A Computational Linguistic Approach to Study Border Theory at Scale

Border Theory suggests individuals create *borders* to manage the transitions between work and family (or, more generally, life) domains. The degree of separation or integration of domains across borders has an impact on the balance between work and life. Previous studies have shown individuals who perceive balance between work and life domains tend to be more satisfied with their lives, reporting higher physical and mental health. At times of crisis, such as during a pandemic, borders can be disrupted, affecting work-life balance and leading to a short- or long-term negative impact on well-being. Border theory provides a systematic lens through which to study these changes. However, changes cannot be studied using interviews or diaries as these are not at the scale required when societal disruptions occur. In this paper, we explore the feasibility of using a computational linguistic approach to operationalize border theory at scale, using readily available social media data. In particular, we make two main contributions. First, we design metrics to measure key characteristics of borders. This involves the application of a transformer-based topic modeling technique, BERTopic, to detect topics from social media data. Second, we apply this operationalization to a case study of around a million tweets posted by nearly two hundred teachers and journalists in the UK from the beginning of 2019 to the end of 2022. In so doing, we longitudinally study and compare the changes in borders between work and life before, during, and after COVID-19 lockdown periods.

CCS Concepts: • **Applied computing → Sociology**; • **Computing methodologies → Natural language processing**.

Additional Key Words and Phrases: border theory, work-life balance, micro-blogs, linguistic analysis, topic modelling

1 INTRODUCTION

Social scientists have long been interested in studying the interface between work and life. This stems from the belief that increasing demands of work have begun to dominate areas of life, creating a sense of work-life imbalance. Prior studies [7, 9, 10] suggest that, in times of crisis, the boundaries of work and life become blurred. This has implications for the well-being of individuals, potentially causing stress and leading to a deterioration of healthy lifestyle behaviors [21, 28]. In order to understand the nature of these implications, the boundaries separating work and life must be thoroughly investigated.

Many theories have been developed to study the work-life interface. Among them, *work-family border theory* [11], hereafter *border theory*, has emerged as the most prominent, given its emphasis on the ways individuals construct, navigate and manage work and non-work life. Border theory explains how employees maintain balance by managing demarcations, or *borders*, between work and non-work life. Recently, researchers have employed border theory to explore the impact of the COVID-19 pandemic on the work-life balance of employees [9, 21, 28, 31, 34]. Studies have identified a decline in the work-life balance of healthcare workers during the pandemic due to the impact of the virus on work-life borders [34]. Other studies found personal life impacted work for expatriates during COVID-19 quarantine [25], while healthy lifestyle behaviors began to deteriorate for employees working in a variety of sectors, including academia and ICT, due to blurred work-life borders [21, 28].

These studies are limited for two reasons. Firstly, methods used tend to involve interviews with a small group of individuals, which is at too small a scale to effectively study changes to work and life when global disruptions occur. For example, only 12 participants were recruited in Mello and Tomei [25] while 24 were recruited in Sahay and Wei [34]. Secondly, these studies often focus on work-family borders, ignoring non-familial activities which may have implications for how employees manage borders over time [1]. To address these limitations, we propose a scalable computational methodology for operationalizing border theory. In particular, we make two main contributions:

- **The development of a computational linguistic methodology to operationalize border theory.** Our key contribution is the design of metrics to quantitatively capture characteristics of work-life borders. To do this, we first apply BERTopic to identify topics of work and life from social media data. Second, we evaluate topics using both quantitative and qualitative methods, before applying our metrics to analyze work-life borders over time.
- **An empirical evaluation of the methodology for UK teachers and journalists during COVID-19.** We apply our computational methodology to study the language of 807,682 tweets posted by 95 teachers and 69 journalists in the UK from the beginning of 2019 to end of 2022. Our findings are used to detect and quantify changes in the work-life balance of UK teachers and journalists before, during, and after COVID-19 lockdown periods. We find borders weakened from the first to the second lockdown for UK teachers compared to journalists. This was met with an increase in the subjective well-being of teachers during the second lockdown.

The remainder of this paper is organized as follows: we begin with a review of relevant literature, both from a social science and from a computational science perspective (Section 2). We then address our first contribution by describing the methodology developed to operationalize border theory (Section 3). Next, we address our second contribution by performing an empirical analysis of our methodology on tweets posted by 95 UK teachers and 69 journalists (Section 4). Finally, we summarize and discuss our findings, pointing out limitations of the work and directions for future research (Section 5).

2 RELATED WORK

2.1 Work-Life Interface

Since the 1970s, many theories [3, 11, 18] have been developed in the social sciences to study the work-life interface. Of these, three emerge as the most studied - conservation of resources (COR) theory [18, 19], boundary theory [3] and work-family border theory [11]. COR theory suggests employees experience emotional exhaustion in work and non-work settings when required to perform behaviors that threaten their basic values. While much research has been grounded in this theory [36], COR theory tends to emphasize the work domain over the interplay of work and life. Boundary theory [3] describes the way people assign meaning to work and home life, positing that boundaries can inform transitions between these roles. However, this theory focuses less on the balance between work and life and so is less relevant to our study which aims to explore the relationship between work-life balance and well-being.

2.2 Work-Family Border Theory

Work-family border theory is arguably the most prominent to have emerged from research on the work-life interface [5]. Clark [11] developed work-family border theory in response to the limitations of current research on work and family. This theory explains how employees maintain balance by managing demarcations, or borders, between work and non-work life. Notably, it offers a lens to explore how combinations of factors can impact the work-life balance of employees.

Work-life balance is defined as “satisfaction and good functioning at work and at home, with a minimum of role conflict” [11]. According to Clark [11], borders can be physical, psychological, or temporal. Over time, individuals may either integrate (i.e., blur the borders between work and non-work life) or segment (i.e., separate the borders between work and non-work life) domains across borders. Integrated domains are characterized by a high level of *permeability*, which refers to the degree to which domains come in contact with one another. Domains may also expand and shift over time to enable further integration, enhancing their *flexibility*. Borders that are very impermeable and inflexible are considered to be *strong*, while borders that allow permeations and are flexible are identified as *weak*. As such, we regard *weak* and *integrated* as synonyms in this context, as well as *strong* and *segmented*, and use these terms interchangeably.

Clark [11] suggests weak borders facilitate work-family balance when domains are similar (e.g., for a bed and breakfast owner), while strong borders facilitate work-family balance when domains are different (e.g., for construction or factory workers). Guided by work-family border theory, prior research has demonstrated changes to work-family balance can lead to a decline in well-being [9, 21, 28, 34]. Some of these studies have focused solely on work-family domain. However, Adisa and Gbadamosi [1] claim there are other activities in the non-work domain that are equally important to individuals as family duties, such as exercise, leisure, or societal functions.

2.3 Impact of COVID-19

Recent studies have found the COVID-19 pandemic has impacted areas of work and life for many professionals [22]. The extent of this impact has depended on the profession. For example, some professions had to temporarily stop operating due to restrictions on physical proximity (e.g., the hospitality sector). Others were forced to adapt and relocate their work at home (e.g., teachers). In a study conducting interviews with 13 teachers, An et al. [2] report teachers had little work-life balance during COVID-19, due to heavy workload and having to learn new teaching technologies [2]. Additionally, Sahay and Wei [34] interview 24 nurses finding work-life balance declined due to concerns around the contagiousness and anxiety associated with the COVID-19 virus. While these findings are interesting, the small sample sizes used limit generalizability.

Conversely, studies in the computational social sciences which are both scalable and longitudinal have explored the impact of COVID-19 on society. Inspired by Maslow's hierarchy of needs theory [23], Suh et al. [38] leverage web search interactions to explore changes to a holistic set of human needs during the pandemic in the US. Feldman et al. [14] analyze internet traffic data to investigate changes to user behavior during the pandemic. Ebeling et al. [13] and Poddar et al. [29] study attitudes towards COVID-19 vaccination on Twitter, using topic modeling to identify the concerns of groups with different attitudes. Anti-vaccine attitudes may be exacerbated by the spread of misinformation and health-related rumors on social media, as Yang et al. [41] and Sharma et al. [35] suggest. Verma et al. [39] extend these studies by investigating the causal relationship between sharing misinformation on Twitter and experiencing worsened anxiety during the pandemic. After collecting COVID-19-related tweets from January 2019 to July 2020, these authors train a machine learning classifier to detect misinformation, while employing a classifier developed in Saha et al. [32] to score the level of anxiety in tweets. While these studies offer interesting insights, less attention has been paid to applying these methods to specific segments of society (e.g., specific professions), and addressing work-life balance.

Informed by these past studies, in this paper we propose a computational methodology to study the impact of COVID-19 on the work-life balance of UK teachers and journalists. Prior studies [2, 34] tend to comprise cross-sectional interviews of a small group of individuals, which is at too small a scale to effectively study changes to work and life when global disruptions occur. We propose a scalable and longitudinal approach that leverages readily available micro-blogging data, instead of interviews or diaries, to define metrics capturing key border theory constructs (namely, flexibility and permeability). Given recent research has called for an extension to border theory that incorporates non-familial activities in the non-work domain [1], we do not start with any preconception about what borders to use. Rather, we use a bottom-up approach to discover topics from what users openly discuss in their micro-blog posts. In the following sections, we explain our methodology for operationalizing border theory before applying this to a case study of UK teachers and journalists.

3 BORDER THEORY OPERATIONALIZATION

In this section, we address our first contribution by describing the methodology developed to operationalize border theory. The methodology comprises three steps: Data Collection and Preprocessing, Topic Modeling, and Metrics Design. We have made the code and anonymized data publicly available.[1]

3.1 Step 1: Data Collection and Preprocessing

As mentioned in the previous sections, we collect data from a micro-blogging platform, namely Twitter, instead of using data from interviews or diaries. Twitter is among the most popular micro-blogging platforms, with 253 million monetizable daily active users reported in March 2023 [27]. It is therefore a good lens into society. Twitter users often self-declare their professions, usually by using either hashtags or profile descriptions. We sample users based on whether they self-declare their profession in their profile description. This is done to obtain a list of Twitter ids which we can use as seeds to collect tweets. After obtaining the ids of our population sample, we collect tweets from these users posted in a given period covering a crisis event. This period could correspond to months or years depending on the severity of the crisis event and the duration we aim to study. We define a crisis event as a decisive historical moment that causes major disruption to society (for example, a health or financial crisis). We collect tweets from self-declared communities of professionals who may have experienced disruption to their work-life balance from this crisis event. Subsequently, we query the Twitter API and crawl all tweets from identified users. Given we aim to support longitudinal studies, we only sample users who tweet throughout the period under study; users who do not are discarded from the sample.

After obtaining tweets for all users, we filter out users whose total number of tweets is less than a specified threshold. We choose the threshold depending on the duration of the study period. This is done to ensure we select users who are very active, such that their tweets might represent daily summaries of their life, akin to diary entries. In future, we will study the impact of lowering this threshold on the methodology.

After collecting, sampling, and filtering the data, we work through the following data processing steps. First, we preprocess the raw data by tokenizing and lemmatizing tokens. We remove stopwords, punctuation, and symbols, including '#', '@', and URLs, since these do not typically contribute to the semantic meaning of Twitter posts. Secondly, words which have a length less than two characters are removed. Our final dataset comprises all tweets posted by users of a given occupation before, during, and after the crisis event.

3.2 Step 2: Topic Modeling

To investigate whether we could identify tweets expressing work and life from users of a given profession, we first applied a topic modeling technique known as BERTopic [17]. BERTopic is a topic modeling framework that uses clustering algorithms to automatically obtain dense topics in a collection of documents, such as tweets. It assumes semantically-similar documents form human-interpretable topics. It requires a corpus of documents and a pre-trained language representation model as input. We use tweets as our corpus of documents and the 'all-MiniLM-L6-v2' sentence transformer model. This model was chosen because it was developed as a sentence and short

[1] https://anonymous.4open.science/r/Border-Theory-0801/README.md

paragraph encoder, which is more appropriate in our study compared to models that were trained on longer documents. We also train the model on n-grams between 1 and 3 words to capture more context in the tweets.

After dimensionality reduction, BERTopic finds dense areas of similar tweets in the vector space using HDBScan [24], a density-based clustering algorithm. Unlike other topic modeling approaches, BERTopic does not require the number of clusters as input. However, prior research highlights how this can produce a large number of clusters which jeopardize their semantic interpretation [13]. To address this, we replace HDBScan with mini-batch k-means clustering which enables us to fix the number of clusters. We experimented with different cluster sizes (specifically, 5, 10, 15, 20, 40, and 60). This online approach, to clustering reduces the memory necessary for training the BERTopic model by enabling the model to learn incrementally from a mini-batch of instances. This is important given our scalable approach requires the BERTopic model to run on many thousands of input documents. Finally, BERTopic uses a class-based term frequency inverse document frequency (c-TF-IDF) algorithm to create topic-word distributions by comparing the importance of words in clusters. A topic is represented as a list of top 10 words.

Furthermore, after identifying BERTopic topics for our tweets, we evaluate the topics in two ways - quantitatively and qualitatively. We quantitatively evaluate the topics using topic diversity and topic significance metrics. We chose these metrics over standard coherence metrics since the latter can often be sensitive to noise in topics [8]. This is not useful for our analysis since we want to highlight topics that have related words. Topic diversity is defined as the percentage of unique words for all topics. This measure ranges from $[0, 1]$ where 0 indicates redundant topics and 1 indicates more varied topics. Topic significance is the Kullback-Leibler (KL) divergence. Specifically, we compute the mean of the divergences between the topic-word distributions and the uniform distribution. A topic-word distribution where a large number of words are highly probable is more likely to be insignificant, such that the KL-uniform score will be low. Moreover, we qualitatively evaluate the topics in the following way. First, we inspect the top 10 words (ordered by their c-TF-IDF score) associated with each topic. This is done to assign a meta-label representing the key theme found in each topic. Second, to gain confidence tweets in each topic convey the assigned meta-label, we inspect 100 random tweets associated with the topic. Topics are subsequently grouped into either work or life categories based on the nature of the label.

We chose BERTopic over other topic modeling approaches (such as Latent Dirichlet Allocation (LDA) [6] or Latent Semantic Analysis (LSA) [12]) given its competitive performance on topic significance and diversity. The latter is particularly important to our study given we assume our data is diverse enough to be distinctly segmented into categories of work and life. These quantitative evaluation metrics were also used for the selection of the number of clusters in our analysis.

3.3 Step 3: Metrics Design

In this subsection, we describe the metrics used to quantify border theory constructs. First, we describe our method for determining borders. Second, we define metrics to measure border characteristics, namely permeability and flexibility. In this paper, we focus on operationalizing temporal borders. We defer an analysis of spatial and psychological borders for future research.

As previously mentioned, borders are defined as lines of demarcation between work and life domains. We determine temporal borders of work and life domains collectively for all users in the following way. First, for each day in a week (Monday to Sunday), we concatenate all tweets posted on that day within a given period. Second, we identify the time (in seconds) at which these tweets were posted in the day. Third, we calculate the interquartile range (IQR) of tweet frequency. For example, if we wanted to determine temporal borders for work tweets on Mondays from January to February 2019, we would first concatenate all work tweets posted on every Monday from January to February 2019. We would then calculate the daily frequency of these tweets before determining the border using the IQR. The IQR is an appropriate metric for two reasons. Firstly, it measures the range of the middle 50% of the daily tweet frequencies, determining the point at which the bulk of domain-related discussions begins and ends. Secondly, it enables us to quantitatively measure work and life tweet frequency over time, capturing changes in the temporal boundaries separating work- from life-related discussions. We emphasize that borders can be constructed for individual users using a similar methodology, by concatenating tweets posted on a given day for a single user.

Once we have determined borders, we define metrics to calculate the characteristics of borders. According to Clark [11], permeability and flexibility are the two main characteristics of borders. Recall that permeability is the degree to which elements from one domain may enter the other. Flexibility refers to the extent to which domains can contract or expand to accommodate the other. Since we focus on temporal borders, we design metrics to capture permeability and flexibility as follows.

Permeability. To determine temporal permeability, we calculate the ratio of the overlap of the IQR for work and life and the length of the IQR:

$$\text{Permeability}(d,t) = \frac{Q3_{min}(d,t) - Q2_{max}(d,t)}{Q3_{max}(d,t) - Q2_{min}(d,t)} * 100 \tag{1}$$

where $Q2_{min}(d,t)$ and $Q2_{max}(d,t)$ are the minimum and maximum of the second quartile and $Q3_{min}(d,t)$ and $Q3_{max}(d,t)$ are the minimum and maximum of the third quartile on a given day d for a given period t. The numerator in Equation 1 represents the overlap of work and life IQR, while the denominator represents the length of the IQR regardless of work or life. We use Equation 1 to measure temporal permeability since it captures the degree to which users tweet about work and life around the same time.

Flexibility. We define temporal flexibility using two complementary metrics: the distance of the IQR and the shift in the IQR for work and life tweets over time. We do this because we want to determine the degree to which borders expand or contract (which we define as flexibility-distance), as well as their capacity to be shifted over time (which we define as flexibility-shift), both of which are important components of border flexibility [1]. Firstly, the flexibility-distance is computed as follows:

$$\text{Flexibility-distance}(i,d,t) = Q3(i,d,t) - Q2(i,d,t) \tag{2}$$

for $i \in \{work, life\}$ for a given day d in a given period t. We can use Equation 2 to assess the variability of the central portion of work and life tweet frequency over time. Secondly, the flexibility-shift is computed as

$$\begin{aligned}\text{Flexibility-shift}(i,d,t) =& [|Q2(i,d,t) - Q2(i,d,t+1)|,\\ & |Q3(i,d,t) - Q3(i,d,t+1)|]\end{aligned} \tag{3}$$

for $i \in \{work, life\}$ for a given day d in a given period t. Equation 3 determines the extent to which the IQR has shifted over time.

3.4 Quantifying Well-Being

Prior literature has shown a relationship exists between work-life borders and well-being [9, 34]. Therefore, measuring well-being is an important step to complete the operationalization of border theory. However, well-being is a general and abstract concept which can be measured in different ways [40]. In this study, we make the simplifying assumption that we can capture aspects of it using NLP sentiment analysis of tweets.

Motivated by prior work [26, 30], we develop a lexicon-based approach to examine tweet sentiment. We select the Valence Aware Dictionary and Sentiment Reasoner (VADER) lexicon which performs a polarity classification of tweets (positive/negative). VADER was chosen given its previous use as a basis to infer subjective well-being [4], and also because it is "specifically attuned to the sentiments expressed in social media" [20], which fits our purpose.

To determine the tweet sentiment, we first use VADER to compute a positive, negative, and neutral sentiment score for each tweet in a given day and a given period. Second, we compute the compound sentiment score by summing the positive, negative, and neutral scores before normalizing values between -1 (most extreme negative) and $+1$ (most extreme positive). We assume all compound values ≥ 0 are positive tweets and all values < 0 are negative tweets. Finally, we adapt the measure of subjective well-being proposed by Zhou et al. [43] to compute the daily subjective well-being score as:

$$\mathrm{swb}(u, d, t) = \frac{N_{pos}(u, d, t) - N_{neg}(u, d, t)}{N_{pos}(u, d, t) + N_{neg}(u, d, t)} \tag{4}$$

where $N_{pos}(u, d, t)$ and $N_{neg}(u, d, t)$ denote the number of positive and negative tweets for a user u on a given day d in a given period t. Note that $swb(u, d, t) \in [-1, +1]$, where -1 is extremely negative well-being while $+1$ is extremely positive well-being. We calculate $swb(u, d, t)$ for all tweets, as well as separately for work and life tweets. The latter enables us to determine the extent to which the subjective well-being of a user changes depending on whether they tweet about work or life.

4 CASE STUDY: UK TEACHERS AND JOURNALISTS

In this section, we apply our computational methodology to study the language of 807,682 tweets posted by 95 teachers and 69 journalists in the UK from the beginning of 2019 to the end of 2022, before, during, and after COVID-19 lockdown periods.

Our aim was to study Twitter users by profession and location. The former was motivated by our desire to understand how COVID-19 impacted the work-life balance of individuals differently depending on their profession. The latter was important to identify professionals from the same country, such that we could ensure lockdown-related restrictions were the same for these workers. We chose to study UK teachers and journalists because these represent communities of professionals that continued to work during the pandemic, but adapted to changing working conditions differently [22]. For example, teachers were forced to relocate their work at home and adapt to online instruction, while journalists were used to remote work before the pandemic and arguably faced fewer barriers to adaptation as a result [15]. We therefore needed an approach to identify Twitter users by profession and location combined.

First, we identified local trade unions in an attempt to obtain most of the local users who could be either teachers or journalists. We identified the Twitter accounts of these trade unions and the followers of these accounts. We considered accounts of the following trade unions in the UK: Scottish Secondary Teachers Association, Association of Headteachers and Deputes in Scotland, the National Association of Head Teachers Northern Ireland, and the National Union of Journalists. We obtained all followers from each trade union account. Table 1 displays a summary of these accounts.

Second, we filtered out followers of these accounts who have less than 2000 tweets in total. We chose a threshold of 2000 because we aimed to get users who are very active, such that their tweets might represent daily summaries of their life, akin to diary entries. For all followers, we discovered only a small proportion of these users are active. For example, of all users following the Scottish

Teacher Trade Union	Twitter Handle	Number of Followers
Scottish Secondary Teachers Association	@SSTAtradeunion	2,564
Association of Headteachers and Deputes in Scotland	@AHDScotland	2,140
National Association of Head Teachers Northern Ireland	@NAHTNInews	2,692
National Union of Journalists	@NUJofficial	41,162

Table 1. Summary of Twitter data crawled.

Dataset	Prec.	Rec.	F_1
Scottish + Irish Teachers	0.88	0.83	0.86
Journalists	0.91	0.82	0.86

Table 2. Performance evaluation of automated tool for detecting professionals.

Secondary Teachers Association and Association of Headteachers and Deputes in Scotland accounts, only 5% of these users have greater than 2000 tweets in total. Third, we determined the profession of these users by applying a filtering technique. Motivated by prior research [37], we develop an automated method to determine the occupation of a user based on their tweet description field. To do this, we first tokenize the text in the description field and construct a list of words representing variations of the teaching and journalism professions, respectively (such as 'head teacher' or 'head of department' for teachers). Next, we search the description field for tokens matching any of the words in our list. Finally, we extract the subset of users whose occupation has been identified.

To reduce the number of false positives (i.e., users who are wrongly identified as teachers or journalists), we perform a manual inspection of the description field of these users. To reduce the number of false negatives (i.e., users who are wrongly absent from the teacher or journalist dataset), we perform a manual inspection of 50 tweets of all users who are not present in the teacher or journalist dataset. Table 2 displays the precision, recall and F_1 scores for our automated tool for detecting teachers and journalists from all users based on the description field. From Table 2, we can see that the model performs well. For teachers, false positives exist usually in the form of users who were retired teachers. Similarly, false negatives exist because the model is unable to identify teachers from the description field alone.

Furthermore, we grouped the Scottish Secondary Teachers Association and the Association of Headteachers and Deputes in Scotland accounts given that they both represent Scottish teachers. Hereafter, 'Scottish teachers' will refer to teachers identified from these accounts, while 'Irish teachers' will refer to teachers identified from the National Association of Head Teachers Northern Ireland. Table 3 reports the total number of users and total number of tweets collected for Scottish teachers, Irish teachers, and Journalists.

4.1 Topics Detected

After identifying users considered to be UK teachers and journalists, and their respective tweets, we apply BERTopic to identify topics separately for each community. We use mini-batch k-means

Group	Number of Professionals	Number of Tweets
Scottish Teachers	68	337,520
Journalists	69	299,255
Irish Teachers	27	170,907

Table 3. Summary of tweets collected for identified teachers and journalists.

clustering to fix the number of BERTopic clusters to 5. We experimented with generating topics ranging from 5 to 60. However, we found that topic diversity (which measures the percentage of unique words for all topics) declined when the model produced topics greater than 5, highlighting these topics may not be unique. To avoid producing very general topics, we fixed the number of topics to 5. We also thought 5 was a reasonable number to discern patterns of work and life from the input documents.

Tables 5, 6, and 7 display the topics identified for Scottish teachers, Irish teachers, and journalists, respectively. For each topic, we include the top 10 keywords (ordered from highest to lowest c-TF-IDF score), number of tweets, and a representative tweet. We perform a two-step topic validation process.

Step 1: Quantitative Validation. We evaluate topics using topic significance and diversity metrics. Table 4 displays these results. The topic significance value is small if topic distributions are similar. A value of 1.38, 1.36, and 1.35 for Scottish teachers, Irish teachers, and journalists respectively gives us confidence in the quality of our topics. Similarly, a diversity of 0.82 and 0.78 for Scottish teachers and journalists respectively indicates our topics are varied. A diversity of 0.70 for Irish teachers suggests these topics are potentially more general compared to topics produced for Scottish teachers and journalists.

Step 2: Qualitative Validation. We examine the content of the topics to determine a meta-label. Firstly, we qualitatively inspect the top 10 words (ordered by c-TF-IDF score) associated with each topic. We do this to assign a meta-label representing the key theme found in each topic. Secondly, to gain confidence tweets in each topic convey the assigned topic label, we inspect 100 random tweets associated with the topic. Once we have labeled each of the topics, we group them into either work or life categories. For Scottish Teachers, we grouped the *Teaching* and *Education* topics into the 'work' category and the *Entertainment*, *Politics*, and *Life* topics into the 'life' category. For Irish teachers, we grouped the *Education* and *Curriculum* topics into the 'work' category and the *Life*, *Politics*, and *Teaching Unions* topics into the 'life' category. For journalists, we grouped the *COVID-19 Coverage*, *General News Coverage*, and *Sports Coverage* into the 'work' category and the *Entertainment* and *Life* into the 'Life' category.

We find similar topics identified for Scottish and Irish teachers. For example, in the 'work' category, both teachers discuss topics related to education, with Irish teachers focusing on topics related to the school curriculum. In the 'life' category, we find some topics are about family while others are not. For example, the *Life* topic in Table 5 comprises tweets about family (e.g., 'Lovely day for a walk with the 2 little ones. #FamilyTime'), while other topics in the life category relate to non-familial activities (*Entertainment* and *Politics*). This supports the claim made in recent literature [1] that the non-work domain can include activities unrelated to familial duties. Topics identified in the 'work' category for journalists suggests journalists tend to use Twitter as a platform to disseminate news coverage, rather than discuss events related to being a journalist. This is perhaps

Teacher Group	Topic Diversity	Topic Significance
Scottish Teachers	0.82	1.38
Irish Teachers	0.70	1.36
Journalists	0.78	1.35

Table 4. Topic evaluation.

Category	Topic	Top 10 Keywords	Number of Tweets	Representative Tweet
Work	Teaching	day, book, school, morning, read, interest, class, birthday, weekend, wordle	30,139	*I'm going to really miss my S6 class. What a great bunch.*
	Education	school, teacher, teach, student, education, classroom, support, interest, practice, lesson	68,378	*@user_x @user_x @user_x Given your 20 years experience you are aware that of the 'holiday' entitlement, 8 weeks of it is unpaid? The contracts are extremely clear on that regard. If the council wish to pay me for my services, I'll happily work some of the summer break."*
Life	Entertainment	look, man, yes, team, today, watch, scotland, luck, hope, win	83,051	*Well played @user_x in a gripping game. I thought @user_x could still take the win right up to the final play. Credit for playing with a man down for 30 minutes.*
	Politics	people, work, support, scotland, government, thing, vote, change, party, family	77,382	*@user_x The answer is to repeal the Coronavirus Act right now! It won't stop the attempt, but it would change the situation so that they can't extend them, but would need to get new powers. When will that happen @user_x @user_x @user_x???*
	Life	day, week, today, morning, tomorrow, night, holiday, birthday, game, school	60,141	*Lovely day for a walk with the 2 little ones. #FamilyTime*

Table 5. Overview of topics identified by BERTopic for Scottish Teachers.

unsurprising given Twitter is widely considered an essential tool for reporters, serving as a medium for broadcasting and gathering news. Conversely, topics in the life category tend to comprise tweets about leisure and entertainment, reflecting identified topics for Scottish and Irish teachers. This might suggest life-related topics remain somewhat consistent across communities.

4.2 Changes in Borders

4.2.1 RQ1. How do borders change over COVID-19 lockdown for UK teachers and journalists? After determining borders, we characterize them quantitatively in terms of permeability and flexibility. We do so for three main periods of time:

- *First COVID-19 Lockdown*: The first national lockdown when schools were closed and people were ordered to stay at home (2020/03/23 to 2020/06/01).
- *Second COVID-19 Lockdown*: The second national lockdown when restrictions were reintroduced in the UK (2020/11/05 - 2020/12/02).
- *Third COVID-19 Lockdown*: The final national lockdown (2021/01/06 - 2021/03/08).

Category	Topic	Top 10 Keywords	Number of Tweets	Representative Tweet
Work	Education	teacher, teach, education, staff, kid, support, lesson, leader, curriculum, student	19,639	*@user_x @user_x Oh I agree with you. For me a good teacher has connection with all their pupils, plans for their needs and will use a whole gamut of resources including PowerPoint (sometimes) to accommodate their different learning styles.*
	Curriculum	pupil, staff, education, teacher, teach, curriculum, student, geography, lesson, interest	15,127	*@user_x @user_x @user_x In fact, I'm getting a STEM project going this year with 6th formers along with @user_x to help geography, physics, chemistry & biology to work together to explore climate change & how we might use remote sensing to explore it.*
Life	Life	day, today, thankyou, morning, week, enjoy, congratulation, amaze, cheer, christmas	38,705	*@user_x Congratulations Sharon. So proud of you. Lovely to see you, your girls and your all family yesterday. Thank you for the lovely pic.*
	Politics	think, work, government, evidence, term, behaviour, support, approach, child, interest	21,505	*@user_x I live in Northern Ireland. We are now the world record holder for a democracy going the longest without a functioning government. I'm afraid I'm more than a wee but cynical about the extent to which sense can overcome political intransigence and vested interest!*
	Teaching Unions	day, week, work, interest, start, morning, event, plan, support, month	33,601	*@user_x The problem is you are operating under the assumption that it is possible to plan a safe return. The unions are saying that under the current framework offered it is not. Therefore no engagement. Headteachers should be supporting unions, do not open if it is unsafe.*

Table 6. Overview of topics identified by BERTopic for Irish Teachers.

Category	Topic	Top 10 Keywords	Number of Tweets	Representative Tweet
Work	COVID-19 Coverage	work, day, news, week, covid, health, coronavirus, journalist, job, police	33,264	*Minister says nine people have breached the quarantine order introduced over the weekend to combat #coronavirus. Seven returned inside after a warning. Two said to be on the run and now "wanted" by the authorities.*
	General News Coverage	people, woman, government, country, news, journalist, tweet, war, twitter, family	37,690	*BREAKING: Four people have been arrested in connection with the murder of Journalist Lyra McKee in Derry - Londonderry's Creggan estate on April 18th. The 'New IRA' say they were responsible for the gun attack.*
	Sports Coverage	police, goal, today, league, football, road, bbc, london, city, park	33,264	*GOALL 1-0! Outstanding goal by Raul Jimenez. After all the domination from the hosts. It's the visitors who break the deadlock. His first goal of the season for the Mexican. Welcome back Raul Jimenez a key man for Wolves this season!*
Life	Entertainment	day, night, game, today, play, louth, goal, team, football, tonight	81,772	*Thought I'd take my daughter to see the last Arsenal game of the season, seeing as she's a massive Gooner. Come on you Gunners.*
	Life	day, week, work, business, month, interest, road, morning, weekend, shop	33,106	*Irish Water is bringing in a six-week hosepipe ban first thing in the morning but has been refusing to confirm the plan on the record since Friday at least. Worst drought in about a century and a half by the way.*

Table 7. Overview of topics identified by BERTopic for Journalists.

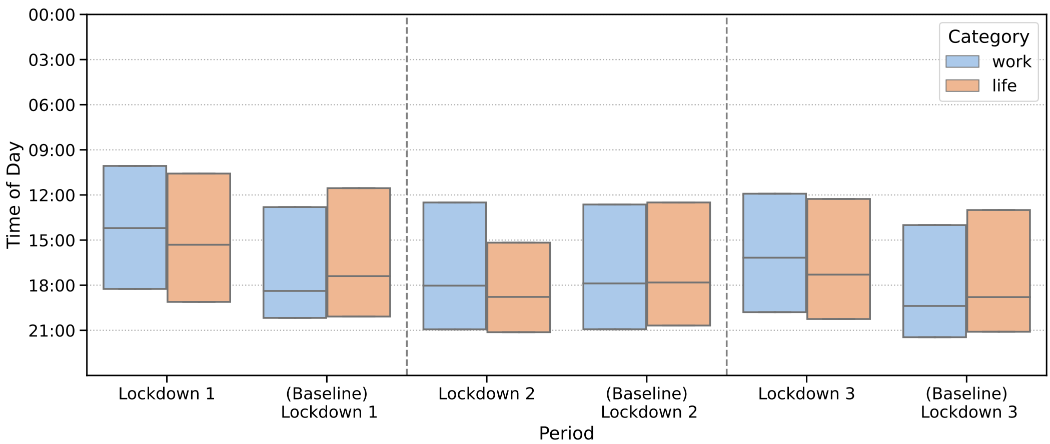
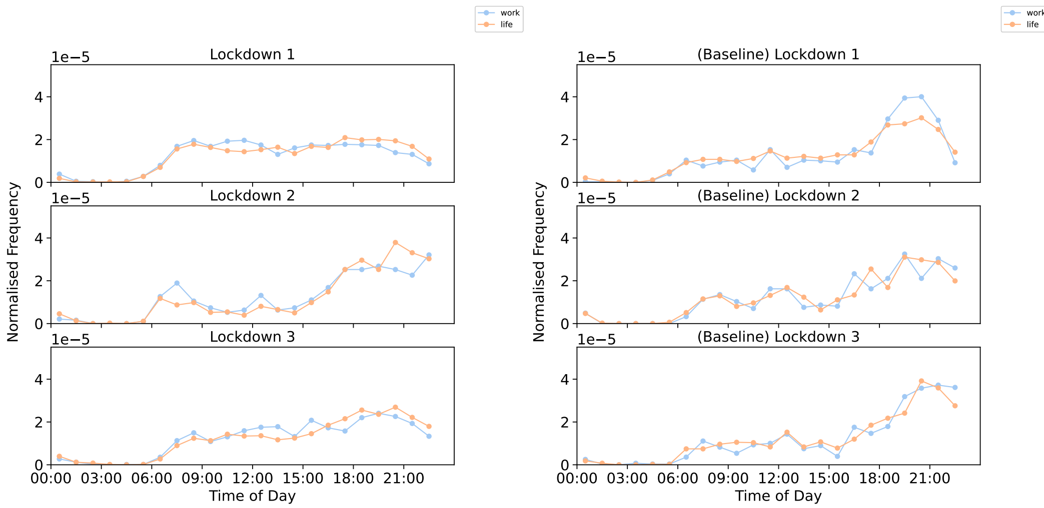


Fig. 1. IQR of tweet frequency for Scottish teachers on weekdays, for each COVID-19 lockdown period.

We focus on these three periods to ensure there is no ambiguity regarding the timeline of these crisis events. Using the metrics outlined in the Border Theory Operationalization section, we compute the daily permeability and flexibility for Scottish teachers, Irish teachers, and journalist tweets for each period of COVID-19 lockdown. To answer RQ1, we consider two sub-questions:
1. How does the temporal flexibility of work and life borders change in each COVID-19 lockdown period? For each period under study, we compute the distance and shift in the IQR of work and life tweet frequency on weekdays, for all Scottish teachers, Irish teachers, and journalist tweets. While we have results for weekends, we do not observe any noticeable changes. Therefore, in the interest of space, we choose to present results for weekdays only. We also compute the distance and shift of work and life tweet frequency for a baseline period (hereafter, pre-lockdown baseline), which we define as the same months of the lockdown period, but in 2019. As shown in Figure 1, the IQR of life tweet frequency for Scottish teachers is shortened from the first lockdown to the second, before being extended by the third lockdown. Comparatively, the IQR of work tweet frequency remains mostly stable in terms of distance throughout each lockdown. Compared to the pre-lockdown baseline, the IQR for life in the second lockdown shifts, indicating a delay in the time to which the bulk of life discussions takes place. This suggests that the second COVID-19 lockdown may have contributed to an increase in the overall temporal flexibility of work-life borders for Scottish teachers. This broadly tracks with prior studies that have acknowledged sudden changes to human behavior caused by lockdown-related mobility restrictions, such as shifts in the interests of certain foods [16]. Furthermore, the temporal borders of the life domain were more flexible than the work domain for Scottish teachers during the second lockdown compared to a baseline period. To gain confidence in these results, we compared the distribution of the IQR of both work and life tweets across each lockdown period. Table 8 shows the results of a two-sample Kolmogorov-Smirnov test. In each case, the *p-value* < 0.05, confirming the difference in the IQR values is statistically significant.

These results are interesting when compared to the behavior of work and life tweet activity on weekdays for each COVID-19 lockdown period and their respective baselines. Figure 2 displays the frequency distribution of work and life tweets for Scottish teachers, per lockdown period (a) and baseline (b). We normalized the tweet frequency distribution such that the integral of the values sums to 1. In the first and third lockdowns, work and life frequency is much less varied compared



(a) Frequency per Lockdown Period

(b) Frequency per Baseline period (2019)

Fig. 2. Normalized frequency distribution of work and life tweets for Scottish teachers on weekdays, for each COVID-19 lockdown period.

Category	Lockdown Comparison	
	L1 vs L2	L2 vs L3
Work	$p < 0.001$	$p < 0.001$
Life	$p < 0.001$	$p < 0.001$

Table 8. P-values of the Kolmogorov-Smirnov test for the distribution of the IQR of Scottish work and life tweets on weekdays, across COVID-19 lockdown periods. L1 = Lockdown 1, L2 = Lockdown 2, L3 = Lockdown 3. Significance level of $\alpha = 0.05$.

to the frequency in their respective baseline periods. This occurs at a time when the flexibility of work-life borders does not change significantly. This might indicate border flexibility has little impact on the tweet activity during lockdown compared to a pre-lockdown baseline. However, the frequency distribution in the second lockdown is arguably more varied compared to the other lockdowns. This might indicate a relationship between border flexibility and tweet activity, hinting at the impact of flexible borders on the tweet behavior of Scottish teachers during the second lockdown. Additionally, the normalized frequency of work and life in the first and third lockdown remains somewhat flat over time compared to the second lockdown, which shows an increasing trend from 15:00 to 21:00. This follows a similar pattern to the baseline frequencies, potentially indicating a perceived return to normality before the onset of the third lockdown.

As shown in Figure 3, we find the IQR for Irish work and life tweets is shortened from the first to the second lockdown, before being extended by the third lockdown. The latter observation is more distinct for the work IQR which, by the third lockdown, returns to levels comparable to the first lockdown. This is a similar pattern to the flexibility of work-life borders for Scottish teachers, which also increases during the second lockdown. Compared to the baseline period, the temporal borders of the life domain appear to shorten across all lockdowns, indicating a reduction in the

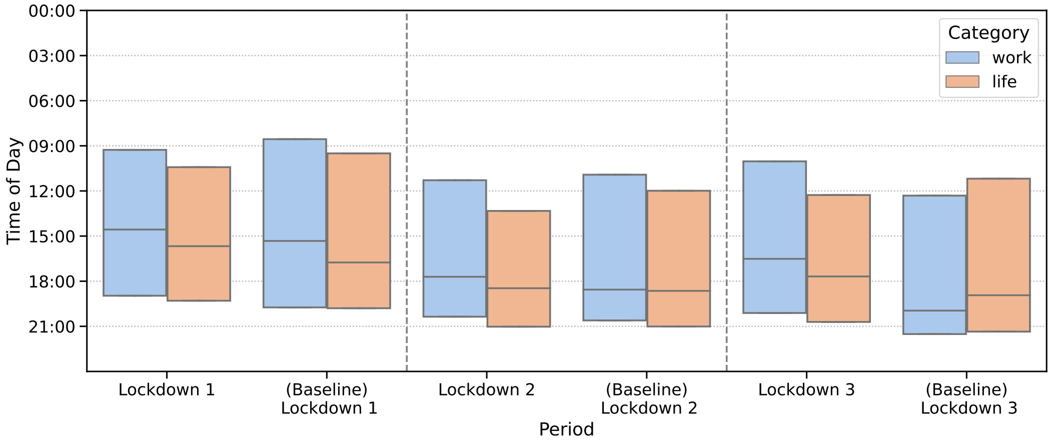
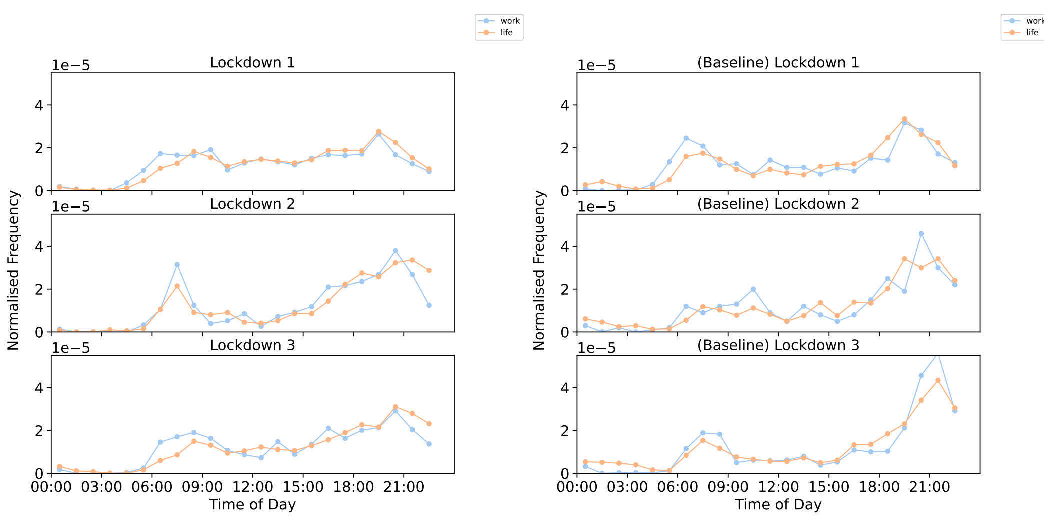


Fig. 3. IQR of tweet frequency for Irish teachers on weekdays, for each COVID-19 lockdown period.



(a) Frequency per Lockdown Period

(b) Frequency per Baseline period (2019)

Fig. 4. Normalized frequency distribution of work and life tweets for Irish teachers on weekdays, for each COVID-19 lockdown period.

time to which life discussions took place during lockdown. Similarly, when viewing the normalized frequency distribution of work and life tweets for Irish teachers in Figure 4, we find a more varied distribution in the second lockdown. Specifically, there is a reduction in the normalized frequency for both work and life tweets from 09:00 to 15:00 during the second lockdown, compared to the first and third lockdown. This may suggest temporal border flexibility is associated with decreasing tweet behaviour of Irish teachers, since the frequency of work and life tweets decreases as borders shift during this period.

Compared to both Scottish and Irish teachers, the IQR for UK journalist work and life tweets (as shown in Figure 5) does not change significantly over time. Temporal flexibility remains somewhat

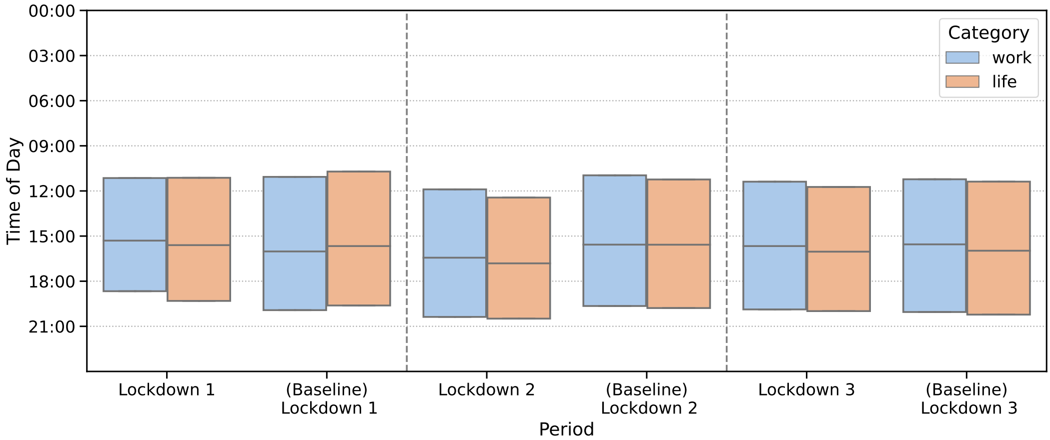
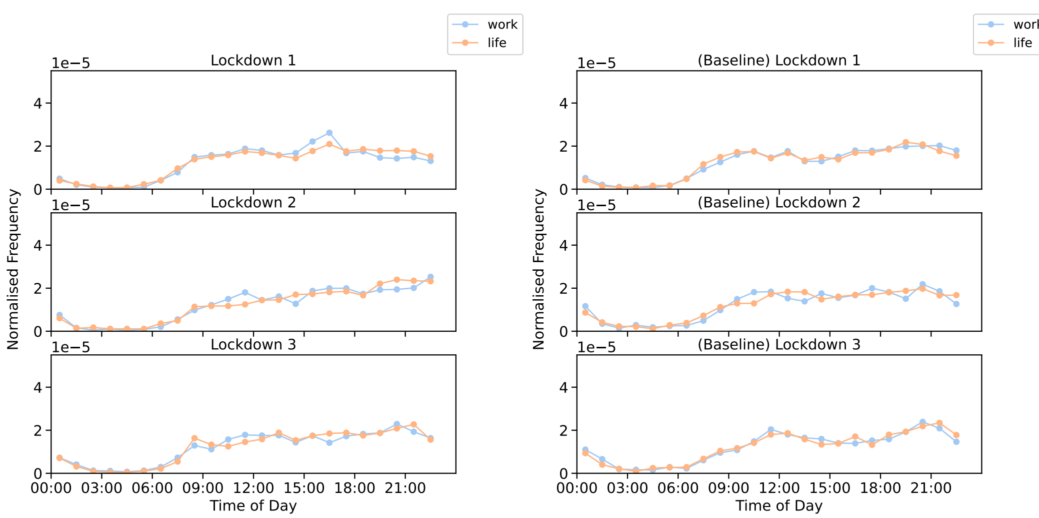


Fig. 5. IQR of tweet frequency for journalists on weekdays, for each COVID-19 lockdown period.



(a) Frequency per Lockdown Period

(b) Frequency per Baseline period (2019)

Fig. 6. Normalized frequency distribution of work and life tweets for journalists on weekdays, for each COVID-19 lockdown period.

comparable during each lockdown and their respective baselines. Additionally, as displayed in Figure 6, the normalized frequency distribution of work and life tweets during lockdown is mostly comparable to the baseline period. This might suggest COVID-19 did not have a significant impact on the temporal flexibility of journalists compared to teachers. This is perhaps unsurprising given journalists were arguably more familiar with remote work prior to the pandemic compared to teachers [15, 42], and so were able to adapt to working from home more seamlessly.

2. How does the temporal permeability of work and life borders change in each COVID-19 lockdown period? Table 9 displays the results of temporal permeability for Scottish teachers. For each of the three lockdown periods (indicated by the emboldened cells), we find temporal

Period	Year			
	2019	2020	2021	2022
Mar to Jun	89%	**87%**	89%	98%
Nov to Dec	96%	**67%**	98%	77%
Jan to Mar	95%	93%	**90%**	97%

Table 9. Border permeability for Scottish teachers during weekdays. Emboldened cells indicate lockdown periods.

Period	Year			
	2019	2020	2021	2022
Mar to Jun	91%	**85%**	77%	76%
Nov to Dec	85%	**72%**	80%	62%
Jan to Mar	88%	75%	**73%**	94%

Table 10. Border permeability for Irish teachers during weekdays. Emboldened cells indicate lockdown periods.

Period	Year			
	2019	2020	2021	2022
Mar to Jun	93%	**92%**	96%	83%
Nov to Dec	95%	**92%**	80%	91%
Jan to Mar	96%	98%	**95%**	84%

Table 11. Border permeability for journalists during weekdays. Emboldened cells indicate lockdown periods.

permeability falls, only to recover in the post-lockdown period. This is most evident from November to December, where permeability falls by 29% from 2019 to 2020 (lockdown 1), before increasing by 31% in 2021. This is partly caused by the shortening of the life tweet IQR from the first to the second lockdown (see Figure 1), indicating increased flexibility. As shown in Tables 10 and 11, a similar pattern is found for Irish teachers and journalists, where temporal permeability falls from before a given lockdown to the lockdown period. However, this observation is more subtle for journalists, where border permeability does not change dramatically from a pre-lockdown baseline to a lockdown period.

4.3 RQ2. What implications might this have for the work-life balance and well-being of UK teachers and journalists?

Previous research has shown work-life balance has implications for well-being [9, 21, 28, 34]. To explore this relationship, we compute Equation 4 to determine the subjective well-being of teachers. Firstly, we compute this equation for all tweets, regardless of whether they are related to work or life. Figures 7 and 8 display these results for Scottish and Irish teachers, respectively. In both cases, we find a notable change in the subjective well-being from the first to the second lockdown, with the IQR shifting towards more positive values. Additionally, the subjective well-being of the second lockdown shifts towards more positive values compared to its baseline. This is more evident for Irish teachers, where all tweets in the IQR are positive during the second lockdown. This might

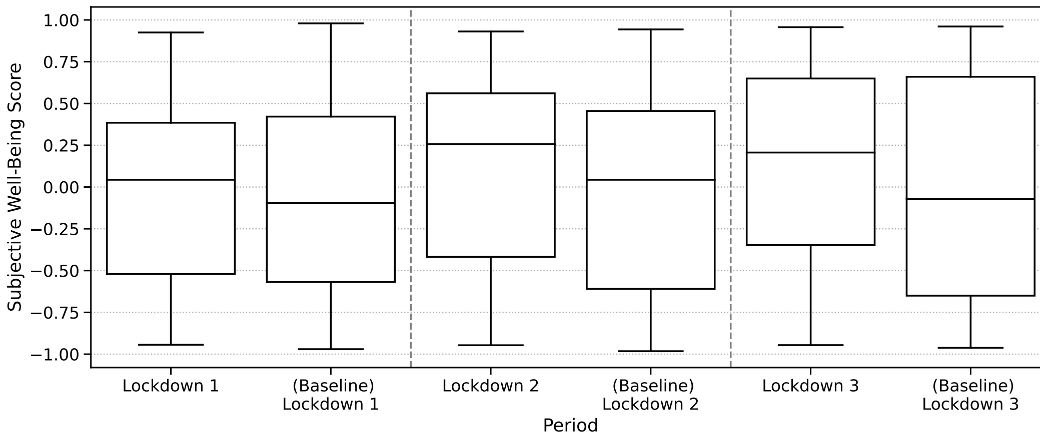


Fig. 7. Subjective well-being of Scottish teachers on weekdays, for each COVID-19 lockdown period.

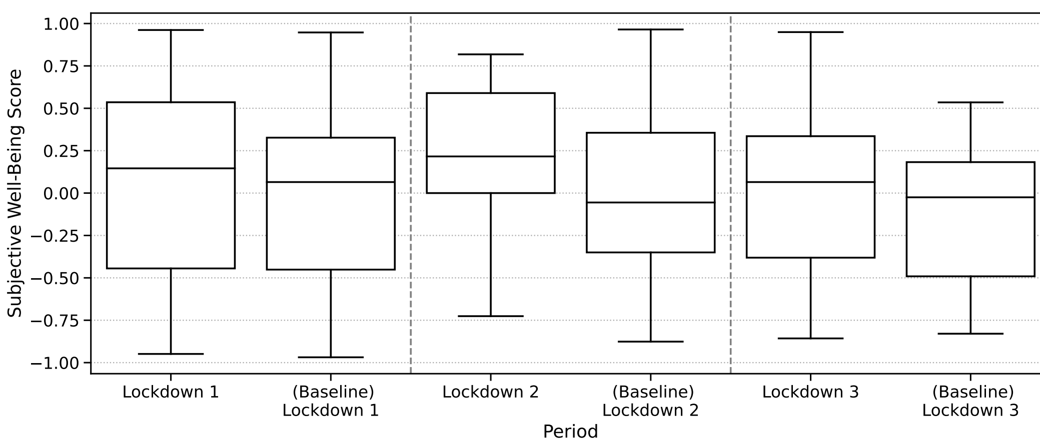


Fig. 8. Subjective well-being of Irish teachers on weekdays, for each COVID-19 lockdown period.

indicate flexibility is correlated with subjective well-being, given that an increase in the former is accompanied by an increase in the latter. It might follow that the well-being of Scottish and Irish teachers did not suffer greatly during the second lockdown, assuming teachers had become accustomed to working from home and were able to keep work-life domains impermeable. In Figure 9, we find the IQR of the subjective well-being of journalists shifts towards more negative values during lockdown compared to the baseline period, for the first and second lockdown. This tracks with prior studies that have found social media posts during lockdown contain a higher frequency of mental health expressions than a comparable dataset from the same period in the previous year [33]. It is particularly interesting given the IQR of tweet frequency for journalists exhibits little flexibility compared to Scottish and Irish teachers. However, it is important to note that this may be the case if journalists are reporting negative sentiment news in their tweets during the pandemic compared to the baseline period. To test this, we compute Equation 4 for life-related tweets of Journalists only. Figure 10 displays these results. We can see that the subjective well-being of journalists shifts towards more negative values for the first lockdown only, with a comparable

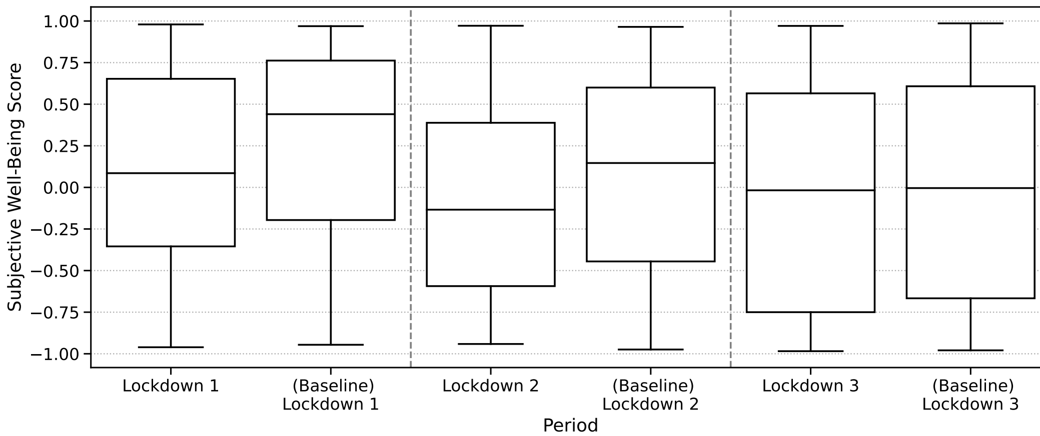


Fig. 9. Subjective well-being of journalists on weekdays, for each COVID-19 lockdown period.

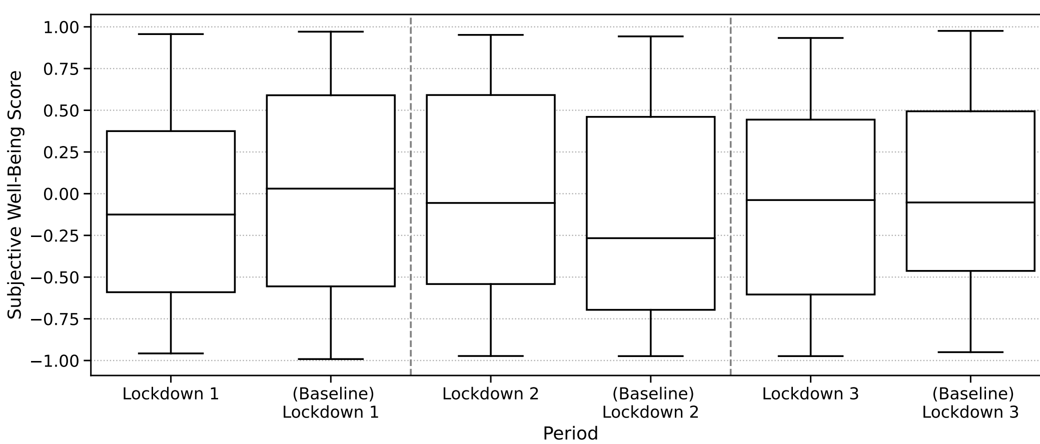


Fig. 10. Subjective well-being of life tweets for journalists on weekdays, for each COVID-19 lockdown period.

distribution for the second and third lockdown. This emphasizes the potential impact of the first lockdown on the subjective well-being of Journalists in both work and life domains.

Secondly, we compute Equation 4 separately for work- and life-related tweets. Figures 11 and 12 display these results for Scottish teachers. We arguably see less variability, albeit subtle, in the subjective well-being of work-related tweets (Figure 11), with little change in the shift of the IQR throughout the lockdown and baseline periods. This may suggest work-related tweets are more neutral by nature, which tracks with our intuition since they occur in a more professional setting that life-related tweets.

5 DISCUSSION AND CONCLUSION

According to Clark [11], weak borders facilitate work-life balance when domains are similar, while strong borders facilitate work-life balance when domains are different. We define similar domains as work-life domains that are placed in the same physical space (such as work from home scenarios). Alternatively, domains can be considered different if work and life activities occur in different

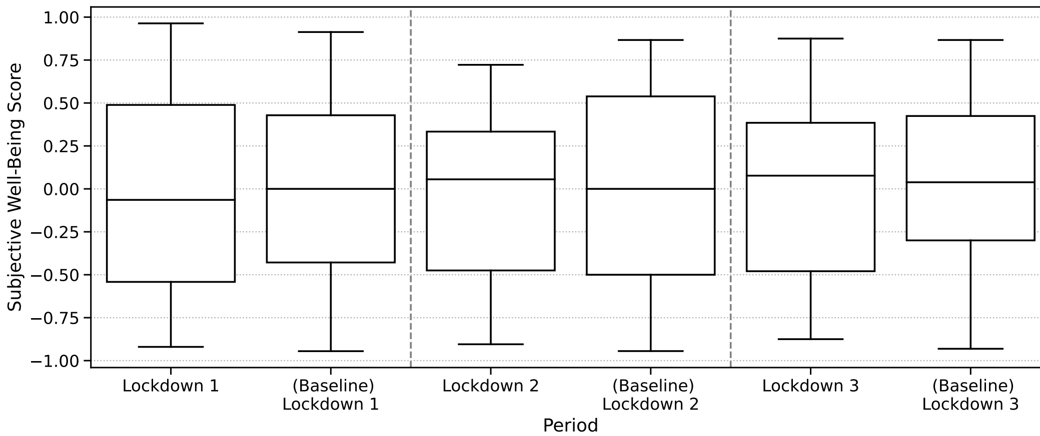


Fig. 11. Subjective well-being of work tweets for Scottish teachers on weekdays, for each COVID-19 lockdown period.

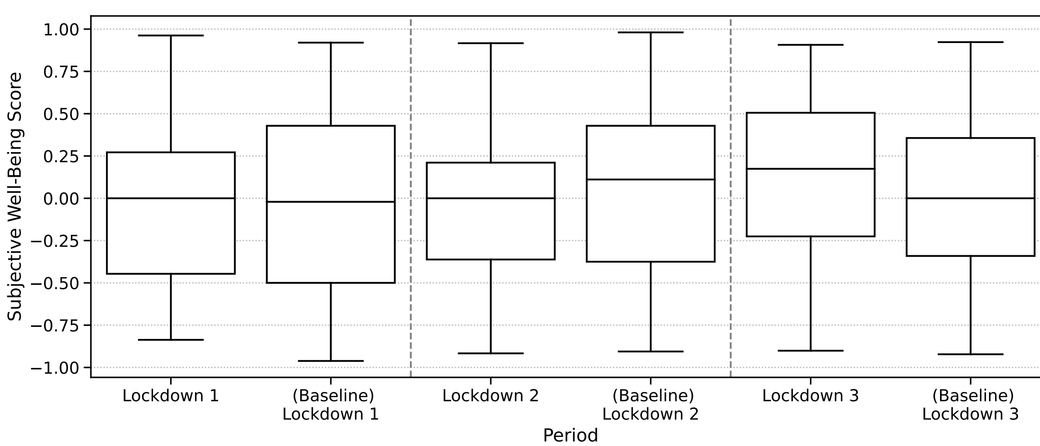


Fig. 12. Subjective well-being of life tweets for Scottish teachers on weekdays, for each COVID-19 lockdown period.

physical spaces. Given this definition, we consider work-life domains for UK teachers and journalists to be more similar during lockdown due to remote working.

For Scottish teachers, flexibility increases (see Figure 1) but permeability falls by 20% (see Table 9) from the first to the second lockdown. Likewise, flexibility increases from the first to the second lockdown for Irish teachers (see Figure 3) while permeability falls by 13% (see Table 10). Given this result, it is difficult to determine the strength of borders for both groups of teachers. However, we might argue borders 'weakened' from the first to the second lockdown, given the notable change in flexibility during this period. This might make intuitive sense. For both groups of teachers, work and life domains may have become more flexible to adapt to changes caused by the second lockdown. However, the decline in permeability could signal how teachers had become accustomed to working at home by the second lockdown, such that some degree of separation between work and life domains was possible. For journalists, the minimal change in temporal flexibility and permeability across lockdowns may suggest there are no significant borders separating work from life. Compared to teachers, who were forced to adapt to remote teaching, journalists were faced with arguably fewer boundaries to how they conducted their work in pre-lockdown periods. Indeed, journalists have been working away from newsrooms or freelancing with flexible working conditions for decades [42]. While this does not overlook the potential disruption to journalists' work-life balance during lockdown, it acknowledges the difficulty in determining the strength of borders given borders between work and life are not obvious for journalists.

This work explores the feasibility of operationalizing border theory by means of a computational linguistic approach. It applies this methodology to study how work-life borders changed for teachers and journalists before, during, and after COVID-19 lockdown periods. This study is motivated by the need to understand how crisis events affect work-life balance, and the implications this has for well-being. We believe our methodology constitutes a first step towards determining work-life borders and exploring changes in their characteristics over time. It also offers pathways for future research in the social sciences. Part of the motivation for this research was the recognition that social science studies of work-life balance can be small scale and cross-sectional, limiting the generalizability of research findings. We illustrate how scalable and longitudinal approaches can be employed to address this, supporting the discovery of previously hidden signals in the ways individuals behave in times of crisis.

5.1 Limitations and Future Work

One limitation is related to the data collected for the case study. The sample size is small and self-selection biases may be introduced since users may self-select into setting up a Twitter account, posting about topics related to work and life, and following specific trade union accounts. We acknowledge that other platforms, such as Reddit, could have been used alongside Twitter to identify individuals who may self-declare their profession (for example, in relevant subreddits). We believe this could increase the diversity and representativeness of the data. Furthermore, individuals posting about either work or life on Twitter may not be a major limitation, since we do not assume anything about the content users tweet about, but rather infer topics from tweets bottom-up. We emphasise that we only collect tweets from users who follow teacher trade unions because we aim to identify users who could be from the same geographical location. An alternative NLP approach could have been developed that identifies a user's location from their profile, but this was beyond the scope of our study. We do however encourage researchers to address these limitations in future studies.

A second limitation is that this research lacks a comparison to other occupational groups, since we only compare the results for British teachers and journalists. Future research will compare a broader range of occupational groups to enable an analysis of work-life boarders across a more representative pool of professionals.

A third limitation of our methodology is that we have not externally validated the BERTopic topics. Currently, we internally validate the BERTopic output using quantitative and qualitative metrics. However, we believe that a potential further validation of the BERTopic model to distinguish tweets that semantically belong to work and life is needed. For example, future work might leverage human validation techniques, such as crowdsourcing. Online platforms, such as Appen or Amazon Mechanical Turk, could be used to verify the accuracy of our BERTopic model and our method for grouping topics into work and life. We also encourage researchers to explore other methods to reduce bias by identifying a broader pool of users to verify the classification.

Finally, we only explore a portion of work-family border theory that deals with temporal borders. Future work might extend the present findings by integrating an analysis of other border theory constructs, such as spatial and psychological borders.

ETHICAL STATEMENT

This work is based completely on public data and does not contain private information of individuals. Our dataset has been collected in accordance with the Twitter Developer Agreement and Policy and related policies. We have not violated any ethical principles in the collection and interpretation of the data in our study. Despite working with public data, excerpts used to support the qualitative analysis were anonymized and paraphrased, to avoid traceability and identifiability of individual tweets.

We acknowledge that the inclusion of special category information, though not intentional, may occur during the process of collecting Twitter data. For example, since we select users who follow UK trade unions as part of our methodology, it may be the case that users reveal their trade union membership (which is regarded as a special category under GDPR) in their tweets. We emphasise that this data will only remain present in a dataset that has been de-identified (in terms of removing Twitter handles). We do not use any special category data in our analysis. Additionally, any reference to Twitter users that are used as examples in the report are anonymized (e.g., replacing Twitter handles with '@user_x' in tweets included in Tables 5 and 6).

REFERENCES

[1] Toyin Ajibade Adisa and Gbolahan Gbadamosi. 2021. Work-life border control model: A re-think of border theory. *Work-Life Interface* (2021), 25–53.

[2] Yunjo An, Regina Kaplan-Rakowski, Junhe Yang, Jenna Conan, Widad Kinard, and LeaAnne Daughrity. 2021. Examining K-12 teachers' feelings, experiences, and perspectives regarding online teaching during the early stage of the COVID-19 pandemic. *Educational Technology Research and Development* 69, 5 (2021), 2589–2613.

[3] Blake E Ashforth, Glen E Kreiner, and Mel Fugate. 2000. All in a day's work: Boundaries and micro role transitions. *Academy of Management Review* 25, 3 (2000), 472–491.

[4] Krishna C Bathina, Marijn Ten Thij, Danny Valdez, Lauren A Rutter, and Johan Bollen. 2021. Declining well-being during the COVID-19 pandemic reveals US social inequities. *PloS ONE* 16, 7 (2021), e0254114.

[5] Zainab Bello and Garba Ibrahim Tanko. 2020. Review of work-life balance theories. *Global Academy of Training and Research (GATR) Enterprise* 8, 4 (2020), 217–227.

[6] David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent Dirichlet Allocation. *Journal of Machine Learning Research* 3, Jan (2003), 993–1022.

[7] Hanifa Bouziri, David RM Smith, Alexis Descatha, William Dab, and Kévin Jean. 2020. Working from home in the time of COVID-19: how to best preserve occupational health? *Occupational and Environmental Medicine* 77, 7 (2020), 509–510.

[8] João Marcos Campagnolo, Denio Duarte, and Guillherme Dal Bianco. 2022. Topic coherence metrics: How sensitive are they? *Journal of Information and Data Management* 13, 4 (2022).

[9] Vânia Sofia Carvalho, Alda Santos, Maria Teresa Ribeiro, and Maria José Chambel. 2021. Please, do not interrupt me: work–family balance and segmentation behavior as mediators of boundary violations and teleworkers' burnout and flourishing. *Sustainability* 13, 13 (2021), 7339.

[10] Uracha Chatrakul Na Ayudhya, Rea Prouska, and T Alexandra Beauregard. 2019. The impact of global economic crisis and austerity on quality of working life and work-life balance: A capabilities perspective. *European Management Review* 16, 4 (2019), 847–862.

[11] Sue Campbell Clark. 2000. Work/family border theory: A new theory of work/family balance. *Human Relations* 53, 6 (2000), 747–770.

[12] Scott Deerwester, Susan T Dumais, George W Furnas, Thomas K Landauer, and Richard Harshman. 1990. Indexing by latent semantic analysis. *Journal of the American Society for Information Science* 41, 6 (1990), 391–407.

[13] Régis Ebeling, Carlos Abel Córdova Sáenz, Jéferson Campos Nobre, and Karin Becker. 2022. Analysis of the influence of political polarization in the vaccination stance: the Brazilian COVID-19 scenario. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 16. 159–170.

[14] Anja Feldmann, Oliver Gasser, Franziska Lichtblau, Enric Pujol, Ingmar Poese, Christoph Dietzel, Daniel Wagner, Matthias Wichtlhuber, Juan Tapiador, Narseo Vallina-Rodriguez, et al. 2021. A year in lockdown: how the waves of COVID-19 impact internet traffic. *Communications of the ACM* 64, 7 (2021), 101–108.

[15] Jose A García-Avilés. 2021. Journalism as usual? Managing disruption in virtual newsrooms during the COVID-19 crisis. *Digital Journalism* 9, 9 (2021), 1239–1260.

[16] Kristina Gligorić, Arnaud Chiolero, Emre Kıcıman, Ryen W White, and Robert West. 2022. Population-scale dietary interests during the COVID-19 pandemic. *Nature Communications* 13, 1 (2022), 1073.
[17] Maarten Grootendorst. 2022. BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794* (2022).
[18] Stevan E Hobfoll. 1989. Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist* 44, 3 (1989), 513.
[19] Stevan E Hobfoll. 2011. Conservation of resource caravans and engaged settings. *Journal of Occupational and Organizational Psychology* 84, 1 (2011), 116–122.
[20] Clayton Hutto and Eric Gilbert. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 8. 216–225. Issue 1.
[21] Sophie Leroy, Aaron M Schmidt, and Nora Madjar. 2021. Working from home during COVID-19: A study of the interruption landscape. *Journal of Applied Psychology* 106, 10 (2021), 1448.
[22] Susan Lund, Anu Madgavkar, James Manyika, Sven Smit, Kweilin Ellingrud, Mary Meaney, and Olivia Robinson. 2021. The future of work after COVID-19. *McKinsey Global Institute* 18 (2021).
[23] Abraham Harold Maslow. 1943. A theory of human motivation. *Psychological review* 50, 4 (1943), 370.
[24] Leland McInnes, John Healy, and Steve Astels. 2017. Hdbscan: Hierarchical density based clustering. *Journal of Open Source Software* 2, 11 (2017), 205.
[25] Sylvia Freitas Mello and Patricia Amelia Tomei. 2021. The impact of the COVID-19 pandemic on expatriates: A pathway to work-life harmony? *Global Business and Organizational Excellence* 40, 5 (2021), 6–22.
[26] Lewis Mitchell, Morgan R Frank, Kameron Decker Harris, Peter Sheridan Dodds, and Christopher M Danforth. 2013. The geography of happiness: Connecting Twitter sentiment and expression, demographics, and objective characteristics of place. *PloS ONE* 8, 5 (2013), e64417.
[27] Hannah Murphy and Tabby Kinder. 2023. Elon Musk says Twitter may reach positive cash flow by second quarter. https://www.ft.com/content/ccb40e03-099f-4bfe-ad34-2e6c3ec88c81
[28] Helen Pluut and Jaap Wonders. 2020. Not able to lead a healthy life when you need it the most: Dual role of lifestyle behaviors in the association of blurred work-life boundaries with well-being. *Frontiers in Psychology* 11 (2020), 607294.
[29] Soham Poddar, Mainack Mondal, Janardan Misra, Niloy Ganguly, and Saptarshi Ghosh. 2022. Winds of change: Impact of COVID-19 on vaccine-related opinions of Twitter users. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 16. 782–793.
[30] Daniele Quercia, Jonathan Ellis, Licia Capra, and Jon Crowcroft. 2012. Tracking "gross community happiness" from tweets. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*. 965–968.
[31] Devin J Rapp, J Matthew Hughey, and Glen E Kreiner. 2021. Boundary work as a buffer against burnout: Evidence from healthcare workers during the COVID-19 pandemic. *Journal of Applied Psychology* 106, 8 (2021), 1169.
[32] Koustuv Saha, Benjamin Sugar, John Torous, Bruno Abrahao, Emre Kıcıman, and Munmun De Choudhury. 2019. A social media study on the effects of psychiatric medication use. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 13. 440–451.
[33] Koustuv Saha, John Torous, Eric D Caine, and Munmun De Choudhury. 2020. Psychosocial effects of the COVID-19 pandemic: large-scale quasi-experimental study on social media. *Journal of Medical Internet Research* 22, 11 (2020), e22600.
[34] Surabhi Sahay and Wan Wei. 2021. Work-family balance and managing spillover effects communicatively during COVID-19: Nurses' perspectives. *Health Communication* (2021), 1–10.
[35] Karishma Sharma, Yizhou Zhang, and Yan Liu. 2022. COVID-19 vaccine misinformation campaigns and social media narratives. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 16. 920–931.
[36] Melika Shirmohammadi, Wee Chan Au, and Mina Beigi. 2022. Antecedents and outcomes of work-life balance while working from home: A review of the research conducted during the COVID-19 pandemic. *Human Resource Development Review* (2022), 15344843221125834.
[37] Luke Sloan, Jeffrey Morgan, Pete Burnap, and Matthew Williams. 2015. Who tweets? Deriving the demographic characteristics of age, occupation and social class from Twitter user meta-data. *PloS ONE* 10, 3 (2015), e0115545.
[38] Jina Suh, Eric Horvitz, Ryen W White, and Tim Althoff. 2021. Population-scale study of human needs during the covid-19 pandemic: Analysis and implications. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*. 4–12.
[39] Gaurav Verma, Ankur Bhardwaj, Talayeh Aledavood, Munmun De Choudhury, and Srijan Kumar. 2022. Examining the impact of sharing COVID-19 misinformation online on mental health. *Scientific Reports* 12, 1 (2022), 1–9.
[40] Chao Yang and Padmini Srinivasan. 2016. Life satisfaction and the pursuit of happiness on Twitter. *PloS ONE* 11, 3 (2016), e0150881.
[41] Wenjie Yang, Sitong Wang, Zhenhui Peng, Chuhan Shi, Xiaojuan Ma, and Diyi Yang. 2022. Know it to defeat it: Exploring health rumor characteristics and debunking efforts on Chinese social media during COVID-19 crisis. In

Proceedings of the International AAAI Conference on Web and Social Media, Vol. 16. 1157–1168.
[42] Li Zeng, Dharma Dailey, Owla Mohamed, Kate Starbird, and Emma S Spiro. 2019. Detecting journalism in the age of social media: three experiments in classifying journalists on twitter. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 13. 548–559.
[43] Xinyi Zhou, Shengmin Jin, and Reza Zafarani. 2020. Sentiment paradoxes in social networks: Why your friends are more positive than you?. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 14. 798–807.

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