Emergent Twitter publics through political scandal: an example from the Covid-19 Crisis in the UK

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Abstract

This study examines how emergent Twitter publics are organised and engage with political scandal and personalisation during Covid-19 in the UK. The analysis is centred on a series of media events around Chief Adviser to the then-UK Prime Minister, running from May 2020 to May 2021. The samples comprises original tweets that contain key hashtags, amounting to 38,326 items. These are subject to topic model analysis to identify semantic fields, before using critical discourse analysis. We find hashtags help constitute emergent Twitter publics, and that tweets follow conversational patterns and conspire in tactics of intertextuality. Dissention to government conduct engages resourcefully with the affordances of Twitter: constituting publics, shaping discourse, and articulating with parallel discussions on political performance. Further, a computational approach can systematise the identification of domains of discourse and relevant lexical sets, providing an evidence-based understanding of even novel and emergent political discourses in online discussion.

Keywords: Computational discourse analysis, Political personalisation, Twitter, Semantic Fields, Topic Models

Introduction

With its obligation for physical distancing, the Covid-19 pandemic has attracted considerable academic interest in the uses of social media platforms. Many studies have sought to establish the success of social media in delivering positive outcomes, such as the minimising loneliness (Koh and Liew 2020) and improving effectiveness in medical services (Wong et al. 2020). Critical scholars too have been tracking social media culpability in sowing misinformation on the pandemic (Bode and Vraga 2021; Freiling et al. 2021), as well as their platforming of pandemic-related racism, xenophobia and violence (Abidin and Zeng 2020; Babvey et al. 2020). Taken as a whole, these studies attest to social media's various roles and possibilities in shaping what the pandemic's lexicon calls 'a new reality'.

We are interested in the emergent composition of this new reality, and in particular the increasing dependence of political discussion on digital platforms and social media. Applying a critical discourse analysis (CDA) framework to social media, Krzyżanowski (2018) looks at how governments, official spokespeople and the public engage Twitter in a manner that may challenge, but ordinarily sustains, conversational patterns and political power relations. From a related perspective, Strange (2022) shows how the UK government discourse on Twitter has individualised responsibility for the Covid-19 pandemic, positioning 'public recklessness' as an alibi for governmental mismanagement.

As Strange (2022) argues, these analyses are lent urgency by the determination of neoliberal and populist political figures worldwide to use social media such as Instagram and Twitter to broaden their appeal. The deployment of Twitter by renegade politicians such as Donald Trump as a direct route for top-down political communication (Smith and Higgins 2020), has been variously presented as a dynamic and liberating celebration of 'free speech' (Stolee and Caton 2018: 155), or as the cynical exploitation of political and cultural echo chambers to give unwarranted salience to preposterous political claims and discursive correspondences (Boulianne et al. 2020).

In this article, we also propose to use critical discourse analysis (CDA) to analyse social media content, in a manner that foregrounds how the tactics of language are deployed in the exercise and reproduction of relationships and arrangements of political and cultural power (Wodak and Meyer 2016). Our selection of content is rooted in an

interpretation of 'media events' and their relationship with political communications practice, on the understanding that such events choreograph and inform public and media agendas. While the particular manner in which we use CDA calls upon what Krzyżanowski (2018) identifies as the conversational patterns associated with political discourse on Twitter, our adaption of this stresses that Twitter data can and should be subject to computational analysis in order to identify semantic fields and organise analysis.

Personalisation and political scandal

In reflecting upon the mediatisation of politics, two parallel areas of interest have been dominant. First, there has been the increasing personalisation of the political sphere. This stems from a more comprehensive popularisation of political communication, where a fixation on the individual panders to the media-facing demands of celebrity culture (Drake and Higgins 2006; Wheeler 2013). Recent work on the personalisation of politics has concentrated on the role of the charismatic leader in the escalation of neoliberal and populist politics (Higgins 2019; Schneiker 2019). Boris Johnson, UK Prime Minister during this stage of the pandemic, offers a commonly-cited example of contemporary political charisma (Honeyman 2022), embodying the political anti-hero in his conspicuous non-conformity and what Moffitt (2016) calls 'bad behaviour'. While these qualities form a significant part of the performative repertoire of Boris Johnson, as the article progresses we will see them still more prominently in his chief adviser Dominic Cummings.

These populist imperatives towards the indecorous articulate with the second area of interest, which is a fixation on and the management of 'political scandal' as a means of lending colour and interest to politics. Thompson (2000) argues that the political scandal has come to the fore as a driver of how politics is mediated, and here we look at the role that social media plays in critically responding to political activities, in representing, amplifying and shaping blame and controversy.

The renown accorded to Dominic Cummings occupies a trajectory of increasing prominence that UK government advisors have enjoyed since the late 1990s (see Jones

2000). Even under ordinary conditions, the communications advisor occupies a problematic space in the democratic arrangement, lacking both appropriate democratic accountability and public transparency (Garland 2018). To this, Cummings has added a layer of public performance: projecting an opportunistic neoliberal philosophy through an affectedly eccentric demeanour, helpfully chronicled in a weblog maintained since November 2013. Indeed, Cummings used this weblog five months into his appointment to reaffirm this maverick status, enjoining 'super-talented weirdos' and 'misfits' to come guide government policy (Cummings 2020). Cummings' enactment of an extraordinary self is a purposeful reflection of a government's rebellious communications strategy, but also provides essential context for the reading of his contribution to government policy and performance.

The analysis of Twitter

However, while the blog expresses Cummings' crafted nonconformity, Twitter can claim a still more dispersed and uninhibited set of voices and perspectives. Affordances provided by Twitter allow the formation of ad hoc issue publics in response to crucial political events (Bruns and Burgess 2011) and a wide range of studies examine how the platform is used for political purposes (D'heer and Verdegem 2014; Schneiker 2019; Smith and Higgins 2020). Twitter is a stimulating platform for political analysis precisely because of these associations with unconventionality and its bypassing the apparatus of conventional political communication. It is therefore crucial that we conceive of a methodology which does not predefine the dominant terms, but rather seeks to reveal them as they emerge, fully capturing a digital public sphere characterised by what Dahlgren (2005) describes as 'plurality'. An appropriately macroscopic approach is therefore needed to comprehend the mesh of different topics and conversations within and across the platforms that constitute emergent public dialogue. Such an approach requires computational work, such as the access that platform Application Programme Interfaces (APIs) provide to extensive samples. This study therefore calls upon topic model analysis, which is a machine learning approach that uses a suite of algorithms to annotate documents with thematic information (Blei 2012). This is used to identify topics driven by hashtagged Twitter conversations that are

related to the events. Topic model analysis has been applied to analyse large volumes of tweets, data related to Covid-19 in particular (Gupta et al. 2021; Koh and Liew 2020). While mapping the Twitter public dialogue surrounding the dramatic events relating to Dominic Cummings, the article also develops a systematic approach for choosing lexical sets that allows examination of various semantic fields in digital media data.

The use of hashtags

In keeping with the participatory platform on which they are used, hashtags serve both social and technical ends. Zappavigna (2018) describes hashtags as 'semiotic technology', designed, as Zhao and van Leeuwen (2014: 72) express it, 'for meaning-making [but with] meaning-making potentials built into the technology through various semiotic modes (e.g. layout, texture, colour, sound, etc.)'. Understanding hashtags therefore plays a crucial role in understanding how Twitter is used and understood, 'sensemaking habits that make use of a range of possible social interactions: including searches that utilize social and expertise networks or that may be done in shared social workspaces' (Evans and Chi 2008, 485). This is enabled by navigable links enacted by the use of the '#' symbol with a given text that allow users to access content marked by a specific hashtag and navigate a trail of interconnected hashtags. Moreover, hashtags serve both as recognisable signposts towards the discourse and produce shared meanings and associations between users, providing the conditions we associate with 'intertextuality' (Fairclough 1995), where popular forms and tropes are mobilised as part of the communicative exchange. Our analysis will be concerned with the extent to which related formations of intertextuality are also used to situate tweets within an established political and cultural discursive ecosystem. This work will therefore try to understand the manner in which hashtags operate within broader discourses around popular and political communication in order to express and construct ad hoc political publics.

Semantic fields

Identifying semantic fields is key to understanding hashtagged digital media discourse as it allows the extraction of those key words that both characterise and mark out online discussions and interventions. Computational identification of semantic fields can serve as a solution that addresses issues of using general metrics, such as the number of views and 'likes' in identifying items of digital text for analysis. In linguistics, the concept of the semantic field came to prominence through the work of Lyons (1977), who saw semantic fields in their social constructivist sense as crystallising and perpetuating beliefs and values. Later research has focused on semantic fields as key to the creation of metaphors, by re-ordering the relations of one field by mapping them on to the existing relations of another field. Brinton (2000, p.112) defines 'semantic field' or 'semantic domain' and relates this to the linguistic concept to hyponymy:

> Related to the concept of hyponymy, but more loosely defined, is the notion of a semantic field or domain. A semantic field denotes a segment of reality symbolized by a set of related words. The words in a semantic field share a common semantic property.

In their general sense, lexemes in a semantic field are not necessarily synonyms, but are all used to talk about the same general phenomenon. Synonymy requires lexemes to share a sememe or seme, but the semantic field is a larger area surrounding those. A meaning of a lexeme is dependent partly on its relation to other words in the same conceptual area. Types of semantic fields vary from culture to culture, but here we are using the term to refer to the lexemes found in our sample to explore positive and negative connotations. In particular, semantic fields are useful in helping us understand the interpretation of metaphors. Drawing on the work of Gannon and Czerniewska (1980), we can consider the example given in Table 1 for the lexeme CLOWN, which can be considered as contributing a different meaning to each of the sentences below. In each case, the lexeme under discussion is coherently replaceable by one of the others listed.

Table 1: Semantic fields and lexemes

A	It was	the clowns the lion tamer the dancing elephants	who entertained us between the prancing horses and the acrobats.
B	He was	a clown a stand-up comic a dancer	before he garnered awards for mime.
C	He was	a clown a liar a buffoon	who could not be trusted.

The exact nature of the 'semantic space' that our vocabulary divides up for us is not always easily formulated, as is the case of the colour spectrum beloved of early semioticians. Taking an example lexeme from Figure 4, we consider the nature of the semantic space that is divided up by the words that the description CLOWN relates to, we can identify three different semantic fields:

A: a circus act;

B: a form of performance artist

C: someone who can't be taken seriously.

From sentences A and B, we can see how the meaning of CLOWN shifts from association with a circus, to as one performance amongst many that can take place on a stage. However, if we move to sentence C, we will see how this changes again but here into a metaphor, taking with it some of those properties of comedic performance that belong to sentence A whilst also retaining some of the elements of 'circus' that include fecklessness and irresponsibility (as also found in the metaphor of 'running away to the circus'). It is when a lexeme is used in conjunction with other lexemes that we can identify most clearly its meaning in context. In the case of CLOWN, it is generally found as a metaphor that is

associated with negative judgement, particular applied in a context of government and political policy.

Despite their significance, observing semantic fields within the context of social media can be challenging for several reasons. First, the availability of large volumes of data via Application Programming Interfaces (API) demands techniques to automate cleaning and analysing datasets. Second, such techniques may cause decontextualization as data is taken out of context, particularly within big data analysis (Boyd and Crawford 2012). Therefore, computational methods that can identify associations among words are needed in order to identify semantic fields in relatively large samples. Topic model analysis is an increasingly popular method used to identify topics in text data, such as large samples of tweets (e.g., Gupta et al. 2021). This method uses probabilistic models to identify groups of words that can characterise topics within a corpus. For instance, Hou et al. (2021) showed that words such as 'disinfection', 'contact', 'aerosol' and 'droplet' relate to the route of transmission while words including 'epidemic', 'China', 'spread', 'global' indicate global attention to the pandemic. In our sample, we are able to place lexemes into an appropriate semantic field because of the contexts in which we find them. For example, we will see from the metaphor that 'clown' offers a metaphor of negative judgement rather than a literal reference to a circus act because of the surrounding text in the Tweet and its place within a political network. It is therefore at the analytic stage that we identify the significance of these words in the overall discourse. In this approach, the interpretation of the topics and groups of words that represent each topic are therefore informed by our understanding of those semantic fields that give them context and political meaning.

Gathering the Data

The tweets we examine are drawn from discussion around the events outlined below. These are chosen to help us explore our interest in personalisation and scandal, and are occasioned by Cummings' conduct during lockdown. While Covid-19 and its management was a prevalent issue in social media in general, the focus and topicality of discussion was driven by political circumstances. Given this context of a global pandemic, UK politics saw a dramatic chain of narratives that generated public reaction and required government

response and subsequent political action. While acknowledging that each stage is composed of a variety of communicative and environmental developments, we identify this series of 'media events' as related sets of activities that are expressed and discussed primarily through their mediation (Boorstin 1963; Couldry et al. 2010). The three events we focus on relate to the activities of the above-discussed Dominic Cummings:

1. The public exposure of a trip by Cummings to Durham in March 2020, contrary to current lockdown rules (BBCNews 2020b, 2020a);

2. Cummings' departure from Downing Street in November 2020 (Guardian 2020a), and;

3. Cummings' retaliatory communications on Boris Johnson, over April and May 2021 (Guardian 2021).

Our data collection strategy is focused on observing how Twitter users discussed the above events using #DominicCummings, while running a parallel analysis of content related to Boris Johnson. Based around these events, data was collected at three different points between May 2020 and May 2021 using the Twitter search API. After the initial trip and its exposure, captured in the dates from May 26 to 27 and November 7 to 19, 2020 and from April 17 to 29 and May 21 to 27 in the following year. Table 2 specifies the time periods covered by each sample. It should be noted that sample size and the starting date was not uniform across different datasets as they were captured when the hashtags were heavily used and samples returned by Twitter API vary across searches.

Twitter hashtags #DominicCummings and #BorisJohnson started trending again on Twitter when media reported on November 13, 2020 (Guardian 2020a) that Boris Johnson had fired Cummings. Accordingly, a second pair of datasets were obtained in November 2020 to cover Cummings' departure from Number 10. Subsequently, over April and March 2021, Dominic Cummings launched a series of statements questioning Boris Johnson's integrity and competence (BBCNews 2021). Then on May 26, Cummings appeared before a parliamentary committee as a witness (Committees.parliament.uk 2021). In the seven-hour

long hearing, Cummings directed a series of attacks against Johnson as well as the incumbent Health Secretary Matt Hancock (Guardian 2021). In order to capture the broad public discourse surrounding Cummings' statements and committee appearance as it unfolded on Twitter, we collected four more datasets representing #DominicCummings and #BorisJohnson covering Twitter activity from May 24 to 27. The final sample (Table 2) amounted to eight datasets which included 38,326 original tweets after removing retweets. Sample size and the duration covered by each sample depended on Twitter API rate limits as well as the intensity of user engagement within each hashtag.

Table 2: Sample

Hashtag	*N*	Period/Date
#DominicCummings	1,822	May 27, 2020
#LiaisonCommittee	13,008	May 27, 2020
#DominicCummings	1,737	Nov 13-19, 2020
#BorisJohnson	6,217	Nov 07-14, 2020
#Johnsonmustgo	3,687	April 17-25, 2021
#DominicCummings	1,063	April 21-29, 2021
#BorisJohnson	3,069	May 24-27, 2021
#DominicCummings	7,723	May 21-27, 2021

Analytical Approach

Topics were identified based on a series of topic models using Latent Dirichlet Allocation (LDA) (Blei et al.2003). LDA is a generative probabilistic model used to describe the content of a given text corpus. This approach examines text documents and identifies latent topics representing the corpus. Each topic in the corpus is characterised by a set of lexemes, the discursive significance of which we explore in the analysis. Topic model analysis was conducted in three steps. First, we ran a series of LDA based topic models to

extract topics from each dataset. For analysis purposes, each Tweet was considered as a document. The R textmineR package allows the calculation of a geometric interpretation of R^2 (a coefficient of determination), which serves a measure of goodness-of-fit for topic models. A minimum threshold for R^2 was set at 0.10 as it indicates reasonable ability of the model to explain variability in data. Initial analysis showed that, in general, a *K* value of 100 for each model results in a R^2 value above .10. Jones (2019) observed that the R^2 value increases with the estimated number of topics. However, in our data *K* values above 100 did not yield a substantial increase in R^2.

Despite the popularity of topic model analysis, there is a lack of work that uses a systematic approach to select topics extracted by topic modelling algorithms for interpretation, in particular in political discourse. To address this, this study uses an estimate of coherence for selecting topics for interpretation. Coherence metric provided by textmineR calculates probabilistic coherence of a topic that approximates its semantic coherence. This measure calculates P(b|a) - P(b), where {a} is more probable than {b} in the topic for each pair of words {a, b} in the top M words in a topic (Jones 2017). Coherence estimates show how words within a topic are associated and help distinguish between semantically interpretable topics and topics that are outcomes of statistical inference (Cristian 2020). We selected four topics with the highest coherence values for each sample. While we expand on these below, they can be summarised as: 1) civic duty 2) effectiveness 3) corruption, and 4) internal government issues. Informed by our use of semantic fields, the most frequently used words in each topic were used to identify specific examples for interpretation. Probabilistic prevalence was also calculated and it was normalised to a sum of 100. Further, Pearson's Correlation Co-efficient was calculated to examine the relationship between coherence and prevalence.

Table 3: Model Fit (R^2 Statistics)

Hashtag	R^2
#DominicCummings (May 2020)	0.397
#LiaisonCommittee (May 2020)	0.102
#DominicCummings (Nov 2020)	0.204

#BorisJohnson (Nov 2020)	0.121
#Johnsonmustgo (April 2021)	0.393
#DominicCummings (April 2021)	0.145
#BorisJohnson (May 2021)	0.175
#DominicCummings (May 2021)	0.105

The coefficient of determination (Jones 2019) is a goodness-of-fit measure that can help assess whether LDA models should capture variability in data. Using this standard metric for assessing results of topic models, the coefficient shows overall quality of topic models and indicates whether the outcomes can be used to make valid claims about data. Jones notes that the metric is easy to interpret, allows cross comparison of corpora, and may appeal to lay audiences as it resembles general linear regression. Table 3 shows R^2 values for each topic. These results are convincing as R^2 values were higher than 0.10 for all the models. This suggested that the topic models can explain variability in each dataset to a considerable extent. In particular, two datasets had considerably high R^2 values (#DominicCummings, May 2020: $R^{2=}$ 0.397; #Johnsonmustgo, April 2021, $R^{2=}$0.393)

Coherence and Prevalence of Topics

Table 4: Descriptive Statistics (Coherence and Prevalence)

Hashtag	Coherence			Prevalence		
	Min	Max	Median	Min	Max	Median
#DominicCummings (May 2020)	0.006	0.373	0.075	0.765	2.209	0.953
#LiaisonCommittee (May 2020)	0.000	0.297	0.040	0.770	1.821	0.965
#DominicCummings (Nov 2020)	0.014	0.596	0.093	0.775	2.121	0.950
#BorisJohnson (Nov 2020)	0.000	0.524	0.055	0.757	1.731	0.951
#Johnsonmustgo (April 2021)	0.000	0.534	0.070	0.689	6.250	0.858
#DominicCummings (April 2021)	0.000	0.714	0.096	0.790	2.580	0.925

#BorisJohnson (May 2021)	0.003	0.863	0.063	0.749	2.113	0.944
#DominicCummings (May 2021)	0.006	0.354	0.045	0.808	1.823	0.959

Table 5: Correlations

Hashtag	Correlation	*p*
#DominicCummings (May 2020)	0.330	0.000
#LiaisonCommittee (May 2020)	0.350	0.000
#DominicCummings (Nov 2020)	0.290	0.003
#BorisJohnson (Nov 2020)	0.290	0.003
#Johnsonmustgo (April 2021)	0.510	0.000
#DominicCummings (April 2021)	0.210	0.035
#BorisJohnson (May 2021)	0.110	0.270
#DominicCummings (May 2021)	0.280	0.005

Table 4 shows minimum, maximum and median values for coherence and prevalence scores. Although the hashtag #BorisJohnson representing May 2021 and #DominicCummings obtained in April 2021 had topics with slightly higher coherence values than other datasets, the median values indicated that the datasets do not highly differ from each other in terms of coherence of topics. The median prevalence scores were similar across datasets. However, #Johnsonmustgo (April 2021) constructs a topic with considerably higher maximum prevalence value (6.25) than others. Table 5 provides correlations between coherence and prevalence values for each dataset. The results showed that correlations between coherence and prevalence values were significant for all except two hashtags (#DominicCummings- April 2021 and #BorisJohnson- May 2021). This provides evidence to demonstrate that topics that are semantically more coherent than others are prevalent to a significant degree in our data, which further confirms the use of coherence as a basis to select topics for interpretation.

Discussion

Four topics with high coherence values were selected from each hashtag for analysis: civic duty and integrity amongst politicians; effectiveness of government decisions; corrupt behaviour in politics; and internal issues within government. Table 6 provides ten frequently used words across these topics. From an overall viewpoint, the topics indicate a digital public that is highly critical of Johnson and the government.

Table 6: Topics with High Coherence Values

Hashtag	Coherence Value	Words Representing LDA Topics
#DominicCummings (May 2020)	0.373	mp, dhesi, singh, tanmanjeet, cummings, everything, become, unaccountable, fighting, symbol
	0.349	civic, duty, cummings, hancock, isolate, self, says, follow, self, now
	0.314	press, conference, garden, rose, questions, pm, watching, know, leading, bullshit
	0.309	minister, prime, cummings, boris, live, lying, country, cabinet, advisor, abide
#LiaisonCommittee (May2020)	0.297	prime, minister, uk, boris, actual, become, country, clown, ladies, funny
	0.284	car, crash, committee, tv, live, absolute, wreck, watching, slow, eyesight
	0.262	trace, track, committee, amp, system, contact, trust, download, place, anyone, nhs
	0.258	yvette, cooper, go, absolutely, love, take, absolutely, hero, bow, girl
#DominicCummings (Nov 2020)	0.499	patel, priti, report, bullying, chance, johnson, bbc, breakfast, acting, advising
	0.448	puppet, image, spitting, master, cummnings, pick, used, fired, show, acting

	0.388	lee, dom, cain, never, chief, still, staff, going, strings, charge
	0.353	princess, nuts, carrie, wonder, westminster, whitehall, next, boris, acting, afraid
#BorisJohnson (Nov 2020)	0.524	boris, royal, family, echr, house, commons, trial, conservatives, case, solicitors
	0.386	prime, minister, read, today, ministers, plans, statement, majority, black, power
	0.314	downing, street, year, leave, end, christmas, adviser, senior, infighting, post
	0.220	government, law, international, lords, break, johnsons, plan, internalmarketbill, defeat, house,
#Johnsonmustgo (April 2021)	0.534	jennie, avfc, forasalles, juliette, jennie, jklive, lovely, writer, masumiyet, nffc
	0.482	fucking, disgrace, absolute, thought, make, abysmal, accept, accounts, acted, integrity
	0.385	downing, street, will, corruption, back, like, take, pm, current, whenever
	0.333	pandemic, cobra, meetings, time, lives, missed, destroyed, lost, football, meeting
#DominicCummings (April 2021)	0.714	secrets, official, act, sign, dont, anymore, commons, piers, sunak, boris
	0.647	blaming, editors, newspaper, tories, leaks, acceptable, accident, admit, affair, aid
	0.61	herd, immunity, short, wanted, difference, something, says, covid, acceptable, accident
	0.556	pm, civil, servant, top, cummings, cabinet, flat, review, secretary, lockdown
#BorisJohnson (May 2021)	0.511	downing, street, tory, conservatives, mess, led, utter, distracted, dysfunctional, shambolic
	0.452	fellow, read, many, thanks, heard, please, blog, dear, post, scheme
	0.451	bodies, pile, died, people, high, thousands, boris, economy, conservatives, carrie

	0.428	herd, immunity, plan, always, lockdown, cummings, pm, confirmed, came, denied
#DominicCummings (May 2021)	0.328	plan, immunity, herd, march, government, lockdown, covid, strategy, pandemic, place
	0.285	castle, barnard, cummings, trip, go, lockdown, govt, us, bond, crazy
	0.278	care, homes, people, covid, back, home, sent, around, tested, elderly
	0.265	downing, street, public, failed, government, needed, utter, parliament, indictment, farce

Our data shows that words that indicate negative sentiments range across the topics. Corresponding with particular discursive fields, some of these are drawn from a political lexicon, such as 'unaccountable', 'infighting', 'corruption', and 'failed'. Others call upon a popular, conversational lexicon, including 'bullshit', 'lying', 'clown', 'wreck', 'puppet', "nuts", 'destroyed', 'mess' and 'farce'. Hinted at by 'nuts', still others occupy an informal psychotherapy frame: 'dysfunctional' and 'crazy'. In a way we will explore in more detail below, this has implications for the tenor of the discussion. Consistency of negative sentiments across samples show that the hashtags have acted as an organising 'technology' (Zappavigna 2018) for ad hoc critical publics to emerge in response to each event. However, since each of these topics constitutes a distinct thread within the overall theme, the following sections will examine them in turn, in order to reveal the discrete patterns of colocation in each.

Joining the Fray: Conversationalisation and Intertextuality

The most coherent topic in #DominicCummings (May 2020) (coherence value: 0.373) showed reactions to tweets sent by the Opposition, especially using Twitter functionality to quote specific tweets. For instance, our sample included a quote Tweet that with the text 'The quicker the better before someone gets hurt' in reaction to the following Tweet sent by Labour Party politician Tanmanjeet Singh Dhesi (Figure 1). As well as typifying what Krzyżanowski (2018) identifies as the imperative to 'conversation' that Twitter imposes, the inclusive pronoun 'we' implicitly aligns the Twitter public with Dhesi's interpretation of real-

world consequences. The frequency with which this Tweet is quoted positions Dhesi's contribution at the centre of the discussion, helping define and reflect those coherence values that characterise the topic overall.

Figure 1: Tanmanjeet Singh Dhesi's Tweet

The success of this tweet in contributing to the overall discourse can be partially attributed to the institutional position of Dhesi as a member of the opposition Labour Party, and the holder of a blue tick. Every bit as much, however, the purchase of the Tweet can be explained by the adroit use of antistrephon, quoting Cumming's own words against him. This is manifest firstly in the ventriloquisation of Cummings' broadly populist field in defining his foes as the reactionary forces of the 'unaccountable, unelected establishment elite'. More directly though, the Tweet cites and redirects Cummings' Brexit slogan to 'take back control'. Indeed, as seen in Table 4, the colocation of 'take' and 'back' has become associated with more general attacks on government performance in the hashtag #Johnsonmustgo. Dominic Cummings occupied a prominent role in this government and previous associated controversies, and is the individual to whom criticism is directed, and we will look to the hashtag associated with him later. Second to Dominic Cummings, as we can see in Table 4, the hashtag for #LiaisonCommittee is the most prominent mechanism for gathering contributions confronting the democratic gap described above by holding Cummings to account, this time in a manner that draws upon the proceedings' institutionally sanctioned lexical field, and enables the tweets themselves to draw upon a wider expressive range, while remaining party to the emergent public.

Figure 2 shows a Tweet ostensibly directed towards the Prime Minister, that exemplifies the problematic democratic legitimacy of Cummings discussed above. It lauds the intervention of Labour MP Yvette Cooper, in a manner that flouts Grice's maxim of quantity by providing an unnecessarily precise timing for Cooper's intervention; outwardly highlighting the exceptional opportunity for transparency afforded by the event – Johnson can be disposed of in short order, when the chance arises – while adding the imperative that Cummings is the one that holds real power ('clearly the real Prime Minister'). It also engages in a form of conversationalisation (Fairclough 1992; Krzyżanowski 2018), by inviting the reader's assent through the phrasing of the assertion of Cummings' status over Johnson as a rhetorical question ('Can we stop calling…').

Similar patterns of conversationalisation dominate the two tweets given in Figure 3, addressed to Cummings and Johnson in turn. Both tweets in Figure 3 include expressive punctuation marks, including an exclamation mark in the first and scare quotes and elliptical dots in the second, along with the platform-specific informal emotive marker of the crying emoji. In the first, we see the mock-exclamation 'oh god' performing spontaneous emotion, along with examples of the high-frequency phrasing of 'car crash' (see Table 4). The second Tweet also sees the hashtag accompanied by a list of negative lexemes, which are then landed on their target by the mock-revelatory sentence fragment 'And this is our prime minister'. The crying emoji is followed by the figure detailing the approximate number of deaths, the horror of which is highlighted by the use of block capitals for DEAD, with its associations with the raised voice.

Figure 2: A Tweet that Appreciates Yvette Cooper

Figure 3: Conversationalisation

(a)

(b)

The two tweets given in Figure 4 also demonstrate in different ways how the Tweets anchor the hashtag within themes of wrongdoing, appropriate to engagement with and construction of political scandal. The first expresses criticism of the government's handling of the pandemic whilst complementing the Opposition MP, Yvette Cooper. The lexemes attached to Cooper's actions conjure up metaphors of precisely-directed violence – 'skewer', 'nailed' – the physical agency of which contrasts with those lexemes attached to Johnson, whose stewardship is defined in the negative descriptive nouns 'hypocrisy', 'contempt' and 'scandal'. We see similarly negative terms applied in the second Tweet, including the amplifying phrase 'bare face lying' (another example of the maxim of quantity sacrificed in the name of negatively-charged descriptive eloquence). However, prefiguring the intertextuality we will discuss in more detail later, this Tweet also invites those publics concerned in broader moral scandals around the abuse of power by including a hashtag relating to high-profile criminal Jeffrey Epstein ('#jeffreyepstein').

Figure 4: Wrongdoing

(a)

(b)

We see various ways of situating the tweets within the broad spectrum of political culture. On the one hand, the hashtag #LiaisonCommitee dominated in organising these critical network publics, and was associated with hashtags corresponding to the main players, #BorisJohnson and particularly #DominicCummings. These are emphatic in using hashtags to occupy a conventional political lexicon, gathering discursive clusters of public around the names of the political figures involved. However, as the following Tweet's use of #Dominic Cummings shows (see Figure 5) other uses of the #DominicCummings hashtag draw upon a recognisable intertextual correspondence between politics and a wider popular and literary culture. Whereas the above Tweet called upon a shared understanding of the recent news agenda – specifically the Epstein case – this Tweet produces an involved intertextual parallel with invoking the venality of the pigs in George Orwell's political parable *Animal Farm*.

Figure 5: Intertextuality

Semantic fields and intertextuality: the use of 'Ladies and Gentlemen'

It is apparent that the appropriation of semantic fields is complex and tactical, and offer a variety of ways of representing the political. Earlier, we spoke of an increased

emphasis on personalisation in politics, focussed here on the main protagonists Cummings and Johnson, manifest and organised using their names as hashtags. However, we can draw upon semantic fields and their scope for intertextuality to reveal more subtle ways in which the individual is foregrounded in the text of the tweets. Alongside expected items such as the formal designation 'Prime Minister' and the above-discussed description 'clown', the item 'ladies' enjoys a frequency of 0.297 in association with the hashtag #laisoncommittee (Figure 4). The frequency of 'ladies' is perhaps unexpected and warrants closer examination. In this, we can see that it belongs to the collocation 'ladies and gentlemen'. Figure 6 shows four examples of the item in use.

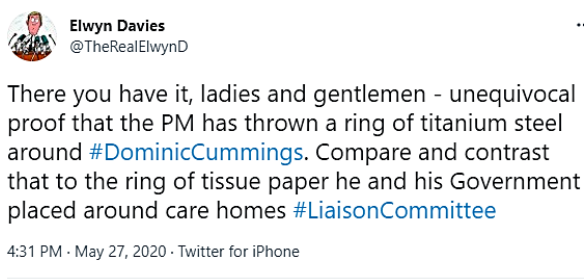
Figure 6: The Use of "Ladies and Gentlemen"

(a)

(b)

(c)

(d)



The conventional pairing of 'ladies and gentlemen' has strong associations with variety theatre, as a manner of addressing the audience to introduce the next act. All are presented as ritualised introductions for Boris Johnston. In none of the examples is Johnston named, but instead is either given the institutional title of Prime Minister or the relational role of 'leader'. This performed hyper-formality thereby imposes the semantic field of popular theatre into politics, and positions the Prime Minster as akin to a variety act. In terms of its broader utility in the popular field, we usually find 'ladies and gentlemen' used to prefigure a significant reveal, here foregrounding an association between the Prime Minister's performance and theatrical farce. Indeed, this prominence of an intertextual comedic discourse is still more firmly anchored in the use of a meme from BBC satire *The Thick of It*, showing world-weary Minister Peter Mannion (played by Roger Allam) reverting to everyday pleasures to alleviate his weary exasperation ('I'm bored of this, I'm going for a Twix').

Hashtags and Punning: Creative Expansions

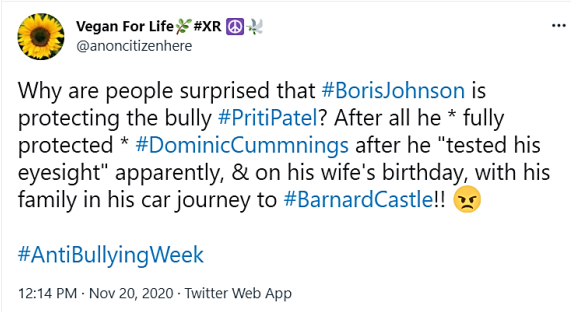
On November 13 Dominic Cummings' resignation alter the conditions of the Twitter exchanges considerably, with a sharper focus on corruption and behaviour, including from elsewhere in the political public sphere. This coincided with a report that found the then-Home Secretary Priti Patel had bullied staff. Figure 7 shows three tweets that discuss the report's findings.

Figure 7: Tweets about Priti Patel

(a)

(b)

(c)



At this point, the most coherent topic in #DominicCummings (Nov 2020, coherence value: 0.499) includes the lexemes ‘patel’, ‘priti’, ‘report’, and ‘bullying’. tweets given in Figure 7 show how users refer to Priti Patel’s behaviour within a public formed around incidents involving Dominic Cummings. The examples show strategic use language beyond the hashtags, advocating Prime Ministerial action against Patel. In the first example (Figure 7c), the user positions the hashtags #BorisJohnson, #PritiPatel, #DominicCummings and #BarnardCastle in a way that they help form a coherent message, using the hashtags to cohere the various interested users as part of an inward and outward-facing metadiscourse of political publicness (Zappavigna 2018). As the examples show, the homophonic potential of Priti Patel’s name – where it puns with ‘pretty’ – is exploited by users (Figure 7 a and b). While ‘pretty’ can be taken to ascribe attractiveness, here an alternative meaning is used to amplify a selection of negative adjectives – #PritiNasty, #PritiAwful – each playing on the intentionality and currency ordinarily associated with hashtags.

However, it is important to note that Patel’s introduction does not alter the topic, but rather broadens its reach and multiplies its implications. This third Tweet (Figure 7c) also uses the hashtag #AntiBullyingWeek, but linking to the failure of Johnson to act on an earlier transgression by Cummings. In this Tweet, we again see the use of conversational strategies, with the opening sentence phrased as a question. The follow up then uses the conventional print strategy of adding emphasis with asterisk marks; in this case, foregrounding Johnson’s failure to condemn Cummings’ actions. The Tweet then goes on to cite the widely-derided explanation by Cummings that he was ‘testing his eyesight’, using the disalignment tactic of scare quotes to stress the contestability of Cummings’ account; an incredulity emphasised by the use of ‘apparently’ before further details of the escapade are

given. Thus the Tweet asserts an overarching frame around political scandal, combining the recklessness of Cummings' actions, Johnson's lack of criticism for them, and the adjudged bullying by Patel.

Towards Shared Creative Descriptive Practices amongst Publics

We have pointed to some of the creative uses of language to be found amongst those publics gathered by relevant hashtags. While the networks surrounding these tweets draw upon and form a combative relationship with government in general, they also play out within a discursive environment informed by shared affinities and understanding, that may be confidently deployed in creative descriptive practices. The following Tweet (Figure 8a) uses the derogatory nickname 'Princess Nut Nuts' for Carrie Symonds, then-fiancée of Boris Johnson. The nickname had been circulating in the media for several months, initially in connection to a story about Symonds' alleged over-reaction to a negative news story concerning the family dog. This earlier story is reflected in tweets mobilising this nickname, with this user exploiting its genealogy to pun on the metaphor 'cat fight' (meaning a petty squabble) with the outwardly coherence-breaching in-joke '& dog'.

'Nut Nuts' is used in a different way in Figure 8c. In incorporating the nickname into the colloquial phrase to ascribe mental instability. Without naming the target explicitly, this again requires the understanding of the participating public that 'Nut Nuts' refers to Carrie Symonds. As such, it is an intertextual reference where the interpretation is open only to those who are already familiar with this nickname, and so acts as an in-group strategy.

However, while a common well of political and cultural references can act as the binding agent for such ad hoc publics, the true extent of this shared know-how has to be treated with caution. The tweet given in Figure 8b also uses this nickname 'Princess Nut Nuts'. While the tweet tags Carrie Symonds, the official Twitter page of the Prime Minister's Office (@10DowningStreet), as well as Johnson's account (@BorisJohnson), the tweet draws on a complex metaphor relating to horror film *Se7en,* where the narrative climax involves

the head of a character delivered in a box. However, assuming that this intertextual reference might not be accessible to everyone, a separate tweet is embedded that details the cast and director to contextualise the otherwise-oblique reference.

Conclusion

While seeking new ways to comprehend this in the white heat of social media, this article is concerned with the distribution of discursive and political power. In the management and responses to political scandal there, we describe a dialogic exchange, where government activities designed to guide the media agenda produce an agonistic social media response. In the context of the personalisation of politics and the power this accords, the agency of Cummings increases as we move from one event to the next, where any 'pre-planned' quality is inflated (Dayan and Katz 1992: 9). This escalates from the unwanted media exposure of 1. (Cummings' exposed trip to Durham), through the media-choreographed departure of 2. (Cummings leaving his government post, including exiting past a phalanx of waiting cameras), to the strategic public statements of 3 (Cummings' post-departure statements on government behaviour). Yet throughout, it is apparent that the affordances of social media enable an equal escalation of critical response.

The critical nature of narratives identified by topics models show that Twitter has served as a platform for public scrutiny. In particular, the key themes reflected by the most coherent topics, such as civic duty, behaviour and integrity of politicians, and effectiveness of decisions made by the government show that such scrutiny sustains across events. Hashtags, as affordances, serve as digital markers that assemble such scrutiny into interconnected publics.

Discourse analysis of the content of tweets has shown a high level of intertextuality. Much of this foregrounds wit and humour in a manner designed to mitigate the seriousness of the situation or highlight its occasional absurdity. These discursive practices also serve as a common currency of critical exchange that gathers Twitter users around political

controversies that are not subject to conventional forms of accountability. On the other hand, analysis does also indicate possible 'echo chambers' in which these tweets can only be fully understood by like-minded users with similar political capital. That the tweets in our sample all show an overwhelmingly negative attitude towards the government (with additional strains of misogyny in the case of the Prime Minister's spouse) could be said to underline this observation.

Attention to communicative tactics such as intertextuality, allied with what Krzyżanowski (2018) identifies as the contraints and possibilies of conversation, enables critical discourse analysis to make effective use of the results of a software-produced survey. The method suggested in this study can serve as a systematic basis for choosing individual utterances for close reading of content. This avoids the limitations of drawing samples on the basis of vanity metrics such as the number of views and Twitter 'likes'. As we have shown, the combination of computation and semantic fields has allowed us to go beyond the usual small sample conclusions that can be reached in conventional linguistics to produce more informed analysis: responding to challenges of selectivity. In doing this, we have also been able to offer some optimism that dissatisfaction with government's action and answerability can produce a creative and dynamic use of Twitter's conventions and affordances.

References

Abidin, Crystal, and Jing Zeng. 2020. "Feeling Asian Together: Coping with #COVIDRacism on Subtle Asian Traits." *Social Media and Society* 6 (3). https://doi.org/10.1177/2056305120948223.

Babvey, Pouria, Fernanda Capela, Claudia Cappa, Carlo Lipizzi, Nicole Petrowski, and Jose Ramirez-Marquez. 2020. "Using Social Media Data for Assessing Children's Exposure to Violence during the COVID-19 Pandemic." *Child Abuse and Neglect*, no. September: 104747. https://doi.org/10.1016/j.chiabu.2020.104747.

BBCNews. 2020a. "Coronavirus: I Don't Regret What I Did, Says Dominic Cummings." https://www.bbc.co.uk/news/uk-politics-52800595.

———. 2020b. “Dominic Cummings: Fact-Checking the Row.” https://www.bbc.co.uk/news/52828076.

———. 2021. “Dominic Cummings Launches Attack on Boris Johnson’s Integrity.” https://www.bbc.co.uk/news/uk-politics-56863547.

Blei, David M. 2012. “Probabilistic Topic Models.” *Communications of the ACM* 55 (4): 77–84.

Blei, David M, Andrew Y Ng, and Michael I Jordan. 2003. “Latent Dirichlet Allocation.” *Journal of Machine Learning Research* 3: 993–1022.

Bode, Leticia, and Emily K. Vraga. 2021. “Correction Experiences on Social Media during COVID-19.” *Social Media and Society* 7 (2). https://doi.org/10.1177/20563051211008829.

Boorstin, Daniel J. 1963. *The Image, or What Happened to the American Dream.* New York. Atheneum.

Boulianne, Shelley, Karolina Koc-Michalska and Bruce Bimber. 2020. “Right-wing populism, social media and echo chambers in Western democracies.” *New Media and Society* 22 (4): 585-727. https://journals.sagepub.com/doi/epub/10.1177/1461444819893983

Boyd, Danah, and Kate Crawford. 2012. “Critical Questions for Big Data.” *Information Communication & Society* 15 (5): 662–79.

Brinton, Laurel J. 2000. *The Structure of Modern English: A Linguistic Introduction*. Amsterdam: John Benjamins.

Bruns, Axel. 2008. “Life beyond the Public Sphere: Towards a Networked Model for Political Deliberation.” *Information Polity* 13: 65–79.

Bruns, Axel, and Jean Burgess. 2011. “The Use of Twitter Hashtags in the Formation of Ad Hoc Publics.” In *Paper Presented at the 6th European Consortium for Political Research General Conference*. University of Iceland, Reykjavik.

Committees.parliament.uk. 2021. “Oral Evidence: Coronavirus: Lessons Learnt, HC 95.” 2021. https://committees.parliament.uk/oralevidence/2249/html/.

Couldry, Nick., Andreas Hepp and Friedrich Krotz. eds. 2000. *Media Events in a Global Age*. London: Routledge.

Cristian, Joe. 2020. "Topic Modeling LDA Using TextmineR and Tidytext." https://rstudio-pubs-static.s3.amazonaws.com/643113_f2daf42a1919425194df1b50fe8bdbaa.html.

Cummings, Dominic. 2020. "'Two hands are a lot' — we're hiring data scientists, project managers, policy experts, assorted weirdos…", January 2, https://dominiccummings.com/2020/01/02/two-hands-are-a-lot-were-hiring-data-scientists-project-managers-policy-experts-assorted-weirdos/

D'heer, Evelien, and Pieter Verdegem. 2014. "Conversations about the Elections on Twitter: Towards a Structural Understanding of Twitter's Relation with the Political and the Media Field." *European Journal of Communication* 29 (6): 720–34. https://doi.org/10.1177/0267323114544866.

Dahlgren, Peter. 2005. "The Internet, Public Spheres, and Political Communication: Dispersion and Deliberation." *Political Communication* 22 (2): 147–62. https://doi.org/10.1080/10584600590933160.

Dayan, Daniel and Elihu Katz. 1992. *Media Events: the Live Broadcasting of History*. Cambridge, MA: Harvard University Press.

Drake, Philip and Michael Higgins. 2006. "I'm a celebrity, get me into politics", in Su Holmes and Sean Redmond (eds) *Framing Celebrity: New Directions in Celebrity Culture*. London: Routledge, pp. 87-100.

Evans, Brynn M., and Ed H. Chi. 2008. "Towards a Model of Understanding Social Search." *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*, 485–94. https://doi.org/10.1145/1460563.1460641.

Fairclough, Norman. 1992. *Discourse and Social Change*. Cambridge: Polity.

Fairclough, Norman. 1995. *Media Discourse*. London: Arnold.

Fang, Hua A., Hunter Boudreau, Saad Khan, Nikhi P. Singh, Soroush Rais-Bahrami, Timothy W. King, Britney Corey, and Herbert Chen. 2021. "An Evaluation of Social Media Utilization by General Surgery Programs in the COVID-19 Era." *The American Journal of*

Surgery, no. xxxx. https://doi.org/10.1016/j.amjsurg.2021.04.014.

Freiling, Isabelle, Nicole M. Krause, Dietram A. Scheufele, and Dominique Brossard. 2021. "Believing and Sharing Misinformation, Fact-Checks, and Accurate Information on Social Media: The Role of Anxiety during COVID-19." *New Media and Society*. https://doi.org/10.1177/14614448211011451.

Garland, Ruth, 2018. "Is post-truth another word for political spin or a radical departure from it? Evidence from behind the scenes in UK government communications, 1997-2015." *International Journal of Media and Cultural Politics* 14 (3): 333-50. https://www.ingentaconnect.com/content/intellect/mcp/2018/00000014/00000003/art00005

Gannon, Peter, and Pam Czerniewska. 1980. *Using Linguistics: An Educational Focus*. London: Edward Arnold.

Guardian. 2020a. "Boris Johnson Boots out Top Adviser Dominic Cummings." Guardian, The. https://www.theguardian.com/politics/2020/nov/13/dominic-cummings-has-already-left-job-at-no-10-reports.

———. 2020b. "'Did You See Evidence?': Meg Hillier and Yvette Cooper Question Johnson on Cummings - Video." https://www.theguardian.com/politics/video/2020/may/27/did-you-see-evidence-meg-hillier-and-yvette-cooper-question-johnson-on-cummings-video.

———. 2021. "Cummings Lambasts Johnson in Damning Account of Covid Crisis." https://www.theguardian.com/politics/2021/may/26/boris-johnson-is-unfit-to-be-prime-minister-says-dominic-cummings.

Gupta, Marichi, Aditya Bansal, Bhav Jain, Jillian Rochelle, Atharv Oak, and Mohammad S. Jalali. 2021. "Whether the Weather Will Help Us Weather the COVID-19 Pandemic: Using Machine Learning to Measure Twitter Users' Perceptions." *International Journal of Medical Informatics* 145 (November 2020): 104340. https://doi.org/10.1016/j.ijmedinf.2020.104340.

Higgins, Michael. 2019. "The Donald: celebrity, authenticity and accountability", in Catherine Happer, Andrew Hoskins and William Merrin (ed) *Trump's Media War*.

Basingstoke: Palgrave, pp. 129-141.

Higgins, Michael and Angela Smith. 2014. "Disaffiliation and belonging: Twitter and its agonistic publics", *Sociologia e Politiche Sociali* 17(2): 77-89.

Honeyman, Victoria. 2022. "The Johnson factor: British national identity and Boris Johnson." British Politics https://link.springer.com/article/10.1057/s41293-022-00211-0

House, The. 2020. "Inside the Liaison Committee as Senior MPs Prepare to Grill Boris Johnson on Coronavirus and Dominic Cummings." https://www.politicshome.com/thehouse/article/liaison-committee.

Jones, Nick. 2000. *Sultans of Spin*, London: Gollancz.

Jones, Tommy. 2017. "Question: Which Coherence Measure Used? Useful for Topic Model Validation?" Https://Github.Com/TommyJones. https://github.com/TommyJones/textmineR/issues/35.

———. 2019. "A Coefficient of Determination for Probabilistic Topic Models." http://arxiv.org/abs/1911.11061.

Koh, Jing Xuan, and Tau Ming Liew. 2020. "How Loneliness Is Talked about in Social Media during COVID-19 Pandemic: Text Mining of 4,492 Twitter Feeds." *Journal of Psychiatric Research*, no. November. https://doi.org/10.1016/j.jpsychires.2020.11.015.

Krzyżanowski, Michal. 2018. "Social media in/and the politics of the European Union: politico-organizational communication, institutional cultures and self-inflicted elitism." *Journal of Language and Politics* 17 (2): 281-304. https://benjamins.com/catalog/jlp.18001.krz.

Lyons, John. 1977. *Semantics.* Cambridge: Cambridge University Press.

Moffitt, Benjamin. 2016. *The Global Rise of Populism: Performance, Political Style, and Representation.* Stanford: Stanford University Press.

Schneiker, Andrea. 2019. "Telling the Story of the Superhero and the Anti-Politician as President: Donald Trump's Branding on Twitter." *Political Studies Review* 17 (3): 210–23. https://doi.org/10.1177/1478929918807712.

Smith, Angela and Michael Higgins. 2020. "Tough guys and little rocket men: @RealDonaldTrump's Twitter feed and the normalisation of banal masculinity." *Social Semiotics* 30 (4): 547-562. https://www.tandfonline.com/doi/abs/10.1080/10350330.2020.1763657

Stolee, Galen and Steve Caton. 2018. "Twitter, Trump, and the base: a shift to a new form of presidential talk?" *Signs and Society* 6 (1): 147-165. https://www.journals.uchicago.edu/doi/epdf/10.1086/694755

Strange, Louis. 2022. "Covid-19 and public responsibility: a multi-modal critical discourse analysis of blaming the public during the UK's third wave." *Linguistic Landscape* 8 (2-3): 168-183. https://www.jbe-platform.com/content/journals/10.1075/ll.21034.str.

Thompson, John B. 2000. *Political Scandal: Power and Visibility in the Media Age*. Cambridge: Polity.

Wheeler, Mark. 2013. *Celebrity Politics*. Cambridge: Polity.

Wodak, Ruth and Michael Meyer. 2016. "Critical discourse studies: history, agenda, theory and methodology", in Ruth Wodak and Michael Meyer (eds) *Methods of Critical Discourse Studies* (3rd edition). London: Sage, pp. 1-22.

Zappavigna, Michele. 2018. *Searchable Talk: Hashtags and Social Media Metadiscourse*. London: Bloomsbury.

Zhao, Sumin, and Theo van Leeuwen. 2014. "Understanding Semiotic Technology in University Classrooms: A Social Semiotic Approach to PowerPoint-Assisted Cultural Studies Lectures." *Classroom Discourse* 5 (1): 71–90. https://doi.org/10.1080/19463014.2013.859848.