Work-from-home (WFH) during COVID-19 pandemic – A netnographic investigation using Twitter data

Purpose – This paper aims to create a better understanding of the challenges posed by work from home (WFH) during the ongoing COVID-19 pandemic, to investigate the public sentiment towards this transition, and to develop a conceptual model incorporating the relationships among the factors that influence the effectiveness of WFH.

Design/methodology/approach – This paper uses netnography method to collect data from the Twitter platform and uses Python programming language, Natural Language Processing (NLP) techniques, and IBM SPSS 26 to conduct sentiment analysis and directed content analysis on the data. The findings are combined with an extensive review of the remote work literature to develop a conceptual model.

Findings – Results show the majority of tweets about WFH during the pandemic are positive and objective with technology and cyber security as the most repeated topics in the tweets. New challenges to WFH during pandemic include future uncertainty, health concerns, home workspaces, self-isolation, lack of recreational activities, and support mechanisms. In addition, exhaustion and technostress mediate the relationship between the antecedents and outcomes of WFH during the ongoing COVID-19 pandemic. Finally, the fear of pandemic and coping strategies moderate these relationships.

Originality – This paper is one of the first efforts to comprehensively investigate the challenges of WFH during a crisis and to extend the remote work literature by developing a conceptual model incorporating the moderating effects of fear of pandemic and coping strategies. Moreover, it is the first paper to investigate the tweeting behavior of different user types on Twitter who shared posts about WFH during the ongoing pandemic.

Keywords: COVID-19 pandemic; natural language processing; remote work; sentiment analysis; Twitter; work from home

1. Introduction

The ongoing Covid-19 global pandemic has affected our personal and work lives, especially due to the frequent lockdowns used in most countries to curb the spread of the virus (Guardian, 2020). Several organizations have rolled out the mandatory work from home (WFH) settings around the globe, pushing everyone into a remote work mode. The sudden and communal transition made everyone work at their improvised workstations at home with all family members around. Many people were forced to change their bedroom, kitchen, dining area, and couches to their mutual workspaces, and many had to use the same space as their kid's play station (Toniolo-Barrios and Pitt, 2021). The closure of schools and day-cares has also forced many parents to be an employee and a full-time career at the same time (Gorlick, 2020). Similarly, the rapid transition to online working using video conferencing tools has also resulted in greater levels of fatigue for everyone (Fosslien and Duffy, 2020).

Past research on WFH has identified several challenges, including poor work-life balance (Charalampous et al., 2019), ambiguous tasks (Perry et al., 2018), increased stress and limited social interactions with colleagues (Grant et al., 2013), and lack of motivation (Toniolo-Barrios and Pitt, 2021). Moreover, the mandatory transition to WFH during a crisis can be more challenging than compared to WFH in normal times, such as distractions due to the presence of family members, increased health concerns, future uncertainty, and the risk of greater domestic violence (Toniolo-Barrios and Pitt, 2021). Due to these unprecedented challenges, people may perceive themselves as less productive and struggle with more stress and mental health issues (Toniolo-Barrios and Pitt, 2021).

In such a situation, it is the responsibility of managers to keep employees productive by identifying and addressing the challenges they face during this shift and through this, help them with improved wellbeing and better mental health. Accordingly, identifying a broad range of challenges associated with WFH during the pandemic is essential to help managers understand the problem and deal effectively with conditions related to the mandatory transition to WFH when a crisis happens. Despite growing research on the challenges posed by the mandatory transition to WFH during a crisis (e.g. Butler and Jaffe, 2021; Li et al., 2020; Steidtmann et al., 2021), there is still no comprehensive understanding about this topic. Hence, this study aims to explore the challenges of mandatory, quick, and communal transition to WFH during the pandemic.

Moreover, despite the growing challenges posed by WFH, most governments and organizations believe that it is a viable option for the long term (BBC News, 2020; CNBC, 2020). Some organizations consider WFH as an excellent policy to continue, and some companies claim it is unlikely to return all their staff to their buildings again (Haag, 2020). These measures significantly impacted labor market participation across the workforce, with a significant decrease in employment from 396 million to 282 million in a month (Deshpande, 2020; The Hindu, 2020). On the other hand, although organizations save the risks and maintenance costs (The Guardian, 2021b) and welcome permanent WFH conditions, employees face severe stress (The Guardian, 2021a). Hence, in addition to identifying the challenges of WFH, organizations need to pay careful attention to employees' sentiment toward this transition. Knowing that employees' emotions significantly affect their job performance (Lee *et al.*, 2011), satisfaction, and productivity, managers need to understand employees' emotions toward WFH before making any long-term decisions.

Prior research shows that employees forced to WFH during pandemic went through different emotional journeys and they reported mixed results. While some people suffered from post-pandemic stress, others found WFH as an opportunity to realize their competencies and strengths (Prasad et al., 2020) and testified positive sentiments (e.g. Dubey and Tripathi, 2020; Wrycza and Maślankowski, 2020). Accordingly, it is important to understand what the general sentiment toward WFH is during pandemic. Hence, this study aims to explore how people feel about the mandatory, quick, and communal transition to WFH during the pandemic (i.e., positive, negative, or neutral). During these unprecedented times, the self-isolation rules have resulted in a dramatic rise in the use of social media platforms by the public to connect with each other, get information, and share their opinions online.

The huge amount of information generated on social media platforms creates a valuable source of data to tap into and leverage understanding of a topic from a public perspective. Moreover, in situations that require identifying and addressing issues in real-time to improve quality of life, prior studies suggest collecting and analysing data posted on social media platforms and capture meaningful trends (Kavanaugh et al., 2012). "Monitoring these patterns and themes over time could provide officials with insights into the perceptions and mood of the community that cannot be collected through traditional methods" due to time, budget, and geographical limitations (Kavanaugh et al., 2012; p. 481). For instance, conducting interviews and focus groups take a lot of time and the collected data reflects the perspective of a small group of participants. Similarly, collecting data through the survey is time-consuming, expensive, and it is subject to geographical limitations. Hence, data mining of the real-time social media posts is required to improve managers' awareness of real-world events, such as WFH during the pandemic, gather broader public perceptions, and access segments that are less likely to take part in traditional ways of data collection.

Among various social media platforms, Twitter is one of the most favorite platforms with many active users where individuals and institutions tweet their thoughts and ideas, share news, and retweet others' tweets (Saha et al., 2017). Thus, Twitter is a suitable platform to explore the public's perspective on a topic. Accordingly, the present study uses the publicly available data posted on Twitter as the data source and uses the netnography methodological approach to identify the challenges attributed to this transition and understand emotions toward WFH during the pandemic. With the support of existing literature and the results from the exploratory research, we then develop a conceptual framework to understand the macro-level, meso-level, and micro-level factors and intervening elements that influence the transition to mandatory, quick, and communal transition to WFH during pandemic. Accordingly, this study explores people's feelings regarding the transition to WFH and the underlying factors. With the support of existing literature and the results from the exploratory research, we also develop a conceptual framework that presents the dynamics of various factors identified. To summarize, we address the following research questions in this paper:

RQ1: How do people feel about the mandatory, quick, and communal transition to WFH?

RQ2: Which macro-, meso-, and micro-level factors may impact the transition to WFH?

RQ3: What are the intervening factors that may influence the transition to WFH?

2. Literature review and theoretical background

2.1. Work from Home (WFH)

Work from home (WFH) started with the advancement in technology that made it possible to work from anywhere. WFH is derived from the umbrella term distributed work, which explains "arrangement that allows employees and their task to be shared across settings away from a central place of business or physical, organizational location" (Gajendran and Harrison, 2007, p. 1524-1525). The term telecommuting further describes "individuals working from home using technology to communicate back to their workplace" (Charalampous *et al.*, 2019, p.52). Now, terms such as 'working remotely' or 'working from home' are more commonly used instead of telecommuting as these describe "performing work at a location other than one's primary office" (Perry et al., 2018, p. 577), including neutral spaces such as Smart Work Hubs (Malik et al., 2016).

2.2. Challenges of WFH

Prior studies have identified various challenges posed by WFH, such as increased stress levels and limited social interactions (Grant *et al.*, 2013), workload during non-working hours (Charalampous *et al.*, 2019), increased task ambiguity (Perry *et al.*, 2018), and poorer health habits (Prasad *et al.*, 2020). Despite these challenges, many studies found many benefits of WFH, such as longer working hours, flexibility, work-life balance, job autonomy (Prasad *et al.*, 2020), liberty and employee satisfaction (Kelliher and Anderson, 2010), and well-being (Charalampous *et al.*, 2019). Organizations also benefit from WFH with higher productivity through less physical office management and decreased expenses (Prasad *et al.*, 2020). During the recent pandemic, due to the imposed regulations, the adoption of WFH has increased exponentially around the globe.

Prior research raises concerns about this enforced transition, related to work-life balance and parenting arrangements (Manzo and Minello, 2020), social distancing rules and their negative impact on individuals' wellbeing (Prasad et al., 2020), increased workload, technostress, behavioral stress, and higher work-family conflict (Molino et al., 2020). Moreover, the financial instability caused by the economic changes during the pandemic led to higher levels of family stress and domestic violence (Beland et al., 2020). Studies also report the spillover between work and family as another crucial factor creating instability and voluntary turnover from the job during this time (Rubenstein *et al.*, 2020). The challenge of work-life balance is found to be affecting women more than men as female employees are under more pressure for managing the work and family demands (i.e. gender inequality during the pandemic) (Long, 2020; Manzo and Minello, 2020).

2.3. Sentiments toward WFH

Prior research shows while some employees forced to WFH suffered from post-pandemic stress, others found WFH as an opportunity to realize their competencies and strengths (Prasad et al., 2020). There are few studies that analyzed the Twitter data to investigate sentiment toward WFH in the time of pandemic and all of them reported a positive sentiment toward this transition (Dubey and Tripathi, 2020; Mansoor et al., 2020). However, these studies analyzed the tweets altogether. While there are many tweets generated on Twitter by personal users, there are also a huge number of tweets created by business users, news agencies, and marketing services who follow a business purpose on Twitter (Uddin et al., 2014) and the content of their tweets may differ from personal thoughts. Thus, we need to investigate sentiment toward WFH based on different user types.

2.4. WFH: Antecedents and outcomes

WFH and remote work literature identifies their influencers, consequences, and intervening variables. Through a comprehensive review of literature, we identified various outcomes of WFH and classified them into job-related outcomes (e.g. job performance), organizational related outcomes (e.g. productivity), social related outcomes (e.g. social support), stress-related outcomes (e.g. role stress), as well as work-family related outcomes (e.g. family functioning, work-family conflict). The existing literature on WFH presented in Table I consolidates the influence of this type of work arrangement on various outcome variables.

< Insert Table I about here >

Further, the review of the literature identified various constructs that influence the success or failure of WFH. The antecedents are categorized based on job-related influencers (e.g. job autonomy), organizational-related influencers (e.g. organizational culture), information and communication technologies (e.g. ICT), social-related elements (e.g. interpersonal and external interaction), as well as individual-related influencers (e.g. self-efficacy, competency, work-family roles). A similar classification is done to categories the intervening variables comprising of moderators and mediators. The existing literature on WFH in Table II represents the variables that influence WFH. Based on our literature review summarized in presented in Table I and Table II, we attempted to represent the relationship established in WFH literature to develop a framework for existing linkages (see Figure 1).

< Insert Table II and Figure 1 about here >

With the spread of COVID-19 and the restrictions imposed by governments during this phase, WFH gained a lot of attention. Studies show that the impact of WFH on individuals and organizations is directly related to the organization's readiness to develop and implement the WFH strategies, policies, and procedures (Prasad *et al.*, 2020). In this unexpected and unplanned transition, organizations need to develop relevant policies and procedures and provide their employees with the required facilities. Employees also need to keep up with the rapid changes and adapt their working behavior.

3. Exploratory study

The communal and mandatory transition to WFH during the pandemic is a novel scope in the WFH literature and it is necessary to create a better understanding of the topic by exploring its challenges and the general sentiment towards this transition. Due to the exploratory nature of this study, we decided to select a method that enables us to collect the perspectives of a large group of people in a short amount of time and at the same time, do not impact responses by our presence. As the self-isolation rules during this unprecedented period, made social media platforms to be massively used by the public to connect, collect information, and share opinions, we decided to use the data posted on social media as the information source.

We selected Twitter because it is one of the most popular social-media platforms among the Web 2.0 tools, as an impactful micro-blogging service in terms of its ability to connect people globally and providing sentiment-rich data (Kumar and Jaiswal, 2020). Twitter with a huge number of active users is one of the most favored platforms for individuals and institutions to tweet their thoughts and opinions (Saha et al., 2017), share news, or retweet others' tweets. This free social media platform enables the quick and flexible exchange of information, and unlike other social media platforms, the social relationships on Twitter are mainly not based on friendship bonds (Mozas-Moral *et al.*, 2016).

Based on our data source, this study follows netnography as the research method for analyzing Twitter posts about WFH in the period of COVID-19. Supported by prior studies, the growth of online interactions makes netnography a suitable research technique to find information from online discussions and generate insights (Sandlin, 2007). In the pandemic situation, exploring the topic from an online lens is a good choice as based on the ongoing lockdowns, conducting face-to-face exploratory research is not practical and conducting online interviews or focus groups would limit the results to a small group of participants who had time and could easily navigate the online meeting platforms. Netnography helps analyze word counts, sentiments, and natural language similarities to tap into individuals' mindsets in the virtual space. It is a less time-consuming research method (Addeo et al., 2019) and unlike interviews and focus groups, it collects the naturally occurring behavior as people share information online (Sandlin, 2007) or react to other posts. This research method enabled us to automatically record online data in real-time without being obtrusive and access to the research population without geographical limitations (Addeo et al., 2019).

Prior studies have used netnography for analyzing Twitter posts as this approach allows an in-depth exploration of the dynamics of a topic on a virtual channel. Similarly, the current study extracted data from the Twitter platform and used Tweepy library in the Anaconda environment (a distribution of Python 3.7.6) to access the Twitter API for extracting the tweets. We collected the tweets over a three months (July-October 2020) period by when Covid-19 was widespread around the world and people had started to build either positive or negative attitudes towards the mandatory transition to WFH. We collected the data for three months to have a better understanding of the topic and stopped as saturation was reached. All the tweets were in English with no geographical limitation and contained at least one of the following search terms in their text or hashtags: Set 1: Covid-19, Covid19, Coronavirus, Corona, Outbreak, Pandemic, Quarantine; and Set 2: Working from home, Work from home, Work at home, Home office, Workfromhome, Workingfromhome, Remote work, WFH.

We analyzed the tweets for sentiments and content to identify the constructs and their interrelationships. As the growth of online platforms generates a high volume of unstructured, subjective, vague, and diverse opinion-rich information (i.e. big data), to handle this fuzziness, soft computing techniques such as sentiment analysis and text classification are becoming a growing field (Kumar and Jaiswal, 2020) through which people's emotions and opinions about topics and events are processed. "Sentiment refers to a personal point of view, feeling, emotion or expression towards something" (Ahuja and Dubey, 2017, p. 3) and "sentiment analysis allows the identification, extraction and quantification of feelings and emotions expressed in a text" (Mingione *et al.*, 2020, p. 312).

Sentiment analysis is becoming a popular method to mine *Twitter* posts with an application in various domains, such as politics, remote work (Sharma *et al.*, 2020; Dubey and Tripathi, 2020), and other general topics. The current study extends the prior research in this scope by applying sentiment analysis to capture the polarity and subjectivity of tweets posted on Twitter about WFH during the pandemic and investigate Twitter users' tweeting behaviors. Sentiment analysis uses polarity, subjectivity, and emotions attributed to textual data. To process the tweets' polarity and subjectivity, we used TextBlob, a built-in model in Python that can calculate polarity and subjectivity values (Ahuja and Dubey, 2017; Saha *et al.*, 2017; Yaqub et al., 2018). This provides "a simple API for diving into common NLP tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more" (TB, 2020). The polarity explores whether the sentiment is negative, neutral, or positive (Hasan *et al.*, 2018; Mingione *et al.*, 2020). "Polarity analysis using Python Textblob, words in the lexicon are assigned scores for negative and positive polarity" (Yaqub et al., 2018; p.4), which uses a continuum ranging from -1 to +1 to categorize the tweets to imply negativity (-1 to 0), neutrality (0), and positivity (0 to +1).

In order to understand whether the tweets about WFH during the pandemic were mainly personal emotions or functional information, we assessed the subjectivity and objectivity of the tweets. To explain, textual data can be written in an objective or subjective manner. Subjective texts tend to describe people's emotions, opinions, and beliefs while objective texts are usually used for stating facts and functional information and they are considered as non-emotional (Saleh et al., 2021). Similarly, subjective tweets contain positive or negative emotions while objective tweets are mainly neutral. Prior studies contend that for decision-making purpose, objective texts (which are truths) are better than subjective ones (which are just opinions) (Machan, 2017). A subjectivity score ranging from 0 (objective) to 1 (subjective) is assigned to each tweet, based on whether it represents a subjective or an objective meaning (Hasan *et al*., 2018, p. 7).

Further, content analysis is employed to identify the major themes in the Twitter data, and it is defined as "a set of analytical techniques (syntactic, lexical and thematic), in which systematic and objective procedures are employed to describe the content of messages, using qualitative or quantitative indicators that allow knowledge to be inferred" (Oliveira *et al.*, 2013, p. 74). For this aim, we first identified the most repeated words in the text corpus and for this, we used the Natural Language Toolkit (NLTK) package in Python to tokenize the text and remove the stop words. Through the Counter function in collections, we searched for the most common words and used the Pandas library to create a data frame. After identifying the most common words in the text corpus, we followed the direct content analysis (DCA) method for analysis purpose (Hsieh and Shannon, 2005). We determined the codes based on the most repeated words and manually grouped them under different categories. Based on the content similarity, the categories were then grouped under different themes (inspired by the literature review). We then had two independent raters judge if each word represents the category assigned to on a categorical scale (i.e. 0= not representative, 1= representative).

Finally, for inter-rater agreement, we measured Cohen's kappa (κ) test using IBM SPSS 26.

4. Results of exploratory study

During this study, 151,175 tweets posted on Twitter, having at least one of the combinations of search terms were collected. We extracted the tweet text, hashtag, creation date, number of followers and friends per user, and retweet status. By retweet status, we looked at the times a tweet was retweeted and used it to groups our data into tweets that are not retweeted, retweeted once, or retweeted more than once. As this study uses text-mining of Twitter data to address the research questions, there is no certainty that posts on Twitter necessarily represent individuals' perspectives. While there are many tweets generated on Twitter by personal users, there are also a huge number of tweets created by business users, news agencies, and marketing services who follow a business purpose on Twitter (Uddin et al., 2014) and the content of their tweets may differ from personal thoughts.

Accordingly, to have a better understanding of individuals' sentiment towards WFH, we need to categorize the tweets based on different user types and analyses sentiment of each group separately. This provides us with a better understanding of personal emotions and sentiments toward WFH for each group of users. In this context, Krishnamurthy et al. (2008) categorized Twitter users into three groups that is 1) *broadcaster* who has "a much larger number of followers than they are following"; 2) *acquaintances* who "tend to exhibit reciprocity in their relationship"; and 3) *miscreants* (e.g., spammers or stalkers) or evangelists, who follow "a much larger number of people than they have followers" (p.20), whereas, Java *et al.* (2007) categorized the users into 1) *information source* who has a large number of followers; 2) *friends* who follow their friends, family, and co-workers and similar people follow them; and 3) *information seeker* who mostly follow other users but might rarely post. Using the above categorization, we classified Twitter users into five types: evangelists /miscreants, information seekers, acquaintances/friends, information source and broadcasters based on their number of followers and friends as presented in Table III.

< Insert Table III about here >

4.1. Sentiment analysis: Polarity

By analyzing the strength of the text's polarity, we can decide whether the positive or negative sentiment expressed by a text on a subject is weak, mild, or strong (Taboada, 2016). Hence, to better understand the strength of tweets' polarity, we categorized them in different groups ranging from strongly negative to strongly positive. Table III presents the polarity range and the frequency of tweets in each group. The mean of polarity scores suggests that most tweets about WFH during the pandemic are either positive or neutral (M=.089, SD=0.22). To explain, 51.9 per cent of tweets are positive (mainly weakly positive), 26.4 per cent are neutral, and only 21.7% are negative.

4.2. Sentiment analysis: Subjectivity

We categorized the subjectivity score on a continuum ranging from strongly subjective to strongly objective for a better interpretation of results. Table III presents the subjectivity range and the frequency of tweets in each group. The mean of subjectivity scores shows that most of the tweets about WFH during the pandemic are objective (M=.36, SD=0.25). To explain, 68.1 per cent of tweets are either weakly or strongly objective, 6.3 per cent are neutral, and only 25.6 per cent of tweets are subjective. Having the majority of tweets as objective demonstrate that the tweets' about WFH during pandemic contained functional information and the analysis output would help with decision making (Machan, 2017).

4.3. Tweeting behavior

In terms of the trend of tweets' polarity, results show that the proportion of positive, neutral, and negative tweets does not follow a consistent direction and can be subject to external factors. For instance, as depicted in Figure 3, on 16th and 31st July, the proportion of neutral tweets exceeds the positive tweets and 20th August had the most negative tweets throughout the whole study period. It is interesting to notice that although before 21st August, the proportion of positive, neutral, and negative tweets fluctuated daily, after this date, it is most consistent with the positive tweets staying at a higher level compared to negative and neutral tweets. However, the tweets' subjectivity follows a consistent trend, and as it is depicted in Figure 4, objective tweets mostly dominate, which may indicate a stabilization of peoples' perceptions and attitudes towards WFH after an initial uncertain period.

< Insert Figures 3 and 4 about here >

In order to have a better understanding of the data structure and investigate whether users' sentiment toward WFH in the time of pandemic and their actions (retweet) has any correlation with their number of followers and friends (i.e. user type), we computed the Pearson correlation (see Table IV). The output shows there is a significant positive correlation between user type and polarity ($r=.044$, $p<.05$) and user type and subjectivity ($r=.029$, $p<.05$). This result shows that in the context of WFH during the pandemic, those users with a much higher number of followers than friends are more likely to disseminate positive and emotional tweets while groups with fewer followers than friends or almost similar number of followers and friends are more likely to share functional information about this topic with less emotional direction. The results also show that user type and retweet ($r= -.093$, $p<.05$), polarity and retweet ($r= -.095$, $p<.05$), and subjectivity and retweet ($r= -.155$, $p<.05$) have significant negative correlations. Hence, twitter users with fewer followers than friends are more likely to engage in resharing others' tweets and negative and objective tweets have a higher chance to be retweeted compared to positive and subjective ones.

< Insert Table IV about here >

We conducted a one-way ANOVA to investigate any significant difference among various user types in terms of the polarity of their tweets. Results depict differences among groups at a significance level of 5 per cent for the three conditions ($F(4, 151{,}170) = 83.824$, p

= 000). Executing Post Hoc comparison using the Tukey HSD test indicates that while at $p<0.05$, there is no significant difference among EM and ISE and EM and AF, the other user types are significantly different from each other. We then analyzed the polarity of tweets posted on Twitter by various user types. It was found that BC and ISO (groups with a much higher number of followers than friends), are the least likely groups to post neutral tweets and they are mostly inclined towards sharing tweets with positive polarity. On the other hand, EM and ISE (groups with a much higher number of friends than followers) are most likely to post neutral tweets, and they are the least interested group in sharing positive tweets. The ANOVA results help us to understand that there is a significant difference among various user types in terms of the polarity of their tweets. Hence, to generate a better understanding of individual rather than business perspective, we may like to focus on the sentiment of tweets posted by users categorized under Information seeker (ISE) and Acquaintances/Friend (AF).

< Insert Table V about here >

Table V shows the proportion of tweets' polarity for each user type. The results show that while almost 49.9% of tweets posted by ISE and AF are positive, 51.1% of their tweets are either neutral or negative. These two groups are more likely to be individuals and represent the perceptions of employees. However, when it comes to groups with a much higher number of followers than friends, such as Broadcasters and Information Source, almost 56% of their tweets are positive which shows that businesses and agencies have engaged in disseminating more positive tweets about WFH during pandemic compared to individuals.

We also analyzed the relationships between the polarity of tweets and their chances of being retweeted. We first divided the tweets into three main categories based on their retweet status: not retweeted, retweeted once, and more than once. The comparison between groups demonstrates that tweets being strongly negative or neutral in terms of polarity, are more likely to be retweeted more than once. However, positive tweets (both weakly and strongly positive) are more likely not to be retweeted than other retweet status groups. Table VI demonstrates the proportion of tweets' polarity based on retweets status. This result shows that the negative content gets more people engaged than positive content which is in line with negativity bias on social media (Bellovary et al., 2021). Social media propagates the message to a larger group of users which may influence the way they perceive WFH.

< Insert Table VI about here >

To understand the relationship between tweets' polarity and subjectivity of the various users, after dividing the tweets into five categories SO, WO, NS, WS, and SS (strongly objective, weakly objective, neutral, weakly subjective, strongly subjective), we computed the proportion of SN, WN, NP, WP, and SP (strongly negative, weakly negative, neutral, weakly positive, strongly positive) in each category. Based on the output (Table VI), most of the strongly negative tweets or strongly positive (i.e. on the extreme ends) are very subjective. Moreover, the majority of tweets that are neutral in terms of polarity found to be strongly objective. This result supports the finding of previous studies that subjective texts tend to describe people's emotion, opinions, and beliefs while objective texts are usually used for stating facts and functional information and they are considered as non-emotional (Saleh et al., 2021). Hence the extreme polarity of messages being subjective may suggest that the users are highly emotional with the topic they are dealing with in their tweets and could be influencing the emotional state of their mind impacting them positively or negatively. To study the relationship between tweets subjectivity and user type, we computed the proportion of tweets posted by each user type: SO, WO, NS, WS, and SS. We found that BC and ISO are the least likely groups to post strongly objective tweets that are mostly inclined towards weakly objective, neutral, or weakly subjective tweets. By contrast, EM and ISE are most likely to post strongly objective or strongly subjective tweets (i.e. on the extreme ends). Table VI also shows the proportion of tweets' subjectivity for each user type.

We also investigated the proportion of SO, WO, NS, WS, and SS in each of the retweet status groups. Comparisons between the three groups of not retweeted, retweeted once and retweeted more than once indicate that strongly objective tweets have a higher chance to be retweeted more than once in comparison to other retweet status groups. However, weakly objective and weakly subjective tweets are more likely not to be retweeted while neutral tweets have a higher chance to be retweeted once. Table VI shows the proportion of tweets' subjectivity based on retweet status. These results show that for WFH during the pandemic, individuals were more interested in functional information and retweeted them more than emotional tweets. To explain, people used social media as a platform to learn during the time of Covid-19 and this is reflected in their behavior in a way that they engaged in retweets when the content of a tweet contained useful information and not just personal opinions.

4.4. Content analysis

To identify the most repeated words in the text corpus, we first used the Natural Language Toolkit (NLTK) package in Python to tokenize the text and remove the stop words. Through the Counter function in collections, we searched for the most common words and used the Pandas library to create a data frame. Then, we determined the codes and manually grouped these words under different categories presented in Table XIII. Based on the content similarity, the categories were grouped under different themes. The existing literature inspired the initial categories and themes (see Table I and II). The words that did not fit in any of the existing categories were placed under a new category. These categories provide insights about the important areas to focus on when it comes to remote work during the pandemic. As two raters judged whether each word represents the category it was assigned to, we ran Cohen's κ to determine if there was an agreement between them. Having the value of Kappa above 0.80 ($\kappa = .823$ (95% CI, .654 to .992), $p < .001$), the output shows a perfect agreement between raters (Landis and Koch, 1977). The content analysis of the tweets about

WFH during pandemic shows that except for pandemic and WFH, Twitter users were mainly concerned about ICT and technology-related constructs. Table VII presents an overview of the output, their frequency, per cent, and supporting references.

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The results from the content analysis of the tweets stated learning as one of the outcomes of WFH during this time (e.g. "*we've learned about time management during the coronavirus pandemic*"; "*the lessons learned from WFH*"). The result also presents satisfaction with work-life balance (e.g. "*have a better work-life balance and be just as effective working from home*"; "*create a work-life balance*"; "*enable more people to work from home where possible, reducing road traffic and improving people's work-life balance*"; "*the Pandemic … is something that has proven to be very productive and promotes a better work-life balance*") as well as wellbeing (e.g. "*accomplish your goals and care for your personal well-being*"; "*pandemic may have given the opportunity to change people's priorities which is more beneficial to their own mental health and well-being*").

The result of content analysis of tweets suggests that the government support (e.g. "*people on low incomes who must self-isolate will be entitled to a government support payment*"; "*the Government announced a new package to support and enforce self-isolation*"), organizational support, ICT facilities, cyber security (e.g. "*looking at cowork options for faster internet*"; "*working from home underlines the need for robust cyber security strategy*"; "*strong IT systems enable remote work and defend network against new cyber threats that have emerged during the crisis*"), and social connectedness (e.g. "*strong social connections help employees feel happier and healthier and build stronger networks*"; "*we know that social wellbeing is impacted by our stress levels, social connectivity, and our sense of productivity - All of which have been negatively impacted by COVID19*") influences the outcomes of WFH. Analysis of tweets' text also reveals that exhaustion and technostress are also caused by WFH (e.g. *“work from home for the past 6 months left me feeling exhausted”; “burnout is real and can lead to WFH exhaustion”;* “*the effects of technostress on the health and safety of workers in times of Covid-19 are concerning*”; “*as many of us continue to work from home during COVID-19, there's increasing incidence of "technostress" and "techno-overload" among workers that needs to be addressed*”).

The most repeated words in the tweets text also demonstrate that coping strategies (e.g. “*cope with increasing challenges of COVID-19*”) as well as fear of pandemic, such as health concerns (e.g. “*deal with common health and behavioral problems that the pandemic has created*”), future uncertainty (e.g. “*many inconveniences of the coronavirus lockdown, including massive job loss and future uncertainty*”), social distancing rules (e.g. “*social distancing rules were adopted, such as limiting the number of customers at a time in shops and providing only table service at bars and restaurants*”), gender inequality (e.g. “*remote work and specifically, virtual meetings, may exacerbate gender inequality*”), and racism against ethnic groups (e.g. “*in the middle of this pandemic, there's an increased spotlight on social issues like racism*”; “*Covid-19 shines a light on a problem that was already there - systemic racism*”) also play an important role when working from home. Next, we develop a conceptual model to explain the influence of WFH during the Covid-19 pandemic.

5. Conceptual model development

Existing literature identified several variables considered during the process of WFH; however, WFH during pandemic would considerably impact the interrelationship of the variables identified. Based on the insights from existing literature and the results based on the exploratory study, we attempt to develop a conceptual model considering the variables most affected during the pandemic (see Figure 2).

< Insert Figure 2 about here >

We found WFH to influence satisfaction with work-life balance and well-being. Existing literature suggests the influence of WFH on family functioning (Dockery and Bawa, 2018; Hill *et al.*, 2003), work-life balance (Sullivan and Lewis, 2001), and work-family conflict (Russell *et al.*, 2007; Golden *et al.*, 2006; Gajendran and Harrison, 2007; Jostell and Hemlin, 2018). During the pandemic, there was a forced WFH due to the growing importance of social distancing and staying safe. Thus, WFH can be considered as a form of job demand in line with the Job Demand-Resource (JD–R) model (Demerouti *et al.*, 2001), a well-established theoretical model in organizational behavior and psychology that elaborates the influence of employees' work demands and the resources they have access to for coping with their work demands. Work conditions include the job demands (physical, psychological, socio-organizational aspects) that induce fatigue leading to burnout. Hence, based on the literature, in this exploratory study, and using the above theoretical underpinning, we propose:

P1: *WFH positively influences an individual's job and familial outcomes of learning, performance, satisfaction with work-life balance, and wellbeing.*

Results from the exploratory study state the impact of governmental support, organizational support, ICT facilities, cyber security, and social connectedness on the various outcomes of WFH. Based on JD-R theory, job resources (physical, psychological, social, or organizational aspects) stimulates personal growth, learning, and development (Hakanen *et al.*, 2006). As a subsequent development, JD–R model introduced personal resources and job resources (Xanthopoulou et al., 2007) that helps the employees to feel positive and have higher self-evaluations (Bakker and Demerouti, 2008). Hence, we classified the factors resulted from the exploratory study into macro, meso and micro-level factors. The macro and meso-level factors were the resources based on the job, and micro-level factors were based on personal resources. At a macro level, government support was considered. The meso-level comprises organizational support, ICT facilities, and cybersecurity, whereas, the conceptual model considers micro-level to include social connectedness and work-life balance. Resources create a motivational pathway by positively influencing the outcomes. Hence, we propose:

P2: *Macro-, meso- and micro-level resources (of government support, organizational support, ICT facilities, cybersecurity, social connectedness, and work-life balance) positively influence individual-, job-, organizational- and familial-level outcomes (of learning, performance, wellbeing and satisfaction with work-life balance).*

Molino *et al.* (2020) confirm the negative influence of workload on technostress leading to behavioral stress. According to transactional stress theory, a situation that is too demanding could appraise the stress felt by an individual (Lazarus and Folkman, 1984). Based on the content analysis, WFH enhances the health impairment process thus increasing exhaustion and technostress. Hence, we propose:

P3: *WFH positively influences exhaustion and technostress.*

According to JD-R theory, resources enhances the wellbeing and positive outcomes, and besides, it buffers the stress created due to the job demand. Based on Conservation of Resources (COR) theory, the presence of personal resources could further mitigate the burnout developed to enhance the wellbeing of the employee. Therefore, resources will support the individual by reducing the employee's level of exhaustion and stress. Hence,

P4: *Resources (government support, organizational support, ICT facilities, cybersecurity, social connectedness, and work-life balance) negatively influence individuals' exhaustion and technostress*.

The continued job stress could lead to health impairment process by exhausting employees mentally and physically leading to energy loss and health problems. Thus, the exhaustion or the stress created will reduce the learning experience, productivity, satisfaction with work and life-creating and ill-being. Hence, we propose:

P5: *Increase in exhaustion and technostress negatively influence an individual's outcomes (of learning, performance, satisfaction with work-life balance, and wellbeing*).

Considering psychologically, COVID-19 is a fear, an unpleasant emotional state triggered due to the threatening stimuli (de Hoog *et al.*, 2008). A plethora of research is conducted to understand and explain the psychological construct, fear in explaining various health issues. Also, the literature suggests various emotional states triggered due to the COVID-19 pandemic. Fear of COVID-19 (Reznik *et al.*, 2020) makes people feel vulnerable and at-risk, and hence it is associated with attitude and behavioral changes in individuals. According to anxiety expectancy theory (Kirsch, 1985), fear is produced during danger expectancies, and this anxiety expectancies lead to avoidance behavior in individuals. Further, coping mechanisms are necessary while dealing with fear, anxiety, and stress, and it is classified as problem-based and emotion-based strategies (Lazarus and Folkman, 1987). The coping mechanism gives confidence in managing the fear that interacts with avoidance expectancies to lead to an approach behavior. Thus, coping strategies mitigate the stress to improve the outcomes. Also, based on the exploratory study, coping strategies as well as fear of pandemic, such as health concerns, future uncertainty, social distancing rules, gender inequality, and racism against ethnic groups seem to play an important role when working from home. Thus,

P6: *Fear of pandemic negatively moderates the influence of (a) extent of remote work and (b) macro-, meso- and micro-level factors on the outcomes (of learning, performance, satisfaction with work-life balance, and wellbeing), and positively moderates the influence of (c) extent of remote work and (d) macro-, meso- and micro-level factors on exhaustion and technostress.*

P7: *Coping strategies positively moderate the influence of (a) extent of remote work, (b) macro-, meso- and micro-level factors, and (c) exhaustion and technostress on the outcomes (of learning, performance, satisfaction with work-life balance, and wellbeing).*

WFH is widely accepted during this pandemic as a mode to reduce the risk from COVID-19. WFH is also found to stay for a longer period with the uncertainty of pandemic and the adoption is now existing making things easier for businesses and corporates. As suggested by literature, WFH could create stress, exhaustion, and burnout, reducing the wellbeing and work-life balance. The fear of pandemic aggravates the issue further while coping mechanisms and strategies could alleviate the situation to derive positive outcomes. The proposed conceptual model helps to understand the dynamics underlying the above process.

6. General discussion

This paper aims to understand the dynamics of WFH in the pandemic situation by studying people's sentiment about the mandatory, quick, and communal transition to WFH and identifying the macro-, meso-, and micro-level factors that are associated with this transition. To meet this aim, a netnographic method was followed and tweets posted on Twitter related to WFH during the pandemic were fetched and analyzed. Despite growing research on the challenges posed by the mandatory transition to WFH during a crisis (e.g. Butler and Jaffe, 2021; Li et al., 2020; Steidtmann et al., 2021), to the best of our knowledge, this is the first research that comprehensively explores the challenges of this transition through analyzing the public perceptions using the real-time social media posts. Moreover, although existing research used the Twitter data to assess public sentiment toward WFH, (e.g. (Dubey and Tripathi, 2020; Wrycza and Maślankowski, 2020)), this is the first research that analyses sentiments based on the Twitter user types and reports the subjectivity versus objectivity of tweets in the context of WFH.

The results of this research reveal that the majority of tweets on the topic of WFH during pandemic were neutral and slightly skewing to positivity which is consistent with the results of prior studies that report tweets about WFH in the time of pandemic mainly hold a positive sentiment (Dubey and Tripathi, 2020; Mansoor et al., 2020). However, these studies analyzed tweets altogether and failed to deep dive into the insights generated by various categories of Twitter users (e.g. personal users, business users (Uddin et al., 2014)). In this research we found that the majority of tweets about WFH posted by those who represent personal accounts (i.e. ISE and AF) were either neutral or negative while those who represent business accounts (i.e. BC and ISO) mostly engaged in sharing positive tweets. Prior studies in the context of natural disaster also report a similar pattern in a way that popular Twitter users were more likely to share positive content (Reynard and Shirgaokar, 2019).

In the present study, this pattern can be affected by employees having their own concerns and stresses around WFH (The Guardian, 2021a). However businesses may consider this as an opportunity to decrease their risks and costs (The Guardian, 2021b; Haag, 2020) and consider it as a viable option for the long term (BBC News, 2020; CNBC, 2020). The other reason is due to the negativity bias on social media, which means that individuals get more engaged with negative content (Bellovary et al., 2021), and are more likely to retweet them (Hansen et al., 2011). Consistent with prior studies, we also found that negative or neutral tweets about WFH during pandemic were retweeted more compared to positive tweets and users representing personal accounts were more engaged in re-sharing these tweets.

To explore the challenges and important scopes of WFH during pandemic, after identifying the most frequent words that emerged in tweets and analyzing them through the content analysis approach, we found that the public were mainly concerned about cyber security and technology. This is in line with prior studies that report technology (Gajendran and Harrison, 2007; Grant et al., 2013; Sue and Lee, 2017) and technostress (Molino et al., 2020) as important challenges of remote working. Consistent with studies on WFH in general (e.g., (Collins et al., 2016; Grant et al., 2013; Sewell and Taskin, 2015)) and WFH in the time of pandemic in particular (Prasad et al., 2020), we found that social distancing rules, lack of social support, and limited interactions with colleagues as the other important challenges of WFH during the pandemic.

Our exploration of the tweets also confirmed that WFH is associated with topics relevant to work-life balance (Gajendran and Harrison, 2007; Golden et al., 2006; Jostell and Hemlin, 2018; Molino et al., 2020; Long, 2020; Russell et al., 2007), poor health habits (Anderson et al., 2014; Mann and Holdsworth, 2003; Molino et al., 2020; Prasad et al., 2020), and ambiguous tasks (Perry et al., 2018). Moreover, consistent with the findings of studies focusing on WFH during this enforced transition, we also found that parenting arrangements (Manzo and Minello, 2020) and increased domestic violence (Beland et al., 2020; Toniolo-Barrios and Pitt, 2021) as important topics discussed by the public on Twitter. The escalated family stress and domestic violence may increase due to the financial instability caused by the economic changes during this time (Beland et al., 2020).

Supported by existing research (Molino et al., 2020; Prasad et al., 2020; Toniolo-Barrios and Pitt, 2021), we also found that health concerns increased during the pandemic. Future uncertainty (Toniolo-Barrios and Pitt, 2021), coping up strategies, and the need for stronger support mechanisms from the organization and the government were also identified as other important topics relevant to WFH during pandemic. Despite these challenges, improved learning emerged as the positive dimension of WFH. After diving into the tweet's text and identifying the main topics discussed by the public, we investigated the extent to which this data contained emotional versus functional information. Having the majority of tweets as objective confirmed that the tweets' about WFH during pandemic mainly contained functional and non-emotional information; hence, the analysis output can help with decision-making purposes (Machan, 2017; Saleh et al., 2021).

Inspired by the exploratory output of this research and WFH literature, we used the JD-R theory to propose a conceptual framework that extends the existing literature to the time pandemic. This conceptual model proposes that macro-level factors (such as government support), meso-level factors (such as organizational support, ICT facilities, and cyber security) and micro-level factors (such as social connectedness and work-life balance) impacts the outcomes of WFH and this relationship is mediated by exhaustion and technostress. We also propose that coping strategies and fear of pandemic (reflected by health concerns, future uncertainty, social distancing, gender inequality, and racism) can play a moderating role.

7. Contributions and implications

This paper contributes to the remote work literature in several ways. Firstly, instead of using interviews or survey instruments to collect data, we followed the netnography method to collect and process the Twitter data that shows the behavior of the users to arrive at generalizable insights. Behavioral data gives better understanding into the situation in focus and would be a good basis for proposing the relationships assigned in the conceptual model. Second, we classified the Twitter users and identified it plays an essential role in understanding the general trend in the polarity and subjectivity. The results led us to understand that post by individuals are less positive compared to posts from the business contributing to the work family boundary conditions. Third, we identified a comprehensive range of elements that play a role in the success or failure of WFH during the pandemic. The elements identified contributes to the literature on factors that influence the WFH. Fourth, the current study is the first to conceptualize the moderating effect of fear of pandemic and coping strategies in the remote work literature based on the behavioral data. The understanding could be contributed to literature on any crisis situation. In every similar situation, the fear of the crisis and the coping strategies could act as the negative and positive moderators respectively. Thus, scholars can focus their attention towards understanding various coping strategies. Finally, the theoretical contribution is summarized in 12 testable propositions included in our conceptual model. In line with the J-DR model, this paper proposes the influence of job demand and resources on outcomes such as learning, performance, satisfaction with work-life balance, and wellbeing. These propositions give direction towards further research.

This study contributes to managers' understanding of how WFH is perceived during the pandemic and provides several useful insights that improve employee and organizational outcomes. The output of this research reveals that for the successful transition to WFH, organizations need to take several factors into account. For instance, employees need to be provided with proper ICT facilities such as a computer or laptop, extended monitor, the internet, webcam, and a headset. Moreover, due to the increase of cyber-crime in COVID-19, we found that for employees working from home, cybersecurity is an important issue that makes it necessary for organizations to take the necessary precautions and planning.

This study also highlights the negative perspective of individuals towards WFH during the pandemic. The underlying reasons could be many including the job insecurity, breach of work family boundary, as well as additional child and adult care responsibilities. Hence, it is vital to support employees, who shifted to WFH, by improving the quality and speed of internal electronic services between various organizational departments (e.g. access to the ICT experts). Another way to support employees would be to provide and disseminate guidelines and professional advice on various topics related to remote work. Particularly, organizations need to provide adequate training and support to does who get stressed when it comes to working with technology. Moreover, as social connectedness and work-life balance positively affect the outcomes of remote work, organizations can facilitate these with regular online meetings. We also highlight the detrimental impact of fears associated with pandemic on WFH outcomes, which may be reduced by organizations by providing the latest health advice to assure employees that their interests will be considered in any future changes.

Organizations also need to support employees' mental health, empower them to fight the hardships of the pandemic, and decrease uncertainty about the future of their careers. Moreover, the criteria for assessing productivity should be communicated to employees to decrease their stress about productivity when working from home. Not only do organizations need to support their staff during this time, but governments also need to provide adequate support to the community which helps them to navigate the difficulties caused by the pandemic. Organizations can also facilitate employees' access to online training materials, which helps them learn and upskill (e.g. access to LinkedIn Learning).

8. Limitations and future research

Our proposed model raises some methodological challenges and important questions for future studies. First, the arguments and underlying propositions raised in the model need to be empirically tested. Second, besides the constructs included in our conceptual model, future studies can use additional constructs associated with WFH in crisis, such as industry type, domestic violence, or border closures. Third, we focused on Twitter users to explore the common topic tweeted about WFH during the pandemic. However, this limits the results to a particular group, and future studies can analyses the content posted on other social media platforms about this topic and compare the outputs. Fourth, based on the keywords we used to collect data from Twitter, we may miss the viewpoints of people who work from home as a student and those who are self-employed. Finally, we did not consider the impact of spillover between work and family, which is one major concern while remote working and hence, future studies could analyses the spillovers in the netnography method and other methods to understand its impact on the outcomes considered.

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Figure 1. Existing linkages to WFH literature: Antecedents, Mediators, Moderators and Outcomes

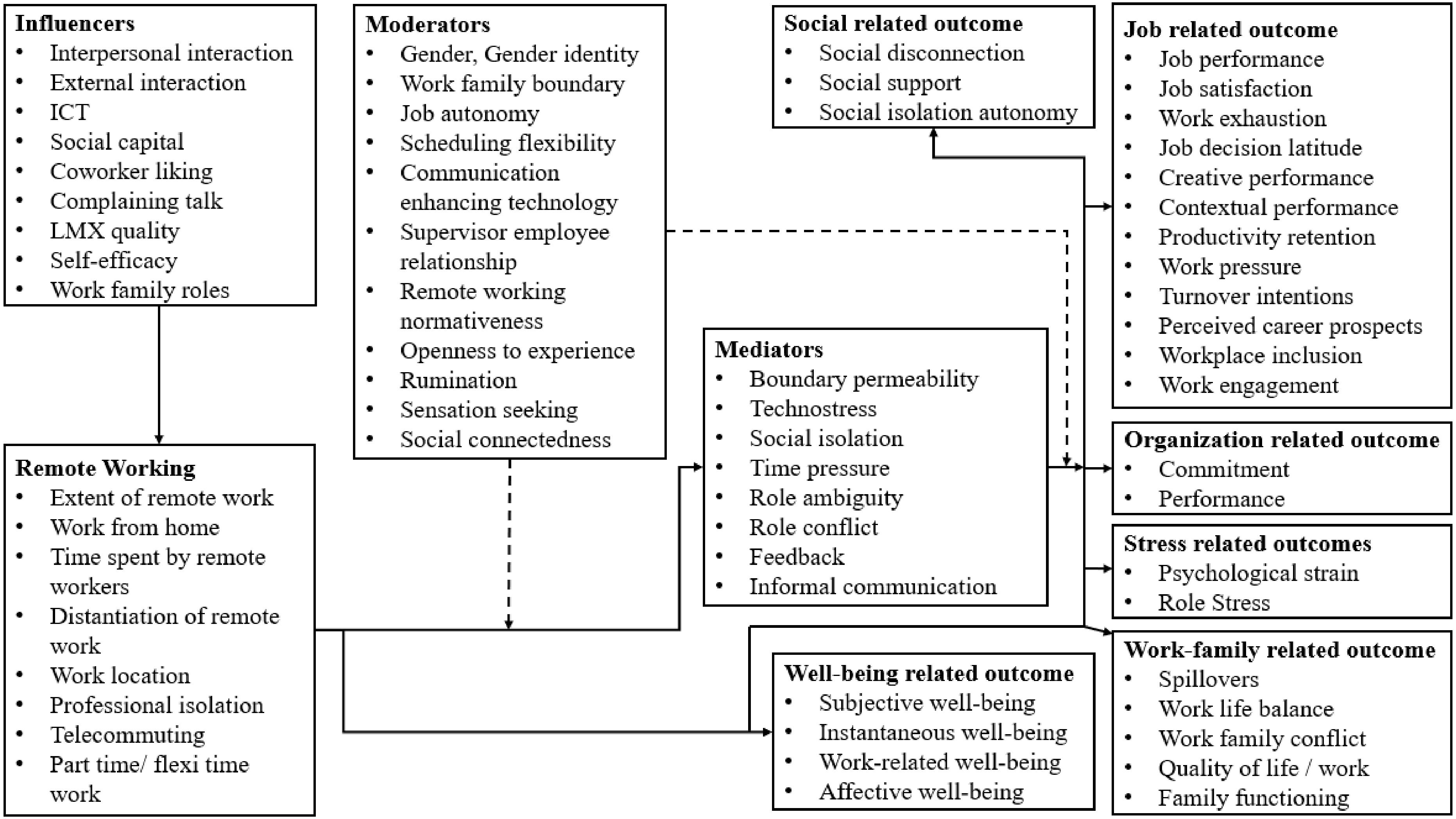
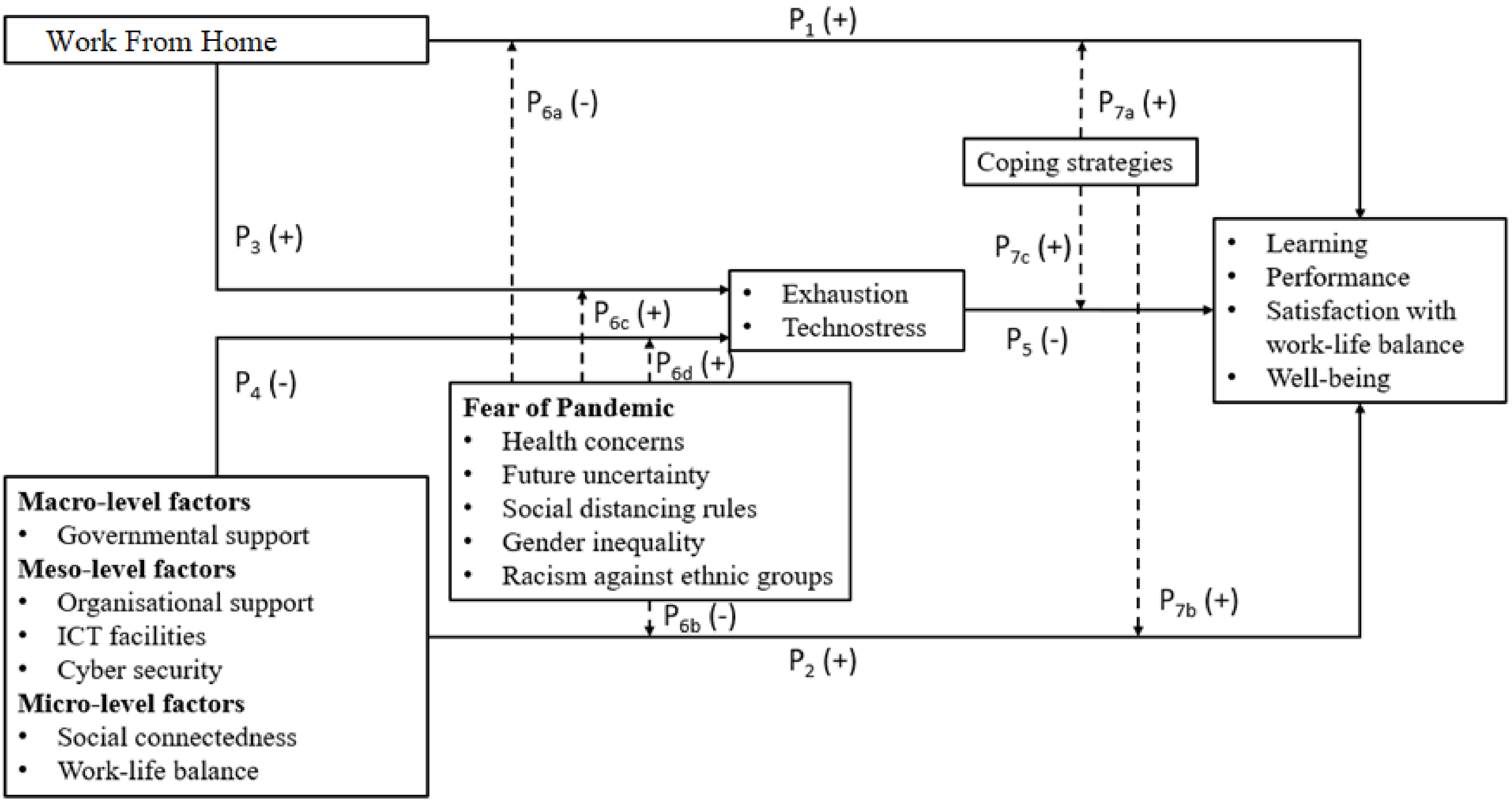


Figure 2. Proposed conceptual model



Note: *P1-P7 above refer to the 12 future research propositions*

Figure 3. Proportion of Tweets based on polarity (per day)

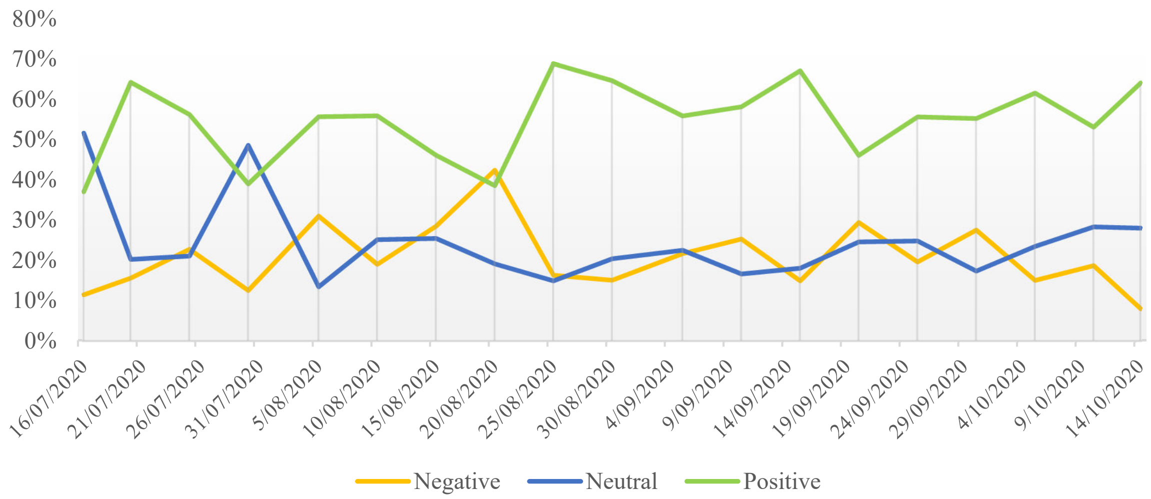


Figure 4. Proportion of Tweets based on subjectivity (per day)

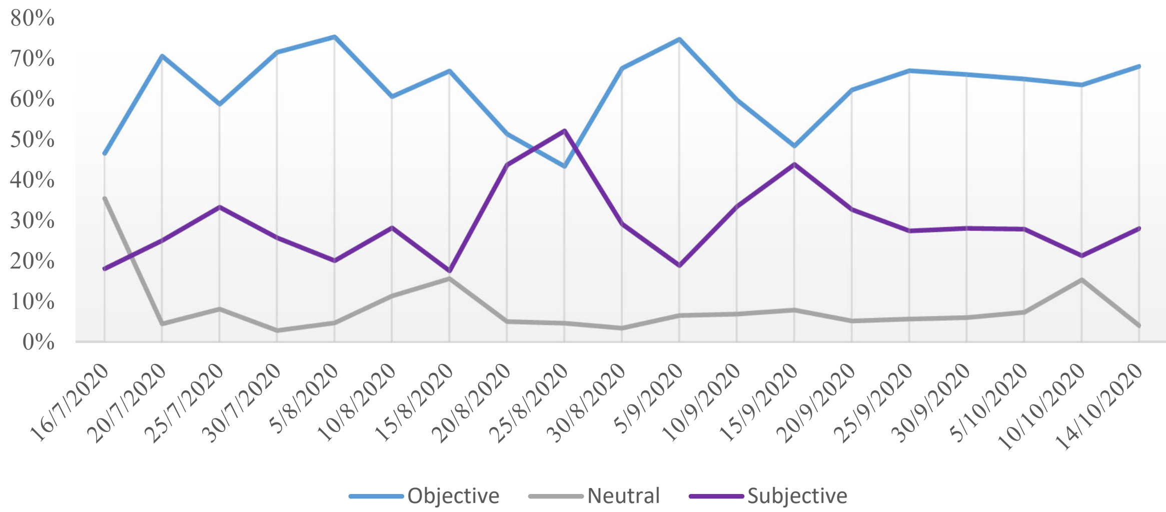


Table I. Outcomes of WFH

Outcome of remote work/ WFH	Positive effects	Negative effects	No effect
Job-related outcomes			
Job performance	Golden and Gajendran (2019) [1] , De Menezes and Kelliher (2017) [1], Vega *et al.* (2015) [1], Gajendran *et al.* (2014) [1], Martin *et al.* (2012) [4], Golden and Veiga (2008) [1], Gajendran and Harrison (2007) [1]	Golden *et al.* (2008) [1]	
Contextual performance	Gajendran *et al.* (2014) [1]		
Job satisfaction	Vega *et al.* (2015) [1], Kelliher and Anderson, (2010) [6], Hornung and Glaser (2009) [1], Golden and Veiga (2008) [1], Gajendran and Harrison (2007) [4]	Sue and Lee (2017) [1]	Morganson *et al.* (2010) [3]
Perceived career prospects/ Job decision latitude	Gajendran and Harrison (2007) [4], Chen and McDonald (2015) [1]		
Work exhaustion		Sardeshmukh *et al.* (2012) (mediator: job resources and demands) [1]	
Turnover intentions		Golden *et al.* (2008) [1], Gajendran and Harrison (2007) [4]	
Work engagement		Sardeshmukh *et al.* (2012) (mediator: job resources and demands) [1]	
Perceive autonomy	Gajendran and Harrison (2007) [4]		
Organisational-related outcomes			

Organisational commitment	Martin *et al.* (2012) [1], Kelliher and Anderson, (2010) [6], Golden and Veiga (2008) [1]		
Productivity	Martin *et al.* (2012) [4]		
Social-related outcomes			
Social support	Collins *et al.* (2016) (among teleworkers) [1]	Collins *et al.* (2016) (with office staff) [1]	
Feeling of isolation/ social disconnection	Sewell and Taskin (2015) [5]		
Stress related outcomes			
Negative emotions	Mann and Holdsworth (2003) [6]		
Work-family related outcomes			
Wellbeing	Anderson *et al.* (2014) [1] ,Vander Elst *et al.* (2017) [1], (madiator: Social support), Giminez-Nadal *et al.* (2018) [1]	Song and Gao (2019) [1], Grant *et al.* (2013) [5]	
Family functioning/ family life/ work life balance	Dockery and Bawa (2018) [2], Sullivan and Lewis (2001) [5]	Hill *et al.* (2003) [1]	
work-family conflict/ work-life conflict	Russell *et al.* (2007) [1], Golden *et al.* (2006) [1],	Gajendran and Harrison (2007) [4]	Jostell and Hemlin (2018) [1]

Note: Study approach: 1= Quantitative, cross-sectional, 2= Quantitative, longitudinal, 3= Quantitative, quasi-experiment, 4= Meta-analysis, 5= Qualitative, 6= Mixed method

Table II. Antecedents, Moderators and Mediators of WFH

Constructs	Antecedent	Moderator	Mediator
Job-related constructs			
Job characteristic		Golden and Gajendran (2019) [1], Sue and Lee (2017) [1],	
Job resources			Sardeshmukh *et al.* (2012) [1]
Strain-based work	Golden (2012) [1]		
Work interruptions		Jostell and Hemlin (2018) [1]	
Job autonomy	Hornung and Glaser (2009) [1]		Gajendran and Harrison (2007) [4], Gajendran *et al.* (2014) [1]
Social space and territoriality/ destination of telework	Sewell and Taskin (2015) [5]		
Organisational-related constructs			
Organisational commitment		De Menezes and Kelliher (2017) [1],	
Organisational culture	Baruch (2000) [5]		
Tech-related constructs			
ICT	Grant *et al.* (2013) [5]	Sue and Lee (2017) [1],	
Telework/ remote work	Golden and Gajendran (2019) [1], Song and Gao (2019) [1], Dockery and Bawa (2018) [2], Giminez-Nadal *et al.* (2018) [1], De Menezes and Kelliher (2017) [1], Anderson *et al.* (2014) [1], Gajendran *et al.* (2014) [1], Gajendran and	Golden (2012) [1]	

	Harrison (2007) [4], Moore (2006) [6], Hill *et al.* (2003) [1]		
Telecommuting intensity		Gajendran and Harrison (2007) [4]	
Social-related constructs			
Interpersonal and external interaction	Windeler *et al.* (2017) [1]		
Supervisor employee relationship	Golden and Veiga (2008) [1]	Gajendran *et al.* (2014) [1]	Gajendran and Harrison (2007) [4]
Co-worker liking	Fay and Kline (2011) [1]		
Social capital	Chen and McDonald (2015) [1]		
Social support		Golden and Gajendran (2019) [1], Bentley *et al.* (2016) [1]	
Interdependence		Golden and Gajendran (2019) [1]	
Isolation			Bentley *et al.* (2016) [1]
Individual-related constructs			
Self-efficacy	Raghuram *et al.* (2003) [1]		
Individual competencies	Grant *et al.* (2013) [5], Baruch (2000) [5]		
Work-family roles, Work family boundaries/ work family conflict	Sullivan and Lewis (2001) [5], Hornung and Glaser (2009) [1], Glaser (2009) [1]		
Gender		Song and Gao (2019) [1], Giminez-Nadal *et al.* (2018) [1]	

Note: Study approach: 1= Quantitative, cross-sectional, 2= Quantitative, longitudinal, 3= Quantitative, quasi-experiment, 4= Meta-analysis, 5= Qualitative, 6= Mixed method

Table III. User Type

User Type	Category	Characteristic	Number of tweets	%age
1. EM	Evangelists/Miscreants	$a \le -2000$	6,121	4.0
2. ISE	Information Seeker	$-2000 < a \le -100$	59,014	39.0
3. AF	Acquaintances/Friend	$-100 < a \le 100$	38,210	25.3
4. ISO	Information Source	$100 < a \le 2000$	28,101	18.6
5. BC	Broadcasters	$a > 2000$	19,729	13.1
Total			**151,175**	**100**
Polarity	**Category**	**Characteristic**	**Number of tweets**	**%age**
1. SN	Strongly negative	$-1 < p < -0.5$	1,780	1.2
2. WN	Weakly negative	$-0.5 \le p < 0$	30,966	20.5
3. NP	Neutral	0	39,910	26.4
4. WP	Weakly positive	$0 < p \le 0.5$	74,541	49.3
5. SP	Strongly positive	$0.5 < p < 1$	3,978	2.6
Total			**151,175**	**100.0**
Subjectivity	**Category**	**Characteristic**	**Number of tweets**	**%age**
1. SO	Strongly objective	$0 < s < 0.25$	52,461	34.7
2. WO	Weakly objective	$0.25 \le s < 0.5$	50,467	33.4
3. NS	Neutral	0.5	9,531	6.3
4. WS	Weakly subjective	$0.5 < s \le 0.75$	29,205	19.3
5. SS	Strongly subjective	$0.75 < s < 1$	9,511	6.3
Total			**151,175**	**100.0**

a=number of followers- number of friends; p= polarity score; s= subjectivity score

Table IV. Correlations matrix

Construct	1	2	3	4
1. User Type	1	$-.093^{**}$	$.044^{**}$	$.029^{**}$
2. Retweet		1	$-.095^{**}$	$-.155^{**}$
3. Polarity			1	$.270^{**}$
4. Subjectivity				1

**. Correlation is significant at the 0.01 level (2-tailed), N= 151,175

Table V. Proportion of tweets' polarity based on user type, retweet status and subjectivity

User types	**SN**	**WN**	**NP**	**WP**	**SP**	**Total**
EM	0.9%	19.0%	31.7%	46.2%	2.2%	100.0%
ISE	1.4%	20.5%	28.2%	47.4%	2.5%	100.0%
AF	1.1%	20.5%	28.0%	47.8%	2.6%	100.0%
ISO	1.1%	20.1%	24.6%	51.8%	2.5%	100.0%
BC	0.7%	20.0%	22.4%	54.1%	2.8%	100.0%
Retweet status	**SN**	**WN**	**NP**	**WP**	**SP**	**Total**
Not retweeted	1.0%	21.4%	14.3%	59.4%	3.9%	100.0%
Retweeted once	1.0%	20.8%	24.3%	50.6%	3.3%	100.0%
Retweeted more than once	1.2%	19.7%	33.3%	43.9%	1.8%	100.0%
Subjectivity	**SN**	**WN**	**NP**	**WP**	**SP**	**Total**
SO	0.2%	13.8%	66.5%	19.4%	0.0%	100.0%
WO	0.1%	30.9%	2.9%	64.9%	1.2%	100.0%
NS	0.8%	5.6%	19.7%	71.3%	2.5%	100.0%
WS	1.2%	21.2%	2.6%	69.5%	5.5%	100.0%
SS	12.3%	13.0%	17.4%	42.3%	15.0%	100.0%

Table VI. Proportion of tweets' subjectivity based on user type and retweet status

User type	**SO**	**WO**	**NS**	**WS**	**SS**	**Total**
EM	39.6%	31.9%	6.2%	15.7%	6.5%	100.0%
ISE	35.9%	32.8%	6.3%	18.6%	6.4%	100.0%
AF	35.1%	33.0%	6.4%	19.6%	5.9%	100.0%
ISO	32.3%	35.0%	6.9%	19.2%	6.6%	100.0%
BC	30.8%	34.1%	9.4%	20.0%	5.7%	100.0%
Retweet status	**SO**	**WO**	**NS**	**WS**	**SS**	**Total**
Not retweeted	22.8%	40.2%	5.9%	24.9%	6.1%	100.0%
Retweeted once	34.1%	31.2%	7.6%	20.6%	6.5%	100.0%
Retweeted more than once	40.3%	30.4%	7.2%	16.0%	6.2%	100.0%

Table VII. Most repeated words in the tweets

Theme	Categories of the most repeated words	Codes (Example of the words in each category)	*f*	%	Existing literature
Pandemic-related	Pandemic	Pandemic, covid-19, corona, crisis, outbreak	116,338	22%	-
Tech-related	Work from home	Work from home, remote work, remote	69,878	13.2%	Golden and Gajendran (2019) [1], Song and Gao (2019) [1], Dockery and Bawa (2018) [2], Giminez-Nadal *et al.* (2018) [1], De Menezes and Kelliher (2017) [1], Anderson *et al.* (2014) [1], Gajendran *et al.* (2014) [1], Gajendran and Harrison (2007) [4], Moore (2006) [6], Hill *et al.* (2003) [1]
Tech-related	ICT	Online, internet, digital, technology, virtual	66,168	12.5%	Grant *et al.* (2013) [5], Sue and Lee (2017) [1], Gajendran and Harrison (2007) [4]
Other	Time. Date, number and place	Today, month, hour, March, time, latest, currently, Hong Kong, American	60,367	11.4%	Social space and territoriality: Sewell and Taskin (2015) [5]
Job-related	Workplace	Office, company, workplace, business	35,583	6.7%	-
Social-related	Social connectedness	Social, public, people, others	30,194	5.7%	*Social support*: Collins *et al.* (2016) *Social disconnection*: Sewell and Taskin (2015) [5]
Social-related	Work Staff	Employee, staff, workforce, worker	29,922	5.7%	-
Stress related	Coping up strategies	Fight, attempt, self-isolate, distancing, asking	22,613	4.3%	-
Stress related	Health issues	Health, tested, cases	19167	3.6%	-
Stress	Future uncertainty	Future, continue,	17,412	3.3%	-

related		shift, return, spread			
Social-related	Support mechanism	Service, support, advice, warning	11,932	2.3%	-
Individual-related	Learning	Learn, inform, study	10,645	2%	-
Social-related	Recreation	Restaurant, travel	9,599	1.8%	-
Work-family related	Family	Family, parent, children	6,252	1.2%	*Family functioning*: Dockery and Bawa (2018) [2], Hill *et al.* (2003) [1] *Work-family conflict*: Russell *et al.* (2007) [1], Golden *et al.* (2006) [1], Gajendran and Harrison (2007) [4], Jostell and Hemlin (2018) [1]
Stress related	Psychological health and wellbeing	Mental, stress	5,384	1%	Mann and Holdsworth (2003) [6], Anderson *et al.* (2014) [1] ,Vander Elst *et al.* (2017) [1], (madiator: Social support), Giminez-Nadal *et al.* (2018) [1], Song and Gao (2019) [1], Grant *et al.* (2013) [5]
Other	Government	Government, minister	5,055	1%	-
Stress related	Challenge	Challenge, trying, force	4,479	0.8%	-
Job-related	Performance	Productivity	3,271	0.6%	Martin *et al.* (2012) [4], Golden and Gajendran (2019) [1] , De Menezes and Kelliher (2017) [1], Vega *et al.* (2015) [1], Gajendran *et al.* (2014) [1], Martin *et al.* (2012) [4], Golden and Veiga (2008) [1], Gajendran and Harrison (2007) [1], Golden *et al.* (2008) [1]
Tech-related	Cyber security	Cyber security	2,964	0.6%	-
Social-related	Racism	Racism	1,579	0.3%	-

Note: Study approach: 1= Quantitative, cross-sectional, 2= Quantitative, longitudinal, 3= Quantitative, quasi-experiment, 4= Meta-analysis, 5= Qualitative, 6= Mixed method; *f*= frequency of occurrence in the tweets; *%*= Proportion of the categories of the most repeated words