Observational Study of Working from Home during the COVID-19 Pandemic
Using Social Media Data

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Abstract

Background: Since March 2020, companies nationwide have started work from home (WFH) due to the rapid increase of confirmed COVID-19 cases in an attempt to help prevent the coronavirus from spreading and rescue the economy from the pandemic. Many organizations have conducted surveys to understand people’s opinions towards WFH. However, the findings are limited due to a small sample size and the dynamic topics over time.

Objective: The study aims to understand the U.S. public opinions on working from home during the COVID-19 pandemic.

Methods: We conduct a large-scale social media study using Twitter data to portrait different groups who have positive/negative opinions about WFH. We perform an ordinary least squares regression to investigate the relationship between the sentiment about WFH and user characteristics including gender, age, ethnicity, median household income, and population density. To better understand public opinion, we use latent Dirichlet allocation to extract topics and discover how tweet contents relate to people’s attitude.

Results: After performing the ordinary least squares regression using a large-scale dataset (N = 28,579) of publicly available Twitter posts concerning working from home ranging from April 10, 2020 to April 22, 2020, we confirm that sentiment of working from home varies across user characteristics. In particular, women tend to be more positive about working from home (p < .001). People in their 40s are more positive towards WFH than other age groups (p < .001). People from high-income areas are more likely to have positive opinions about working from home (p < .001). These nuanced differences are supported by a more fine-grained topic analysis. At a higher level, we find that the most negative sentiment about WFH roughly corresponds to the discussion of government policy. However, people express more positive sentiment when talking about topics on “remote work/study” and “encouragement”. Furthermore, topic distributions vary across different user groups. Women pay more attention to family activities than men (p < .05). Older people talk more about work and express more positive sentiment on WFH.

Conclusions: This paper presents a large-scale social media-based study to understand the U.S. public opinions on working from home during the COVID-19 pandemic. We hope this study can lend itself to making policies both at national and institution/company levels to improve the overall population’s experience of working from home.

Introduction

Background

COVID-19, also known as the coronavirus, first reported in China and then spread to the whole world, has caused 22.3 million confirmed cases and more than 373 thousand deaths in the U.S. by January 11, 2021. To help prevent the virus from spreading and also salvage the economy, companies and schools nationwide have started work/study from home. According to a Gartner survey of 880 global HR executives on March 17, 2020, almost 88% organizations have encouraged or required employees to work from home. Barrero, Bloom, and Davis (2020) have found that working from home might stick even after the pandemic ends. Concerns may arise when it comes to productivity (Feng and Savani 2020), willingness (Palumbo 2020), and future trends (Barrero, Bloom, and Davis 2020; Chung et al. 2020) regarding work/study from home.

Prior Work

Working from home has been a controversial issue which merits a closer look. An investigation shows that WFH might incur side-effects such as a negative impact on work-life balance (Palumbo 2020). This would lead to negative opinions towards WFH when people tweet about it. Other research deep dive into specific categories. A survey of Lithuania’s employees shows that female employees appreciate more than male employees, because the female employees can enjoy a healthier lifestyle while male employees worry about career constraints (Raišienė et al. 2020). However, another survey conducted in the U.S. shows “a gender gap in perceived work productivity”: Before WFH, female and male employees report the same level of self-rated work productivity. After shifting to WFH, male employees perform with better productivity than the female employees (Feng and Savani 2020). As for age, people in their 40s have more negative opinions on WFH because of their unfamiliarity with teleworking. People aged 30-39 have the most positive opinions because they can enjoy time with family and
they are already used to new technologies for teleworking (Raisièn et al., 2020). Previous studies (Barrero, Bloom, and Davis, 2020; Raisièn et al., 2020; Bick, Blandin, and Mertens, 2020) also show that opinions concerning working from home vary across different socioeconomic groups. A similar social media study of public sentiment on working from home has been conducted in the U.K. (Carroll, Mostata, and Thorne, 2020). Results show that in the U.K., more than 70% of tweets concerning working from home have positive sentiment and the main topics include traffic, drink, and e-Commerce.

Similar approaches have been implemented by researchers mining Twitter posts with natural language processing on their attitudes on face masks (Yeung, Lai, and Luo, 2020), using the Valence Aware Dictionary and Sentiment Reasoner (VADER) model (Hutto and Gilbert, 2014) to perform sentiment analysis. Moreover, Twitter data have been used to study many different aspects of COVID-19, such as mining overall public perception towards COVID-19 (Boon-Itt and Skunkan, 2020), college students’ attitudes on the pandemic (Duong et al., 2020), people’s attitude on potential COVID-19 vaccines (Lyu et al., 2020; Wu, Lyu, and Luo (in-press)), pregnant women sentiment analysis during quarantine (Talbot, Charron, and Konkle, 2021), as well as monitoring depression trend on Twitter during the COVID-19 pandemic (Zhang et al., 2021). They all use VADER for sentiment analysis and most of them include time series analysis. In addition, we follow the practice of using Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan, 2003), to identify topics among large text corpus. The M3-inference Model is used by Yeung, Lai, and Luo (2020) to portrait different demographic groups.

**Goal of the Study**

In this study, we intend to understand public opinions on work from home using large-scale social media data. Twitter has been a popular social media platform for people, especially in the U.S., to express their feelings about what is happening around them. In contrast, the Boston Consulting Group used survey data to study employees’ opinions regarding COVID-19 work from home (Duong et al., 2020). However, social media data allows an opportunity for conducting a more timely study of many population-level issues on a larger scale (Jin et al., 2010). We acquire the data with an authorized Twitter developer account using Tweepy. This ensures reliability by acquiring first-hand and sufficient data when conducting the research.

In this paper, we also infer user demographic information using Twitter user information. This is of importance since we can deep dive into the characteristics of those who are more pro-WFH. For example, when we look into gender, we understand that historically mothers have been mostly responsible for caring for children. Therefore, we need the gender information to check whether or not there is any difference in sentiment towards working from home between women and men, as working from home would allow female employees to allocate more time accompanying their children.

Our goal is to understand the U.S. public opinions on working from home during the COVID-19 pandemic. In particular, we focus on the following research questions:

- **RQ1:** Who is more likely to tweet about working from home?
- **RQ2:** How does the sentiment of working from home vary across user demographics?
- **RQ3:** When discussing working from home, what do Twitter users mainly talk about? How does the content correlate with the sentiment of working from home?

To summarize, in a large-scale dataset of publicly available Twitter posts concerning working from home ranging from April 10, 2020 to April 22, 2020, we find that women and older people are more likely to tweet about working from home. After performing the ordinary least squares regression, we confirm that sentiment of working from home varies across user characteristics. In particular, women tend to be more positive about working from home. People in their 40s are more positive towards WFH than other age groups. People from high-income areas are more likely to have positive opinions about working from home.

These nuanced differences are supported by a more fine-grained topic analysis. At a higher level, we find that the most negative sentiment about WFH roughly corresponds to the discussion of government policy. However, people express more positive sentiment when talking about topics on “remote work/study” and “encouragement”. Furthermore, topic distributions vary across different user groups.

**Methods**

In this section, we summarize the data collection process and the methods we apply in the analyses. To address RQ1 and RQ2, we discuss how we infer user characteristics and the sentiment in **Feature Inference**. To investigate RQ3, we describe how we extract the topics of tweets in **Topic Modeling**.

**Data Collection**

We collect related English tweets through Tweepy stream API using keywords and hashtags filtering. The filter keywords and hashtags are “WFH”, “workfromhome”, “work from home”, “#wfh”, “#workingfromhome”. 553,166 unique tweets with 23 attributes posted by 405,455 unique Twitter users ranging from April 5, 2020 to April 26, 2020 are collected. We attempt to infer the gender, age, ethnicity of the Twitter users, extract the population density of the location, and estimate the sentiment of the tweets. There are 405,455 unique users in our dataset, 313,815 of them (77.3%) only tweeted once. After removing duplicates and the users with incomplete features, 28,579 unique Twitter users with all features are included in the dataset.
Feature Inference

Sentiment. A normalized, weighted composite score is calculated for each tweet using VADER (Valence Aware Dictionary for sEntiment Reasoning) [Hutto and Gilbert 2014] to measure the sentiment. The score ranges from -1 (most negative) to +1 (most positive). As validation, we randomly select 194 users’ tweets within one month. By manually labeling the sentiment and comparing the sentiment scores with the VADER scores, we find that the accuracy is 76%, suggesting that the automatic NLP (Natural Language Processing) methods we employ provide adequate estimates of the sentiment of the tweets. Table 1 shows the descriptive statistics of the sentiment score.

Table 1: Descriptive statistics of sentiment score.

| Mean | Std  | Min  | 25%  | 50%  | 75%  | Max  |
|------|------|------|------|------|------|------|
| 0.242| 0.448| -0.967| 0.000| 0.318| 0.617| 0.984|

Age and Gender. We apply the M3-inference model [Wang et al. 2019] to infer the gender and age of each Twitter user using profile name, user name (screen name), and profile description. Age is binned into four groups: <=18, 19-29, 30-39, >=40. The gender distribution of Twitter users is biased on men around 71.8% ([Burger et al. 2011]). A similar pattern is also observed in our dataset, where 57.9% are men, and 42.1% are women. With respect to age, 37.08% of the users in our dataset are older than 40 years old, 37.6% are between 30 to 39 years old, 16.5% are between 19 to 29 years old, and the rest are younger than 19 years old. According to a report of the Pew Research Center,[5] Twitter users are younger than the average U.S. adult. 21% are those aged 18-29, 33% aged 30-49, 26% aged 50-64, and 20% aged 65 and older. The percentages of adults of the Twitter population are 29%, 44%, 19% and 8%, respectively. The pattern in our dataset is more similar to the U.S. adult distribution.

Ethnicity. To estimate the ethnicity of the Twitter users, we apply the Ethnicolr API which makes inference based on the last name and first name or just the last name of the user. To estimate the ethnicity of the Twitter users, we apply the Ethnicolr API which makes inference based on the last name and first name or just the last name of the user. To estimate the ethnicity of the Twitter users, we apply the Ethnicolr API which makes inference based on the last name and first name or just the last name of the user. To estimate the ethnicity of the Twitter users, we apply the Ethnicolr API which makes inference based on the last name and first name or just the last name of the user. Consider the last names and apply “census ln” to infer the ethnicity which contains White, Black or African American, Asian/Pacific Islander, American Indian/Alaskan Native, and Hispanic. In our dataset, White is predominant over other categories with 83.4%, while according to the U.S. Census Bureau [2019], White constitutes 60.1% of the U.S. population; 7.3% are Asian/Pacific Islander, while Asian/Pacific Islander constitutes 6.1% in the U.S.; 6.5% are Hispanic, while 18.5% of the U.S. population are Hispanic; 2.5% are Black or African American, while 13.4% of the U.S. population are Black or African American; American Indian/Alaska Native only constitutes 0.26%. According to the report of the Pew Research Center, the percentages in race/ethnicity are almost the same between U.S. adults and Twitter adult users. Interestingly, the percentages of White and Asian/Pacific Islander are much higher than those in the general population, which could be related to the labor force distributions of these two groups. In 2018, 54% of employed Asian and 41% of employed White, compared with 31% of employed Black or African American and 22% of employed Hispanic worked in management, professional, and related occupations, that can be most likely done at home ([Dingel and Neiman 2020]). Therefore, it is not surprising that there are more White and Asian/Pacific Islander in our dataset due to the disparities in the occupations.

Population density. UZipcode SearchEngine is applied to extract the population density of each user’s location that is self-reported by the Twitter user in the profile information. The population density is categorized into urban (greater than 3,000), suburban (1,000-3,000) and rural (lower than 1,000). In the end, 67.4% are urban, 14.6% are suburban and the rest are rural. The majority of the users of our dataset are from urban areas, which is consistent with the fact that 83% of the U.S. population lived in urban areas,[6] however, there are proportionally fewer urban users in our dataset than in the U.S. population.

Income. To understand the relationship between people’s attitude towards working from home and the gap between rich and poor at users’ locations, we retrieve regional median income from 2019 American Community Survey (ACS). Census Application Programming Interface (API) tools are used to extract median income with an input of city-level user location. The descriptive statistics are shown in Table 2.

Table 2: Descriptive Statistics of the regional median income.

| Mean | Std  | Min  | 25%  | 50%  | 75%  | Max  |
|------|------|------|------|------|------|------|
| 33,338| 10,298| 3,951| 28,072| 31,613| 36,336| 121,797|

Topic Modeling

We use LDA ([Blei, Ng, and Jordan 2003]) to extract topics from the tweets. In our study, we use the stop words package from NLTK library, extended with topic related words (e.g., “work”, “home”). To extract the most relevant topics, we only collect nouns, verbs, adjectives and adverbs lemmas. We use the spaCy package to go through all the words of the tweets, and only include the words whose postag is “NOUN”, “ADJ”, “VERB” or “ADV”. We tune the hyperparameters by nested looping topic numbers, α and β. In the end, we choose num_topics=9, α = 0.91, β = 0.31, with a coherence score $C_v = 0.379.$

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[1]https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/ [Accessed June 4, 2021]

[2]https://www.bls.gov/opub/reports/race-and-ethnicity/2018/home.htm [Accessed March 25, 2021]

[3]http://css.umich.edu/factsheets/us-cities-factsheet [Accessed March 27, 2021]
Results

Sentiment Analysis

In the previous section, we find that when referring to working from home, Twitter users are slightly positive. In this section, we attempt to investigate the relationship between user characteristics and the sentiment of discussions about working from home. We perform an ordinary least squares regression on the dataset n=28,579. Descriptive statistics and bi-variate correlations are shown in Table 3. Table 4 summarizes the result of the ordinary least squares regression.

Women tend to be more positive about working from home. Men are significantly more negative about working from home than women (p < .001). This is consistent with the survey conducted by Fast Company. A more positive sentiment observed in women could be due to the chance in working styles and fewer work hours compared to men (Collins et al. 2020). Previous survey indicates that women favor WFH from a healthier lifestyle perspective (Raišienè et al. 2020).

People in their 40s are more positive towards WFH than other age groups. Age is another perspective. The regression results show that as ages increase, people are significantly more pro-WFH (p < .001). This is consistent with the survey result conducted by Hannah Watkins that Gen Z (people at the point of this report aged from 8-23) are more pro-office than Millennials (aged 24-39). While assumptions exist when it comes to the older employees, who might be unfamiliar with electronic devices and thus become more pro-office. However, according to an article in Financial Times, the case is just the opposite. People aged 40s and older are less likely to be re-employed. Thus, they would like to keep their current jobs while avoiding the risk of getting exposed to COVID-19, especially since this group is most vulnerable to COVID-19. Further details about the topics will be discussed in the following section. It also shows the same pattern as the survey conducted in Lithuania (Raišienè et al. 2020).

People from higher-income areas are more likely to have pro-WFH opinions than the people from lower-income areas. Income is significantly correlated with the sentiment of working from home (p < .001). This aligns with our findings that people from urban areas would be more pro-WFH, since the regional median income would be higher in big cities. This is also in line with the findings of Barrero, Bloom, and Davis (2020) that high-income workers, especially, enjoy the perks of working from home.

Top 8 (Back to office) contains keywords “back” and “office”, and constitutes 13.2%. In this topic, people mostly tweet about their opinions towards the office, will “office” finally come back or when will be able to go back to office. Topic 9 (Leasing) contains keywords “year”, “lease”, etc.
Table 3: Descriptive statistics and the bi-variate correlations. Income is normalized by MinMaxScaler.

| Variables | Mean | SD | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10    |
|-----------|------|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1 Gender (0 = female, 1 = male) | 0.59 | 0.49 |       |       |       |       |       |       |       |       |       |       |
| 2 Age <= 18 (0 = No, 1 = Yes) | 0.09 | 0.28 | -0.04** |      |       |       |       |       |       |       |       |       |
| 3 Age 19-29 (0 = No, 1 = Yes) | 0.16 | 0.37 | -0.21** | -0.14** |       |       |       |       |       |       |       |       |
| 4 Age 30-39 (0 = No, 1 = Yes) | 0.38 | 0.48 | -0.24** | -0.34** |       |       |       |       |       |       |       |       |
| 5 Black or African American (0 = No, 1 = Yes) | 0.03 | 0.16 | -0.01 | -0.07** | -0.02** | -0.01 | -0.05** |       |       |       |       |       |
| 6 Asian/Pacific Islander (0 = No, 1 = Yes) | 0.07 | 0.26 |       |       |       |       |       |       |       |       |       |       |
| 7 Hispanic (0 = No, 1 = Yes) | 0.07 | 0.25 | -0.02** | -0.04** | -0.03** | -0.04** | -0.00 | -0.02** |       |       |       |       |
| 8 Income | 0.25 | 0.09 | -0.04** | -0.07** | -0.01 | -0.01 | -0.04** | -0.00 | -0.02** |       |       |       |
| 9 Urban (0 = No, 1 = Yes) | 0.67 | 0.47 | -0.02** | -0.03** | -0.01 | -0.01 | -0.05** | -0.00 | -0.03** | -0.05** |       |       |
| 10 Suburban (0 = No, 1 = Yes) | 0.15 | 0.35 | -0.02** | -0.02** | -0.01 | -0.01 | -0.02** | -0.00 | -0.00 | -0.09** | -0.60 |       |

Note. * p < .05, ** p < .01.

Table 4: Ordinary least squares regression outputs for public opinion on Working from Home against demographics and other variables of interest.

| Sentiment score | Predictor | B     | SE   | 95% CI |
|-----------------|-----------|-------|------|--------|
| Intercept       | 0.252*** | 0.011 | (0.231, 0.273) |
| Gender (0=Female, 1=Male) | -0.021*** | 0.006 | (-0.032, -0.010) |
| Age <= 18 (0=No, 1=Yes) | -0.084*** | 0.010 | (-0.103, -0.064) |
| Age 19-29 (0=No, 1=Yes) | -0.076*** | 0.008 | (-0.092, -0.060) |
| Age 30-39 (0=No, 1=Yes) | -0.022*** | 0.005 | (-0.034, -0.010) |
| Black or African American (0=No, 1=Yes) | 0.023 | 0.017 | (-0.011, 0.066) |
| Asian/Pacific Islander (0=No, 1=Yes) | 0.003 | 0.010 | (-0.020, 0.020) |
| American Indian/Alaska Native (0=No, 1=Yes) | -0.006 | 0.011 | (-0.027, 0.016) |
| Hispanic (0=No, 1=Yes) | -0.006 | 0.011 | (-0.027, 0.016) |
| Income | 0.143*** | 0.031 | (0.082, 0.203) |
| Urban (0=No, 1=Yes) | -0.007 | 0.007 | (-0.021, 0.007) |
| Suburban | -0.004 | 0.009 | (-0.023, 0.014) |

F-statistic | 15.25*** |
R² | 0.006 |
Adjusted R² | 0.005 |
Sample size | 28,579 |

Note. * p < .05, ** p < .01, *** p < .001.

Table 5: Titles and the top 10 keywords of the topics extracted by LDA.

| Topic | Topic Title | Topic Keywords |
|-------|-------------|----------------|
| 1     | Family activities | dog, try, today, wife, day, last, school, virtual, watch, look |
| 2     | Remote work/study | remote, new, time, covid, learn, great, help, many, support, join |
| 3     | Quarantine | pandemic, stay, safe, day, go, today, let, see, also, think |
| 4     | Dressing | dress, get, enough, adult, day, wear, time, zoom, right, thank |
| 5     | Government and policy | money, less, job, option, able, new, remotely, safely, force, take |
| 6     | COVID side influence | people, still, do, job, good, say, first, place, probably, go |
| 7     | Encouragement | get, lot, world, honestly, fall, reveal, love, week, look |
| 8     | Back to office | go, back, know, office, time, feel, quarantine, hour, tip, covid |
| 9     | Leasing | office, well, year, instead, couple, permanently, think, lease, renew, similarly |
“renew”, “office”, where people argue that some companies might not renew their office lease for the next year, because of how well WFH is working for these companies.

Figure 1: Topic distributions.

Figure 2 shows the average sentiment score of each topic. The average sentiment score of Topic 7 (Encouragement) is the highest (0.460), considered as the most positive topic, compared with Topic 5 (Government and policy), the least positive topic (0.129). As mentioned in the Feature Inference section, the average sentiment score of all the users in our dataset is 0.242. Among these 9 topics, all of them show a positive sentiment towards WFH. Meanwhile, Topic 2 (Remote work/study), Topic 7 (Encouragement) and Topic 8 (Back to office) are above the average; Topic 1 (Family activities), Topic 3 (Quarantine), Topic 4 (Dressing), Topic 5 (Government and Policy), Topic 6 (COVID side influence) and Topic 9 (Leasing) are below the average.

Money and jobs are discussed the most when the government accounts are mentioned. In Topic 5 (Government and policy), “money” and “job” are the most eye-catching keywords in LDA results. As we explore the tweets under this topic, we find there are a number of tweets mentioning government accounts and governor twitter accounts. An example is:

@SenBobCasey @SenToomey @GovernorTomWolf supply chain workers discouraged. Work from home pieces of the chain are essential. TEMPORARY layoffs making more than I am to wait to get called back to work, where’s the incentive to work? Why aren’t we included in stimulus 2.0?

In addition, we also find some tweets about money, where people are kind of worried about their financial status during the pandemic, such as losing money after lay-off by their companies. Based on these findings, since April is still at the early stage of WFH, economics would be a big deal for the government to handle during this period.

Family activities and Remote work/study conflicts in age groups. According to Figure 3, as age goes up, the percentage of people tweeting about Remote work/study is rising; meanwhile, there are less people tweeting about family activities. For people aged from 0 to 18, there are 23.4% of people tweeting about Topic 1 (Family activities) and 8.5% about Topic 2 (Remote work/study). In the age group 19-29, there are 22.4% of people talking about Family activities and 9.4% about Remote work/study. For people in their 30s, there are 17.2% on Family activities and 15.2% on Remote work/study. For people older than 40, only 14.7% of them tweet about Family activities, and 23.5% on the topic of Remote work/study. In the aforementioned topic model summary, Topic 2 (Remote work/study) is a heavy work-related topic, which brings work-family conflicts on the table. Prone, Russell, and Cooper (1992) stated that family boundaries are more permeable than work boundaries. Interestingly, based on our findings, we can conclude that, in the environment of working from home, family boundaries are getting more permeable when it comes to older people. On average, >=40 age group accounts for 37.08% of the study population. However, in Topic 1 (Family Activities), only 30.8% of the tweets are from people older than 40; on the other hand, in Topic 2 (Remote work/study), 52.1% of the tweets are coming from >=40 age group. These interesting patterns are consistent with our findings that family-work boundaries are getting weaker for older people.

Superwomen in WFH. In the previous section, we conclude that women show more positive attitudes than men to working from home. Collins et al. (2020) found that might be because that women tend to reduce more work hours, and we also confirm this finding from the perspective of thematic analysis. By performing the goodness-of-fit test, we find that the topic distributions of men and women (Figure ??) are significantly different (p < .001). According to the difference between the topic distributions of men and women, we think that fewer work hours allow women to spend more time accompanying children and taking care of family. Topic 1 (Family Activities) is one of the topics to which women pay more attention. As we dive deep into the tweets, we find that many tweets are about spending time with the children while working from home. An example is:

That’d be me. I get to work from home and be with my kids. I’m loving every minute of this time with them!!
Figure 3: Topic distributions of age groups.
Discussion

Principal Results

This study represents a large-scale quantitative analysis of public opinions on working from home during the COVID-19 pandemic. Through the lens of social media, we find that gender and age are the most influential features to public opinions about WFH. After performing the ordinary least squares regression, we find that sentiment of working from home varies across user characteristics. In particular, women are more positive about working from home, which could be related to the change of working styles\(^{12}\) and fewer work hours compared to men (Collins et al. 2020). People in their 40s and older tend to be the most pro-WFH than other age groups. It could be due to the fact that people of those ages are the most vulnerable to COVID-19 while also the most difficult ones to get re-employed once they lost their jobs. They also need to work to mitigate the shrinkage of retirement savings that were invested in the sluggish stock market. People from high-income areas are more likely to have positive opinions about working from home, which echoes the findings of Barrero, Bloom and Davis (2020).

These nuanced differences are supported by a more fine-grained topic analysis. At a higher level, we find that all the topics are showing a positive sentiment about WFH. However, people express a more negative sentiment towards the family activity and government. Within the topic of family activity, we notice that women pay more attention to family than men, and we find the superwomen in WFH. When people talk about government and policy, money and jobs are two major concerns. Furthermore, according to our analysis in age groups, we notice that the family work boundary is another issue that varies from different ages. As age increases, more people would like to talk about work rather than family, which implies that family boundaries are getting more permeable than work boundaries.

Implications

Barrero, Bloom and Davis have found that working from home will even stick after the pandemic ends (Barrero, Bloom, and Davis 2020). It is critical to understand public opinions on working from home to help improve their experience and design a more suitable and flexible work policy. Our paper suggests that there are nuanced differences across user characteristics. Policy-makers of the government and companies could design a more customized work policy to not only increase the work productivity but also improve the work satisfaction of their employees. It is also important to address the disparities related to working from home, which have been reported among different racial and socioeconomic groups (Chowkwanyun and Reed Jr 2020; Chang et al. 2020).

Limitations

Our study is focused on the relationship between user characteristics and the sentiment about working from home. However, user occupation can be included in the future analyses. Since the ability to work from home varies among different kinds of jobs (Dingel and Neiman 2020), one potential hypothesis could be that people of different occupations hold different opinions about working from home, thus occupations would have an impact on the sentiment. In addition, there are also some limitations of only using Ethnicolr API to infer ethnicity. The Ethnicolr API is model trained on vote registration data from Florida state. First, using data from a single state (albeit a representative state) may not be ideal, since the pattern of the names can be different between states. For another, the training dataset is imbalanced (non-Hispanic White: 8,757,268; non-Hispanic Black: 1,853,690; Hispanic: 2,179,106; Asian: 253,808). Although these numbers are consistent with the facts of population distribution in the U.S., in the case of training an inference model, we still think using a more balanced dataset could provide a better result.

Conclusions

This paper presents a large-scale social media-based study on who are more likely to tweet about working from home. By performing the ordinary least squares regression, we show how the sentiment of working from home varies across user characteristics. After conducting a content-based analysis, we dissect what Twitter users mainly talk about and how the content correlates with the sentiment of working from home. This paper contributes to a better understanding of

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12\]https://www.fastcompany.com/90477102/4-ways-remote-work-is-better-for-women [Accessed March 24, 2021]
public opinions on working from home during the COVID-19 pandemic and lends itself to making policies both at national and institution/company levels to improve the overall population’s experience of working from home.

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Authors’ Contributions. All authors conceived and designed the study. HL performed data collection. ZX and PL performed feature inference. PL conducted sentiment analysis. ZX applied LDA models. ZX and PL analyzed the data and wrote the majority of the manuscript. All authors edited the manuscript.

Conflicts of Interest

The authors declare that they have no competing interests.

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**Abbreviations**

ACS: American community survey  
API: application programming interface  
COVID-19: coronavirus disease 2019  
HR: human resources  
LDA: Latent Dirichlet Allocation  
NLP: natural language processing  
NLTK: natural language toolkit  
RQ: research question  
VARDER: valence aware dictionary and sentiment reasoner  
WFH: work from home