believe I went phoneless for a Month.
4	with having no phone I honestly can say that I have no idea how I’m pulling this shit off smh. Pray For Me this the real quarantine LOL
5	😕😑 great... no phone for about 2more weeks 🤦‍♂️ F**k My Life.
6	@MzTerriJ That shit boring as hell lol. No tv, no phone, you need some entertaining to do. Yeah it looks nice if you aren’t never been on a trip, but that shit like quarantine LOL.
7	@nolimitod_ I am currently phoneless thanks for reminding me 😭😫😫😫.
8	this phoneless shit is depressing need to hurry up in bring me my new one 😫.
9	Finally got a new phone, yesterday with no phone almost killed me 😭.
10	I don’t have no phone shit is KILLING me! , young.

Table 9: COVID-era Topic 2 sample tweets: Extreme attachment to digital technology.

An important contribution of this study is the use of relevant tweets to study the impact of the COVID-19 pandemic how nomophobia manifests on social media, which ultimately reflects how we relate to the technology. The topic models indicated that before COVID-19, frustration with bad internet service and loss of digital entertainment were the most prevalent manifestations of nomophobia. Although prior research indicates that the COVID-19 pandemic has increased our dependency on smartphones for digital entertainment [5,10], the primary COVID-era concerns around loss of connectivity related to the inability to work from home and the loss of social connection. This is reflective of previous research on the social effects of the COVID-19 pandemic [8-10,12] and highlights the efficacy of social media data in helping us understand how shifts in priorities imposed by social restructuring events like pandemics are reflected in text data from social media. With respect to nomophobia, our data indicate that although loss of social connectivity has always been a key factor in nomophobia [7] this has further increased after the pandemic. In addition, the pressure to use our mobile technology for work-related purposes has imposed a novel dimension to nomophobia-fear associated with the threat that losing mobile connectivity imposes on one’s livelihood. Although a certain amount of reliance on mobile devices for work has persisted for some time, the social quarantine imposed by COVID-19 has brought work-related connectivity to the forefront of smartphone dependency. Whether or not this persists after the pandemic remains to be seen and should provide an interesting avenue for further research on nomophobia in the coming years [13-20].

To the end of planning further research utilizing social media to understand nomophobia, it is useful to highlight some key limitations of this study. Using data from Twitter imposes certain sampling biases. The median age of a Twitter user is younger than the median age of the United States population, and an average Twitter user has higherthan-average educational attainment and household income [21-25]. This bias towards a younger, more educated base may account partially for the prevalence of Tweets related to interference with remote work. It would be interesting to compare these findings with other types of social media such as Facebook or Reddit, which have different demographic bases. A second limitation of this study is that we only utilized Tweets that were in English, thereby restricting our study to posts from English-speaking communities. Smartphone dependency is a global phenomenon, and given that nomophobia is sociocultural rooted, it is reasonable to expect that studies focusing on tweets in other languages would derive findings which align with the social structures imposed by the cultures in these respective communities. Toward cross-cultural studies of nomophobia, mining and interpreting posts from multiple languages is an essential next step. A third limitation is that Twitter posts are relatively brief in comparison to posts on other social media platforms. This brevity facilities access to greater number of posts from a greater number of users. However, social media platforms which allow more text to be posted at one time would likely deliver more explanatory information around ways that nomophobia manifest, including behavioral factors and comorbidities [26-30].

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