

Lessons from lockdown: Media discourse on the role of behavioural science in the UK COVID-19 response

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Abstract

In recent years behavioural science has quickly become embedded in national level policy making. As the contributions of behavioural science to the UK's Covid-19 response policies in early 2020 became apparent, a debate emerged in the British media about its involvement. This served as a unique opportunity to capture public discourse and representation of behavioural science in fast-track, high-stake national policy making. Aimed at identifying elements which foster and detract from trust and credibility in emergent scientific contributions to policy making, in study 1 we use corpus linguistics and thematic analysis to map the narrative around the key behavioural science actors and concepts which were discussed in the 650 news articles extracted from the 15 most read British newspapers over the 12-week period surrounding the first hard UK lockdown from March 2020. We report and discuss 1) the salience of key concepts and actors as the debate unfolded, 2) quantified changes in the polarity of the sentiment expressed toward them and their policy application contexts, and 3) patterns of co-occurrence via network analysis. In Study 2, we investigate how salience and sentiment of key themes observed in traditional media discourse tracked on original Twitter chatter (N = 2,187). In Study 3, we complement these findings with a qualitative analysis of the subset of news articles which contained the most extreme sentiments (N = 111), providing an in-depth perspective of sentiments and discourse developed around keywords, as either promoting or undermining their credibility in, and trust toward behaviourally informed policy. We discuss our findings in light of the integration of behavioural science in national policy making under emergency constraints.

1 Introduction

Public trust in the transparency and reliability of scientific evidence is an important component of effective responses to major challenges and crises (Hendriks, Kienhues, & Bromme, 2015; Pittinsky, 2015). Generally, public perceptions of science are positive: science is often held in high esteem with equally high confidence placed in scientists (e.g., Jonge, 2015; Lamberts, 2017; Lindholm et al., 2018; National Science Board, 2016; Scheufele, 2013; Robert Bosch Stiftung, 2017). However, the application of science in policy has variable success (Sanchéz-Pàramo et al., 2019). Not all science is deemed fit to inform policy (Anvari, Lankens, 2018; Ioannidis, 2018; Stevens, 2020; Cairney, 2020). Determining when a scientific discipline is ready to inform policy is precarious and can be volatile: the criteria for evidence-readiness can vary depending on what is at stake (Ruggeri et al., 2020). In addition, policy is shaped by many pressures other than those based on evidence. Direct competition from other pressures can shape public perceptions and can steer the policy-makers' ability to implement evidence at hand (Cairney, 2020).

In March 2020, the UK was faced with the high-stake policy choice of a national lockdown as Covid-19 spread globally (Kreps and Kriner, 2020). Just like other governments, they had to make this choice in light of the limited available evidence. As scientific evidence about the virus and its effects was sparse, much scientific expertise was drawn on by calling a broad range of scientists onto expert panels to advise (UK Government, 2020). In British policy, unlike many other national governments, one prominent perspective was that of the behavioural sciences.

The integration of behavioural science into UK policy took a number of forms. In particular, the government Scientific Advisory Group for Emergencies (SAGE) developed a behavioural advisory group consisting of prominent UK psychologists, behavioural scientists, and related researchers and policy experts, known as the Scientific Pandemic Influenza Group on Behaviours (SPI-B). The core committee of SAGE also included Dr David Halpern, chief executive of the Behavioural Insights Team (BIT). It is possible that this perspective was particularly well-represented in the UK because behavioural sciences has been embedded in British policy for longer and more widely than in other national systems. The UK Cabinet Office was amongst the first to embed a dedicated behavioural science unit (often called the 'nudge unit') to that effect (Sanders et al., 2018). Arguably, it is in part due to the unit that the effect of nudge as a novel policy instrument (Lourenco et al., 2016) and methods to test for their effectiveness (Della Vigna, Linos, 2020) were demonstrable on national policy level and embedded elsewhere. We have since seen an increasing popularity for the policy approach, as evidenced by the growing number of behavioural insight units that advise national governments on issues involving citizen choices in the last 10 years (Whitehead et al., 2014; Halpern, 2015).

Perhaps most relevant to Covid-19, the behavioural sciences, as the study of human behaviour, can provide valuable insights for managing a pandemic that requires changes to human behaviour and everyday interpersonal contact (Van Bavel et al., 2020). Yet, as the role of behavioural science in the lead up to the lockdown decision in the UK became apparent, public debate around its involvement surged. This left the questions: what caused debate about the role of this emergent science, what were its consequences (if any) and how can we learn from the communication around its scientific contributions to this high-stake policy? To address these questions, this paper provides a key case study on trust and acceptability surrounding the contributions of social and behavioural sciences at a time of crisis (e.g., Nadelson et al., 2014, Huber et al., 2019). Covid-19 took place at a time of widespread use of social media, providing an opportunity to understand how reactions were distributed across society through time. While an emerging body of literature exists on support for behavioural interventions (e.g., Reynolds et al., 2019, Sunstein et al., 2019), far less work has been conducted on trust in behavioural scientists more generally, and no work that we are aware of

Behavioural science representations during COVID-19

examines public support for the inclusion of behavioural scientists in committees advising government and shaping policy.

To study representations and perceptions of behavioural science over the course of the covid-19 policy response, we initially focus on print media (Study 1), followed by twitter as a popular source of social media to track their adhesion (Study 2). Print media retain a significant role in the formation of public opinion (Van Aelst, 2014). Although social media use has risen significantly in recent years (Gil de Zúñiga et al., 2012), many users merely take their cue from social media to follow-up in (online) newsprint (Dutton et al., 2013; Mitchell et al., 2018). For example, Chew and Eysenbach (2010) show that during the H1N1 pandemic, individuals used Twitter to share resource-related posts, with news media websites being the most popular sources to share. In addition, mass media plays an important agenda-setting role: it can direct collective attention and perceived importance (McLeod et al., 1974), shape how severe an issue is perceived to be, and influence how individuals come to perceive their social and political environment (Tyler, 1980; Protess, & McCombs, 2016). In other words, mass media play an important ‘mediating’ role in sharing and shaping how scientific and political expertise is understood by the public (Kim, 2018; Baum and Potter, 2008).

Following from the above, we start with capturing public discourse on the role of behavioural science in this particular policy context in newspaper articles on the topic of behavioural science during the 24-week period surrounding the high-stake policy decision of the first national lockdown in March 2020.

2 Study 1 Newspaper discourse analysis

Top newspapers have been shown to sway common understanding of scientific disciplines and can be used as a proxy to measure understanding of their place in public policy (Schäfer, 2012; Bauer et al., 1994; Mutz & Soss, 1997). As the contributions of behavioural science to the UK’s Covid-19 lockdown policies developed, and debate emerged in the British media about its involvement, we reasoned that, in the lead up to, during and after the UK Covid-19 lockdown period in March 2020, public perceptions of behavioural science contributions to this high-stake UK policy decision should be detectable from newspaper articles. With this in mind, we set out to explore the salience, sentiments and co-occurrence of key behavioural science concepts and actors over the lockdown period of 2020.

2.1 Materials and methods

Materials. In order to capture perceptions of behavioural policies, we retrieved news articles from the online database *Lexis Nexis* for an 8-week window either side of the UK lockdown decision (27th of January 2020 - 10th of July 2020). We drew on the 15 UK newspapers with the highest circulation levels (see Supplementary Material 1). We estimate that articles in these newspapers collectively reached almost 8 million people in print and in digital editions (approximately 12% of the British population) on a monthly basis (Mayhew, 2020; Worldometer, 2020).

Using a snowball method, we developed a query to identify articles relevant to the discussion of behavioural science (see Supplementary Material 2.A for details). The search produced a corpus of 865 articles. Deduplication and removal of incomplete articles resulted in a sample of 679 articles. These were qualitatively reviewed by three coders for relevance to the topic of behavioural science. This left 647 articles (ranging from 1-47 per news outlet; see Supplementary Material 1 for details) for the quantitative analysis of Study 1 (see Figure 1, left for an overview).

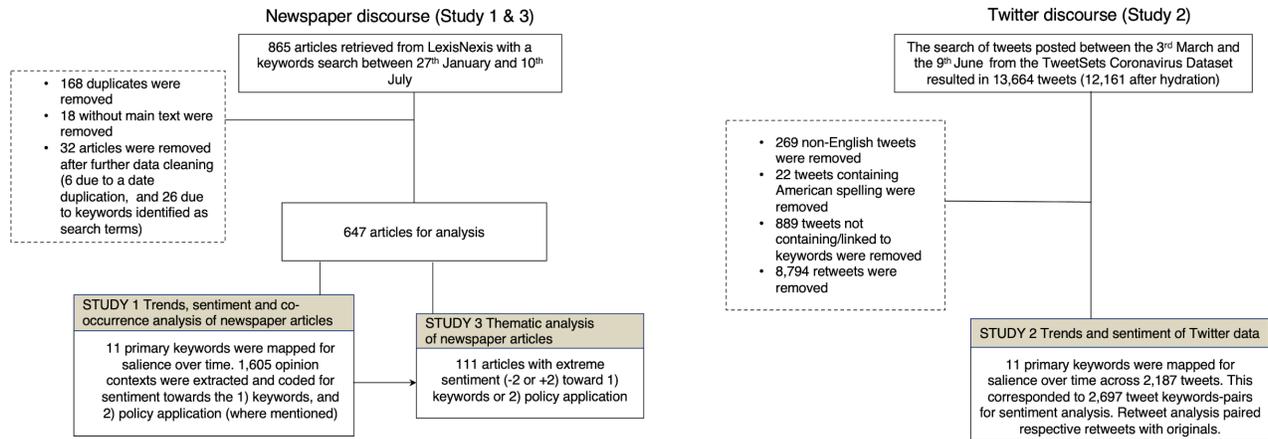


Figure 1: Flowchart of data selection and cleaning process taken for Study 1 (left) and Study 2 (right), followed by selection of articles for thematic discourse analysis in Study 3.

Keyword processing. We defined an initial set of 42 keywords based on the snowball method applied through the search query, to capture public discourse around behavioural science contributions to policy during this time period (see Supplementary Material 3 for a complete set). As one word can be expressed in different ways (e.g. abbreviated, singular/plural form, or by use of synonyms), keywords were grouped to form primary keywords as follows: 1) plurals were standardised into a singular form: e.g. *behavioural science* and *behavioural sciences* as *behavioural science*; 2) synonyms were unified: e.g. *nudge unit* and *behavioural insights team* as *behavioural insights team*; and 3) we integrated semantically related keywords based on expert knowledge: e.g. *nudge*, *nudging*, *nudge theory* and *nudge strategy* were noted as *nudge*. As exceptions to this rule, we kept *psychologist*, *behavioural scientist* and *behavioural economist* as stand-alone primary keywords. As profession names often preface unique actors (as opposed to their plural counterparts, e.g., Professor of Health Psychology Susan Michie VS Professors at Oxford), they lend themselves as proxies for actors not captured in our keyword base.

This resulted in 20 primary keywords: *behavioural science*, affiliated disciplines (*psychology*, *behavioural economics*), behavioural science concepts (*nudge*, *choice architecture*, *irrational behaviour*, *behavioural change*, *behavioural analysis*, *behavioural insights*), commonly named actors in national or international behavioural policy work (*SPI-B*, *Behavioural Insights Team*, *Michie*, *Halpern*, *Chater*, *Thaler*, *Sunstein*, *Kahneman*), and unnamed behavioural science actors (*behavioural scientist*, *psychologist*, *behavioural economist*).

Analyses. Salience. To assess the salience of primary keywords over time, we first removed all ‘parts-of-speech’ apart from nouns or keywords. This is based on the assumption that it is nouns that are the part of speech that represent the content of an article (Stuart, Rayz & Raskin, 2013). A salience score was calculated for each primary keyword per two-week period. The score was a product of the keyword’s normalised corpus frequency (i.e., number of keyword occurrences divided by total word counts per 10,000 words) and the keyword’s relative document frequency (i.e., proportion of articles in which the keyword was mentioned). This composite metric allowed us to account for centrality of a keyword in the narrative of the articles published in the 2-week period (normalised corpus frequency), by the spread in the media of the keyword in the period (relative document frequency; Manning et al., 2008).

Behavioural science representations during COVID-19

Sentiment. Targeted sentiment analysis was used to assess perceptions of behavioural science applied in national public policy context. We first identified all sentences ($n = 1280$) in our corpus where a behavioural science keyword occurred. As a sentence could contain more than one keyword (median=1, range=1-5), this resulted in a sample of 1605 keyword-sentence pairs, termed opinion contexts. Each opinion context was coded manually for sentiment polarity expressed toward each secondary behavioural science keyword on a 5-point scale from -2 (extremely negative), -1 (moderately negative), 0 (neutral), +1 (moderately positive), +2 (extremely positive). Opinion contexts were also reviewed to contain reference to national-level policy (e.g., mention of *government*, *minister*, *no. 10*, see Supplementary Material 3 for a full list). When this was the case, sentiment polarity toward the policy actor applying behavioural science was also rated.

Three independent coders coordinated to produce an intercoder agreement for a subset of cases. To match salience scoring, results were presented for two-week intervals over the period of the first national lockdown of 2020 in three sentiment categories: negative (-1; -2), neutral (0) and positive (+1; +2).

Co-occurrence. Finally, we used keyword co-occurrence analysis to investigate and quantify the association strength between keywords: strong associations indicate that keywords ‘belong to’ the same narrative, whilst weak associations indicate that keywords do not (Callon et al., 1983; Choi, Yi & Lee, 2011). This method allowed us to capture how the conceptual structure of the public narrative around behavioural sciences evolved over the period of the first national lockdown. To allow for reasonable variance in co-occurrence, we opted to move from two-week windows to a pre-, during- and post-lockdown window of analysis.

Co-occurrence between any two keywords was calculated at the article level and expressed by the Dice coefficient: the ratio between the co-occurrence of two keywords and the sum of their individual occurrences multiplied by two (Frakes & Baeza-Yates 1992; see Supplementary Material 6 for details). Simply put, two keywords that never co-occur have a coefficient of 0 and two keywords with identical occurrence have a coefficient of 1¹. We visualised the keyword association network structures, one for each time window, where keywords are displayed in nodes and edge weights reflect the strength of their co-occurrence with others (Katsurai & Ono, 2019; Kim et al., 2020; Liu et al., 2012) using the Python NetworkX 2.5 library (Hagberg et al.2008).

To understand how the relationships between keywords evolved, we calculated and compared the following network- and node-level metrics (Sudhahar et al., 2015):

- (a) *Network density*: the ratio of the actual number of links between keywords to the maximum possible number of links. On a scale from 0 to 1, higher value indicates a cohesive network.
- (b) *Node weighted degree centrality*: the sum of the edge weights for edges incident to that keyword. Higher values indicate more frequent direct links to other keywords.
- (c) *Node weighted between centrality*: the degree to which a keyword stands between others. Higher values indicate greater importance in bridging subsets of keywords.

¹ Note the dice coefficient is influenced by co-occurrence, but also by the individual frequency of the two keywords. Thus, the Dice coefficient can be high even when the co-occurrence is relatively small. For example, if two keywords have overall low frequency but they almost always appear together whenever they appear in an article. To minimise any misrepresentations, we only used the dice coefficient analysis for keywords $n > 20$.

Finally, the changing trend of important keywords in the network was identified by comparing the ranking of keywords for the node centrality metrics (b) and (c) of the three different time periods.

2.2 Results

From all analyses we excluded 9 keywords due to extremely low overall frequency (<30 occurrences over the 24-week period of interest; see Supplementary Material 5.A for details) as they did not provide enough data points across time to determine trends in our metrics of interest. This left 11 primary keywords: *behavioural science*, the discipline terms *behavioural economics* and *psychology*, four of the eight named actors (*Behavioural Insights Team*, *Halpern*, *Michie*, and *SPI-B*), two of three unnamed actors (*behavioural scientist* and *psychologist*), and two of six concept terms (*behaviour change* and *nudge*).

Below, we present trends in salience and sentiment towards behavioural-science keywords over time, followed by reference and sentiment toward public policy application and co-occurrence. As frequently the case in descriptive exploratory studies of linguistic data (e.g., Bian et al., 2016; Kim et al., 2020; Sharma et al., 2020), we contain our results to descriptive findings.

2.2.1 Salience and sentiment of keywords over time

Primary keyword *behavioural science* showed two clear surges: the first started one month prior to the UK lockdown (-2) and ended just after lockdown (+1) and the second rather spike-like surge occurred within a two-week period one month after the ‘hard’ UK lockdown measures eased (+6; see Figure 2 and Supplementary Material 4). Simultaneous to the surges, we see an increase in polar sentiments: positive *and* negative sentiments are greater during these periods as compared to other time-periods. This pattern is reminiscent of one commonly reported: ‘conflict’ is deemed of news value and determines the extent to which journalists pay attention to politics (Van der Pas & Vliegthart, 2016; Galtung & Ruge, 1965; Harcup & O’Neill, 2001).

Behavioural science representations during COVID-19

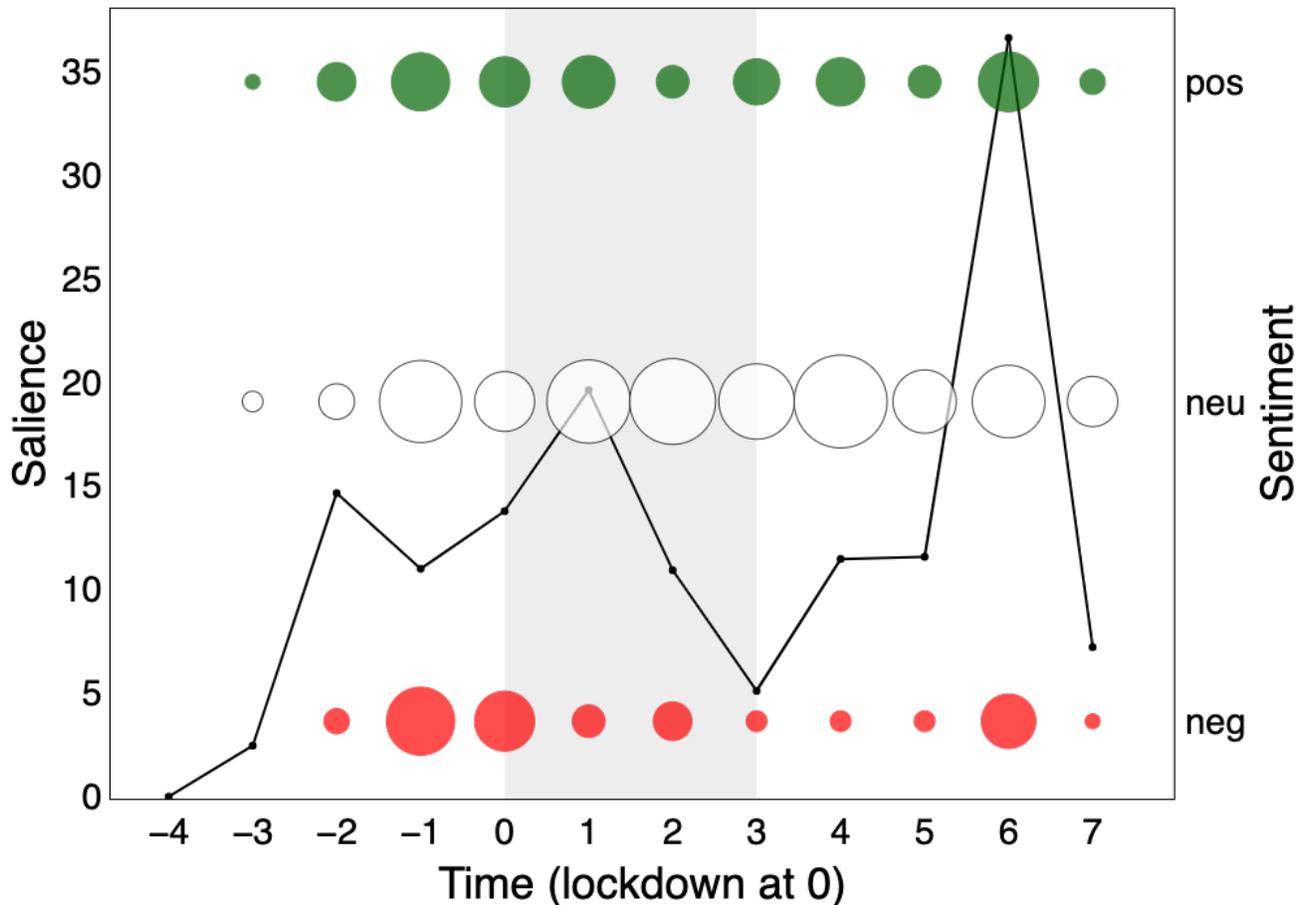


Figure 2: Salience of and sentiment towards the keyword ‘behavioural science’ over a 12 two-week time-period surrounding the first British national lockdown of 2020 (grey area) in print media (top 15 UK newspapers). Salience is calculated for a 2-week period as the normalised keyword frequency (per 10,000 words) multiplied by the proportion of articles that mention the keyword. The size of the bubble is proportional to the count of sentiments in that polarity class towards the keyword.

What seems to associate with the observed divisiveness? Discipline terms and unnamed actors do not show similar sentimental surges. *Psychology* (Figure 2I) seems to show a subdued version of *behavioural science* salience, with notably greater positive than negative sentiment. *Behavioural economics* is in fact largely absent from the narrative, with minimal salience in newspaper articles, but stable polarity over time.

Similarly, unnamed actors, such as *psychologist* (Figure 3H) or *behavioural scientist* (Figure 3D) do not share the surges in sentiment polarity observed for *behavioural science*. Although unnamed actors show a slight uptick in salience, they show a relatively steady (mostly neutral) sentiment.

We reach a different conclusion for named actors and concept terms. Salience for keyword *Michie* also mimics the *behavioural science* trend over time in subdued form, but with positive polarity during the first surge (-1). Keywords *Halpern* and *Behavioural Insights Team* show a nearly identical rise in salience to *behavioural science* in the period leading to lockdown, but rather eliciting a negative response. All actors thus seem to associate with the divisiveness we observe, possibly

holding opposite perspectives. This narrative finds support in that all three actors only seem to emerge as public figures of behavioural science only around this pre-lockdown time period (-1).

A final pattern of divisiveness is aligned with the keyword *nudge*. Although *nudge* was not nearly as salient as other primary keywords, we observe negative sentiment during the first surge. In fact, *nudge* is the only primary keyword, which throughout the 24-week period attracted more divisiveness than neutrality. Moreover, *nudge*, *Halpern* and *Behavioural Insights Team* are the only primary keywords to show greater negative than positive polarity.

What seems to associate with the observed non-divisiveness/neutrality? We are particularly interested in capturing patterns of neutrality as many may deem this to be the category of sentiment best suited to scientific discussion. Here we make three additional observations: 1) keywords *Michie* and *SPI-B* (emerging mid-lockdown) showed increasing presence over time but managed to maintain neutrality. Notably, *Michie* also attracted a small but sustained quantity of positivity over the full period; 2) *psychology* (with a stable and lowered presence in the media) shows to maintain a neutral presence over time and 3) *behaviour change* seems to be largely absent from the narrative, we see a small surge at the point of lockdown (0; one week after the first surge), possibly aligned with an expected moment in time where many needed to change their behaviour. See Supplementary Material 4 for more detail.

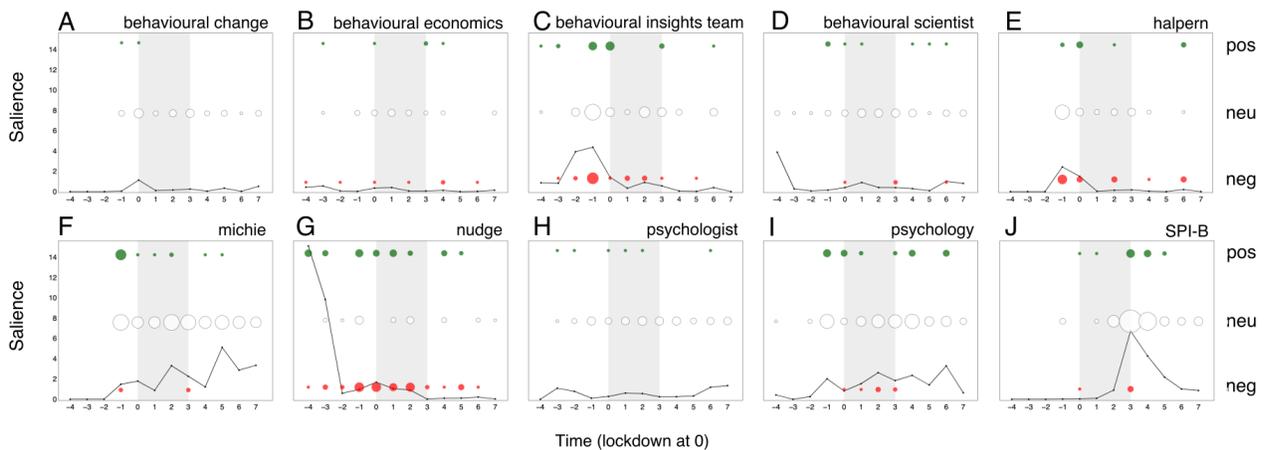


Figure 3: Salience of and sentiment towards the 10 primary keywords over the 12 two-week time period surrounding the first British national lockdown of 2020 (gray area) in print media (top 15 UK newspapers). (A) *behaviour change* (concept), (B) *behavioural economics* (discipline), (C) *behavioural insights team* (named actor), (D) *behavioural scientist* (unnamed actor), (E) *halpern* (named actor), (F) *michie* (named actor), (G) *nudge* (concept), (H) *psychologist* (unnamed actor), (I) *psychology* (discipline), (J) *SPI-B* (names actor). Salience is calculated per 2-week period as the normalised term frequency (per 10,000 words) multiplied by the proportion of articles that mention the keyword. The area of the bubbles is proportional to the count of sentiments towards the keyword.

Finally, we note that our primary keywords do not provide insight into the second surge in divisiveness in *behavioural science* (aside from increased salience without sentimental fluctuation for *Michie* (+6) over this period), which lead to a qualitative inspection of the category of unnamed actors and resulted in identification of an additional key actors: Prof. Stephen Riecher

Behavioural science representations during COVID-19

(supplementary keyword: *Reicher*; see Figure 4). Further attention was paid to this in the qualitative analysis (Study 3).

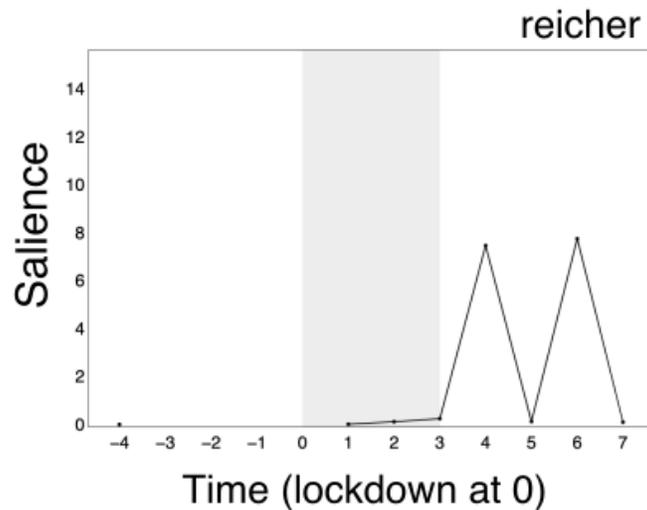


Figure 4: Qualitative inference identified Stephen Reicher as an additional actor. Reicher emerged on the topic of behavioural science toward the latter part of the 24-week time period, corresponding with a surge in saliency (+6).

2.2.2 Sentiment toward keywords in context of public policy application

We complement our understanding of sentiment expressed toward keywords by separating sentiments by those opinion contexts that refer to the application of behavioural science in public policy and those that do not. We display sentiments in three panels (see Figure 5): keyword sentiment when policy *was not* mentioned (top), keyword sentiment when policy *was* mentioned (middle), and sentiment toward policy application in those same opinion contexts (bottom; see data in Supplementary Material 7 and 8).

For *behavioural science*, we observe similar oscillation over time in all three panels, with two noteworthy differences between panels. First, we note higher neutrality and lower negativity towards *behavioural science* in opinion contexts which *did not* mention policy application (62% of neutral and 15% of negative sentiments overall) compared to those which *did* (52% of neutral and 22% of negative sentiments overall). In both contexts, the proportion of neutral sentiments towards *behavioural science* increased in the lockdown period (from 47% to 65% in contexts that *did not* mention policy and from 40% to 54% in contexts that *did*) and remained the highest post-lockdown. When we compare the sentiments toward *behavioural science* and its related *policy actors* in contexts in which both were mentioned (middle, bottom): we observe a much higher (57% overall) proportion of negative sentiments towards the policy actors, increasing across the three time-windows (37% pre-lockdown, 42% during lockdown, 82% post-lockdown), paired with a decreasing proportion of neutral sentiments (60% to 40% to 15% post-lockdown). In opposition, the proportion of negative sentiment towards *behavioural science* shows a decreasing trend (from 37% to 19% to 18%). This suggests a transference of negative sentiment from the science of behaviour to the actors who apply it in this high-stake policy context over time, for sentences that mention policy application. In other words, we do not only see a greater proportion of negativity toward behavioural science when

mentioned in a policy context, than when it is not, but we also see that the majority of this negativity is expressed toward the policy actors, and not behavioural science in itself.

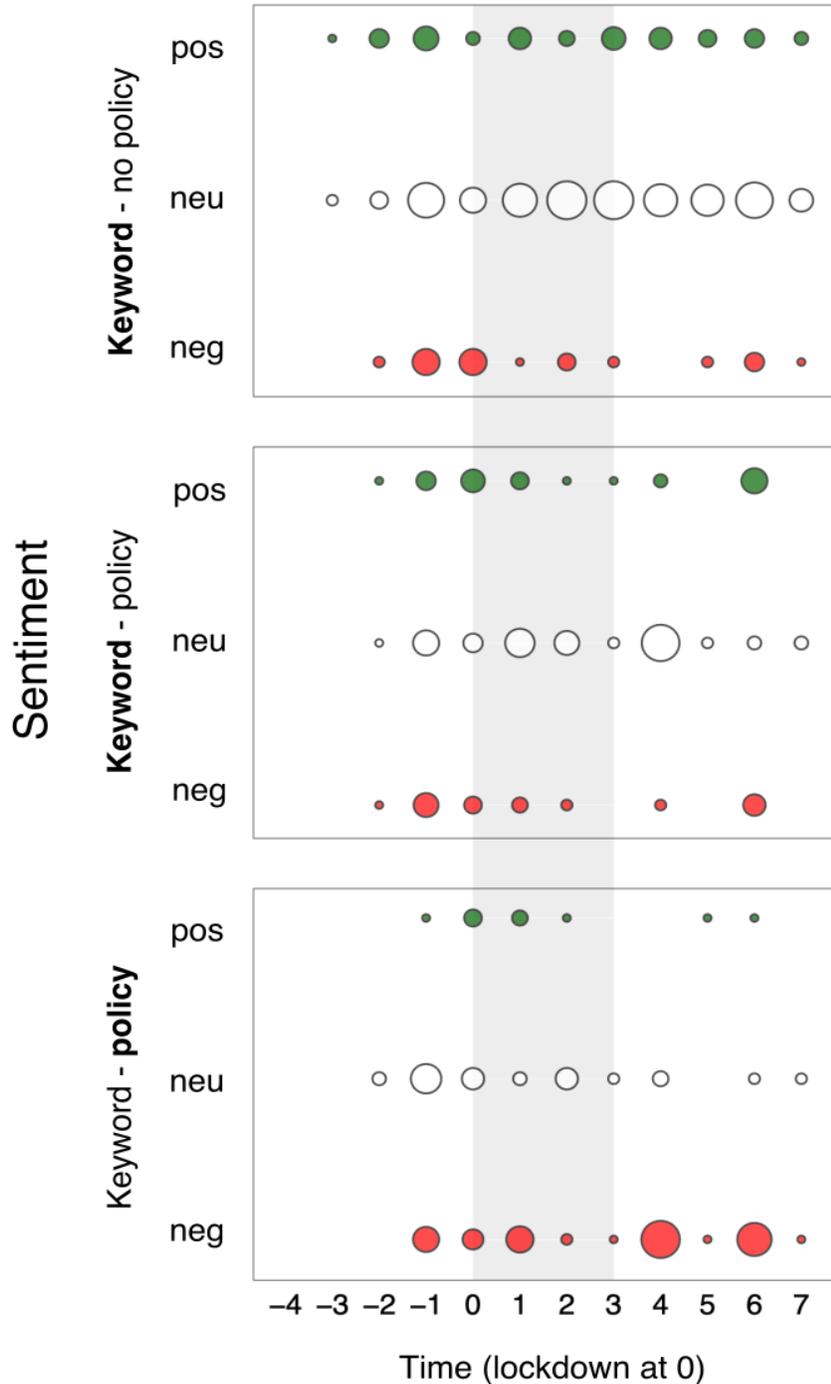


Figure 5: Sentiment towards “Behavioural Science” separated by sentences that do not (top) and do refer to national policy application (middle), and sentiment toward policy contexts of keywords (bottom) over the 12 two-week time period surrounding the first British national lockdown of 2020 from newspaper articles. The area of the bubbles is proportional to the count of sentiments towards the keyword. Reference category in bold.

Behavioural science representations during COVID-19

What may result in the transference of negativity from behavioural science to the policy makers who use it? For sentiments expressed toward keywords in sentences that *do not* refer to policy application (Figure 6, top row) we recount two observations. First, negative sentiment expressed toward behavioural science *not* in reference to policy, the picture is rather simple: prominent negativity is only observed around the concept of *nudge* (46% negative sentiments overall). This divisive, negative leaning pattern shows a small but consistent presence over the 24-week period, with a negative flare in the lead up to and throughout lockdown (echoed in articles which *do* mention public policy). Second, most keywords were more likely to appear in contexts that *do not* mention policy application (range 60-94% of their occurrences). The exceptions (unsurprisingly) *Behavioural Insights Team* and *Halpern*, which appeared in relation to policy actors in 69% and 63% of their occurrences respectively. In opinion contexts where policy was *not* mentioned, all keywords (aside from *nudge*) were discussed in neutral opinion contexts most often.

For articles that *do* mention policy application (Figure 6, middle row) and the sentiment *towards policy* (bottom row), we see a transference of negativity when mentioned alongside *policy actors* for 9 out of 10 keywords (just as *behavioural science*). We also observe two patterns: mentions of the common named actors *Behavioural Insights Team*, *Halpern* and concept *nudge* share approximately equal numbers of negativity *with* the paired policy actors, suggesting a level of coupling pre-lockdown (-2, -1). This whilst discussion of actor *Michie* seemed to avoid negativity nearly entirely at cost to their policy co-mentions, suggesting a level of contrasting pre- (-2,-1), and mid- to end- lockdown (2-5). The latter pattern is echoed over the same time periods by a small but noticeable number of unnamed actors (*behavioural scientist* and *psychologist*) suggesting that a group of scientists may be ‘speaking out’ against behavioural science application in policy.

The contrasting narrative offers insight into the drivers of a second surge in *behavioural science* divisiveness (+6). We observe that *psychologist*, *psychology* and *SPI-B* collectively maintain neutrality, but share in negative sentiment expressed towards the co-mentioned policy application (bottom) in the post-lockdown period.

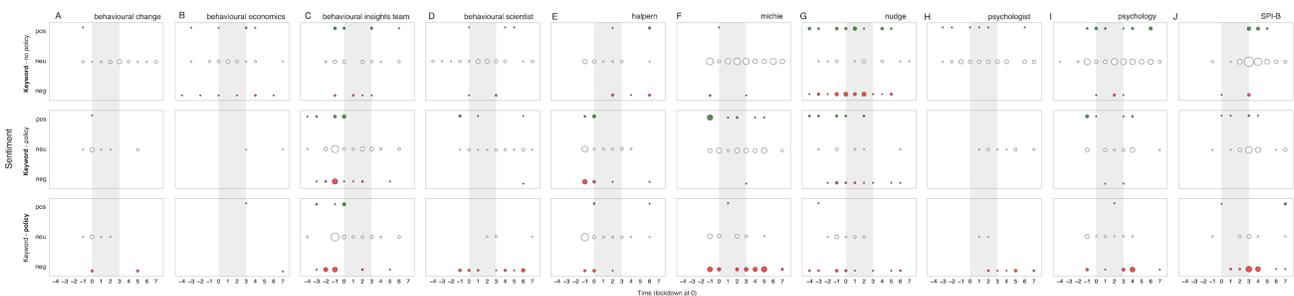


Figure 6: Sentiment towards the 10 primary keywords separated by sentences that do (top row) and do not refer to public policy application (middle row), and sentiment toward policy actors of keywords (bottom row) over a 12 two-week time period surrounding the first British national lockdown of 2020 in newspaper articles. The area of the bubbles is proportional to the count of sentiments towards the keyword. Reference category in bold.

2.2.3 Co-occurrence between keywords

Finally, we look at which keywords, actors and concepts frequently co-occur in articles with one another, complemented by four types of metrics: network density, network clustering, node degree centrality, and node betweenness centrality. To allow for frequencies high enough to measure

co-occurrence (see Supplementary Material 5.A), we opted to look at three time periods: pre-, during- and post- (hard) lockdown (Figure 7; Table 1).

The network structure (see Table 1). Over the hard lockdown period we observe a stronger network density (pre=.56; during=.87; post=.64) and stronger clustering coefficient (pre=.70; during=.91 post =.79). This suggests that keywords were more frequently discussed in contexts with most other keywords, but also consisted of more individual communities of keyword themes (“highly related keywords”). Across time periods, *psychology* is the most central keyword (degree centrality), and *behavioural science* remains in the top 2 for connecting independent clusters of keywords (betweenness centrality). Notably, the other discipline in our set of keywords, *behavioural economics*, bears no structural importance in any of the networks.

Co-occurrence offers three additional insights: *Behavioural Insights Team* surges to a central role (degree centrality) and in bridging subset of keywords (betweenness centrality) during lockdown and then moves further down the rank post-lockdown. *Michie* appears prominent pre- and post-lockdown (degree centrality) but has no role in bridging clusters of keywords. *Behaviour change* and *SPI-B* slowly emerge into centrality post-lockdown, but neither is of structural importance in any of the three time-windows.

Trends in strength of association (see Figure 7). Pre-lockdown sees two strong associations: *Halpern* coupled with *Behavioural Insights Team*, and *Michie* coupled with *psychology* (also connected but to a lesser degree with *behavioural scientist* and *behaviour change*). During- and post-lockdown, we observe that the prior of the two associations is mostly stable (with *nudge* increasing in association to Halpern and *Behavioural Insights Team*), whilst the latter shifts: *Michie* becomes much more frequently associated with *behaviour change* and no longer with *psychology*. Finally, we observe that *SPI-B* slowly solidifies as a third emerging cluster with increasing co-occurrence with *behavioural science* and *psychology*. For other relationships see Supplementary Material 6.

	Pre-lockdown (27 Jan - 22 Mar)	Lockdown (23 Mar - 09 May)	Post-lockdown (10 May - 10 July)
Network density	0.56	0.87	0.64
Network average clustering coefficient	0.70	0.91	0.79
Weighted degree centrality (descending rank)	psychology michie behav._insights_team psychologist nudge halpern behav._change behav._science behav._scientist behav._economics SPI-B	psychology behav._insights_team behav._science (+) halpern (+) psychologist nudge (-) michie (-) behav._change behav._scientist SPI-B behav._economics	psychology michie (+) behav._science psychologist behav._change (+) SPI-B behav._insights_team (-) halpern (-) behav._scientist nudge behav._economics
Weighted betweenness	behav._science psychology	behav._insights_team (+) behav._science	psychology behav._science

Behavioural science representations during COVID-19

centrality (descending rank)	nudge psychologist michie behav_insights_team behav_change halpern behav_economics behav_scientist SPI-B	halpern (+) psychologist psychology behav_change nudge (-) behav_scientist michie (-) SPI-B behav_economics	behav_scientist (+) psychologist nudge (+) behav_change michie SPI-B behav_economics behav_insights_team (-) halpern (-)
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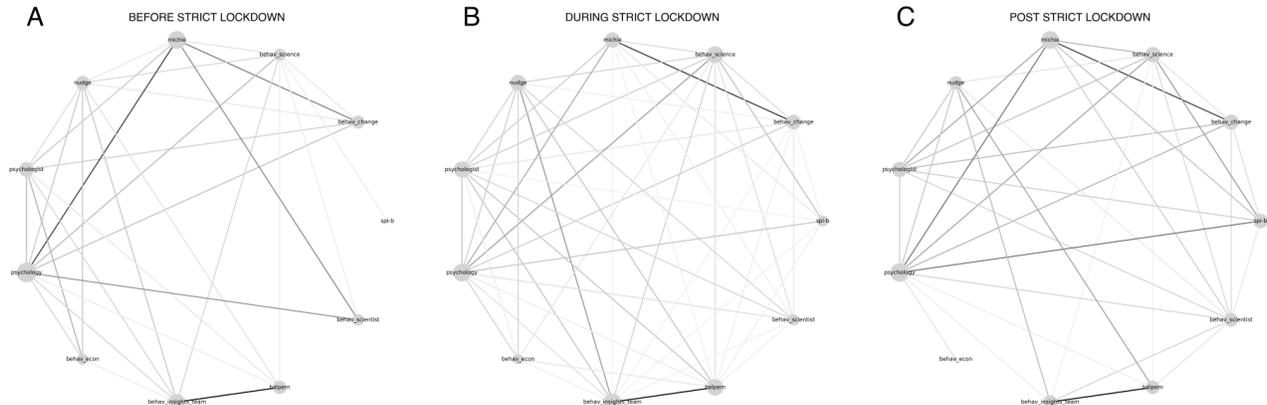


Figure 7: Networks of keyword co-occurrence across the three time periods: pre-lockdown (A), during lockdown (B), and post-strict lockdown (C). Each node represents a keyword. Edgelines represents the strength of the co-occurrence (Dice coefficient) between two keywords. The node size represents the keyword's weighted degree centrality, the number of neighbouring nodes connected to that node.

2.3 Discussion

Our results map the discourse of behavioural science around the UK lockdown decision through trends in keywords and sentiment toward them. We conclude that increased salience can be linked to divisiveness in sentiment, associated with a cluster between *Behavioural Insights Team* and *Halpern* (and later also *nudge*) coupled with policy application of behavioural science in the first (pre-lockdown) wave. This coupling may be a reflection of the embedded relationship between application of behavioural science in governance and the work of BIT. Whilst their collaboration has allowed advancement of applying the science of behavioural science in many public policy areas, one possibility is that the tight relationship was deemed less acceptable under the high-stake policy conditions which were faced.

Nudge, regardless of whether it was coupled with policy application of behavioural science, also seems to stir divisiveness. This may be a sticking point for trust and credibility in the public eye which seems, to a degree, to be generalisable (Hagman et al., 2015; Treger, 2020). Other than that, the application of behavioural science in high-stake policy incurred relatively high negativity in media discourse, but this did not reflect necessarily on the science of behaviour, but rather in reference to its policy counterpart. In relation, a second cluster of associations seems to have been

impactful. Key actors such as *Michie*, *Reicher*, *SPI-B* and the unnamed *psychologist* and *behavioural scientist* contrasted positively to behavioural science application in national-level governance. This suggests that one of the factors to have played into the trust and credibility of behavioural science (and its readiness for policy application) emanated from behavioural science actors themselves speaking out against its potential misuse as a policy tool under the high-stakes circumstances, and this seemed of particular influence a few weeks after the lockdown started to ease.

3 Study 2 Social media discourse analysis

3.1 Introduction

In Study 1, we looked at patterns of salience and sentiment toward behavioural science in newspaper articles over the 24-week period surrounding the first UK lockdown of 2020. This analysis does not tell us how the public responded to these articles. In Study 2, we thus identified a set of publically available Twitter data to examine whether and how these stories were picked up over the same time period. Twitter is amongst the most frequently used social media to investigate public's perceptions across a range of topics (Arribas-Bel et al. 2015; Bian et al., 2016; Bibo et al. 2014; Ordun et al. 2020; Sharma et al., 2020). We reasoned that mapping the salience and sentiments of the identified behavioural science concepts and actors from Study 1 over the same time period in this set, would allow us to identify the nature and extent of concordance of public opinion expressed online with that expressed on print media.

3.2 Materials and methods

Materials. We used the Coronavirus Tweet Ids Version 7 dataset (Kerchner & Wrubel, 2020) from TweetSets, the archive of Twitter datasets for research and archiving managed by George Washington University (Littman, 2008). The Coronavirus dataset contains the tweet IDs of 239,861,658 tweets related to COVID-19, collected between March 3, 2020 and June 9, 2020 from the Twitter API using the tags “coronavirus”, “COVID-19”, “epidemiology”, “pandemic”. This set was selected, as it was the open-source dataset of tweets that most closely reflected the timeframe and context of the news articles retrieved for Study 1.

Similar to Study 1, we developed a query to identify tweets relevant to the discussion of behavioural science and its application to public policy during the covid-19 pandemic (see Supplementary Material 2.B for details). Our query resulted in a dataset of 13,664 tweet IDs, corresponding to around 0.006% of the initial dataset. We then used Hydrator (Documenting The Now, 2020) to hydrate these tweets IDs, i.e., retrieve the text of the tweets and associated metadata from the Twitter API, which resulted in 12,161 tweets.

We removed retweets (8,794) using regular expressions to focus the analysis on original tweets as retweets can inflate the number of unique messages for the sentiment analysis. 269 tweets that were not in English were also excluded. Of the remaining tweets, 462 contained no behavioural science keyword (the keyword was mentioned in another tweet linked from within the tweet) and 427 other tweets only contained coronavirus-related search queries but no behavioural science keywords: they were all excluded from analysis. Finally, we also removed 22 tweets that displayed American spelling of behavioural science keywords (e.g., *behavioral science*). We analysed the remaining 2,187 tweets, corresponding to 2,697 keyword-tweet pairs. See Figure 1 (right) for a step-by-step.

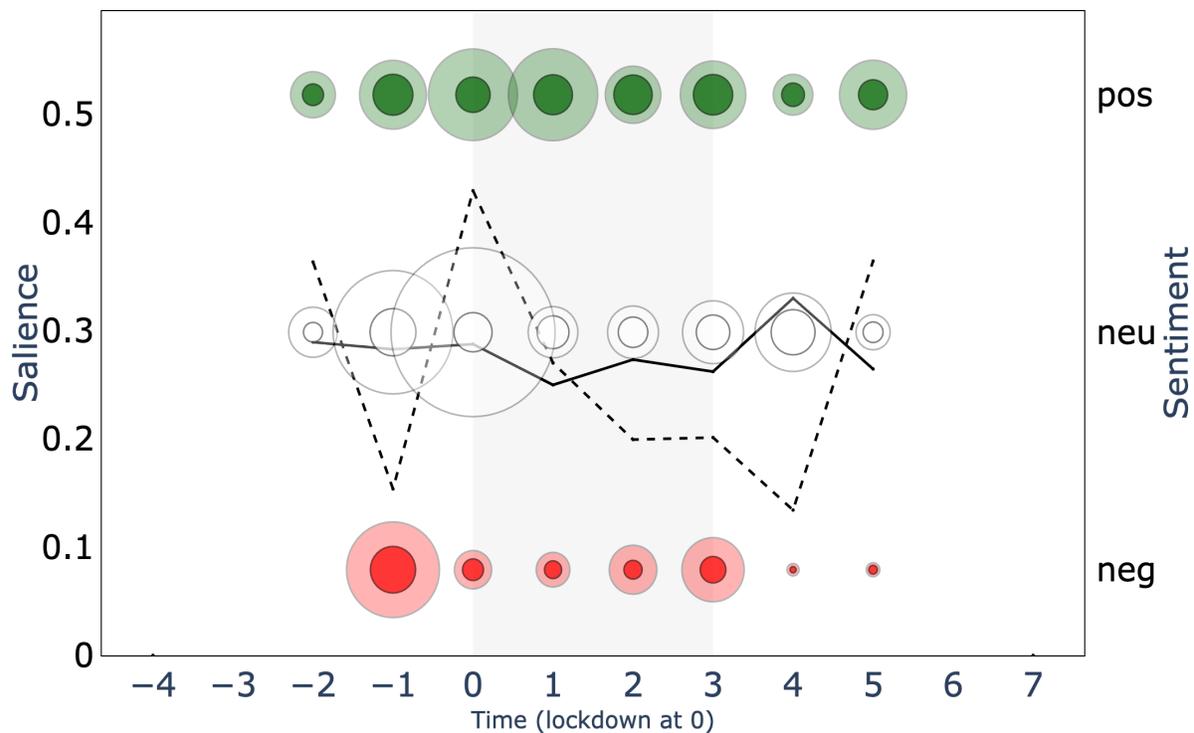
1 **Keyword processing.** To allow for comparison, we focused our analyses on the 11 primary
 2 keywords retained for analysis in Study 1 (see Supplementary material 3 and 5.B for details).

3 **Analyses. Salience.** We used document frequency (the proportions of tweets within a 2-week
 4 period in which the primary keyword occurred) as our measure of salience for the Twitter data. This
 5 differs from Study 1 (where we used document frequency multiplied by normalised term frequency):
 6 on Twitter, keywords tend to appear once per tweet (of 2,697 keyword occurrences, only 122 (4.5%)
 7 contained the same keyword more than once), and the number of total words per tweets is limited
 8 (max. 280 characters) and highly consistent (median = 32 words; IQR = 16 words). To assess
 9 salience over time we calculated two metrics: (i) *Salience (original tweets only)*: the proportion of
 10 total tweets in a given fortnight in which the keyword occurred. (ii) *Salience (accounting for*
 11 *retweets)*: the proportion of total tweets and retweets in a given fortnight in which the keyword
 12 occurred.

13 **Sentiment.** We coded sentiment towards keywords and public policy in original tweets as per
 14 Study 1 but report two sentiment measures: (i) *Sentiment (original tweets only)*: the count of positive
 15 / neutral / negative sentiments towards a keyword per 2-week period; and to account for the reach of
 16 sentiment expressed we also calculate (ii) *Sentiment (accounting for retweets)* by multiplying each
 17 sentiment by the number of times the tweet that contained it was retweeted.²

18 3.3 Results

19 3.3.1 Salience and sentiment of keywords over time



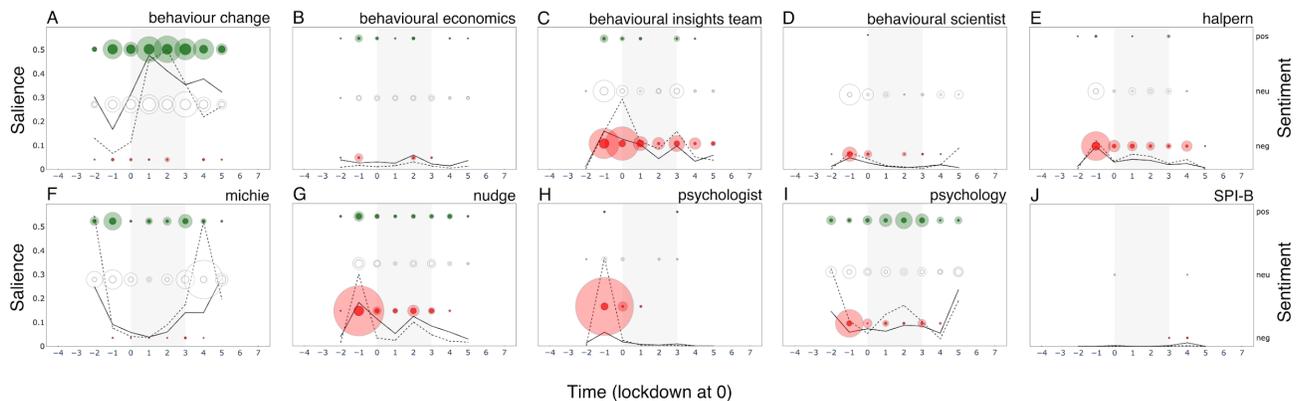
20

² For instance, if in a given 2-week period 4 tweets were published, each with a certain number of retweets, and KwordA appeared in 3 of them as follow: tweet 1a | retweets: 10 | kwordA: 1 | tweet 2a | retweets: 5 | kwordA: 1 | tweet 3a | retweets: 0 | kwordA: 1 | tweet 3a | retweets: 1 | kwordA: 0. Salience (original tweets only) for kwordA in this fortnight would be: $3/4 = 0.75$. Salience (incl. retweets) for kwordA in this fortnight would be: $[(1+10) + (1+5) + (1+0)] / (4 + 16) = 18/20 = 0.9$

21 *Figure 8: Saliency and sentiment of ‘Behavioural Science’ over the 8 two-week time-period*
 22 *surrounding the first British national lockdown of 2020 (grey area) in Twitter data. Saliency is*
 23 *calculated as the proportion of tweets in that 2-week period that mention the keyword. Bold line*
 24 *represents saliency in original tweets only; Dotted line represents saliency accounting for retweets*
 25 *also. The area of the bubbles is proportional to the count of sentiments (red=-2, -1; white=0;*
 26 *green=+1, +2). Full-colour bubbles represent sentiments in original tweets only; shaded-colour*
 27 *bubbles represent sentiments accounting for retweets.*

28 With regard saliency, Figure 8 shows a notably stable trend in original tweets over time, but when we
 29 include retweets (dotted line), we observe a pattern largely similar to that of newspaper articles: two
 30 surges, one during the fortnight at the start of lockdown (0) and one post-lockdown (5). See also
 31 Supplementary Material 9.

32 Regarding sentiments, original tweets that mention *behavioural science* attract similar levels
 33 of divisiveness in the two weeks prior to lockdown (-1; 37% neutral; 27% positive; 36% negative)
 34 and at the end of lockdown (3; 34% neutral, 46% positive and 20% negative) as compared to our set
 35 of newspaper articles. Negative sentiments also similarly reduce as the lockdown eases. We do note
 36 higher levels of positive and neutral sentiments, which remain relatively constant throughout the
 37 entire period, with a noticeable surge in neutral retweets just prior to the start of lockdown (-1 = 52%
 38 of all sentiments; 0 = 74% of all sentiments).



39
 40 *Figure 9: Twitter - Saliency of and sentiment towards primary keywords over 8 two-week time-period*
 41 *surrounding the first British national lockdown of 2020 (in grey): (A) behaviour change (concept),*
 42 *(B) behavioural economics, (C) behavioural insights team (named actor), (D) behavioural scientist*
 43 *(unnamed actor), (E) halpern (named actor), (F) michie (named actor), (G) nudge (concept), (H)*
 44 *psychologist (unnamed actor), (I) psychology (discipline), (J) SPI-B (names actor). Saliency is*
 45 *calculated as the proportion of tweets in that 2-week period that mention the keyword. Bold line*
 46 *represents saliency in original tweets; dotted line represents saliency including retweets. The area of*
 47 *the bubbles is proportional to the count of sentiments (red=-2,-1; white=0; green=+1,+2) towards*
 48 *the keyword. Full bubbles represent sentiments in original tweets only; shaded bubbles represent*
 49 *sentiments accounting for retweets.*

50 Comparing coverage of keywords on twitter (Figure 9, Supplementary Material 9) with that in
 51 newspapers (Figure 3), we see that *Michie* and *behaviour change* even more strikingly attract neutral
 52 and positive sentiment than in print media, and that *behavioural economics* is similarly absent from
 53 the conversation. We also see the same negativity toward *Halpern*, *Behavioural Insights Team* &
 54 *Nudge* just before lockdown. Unlike in media discourse, pre-lockdown negativity is also present for

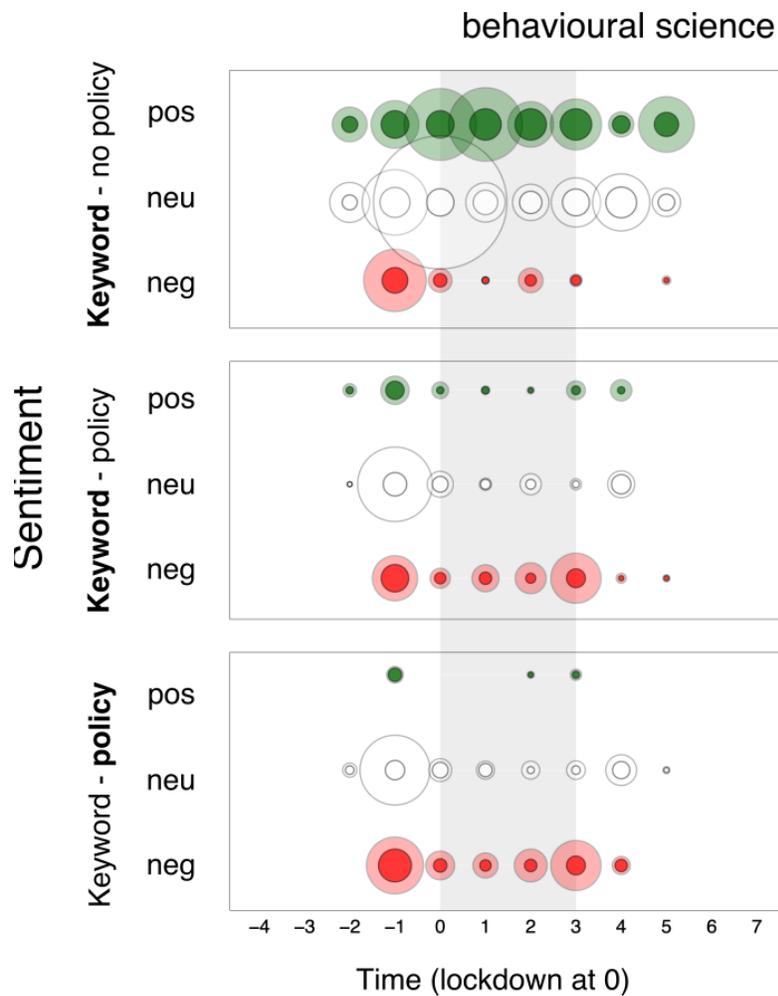
Behavioural science representations during COVID-19

55 *psychology, psychologist* and *behavioural scientist*, suggesting that in the public discourse is
56 extended to the discipline and professions of these actors. And unlike in the newspapers, *SPI-B* is
57 nearly entirely absent from Twitter chatter.

58 Comparing trends in tweets with retweets offers three interesting insights. First, most retweets
59 are of negative sentiment. *Nudge* and *psychologist* see a dramatic surge in retweet (but not tweet)
60 salience just prior to lockdown (-1), corresponding with a burst of such negative sentiment.
61 *Behavioural Insights Team* sees a similar pattern but shifted by two weeks (0). All three keywords
62 see a decrease in tweet/retweet salience and negative sentiment thereafter. Second, *Michie* sees a
63 surge in tweet and retweet salience before (-2) and after lockdown (4 and 5), both retaining high
64 levels of positive and neutral sentiment. Third, *behaviour change* surges (starting from period 0) and
65 remains high in salience throughout the period, in association with positive or neutral sentiments. For
66 these two keywords (unlike all others), positive sentiments are retweeted most.

67 3.3.2 Sentiment toward keywords in context of public policy application

68 How does mention of policy context affect perceptions of behavioural science? Two patterns stand
69 out as distinctive from those in print media. First, a larger majority of positive and neutral sentiments
70 towards *behavioural science* (Figure 10, Supplementary Material 10) are expressed when this is *not*
71 mentioned alongside policy applications (top panel), with a burst of retweets of neutral sentiments (-
72 1, 0). Second, the patterns of sentiments expressed towards behavioural science when policy
73 application *is* mentioned (middle panel), and the sentiment expressed towards policy application
74 itself (bottom panel) is closely matched. Just as in print media, we see a prevalence of negative
75 sentiments throughout the period under consideration, with a burst in negativity just before (-1) and
76 at the end of lockdown (3).

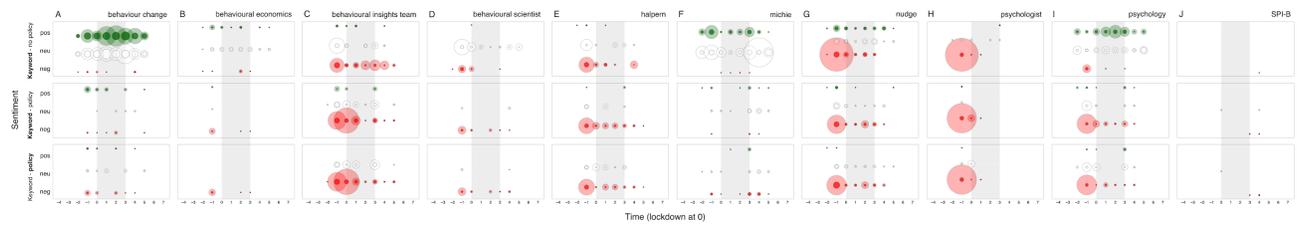


77

78 *Figure 10: Twitter articles - Sentiment towards “Behavioural Science” separated by sentences that*
 79 *do (top) and do not refer to policy application (middle), and sentiment toward policy contexts of*
 80 *keywords (bottom) over the 8 two-week time period surrounding the first British national lockdown*
 81 *of 2020. The area of the bubbles is proportional to the count of sentiments (red = -2, -1; white = 0;*
 82 *green = +1, +2) towards the keyword. Full-colour bubbles represent sentiments in original tweets*
 83 *only; shaded-colour bubbles represent sentiments accounting for retweets.*

84 Separating out the sentiments by mention of policy application for the other primary
 85 keywords on twitter (Figure 11; see Supplementary Material 10 and 11) allows us to capture three
 86 complementary results distinctive from the pattern observed in newspaper articles (Figure 4). First,
 87 the striking majority of positive sentiments expressed towards behavioural science keywords is *not* in
 88 reference to policy in association with 3 primary keywords: *behaviour change* (during lockdown),
 89 *michie* (pre- and post- lockdown), and *psychology* (during lockdown). Second, keywords which
 90 attracted negative sentiment (*Behavioural Insights Team, Nudge, Halpern*) toward policy-referenced
 91 tweets (middle row), attracted similar (not more) negativity in non-policy referenced tweets (top
 92 row). Third, negativity expressed toward keywords (middle row) and its policy application (bottom
 93 row) when mentioned together, is strongly coupled throughout the set of tweets.

Behavioural science representations during COVID-19



94

95 *Figure 11: Twitter articles - Sentiment towards the 10 primary keywords separated by sentences that*
96 *do (top) and do not refer to policy application (middle), and sentiment toward policy contexts of*
97 *keywords (bottom) over the 8 two-week time period surrounding the first British national lockdown*
98 *of 2020. The area of the bubbles is proportional to the count of sentiments (red = -2, -1; white = 0;*
99 *green = +1, +2) towards the keyword. Full-colour bubbles represent sentiments in original tweets*
100 *only; shaded-colour bubbles represent sentiments accounting for retweets.*

101

102 3.4 Discussion

103 As was the case for Study 1, the rapid emergence of negative sentiment toward the embeddedness of
104 behavioural science in the initial phase of Covid-19 restrictions is apparent from Twitter sentiment.

105 Twitter data also held more extreme sentiments, and increasingly coupled sentiment between
106 behavioural science and its policy actors. This may in part be due to Twitter’s succinct
107 communication format (difficult to express contrasting opinions with limited characters) but may also
108 reflect a coupling in actual public opinion. We see some evidence for this: some tweets *did* express
109 contrasting views (e.g., *Michie, nudge, Behavioural Insights Team*), but do not seem to hold the same
110 retweet value. In fact, we see that tweets expressing negative sentiment toward behavioural science
111 *and* its policy counterpart gained most traction overall. Second, we see that negativity is linked to a
112 clustering of *Behavioural Insights Team*, and *Halpern* in the pre-lockdown period (just as in print
113 media), but on twitter the negative sentiment also extends to their professions (*behavioural scientist;*
114 *psychologist*).

115 Further to this, it is not possible to ascertain whether negative sentiment surrounding the
116 behavioural science linked to government policy reflects negative sentiment toward the government
117 transferring onto the involvement of behavioural science, or more general antipathy toward the type
118 of behavioural science approaches employed by the government. It is clear that behavioural science
119 and behavioural change approaches seen as independent of or even in opposition to government
120 policy received a greater deal of both social media attention and positive sentiment, particularly in
121 association with *behaviour change* or *psychology*, something highly consistent with findings from
122 Study 1.

123

124 4 Study 3 Thematic analysis of newspaper articles

125 4.1 Introduction

126 The previous studies provide us with patterns of salience and sentiment toward the behavioural
127 sciences in terms of its perceived ‘place’ in high-stake public policy from journalistic and social
128 media. To better contextualize these insights and examine how levers (or barriers) of trust and

129 credibility towards behavioural sciences in contexts of high-stake policy making are constructed in
 130 the media, Study 3 utilised a qualitative design, analysing a subset of articles from Study 1.

131 **4.2 Materials and methods**

132 A subsample of articles was selected to include all instances of extreme sentiments (+2 or -2). This
 133 included a sample of 1) extreme sentiment towards the behavioural science keywords *and* public policy
 134 keywords, 2) extreme sentiment towards the behavioural science keywords, with neutrality towards
 135 public policy keywords, 3) neutrality towards the behavioural science keywords and extreme sentiment
 136 towards public policy keywords (see Table 2). The total sample of articles (N = 111) was analysed
 137 using NVivo 12.

Table 2. Distribution of selected articles across the three time periods (pre-, during-, and post-lockdown) and sentiments toward Behavioural science and public policy. Note: some articles appear in more than 1 category (overlap in brackets).

	Sentiment toward behavioural science keyword	Sentiment toward policy application	Total number of articles (overlap)
Congruent positive	+2	+2	8 (5)
Incongruent neutral	+2	0	2 (4)
Contrast	+2	-2	7 (7)
Incongruent neutral	0	+2	1 (0)
Incongruent neutral	0	-2	63 (7)
Contrast	-2	+2	0
Incongruent neutral	-2	0	8 (0)
Congruent negative	-2	-2	22 (9)

138

139 The analysis was deductive, informed by the findings from Study 1. In particular, given the
 140 differential coverage of actors, the rise and fall in emphasis on behavioural science and the patterns
 141 found in relation to sentiment towards public policy, the qualitative analysis focused on examining
 142 three questions which emerged from Study 1:

- 143 ● *How is the UK’s approach to the pandemic framed as compared to that of other*
- 144 *national approaches, with regards to trust and credibility?*
- 145 ● *How are the behavioural sciences discussed and compared to other sciences, with*
- 146 *regards to trust and credibility in handling the pandemic?*
- 147 ● *How is Behavioural Science introduced in the articles, under which circumstances*
- 148 *and how does this framing emphasize trust and credibility in the science?*

149 Specifically, the analysis entailed coding for actors (including scientific actors, government
 150 actors and international organisations such as WHO), thematic analysis of sentences describing or

Behavioural science representations during COVID-19

151 discussing Behavioural Science, and sentences mentioning different countries approaches to Covid-
152 19.

153 4.3 Results

154 4.3.1 Behavioural science as part of a national response policy

155 Three themes thought to affect credibility of, and trust in behavioural science were identified in
156 relation to the UK's national approach to the pandemic frame: 1) divergence from that of other
157 countries and global policy recommendation; 2) perceived incongruence between the approach and
158 adherence of most senior members of parliament; 3) expressed concern by scientific experts and
159 government advisors.

160 *Perception of UK policy response as divergent.* Most frequently the UK Covid-19 response is
161 regarded through drawing on a comparative lens, questioning why it deviates so significantly from
162 that of other countries;

163 "Over the next fortnight, as Italy moved to impose a lockdown, France and Spain began to do the
164 same, and Germany embarked on physical distancing measures coupled with Europe's most
165 extensive testing and contact tracing operation, Britain did comparatively little." (Conn et al.,
166 2020)
167

168 In addition, there was frequent mention of how the UK's approach deviated from the one
169 promoted by the World Health Organisation (WHO);

170 "The key principles from WHO are intensive surveillance. [...] Yet the UK government is no longer
171 testing anyone outside of hospitals, he warned. Prof Costello added: "For me and the WHO people I
172 have spoken to, this is absolutely the wrong policy. It would mean it just let's rip." (Mullin, 2020)

173 *Perception of internal incongruence.* The lack of trust towards the national response policy is
174 amplified by frequent reports of appearing incongruence between nationally imposed regulations and
175 the perceived adherence to those regulations by parliamentary personnel in public (e.g. during in-
176 person parliamentary activities) or private by some of its prominent members they themselves had
177 been part of developing (e.g. discussion of Dominic Cummings' action as warranted or disregard for
178 regulations);

179 "Professor Susan Michie, director of the Centre for Behaviour Change at University College
180 London, said: "Whilst the PM was telling people to stay at home and keep at least two metres
181 apart from each other, the House of Commons was open for business and face-to-face
182 parliamentary activities were carrying on." Given the transmission routes of touching contaminated
183 surfaces and breathing in virus-laden droplets, it should not come as a surprise to hear that the PM
184 and Health Secretary have tested positive for coronavirus. "There are many reasons why those in
185 leadership positions, including in Government, should practise what they preach." (Kirby et al.,
186 2020)
187

188 *Concerns from 'allied' scientific advisors and experts.* When critiques like the above come
189 from scientists named and identified as *government* advisors (e.g., as part of the Scientific Advisory
190 Group for Emergencies), the lack of trust towards government is further elevated. We note that this
191 explains in part the positive sentiment expressed toward Prof. Susan Michie in Study 1 and 2, where
192 her positioning as a scientist who aligns herself with a critical public (often using Twitter to do so)
193 functions to position her as a scientist working for the public good (as opposed to in association with

194 government). This is echoed if we look more closely at the most salient tweets in Study 2, where a
195 positive reference to Michie was the third in most retweeted (over 600 times);

196 “Professor Susan Michie of University College London has praised Nicola Sturgeon and Scotland's
197 approach to COVID-19. Another blow for #ColonialQuay and BritNats! #TheNine #COVID19.” (Indy
198 Swim, 2020)

199 Negative perceptions of the UK policy response (in contrast to that of countries perceived to
200 have successfully suppressed infection rates) are also reinforced by drawing on national and
201 international scientific expert whom, as a collective, comment and critique its incoherence with a
202 globally united response to the pandemic;

203 “Public health experts and hundreds of doctors and scientists at home and abroad are urging the
204 UK government to change its strategy against coronavirus, amid fears it will mean the epidemic
205 "lets rip" through the population. They say the UK is turning its back on strategies that have
206 successfully brought down the numbers of infections and deaths in other countries.” (Boseley,
207 2020a)
208

209 The inclusion of scientific experts criticising the Covid-19 response policy opens up
210 assumptions around *which* scientists might support the national approach, as it is argued to be
211 informed by scientific knowledge. Here we see the coupling of behavioural science and public policy
212 emerge, and the negative sentiment spills into how the behavioural sciences are perceived;

213 “The government's strategy has at its heart predictions about human behaviour. [...] Which
214 analyses of human behaviour are government scientists relying on? And how comparable are
215 they? Why is fatigue such a problem for new coronavirus measures, which we might expect would
216 command the same kind of support as a war effort, when the state lives with this "fatigue" in the
217 design of the laws and norms that permanently regulate our lives? We can't answer these
218 questions, because the government's scientists aren't yet disclosing what studies and past evidence
219 underpin their current approach. The government's tactic - one might even call it a nudge - is to
220 appeal to the credentials of its advisers and behavioural scientists, and to trust the experts.” (Yates,
221 2020)

222 In conclusion, perceptions of uniqueness, lack of adherence to regulations by parliamentary
223 members, and experts questioning the science informing the UK strategies lead to a media framing of
224 the UK Covid-19 policy response as neither trustworthy nor credible. Behavioural science is initially
225 introduced as what makes the UK response national approach unique and gets caught in the debate.
226

227 **4.3.2 Behavioural science relative to other sciences**

228 Next, we examined how behavioural science was discussed, in comparison to other scientific
229 approaches, to see which framings did or did not align with public trust and perceived credibility.
230 Here too, we note two themes surrounding trust and credibility: 1) mentions of achievement; 2)
231 scientific experts expressing opposing views.

232 *Mentions of achievement.* We identified which scientific experts were named and how articles
233 positioned the expertise of their respective fields. Unsurprisingly (based on the query) behavioural
234 science actors were mentioned most, followed by public health experts and epidemiologists.
235 Scientific disciplines were often mentioned through academic titles, achievements, previous
236 contributions to policy or other contexts of global threat. These introductions consistently lent
237 credibility to the expertise of all scientists (behavioural and other);

Behavioural science representations during COVID-19

238 “Anthony Costello, a UK paediatrician and former director of the World Health Organization
239 (WHO)...” (Boseley, 2020a)

240 “...a leading behavioural scientist has said. Susan Michie, professor of health psychology at
241 University College London...” (Fisher & Lay, 2020)

242 “...the British scientist leading one of the world's most advanced efforts has said. Sarah Gilbert,
243 professor of vaccinology at Oxford University...” (Thomson et al., 2020)

244 *Sciences in opposition.* Scientific experts were also found to express criticism towards other
245 scientific disciplines. We thus examined for which disciplines this occurred and attempted to distill
246 the impact on their credibility in the eyes of the public. While much criticism voiced by experts was
247 leveraged at the national policy approach (as described above) instances of critique at other sciences
248 were also found;

249 “In March some epidemiologists privately expressed frustration over behavioural scientists
250 advising the government to lockdown later over fears people would tire of restrictions.” (Smyth,
251 2020a)

252
253 Such expressions of concern often associated with unnamed scientific actors (‘immunologist’;
254 ‘epidemiologists’) cast doubt on the validity of the contrasted science. In fact, both of the most
255 frequently retweeted tweets identified in Study 2 negatively contrast behavioural science with
256 epidemiologists;

257
258 “The government’s science advisor is a behavioural psychologist, not an epidemiologist. This is crowd
259 management.” (Seymour, 2020)

260
261 Similarly, articles reveal drivers of credibility and trust in behavioural science in contrast to
262 other sciences, emphasising the need to consider behavioural implications of different policy options;

263
264 David McAdams worries that the health scientists are using simplistic "ad hoc assumptions about
265 behaviour" when complex nudges, such as "effective political leadership", can have big impacts.
266 Understanding motivations properly is vital. Rich people will lock down voluntarily, but poor people
267 may prioritise work. Policies could be tweaked accordingly. [...]. The government's slavish following of
268 epidemiological advice has been a disaster, a lockdown soft enough to leave the UK with a tenth of the
269 world's deaths but hard enough to wipe out up to a third of economic output. (Aldrick, 2020)

270
271 We conclude that credibility is extended to characteristics that highlighted the expertise of a
272 particular individual interviewed or quoted in the articles, but that the contrasting perspectives
273 between disciplines, embodied by the voices of different experts criticizing one another, serve as a
274 barrier to trust and credibility in media surrounding what is deemed suitable science to aid toward a
275 health pandemic. The approach of contrasting is similarly but less frequently found in support of
276 behavioural scientists.

277

278 **4.3.3 Key actors and concepts of behavioural sciences**

279 Lastly, we analyse how key concepts and actors within the discipline are introduced. In
 280 particular, we consider how articulations construct behavioural science as trustworthy or not, with a
 281 focus on its emergent scientific role in high-stake public policy. Here, we separated themes into
 282 barriers and drivers of trust and credibility.

283 **Barriers.** We observed four barriers to trust and credibility: 1) human irrationality and citizen
 284 autonomy, 2) perceived conflicts of interest, 3) behavioural science as being no more than common
 285 sense, and 4) the sparse evidence base for key concepts associated with the science.

286 *Humans irrationality and citizen autonomy.* As one common frame in media discourse,
 287 effectiveness of behavioural science rests on humans acting irrationally. This frame is at times met
 288 with resistance in association with the perceptions that the drive for a national lockdown rested on a
 289 soft (subconscious) ‘nudge’ to overcome non-compliance. This perception aligns with criticism of
 290 policy-initiated behaviour change as a threat to citizen autonomy (Jones et al., 2013; Leggett, 2014).

291 *Perceptions around conflict of interests.* Second, we observe emphasis on semi-privatisation
 292 of Dr. David Halpern and the BIT, in particular in the context of strong negative sentiment;

293 “David Halpern, head of the semi-privatised nudge unit advising Mr Johnson on behavioural
 294 science...” (Parker and Hughes, 2020)

295 “David Halpern, of the part Government-owned Behavioural Insights Team...” (Malnick, 2020)

296
 297
 298 This is important as the initial coupling of the government’s strategy with these actors shows
 299 to be paired with perceptions of being profit-driven. Under high-stake policy making, this may
 300 represent a source of distrust, as previous studies show that unbiased, reliable and transparent
 301 knowledge is associated with independence of other interests (Hendriks, Kienhues, & Bromme,
 302 2015; Pittinsky, 2015).

303
 304 *Perceptions of behavioural science as no more than common sense.* We observe behavioural
 305 science discussed 1) through questioning its evidence-based and readiness for policy application, but
 306 also 2) through the extent to which it is not just more than common sense knowledge;

307 “Behavioural science is not a science. The discipline has been hit by a "replication crisis" - results of
 308 even well-known studies cannot always be reproduced. Few experimental conditions can be controlled
 309 and it is often difficult even to define terms. With little way to prove their hunches wrong, behavioural
 310 scientists often assume they are right. That matters when the "science" is applied to policy decisions.
 311 While many of behavioural science's insights are mere common sense (people are more likely to turn up
 312 for GP appointments when you remind them to), they are dressed up as fact. [...] Besides, behavioural
 313 scientists are lobbyists for their own brand of thinking. They are not impartial advisers, and it is time
 314 the government stopped treating them as such. They should ditch them altogether. There is evidence
 315 enough.” (Gill, 2020b)

316 “Without an all-out national mobilisation plan for social distancing, are the UK government
 317 behavioural and nudge strategies really evidence-based to flatten the peak? Or simply based on
 318 models?” (Mullin, 2020)

319
 320 The use of quotation marks (“”) around the word science was found in other articles, which
 321 functions to express, at best, reservation and at worst a sense of irony towards the perception that
 322 behavioural science is indeed scientific (Weizeman, 2011). Criticisms is expedited as scientific

Behavioural science representations during COVID-19

323 experts are introduced as experts of behavioural science aligned with government, yet subsequently
324 identify as an independent experts;
325

326 “Boris Johnson got his response to the pandemic "disastrously wrong" because he did not listen to
327 behavioural science experts, a government adviser has said. Delaying lockdown because people
328 would get tired of staying at home was "vigorously opposed" by behavioural scientists feeding
329 into the Scientific Advisory Group for Emergencies, said Stephen Reicher, a member of the
330 Scientific Pandemic Influenza Group on Behaviours, a committee of Sage. Taking a swipe at
331 behavioural theories known as "nudge," he said that one view of human behaviour may be "overly
332 dominating in No 10", leading to "bad decisions"." (Smyth, 2020b)

333

334 *Questioning the scientific evidence base for herd immunity, behavioural fatigue or nudge.*
335 Most commonly, the introduction of behavioural science centre around the mention of ‘nudges’,
336 ‘herd immunity’ and ‘behavioural fatigue’;

337 “If 'behavioural fatigue' truly represents a key factor in the government's decision to delay high-
338 visibility interventions, we urge the government to share an adequate evidence base in support of
339 that decision. If one is lacking, we urge the government to reconsider these decisions," wrote Prof
340 Ulrike Hahn from Birkbeck, University of London, and others.” (Boseley, 2020a)

341 “Behavioural science works on the basis that people don't always act rationally, and that "nudges"
342 can be more effective at changing behaviour than diktats from authority.” (Coyle, 2020)

343 The mention of the above concepts frequently emphasizes concern over their scientific basis.
344 We also observed frequent coupling of ‘nudge’ ‘herd immunity’ with public policy application,
345 which in triad is widely criticized in pre- and early lockdown media coverage.

346 Taken together, these themes question the credibility of the discipline in informing policy and
347 come together in Martha Gill’s (2020b) framing of behavioural scientists as not being ‘impartial
348 advisers’, but rather with disguised motives. Here too, we see the use of quotation marks to question
349 the legitimacy of the scientific basis for psychology and nudge. This framing is crucial, as it is also
350 Martha Gill’s tweet that held the highest retweet value (over 900) across the time frame;

351 “This 'science advisor' [Halpern] is a psychologist. I really can't believe we are attempting to 'nudge'
352 our way out of this with soft science when we need hard science. Epidemiologists are the scientists to
353 listen to.” (Gill, 2020a)

354 **Drivers.** Other articles reveal facilitators of credibility and trust in behavioural science. We
355 identify three themes: 1) scientists who alert to the misuse of scientific evidence in government, and
356 2) reference to behavioural science’s ability to capture public opinion and 3) aid in transparent
357 communication.

358

359 *Alerting to the misuse of scientific evidence in government.* These articles distinguished
360 between scientific expertise offered by behavioural science experts, and how they were translated
361 into government action. They alert that the government appropriated policy recommendations around
362 communication and messaging, which in turn fostered trust in behavioural science from media;

363

364 “West also said there had been growing unease among his advisory colleagues about a divergence
365 between the scientific advice and the government's approach. "Those of us on Spi-B have been
366 increasingly concerned about the extent to which the government's approach to the behavioural sciences
367 and the messaging, particularly, has been at 180 degrees from the kind of advice that we have been
368 sending into the Cabinet Office," said West. Members of Spi-B, the advisory group on behavioural

369 science, say their recommendations to set very clear and unequivocal messages for the public to follow
370 have frequently been ignored by politicians.” (Boseley, 2020b)

371
372 *Discussion of capturing public opinion and transparent communication.* In similar critique of
373 government, there is emphasis on how behavioural science measures are useful for capturing public
374 reactions to policy measures, and that the role of the discipline in understanding how to communicate
375 with the public in a transparent and clear manner was seen as crucial for adherence to new measures,
376 but that this was not taken on board by the government.

377
378 We conclude that barriers to trust and credibility arise from questions around the scientific
379 nature of the behavioural sciences, and the purity of intention of behavioural scientists. Drivers of
380 trust and credibility come from decoupling the discipline from the government’s response and
381 stressing its uses for public involvement in scientific practice. For this, criticism from behavioural
382 scientists on the government’s advisory board (SPI-B) plays a key role, as they stress having felt their
383 advice being ‘trashed’ (Boseley, 2020b) or ‘ignored’, echoing the positive sentiment found towards
384 SPI-B in Study 1.

386 4.4 Discussion

387 Overall, we note three layers of insight. First, the UK Covid-19 policy choices were characterised as
388 unique or divergent in some prominent media publications, with the UK lockdown policy described
389 as delaying harder restrictions based on evidence from behavioural science. This is consistent with
390 patterns in Study 1 and 2 whereby behavioural science as embedded in the UK policy response was
391 frequently characterised by negative sentiment, whereas criticism about these same policies by
392 prominent (independent) behavioural scientists is often characterised by positive sentiment.

393 Second, we note that the media awards credibility to scientific evidence under high-stake
394 policy making conditions (perceived to be) valid, transparent and reliable. In contrast, credibility is
395 questioned when other scientific experts (from within or outside the discipline) critique public
396 policies or the scientific evidence that support them. References to epidemiologists, public health
397 experts, clinicians, immunologists were common, and in most instances these actors were presented
398 in ways that lent credibility to their expertise. But if these actors were critical of public policies, this
399 was often driven by questions of ‘what science’ was guiding the choices of policy officials. Hereto
400 (lack of) transparency in addition to a lack of collaborativeness seems to be a driver of outcry.

401 Third, we observe an additional lever of credibility and trust. Particular scientists from within
402 the discipline may cry out to separate their identity from that of the negatively perceived subgroup.
403 With the over-coupling between lockdown policies and behavioural science in the media, we
404 observed an uprising against its characterisation from closely linked experts. Here credibility is
405 undermined by links to scientific actors thought to have conflicts of interest and question the extent
406 to which their contributions can be evidence-based and unbiased. The contrast of independent and
407 dependent scientists’ function to raise awareness of the potential problematic relationship between
408 science and public policy, seen as favouring not the public, but private interests.

409 5 General discussion

410 5.1 Summary of findings

411 Using two distinct data sources (print media and Twitter chatter) and a mixed methodological design,
412 we have mapped media and public discourse surrounding behavioural science contributions to the
413 first UK lockdown decision of March 2020. We find two distinct clusters of actors and concepts in
414 the behavioural sciences to be received differentially by both the media and public: BIT, Dr David
415 Halpern and ‘nudge’ are viewed as embedded with the lockdown policy, coupled with negative
416 perceptions, whilst on the other hand, Prof. Susan Michie, Prof. Steven Reicher and the SPI-B are
417 perceived to be speaking out against these policies. Some of those amongst the second set of actors
418 are also publicly associated with less policy-oriented behavioural science activity, surrounding
419 psychological science and behaviour change, which was regarded as substantially more positive. The
420 public eye, however, is drawn more so to the conflict observed between behavioural scientists
421 embedded with policy and those expressing concern over their choices. This, in turn, shows to affect
422 the perceptions of behavioural science most substantially.

423 How do the behavioural science approaches differ between clusters? One distinction is that
424 positive and neutral sentiment toward behaviour change and psychology was captured by work
425 surrounding the enabling of citizen choice (e.g., handwashing, social distancing), whilst negative and
426 divisive sentiment was associated with behavioural science applied to more embedded and politicised
427 restriction of citizen choice (e.g. lockdown, rules of social isolation). Although this may be so, we
428 also observed negative sentiment toward nudge for not being restrictive enough, so this does not
429 seem to explain the divisive debate entirely. Another contrast between these clusters of actors and
430 concepts is their perceived embedded vs. independent nature from political, as opposed to public,
431 needs. A common issue with embedding scientific practice in policy making is the bias in selection
432 of evidence to suit political needs (Stevens, 2020; Cairney, 2020). In addition, behavioural science as
433 embedded in the Covid-19 policy response was heavily criticized by the media for lack of transparent
434 practices. In contrast, when prominent (independent) behavioural scientists discussed behavioural
435 research as a tool to facilitate public involvement and transparency, its use was rather applauded.

436 **5.2 Behavioural Science and Covid-19 Response: Implications and Recommendations**

437 In light of the barriers and drivers observed in relation to trust and credibility around the integration
438 of behavioural science in national policy making under emergency constraints, we discuss
439 recommendations for 1) informing transparent and ethical communication for future behavioural
440 policy making and 2) their immediate use for shaping communication around the behavioural Covid-
441 19 policy measures.

442 *Ethical and transparent policy making.* The extent to which behavioural science and the
443 political philosophical tradition of libertarian paternalism are conflated requires further attention. In
444 our data, we see that behavioural science and nudging are often conflated, where disagreement about
445 the political philosophical implications of the nudging principles co-occurring frequently with
446 negative sentiment toward policy applications of behavioural science. This was particularly marked
447 during the initial phases of Covid-19 response, where behavioural science was often associated with
448 ‘soft’ approaches to managing the virus, including the notion that behavioural scientists were
449 advocating explicitly or implicitly for a policy of herd immunity. While our results cannot be
450 conclusive about the overall impact of this confusion for ongoing trust in behavioural science
451 approaches in public policy, it was a significant source of enduring negative sentiment toward
452 behavioural science and behavioural scientists and something that needs to be addressed directly by
453 key public figures in the field. Related to this, a substantial body of public opinion expressed
454 concerns that behavioural science could be used in ways that are manipulative and/or bypassing

455 citizen autonomy. Further efforts are needed by leaders in the field to clarify the ethical features of
456 different behavioural policy tools (e.g., Lades and Delaney, 2020).

457 *Clarification of behavioural science as a field.* The development of behavioural-science
458 driven approaches has been a marked feature of British public policy of the last decade. The
459 integration of a behavioural science stream into the government Covid-19 response policy was
460 debated heavily throughout its initial phases. Public representations of behavioural science reflect a
461 high degree of heterogeneity in the use of the discipline term to represent distinct perspectives and
462 streams of research, something that itself may have contributed to confusion among the public.
463 Structured discussion among key public figures and institutions that use this phrase about the nature
464 and historical origins of their work might be particularly helpful in resolving such confusion and
465 clarifying distinctions between distinctive streams of thought. We hope the analysis in this paper
466 could contribute to this process. The extent to which behavioural science research is seen as a
467 valuable input beyond lay intuitions about human behaviour is another important aspect of field
468 clarification. The readiness of various strands of behavioural science to contribute to emergency
469 situations is another feature of public discourse that has also been reflected in recent academic
470 debates (e.g. IJzerman et al., 2020; Lunn 2020).

471 *Transparency about the role of behavioural science in policy.* Overall, the public perception
472 of behavioural science also displays a marked pattern of positivity, with both media and the public
473 expressing positive sentiment about the potential role of behavioural science and behavioural
474 scientists in enabling protective health behaviours, improving citizen involvement in science and
475 pandemic response policy overall. Negative sentiment toward behavioural science and behavioural
476 scientists link to the embeddedness of behavioural science within the lockdown policies of the UK,
477 with suspicions that the ‘divergent’ UK approach may have reflected insufficient separation between
478 the science advice and political decision making. The extent to which the BIT’s financial structure
479 constrains their role in policy was also a feature of public discourse on behavioural science during
480 this period.

481 We observe that the spread of negative sentiment was centred around a relatively small group
482 of interconnected actors. Furthermore, negative sentiments about high stake policy decisions may
483 also gain more traction than those linked to positive sentiment toward behavioural science. It is
484 beyond the scope of the current study to ascertain whether the perception of UK policy being
485 markedly different from other countries due to behavioural science influence is a reflection of the
486 actual policy process. Even if not, a widespread perception of this nature is something that needs to
487 be addressed in the broader field as it could have consequences for the acceptability of behavioural
488 science in policy as well as potentially detracting from the consistency and perceived trustworthiness
489 of emergency responses.

490 *Implications for current pandemic practice.* Behavioural science teams working with
491 government on pandemic response should increase efforts to explain the composition of their teams,
492 engage with the public, and deal promptly with media narratives about the role of behavioural
493 science in policy. Leaders in the field should continue to communicate the role of evidence in
494 informing policy as opposed to setting the broad political direction of policy, and where possible
495 increase efforts to be seen as independent from political processes.

496 5.3 Conclusion and Future research

Behavioural science representations during COVID-19

497 This study is based on analysis of public discourse in one country at a time of a major crisis. Future
498 work comparing the discourse behavioural science across different global settings will give a fuller
499 account of the developing influence of emergent behavioural science on policy. Furthermore, the
500 current study is based on samples of print and social media. An interesting area of future study will
501 be to examine public attitudes and representations directly through surveys and interviews.
502 Generally, an urgent task highlighted by the study of this Covid-19 policy response, is to continue
503 efforts at field definition and role clarification in the behavioural sciences more globally.

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Behavioural science representations during COVID-19

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750 **7 Supplementary Material**

751 7.1 Supplementary Material 1: Table displaying circulation figures by newspaper for 2020 and the
752 newspapers used for the quantitative analysis of Study 1.

753 7.2 Supplementary Material 2: Defining the A) Lexis Nexis query on the topic of ‘behavioural
754 science’ between 20th of January and 10th of May and B) query for the 3rd March and the 9th
755 June Twitter data archive.

756 7.3 Supplementary Material 3: Table of the codebook for primary and secondary keywords used
757 for analysis.

758 7.4 Supplementary Material 4: Trends in salience and sentiment for keywords per fortnight in
759 newspaper articles (Study 1).

760 7.5 Supplementary Material 5: Overall frequency of primary keywords A) in newspaper articles
761 (Study 1) and B) on Twitter (Study 2).

762 7.6 Supplementary Material 6: The dice coefficient formula and co-occurrence strength between
763 keyword pairs per time-period. Pairs are reported in descending order of association in pre-
764 lockdown.

765 7.7 Supplementary Material 7: Sentiments towards keywords separated by public policy
766 application mentions for newspaper articles (Study 1).

767 7.8 Supplementary Material 8: Sentiments towards public policy actors mentioned alongside
768 behavioural science keywords for newspaper articles (Study 1).

769 7.9 Supplementary Material 9: Trends in salience and sentiment for keywords per fortnight in
770 Twitter data (Study 2).

771 7.10 Supplementary Material 10: Sentiments towards keywords separated by public policy
772 application mentions for Twitter data (Study 2).

773 7.11 Supplementary Material 11: Sentiments towards public policy actors mentioned alongside
774 behavioural science keywords for Twitter data (Study 2).

775 **8 Conflict of Interest**

776 The authors declare that the research was conducted in the absence of any commercial or financial
777 relationships that could be construed as a potential conflict of interest.

778 **9 Author Contributions**

779 JGS, AT and SO designed Study 1, 2 and 3. AT lead data processing and analysis for Study 1 and 2.
780 SO lead the data analysis for Study 3. IM, SO, AT, and JGS contributed to sentiment coding for
781 Study 1 and 2. JGS, AT and SO, IM and LDD contributed to discussions and writing the paper.

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787 **12 Data Availability Statement**

788 The datasets generated and analysed for this study will be shared upon request.

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