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A protocol for a discrete choice experiment Lives and Livelihoods: Understanding public preferences and trade-offs for government responses during a pandemic

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ABSTRACT

Introduction: Social distancing and lockdown measures are among the main government responses to the COVID-19 pandemic. These measures aim to limit the COVID-19 infection rate and reduce the mortality rate of COVID-19. Given we are likely to see local lockdowns until a treatment or vaccine for COVID-19 is available, and their effectiveness depends on public acceptability, it is important to understand public preference for government responses.

Methods and analysis: Using a discrete choice experiment (DCE), this study will investigate the public's preferences for pandemic responses in the UK. Attributes (and levels) are based on: (i) lockdown measures described in policy documents; (ii) literature on preferences for lockdown measures; and (iii) a social media analysis. Attributes include: lockdown type; lockdown duration; impact on the health service; number of excess deaths; number of infections; impact on household spending; and job losses. We will pre-pilot the DCE using virtual think aloud interviews with respondents recruited via Facebook. We will collect preference data using an online survey of 4000 individuals from across the four UK countries (1000 per country). We will estimate the relative importance of the attributes, and the trade-offs individuals are willing to make between attributes. We will test if respondents' preferences differ based on moral attitudes (using the Moral Foundation Questionnaire), socioeconomic circumstances (age, education, economic insecurity, health status), country of residence and experience of COVID-19.

Ethics and dissemination: The University of Aberdeen's College Ethics Research Board (CERB) have approved the study (Reference: CERB/2020/6/1974). We will seek CERB approval for all amendments from the developmental and pilot work. Peer-reviewed papers will be submitted, and results will be presented at public health and health economic conferences nationally and internationally. A lay-summary will be published on the Health Economics Research Unit blog.

Strengths and limitations of this study

- The study will provide information on the public's trade-offs regarding health and the wider economic impacts of the COVID-19 pandemic and lockdown measures.
- We will explore preference heterogeneity e.g. how preferences differ according to moral attitudes, age, gender, economic insecurity, health status, covid-19 experience, and country of residence.
- It is not feasible to incorporate all factors that may affect the public preferences (e.g. effect on children through school closures; impact on mental health, impacts on inequalities).
- This study will be undertaken in the UK and may not be generalisable to other countries.

INTRODUCTION

The public health response of governments to the COVID-19 pandemic has differed across countries. Responses have mostly involved some kind of lockdown measure that encourages social distancing[2] to slow the spread of the disease.[1,2] The timing and strictness of these measures has differed across countries. Italy and Spain introduced early strict lockdown measures, while restrictions in Sweden and the Netherlands were less severe.[3,4] Policies in the UK shifted from a more relaxed initial approach towards stricter measures as the pandemic progressed.[5] As lockdowns have eased, we have seen local lockdowns introduced to deal with spikes in infection rates (e.g. Leicester (England), Melbourne (Australia) and Barcelona (Spain).[6,7,8]

The pandemic and the subsequent public health response affect both public health and the economy.[9] Supressing infections has required stringent physical distancing measures, which has had a range of direct and indirect impacts on health as well as the wider determinants of physical and mental health.[10,11] Economic impacts include increased unemployment rates and decreased household income,[12] with certain groups more likely to experience economic hardship.[13,14,15] When lockdown measures are implemented the interests of different people may be in conflict. Public health responses must then balance protecting the population and health care system with the impact on the economy and personal freedoms. A better understanding of public preferences and how they differ across communities may help policy makers decide which interventions to deploy.

Very little is known about public preferences for lockdown policies. Previous research in Singapore and Australia conducted before the COVID-19 outbreak suggests considerable variation in preferences. Cook et al[16] used a Discrete Choice Experiment (DCE) to investigate public preferences for pandemic interventions for emerging infectious disease in Singapore. Whilst respondents preferred more intense interventions, fewer deaths and lower taxes to fund public health measures, the number of infections did not affect their preferences. Respondents were willing to accept a loss of S$370 million at the societal level for the full set of interventions considered and a personal cost of up to S$34 to prevent 30 deaths, S$70 to prevent 80, S$71 to prevent 120 and S$98 to prevent 180-at a national level. The value placed on a strong response (mandatory isolation and quarantine, cancelling all mass gatherings, and island-wide screening), S$74, corresponded to the value placed on preventing 100 deaths. Johnson et al[17] used a DCE to explore public preferences for attributes associated with One Health strategies for emerging infectious disease prevention and control in Australia. They examined trade-offs between risk attributes (zoonotic risk or mortality) and other attributes, expressed as 'willingness to accept' extra cases of severe disease or extra deaths, to avoid compromises in other attributes. Food security was valued most highly, with respondents willing to accept the highest number of additional cases of disease, or deaths, to avoid compromising food security. The next most highly valued attributes were: animal welfare; economic development; environmental health; community cohesion; personal autonomy; and free trade and travel.

More recent work has used the DCE method to understand preferences and trade-offs for responses to the COVID-19 pandemic. Chorus et al[18] elicited preferences of the Dutch adult public for relaxing lockdown. The DCE included attributes related to health, the economy,

[2] Social distancing, also called "physical distancing," means keeping a safe space between yourself and other people who are not from your household.[19]

education, and personal income. They found that, compared to younger people, older people are less willing to sacrifice (per fatality avoided): people with mental health problems; children at an educational disadvantage and households with an income loss. Reed et al[20] explored the extent to which US adults are willing to accept a greater risk spread of COVID-19 to lift social-distancing restrictions and limit the economic impact of the pandemic. They identified 4 preference patterns: risk minimizers who are reluctant to accept any increases in risk (37%); those primarily concerned with time required for economic recovery, accepting increases in COVID-19 risk levels up to 16% to shorten recovery from 3 to 2 years (26%); those who preferred delaying reopening (26%); and those accepting COVID-19 risks beyond 20% to avoid a delay in reopening (13%). Political affiliation, race, household income and employment status predicted preference patterns, with political affiliation being the most important predictor.

AIMS

Building upon these studies, we use the DCE method to estimate how people in the UK make trade-offs between features of lockdown interventions. Specifically, we explore:

- the relative importance of pandemic response features
- trade-offs respondents make between these features e.g. how much household spending are respondents willing to forgo to reduce excess deaths or what increase in job losses they are willing to accept for a decrease in the infection rate?
- the impact of moral attitudes on preferences
- preference heterogeneity based on individuals' circumstances e.g. age, gender, health status, economic security, country/region of residence, experience with COVID-19.
- intended compliance for defined lockdown interventions and consequences

METHODS AND ANALYSIS

Overview of approach and methods

We use an online DCE survey to elicit preferences and combine it with moral attitude data and socio-economic characteristics to model heterogeneity. The DCE is a choice-based survey that quantifies preferences for attributes of goods or services. It assumes that goods or services (in this case pandemic responses) can be described by attributes and the levels of these attributes.[21] Each respondent faces a series of hypothetical scenarios (choice sets) composed of two or more alternatives.[22] In each choice set, respondents are asked to choose their preferred scenario. A DCE enables researchers to gain insight into the relative importance of each attribute and the trade-offs between these.

Development of attributes and levels for the DCE

The first stage of a DCE defines the attributes and levels. Attributes describe different lockdown scenarios (Table 1) and are based on: (i) current and possible future lockdown measures from policy documents e.g. Scientific Advisory Group for Emergencies (SAGE) guidance, government guidance and interventions that have been observed globally in response to the COVID-19 pandemic (see Table 2); (ii) current literature on preferences for lockdown measures;[16,17] and (iii) a social media analysis (see Online Supplementary Material (OSM-1)).

We chose attributes based on (i) and (ii) that described the health and wider economic context of the COVID-19 pandemic and lockdown measures. Then we used social media analysis to gain insight into how these attributes were discussed in the public domain. We conducted localised searches for *tweets* that contained phrases or words that could be used to describe the attributes. We generated a sentiment analysis[23,24] and word-clouds from the *tweets* to illustrate how people were construing these words when related to the attributes. This provided insight as to what was important to the general public and how it was being talked about. We informed the attribute levels using estimates and, if available, evidence of the effects from the pandemic and lockdown across different countries.

The attributes and levels are:

1. Type of lockdown: Lockdowns comprise measures across a number of dimensions (business operation, travel, stay at home orders, etc.). We compile these into types of lockdown that vary in the strictness of restrictions. We describe these using colour coding (Table 3). We include four lockdown types (from least to most restrictive): green, yellow, amber and red (Figure 1). Each level is based on on-going policy discussion during the COVID-19 pandemic and is analogous to the phased approach used in several countries (e.g. England, Scotland, USA, New Zealand).

2. Lockdown length: The number of weeks the lockdown will be in effect. This attribute had four levels: 3 weeks; 6 weeks; 10 weeks; and 16 weeks.

3. Postponement of usual non-urgent medical care: Governments around the world have cancelled usual medical care to deal with staff shortages and help the healthcare system respond to an expected increase in patients. This attribute has three levels: all non-urgent, non-pandemic-related procedures postponed; some non-urgent procedures postponed, and all procedures continue as scheduled.

4. Excess deaths: Refers to the number of excess deaths that occur in a pandemic year compared to historical annual averages; this includes both pandemic and non-pandemic related deaths. Approximately 600,000 people die in the UK each year. It is expected at least 50,000 more people in the UK will die in 2020 than in previous years (an 8% increase (50,000/600,000))[3]. This attribute has four levels, increases of: 1% (6,000 deaths), 5% (30,000 deaths), 10% (60,000 deaths) and 15% (90,000 deaths) in the annual expected UK deaths.

We also report the **number of infections** as a complement to the excess deaths, which refers to the number of people infected as a percentage of the population. To avoid unrealistic combinations for each excess death level we infer a corresponding infection rate, using an Infection Fatality Rate range of 0.6-0.7%[4].[25]

5. Ability to buy things: It is expected that many people will be able to afford less after the pandemic, with the OECD predicting a return in real income per capita to 2016 levels by the end of 2021 in the majority of OECD countries.[26] The lockdown measures may reduce

[3] The expected increases in historical annual deaths for other European countries are Germany 1%, Sweden 4%, France 5% and Spain 8%.

[4] Given not all excess deaths are attributable to COVID-19, estimating the infection rate from total excess deaths is likely to cause an overestimation. Moreover, at the same there is uncertainty of the IFR. In the absence of surveillance testing, it is very difficult to know what is the IFR. We then propose to use a conservative IFR to compensate for the overestimation in infection numbers.

household income because of wage cuts or the shutdown of businesses. The lockdown measures may reduce the supply of goods, and fiscal stimulus may cause inflation in both cases the prices people face will increase.[27] We proxy the impact of the pandemic and lockdown measures on income by referring to how much participants would be able to afford one year after the pandemic began. We illustrate this using a basket of goods that represents the amount of goods the respondent was able to buy prior to the pandemic. Levels represent the percentage of the basket of goods respondents will be able to purchase a year after the start of the pandemic. The attribute has four levels of ability to afford of: 70%, 80%, 90%, and 100% of income.

6. Job losses: OECD projections indicate that the COVID-19 crisis will result in the highest peak in unemployment across OECD economies since the Great Depression, with the unemployment rate forecast to be at 9.4% across OECD countries at the end of 2020 in the most optimistic scenario, and still at 7.7% the year after.[26] This attribute refers to the proportion of people who will lose their jobs as a result of the lockdown. The attribute has four levels: 0 in 100 loses job, 4 in 100 loses job, 15 in 100 loses job, and 25 in 100 loses job.

Experimental design and construction of choice sets

These attributes and levels are combined to create **lockdown scenarios** and paired into choice sets of two scenarios. In each choice task, respondents will be asked to choose their preferred lockdown scenario. We used experimental design techniques to select 24 choice tasks using a D-efficient algorithm.[28] The 24 choice sets were blocked into three sets of eight choice tasks to reduce respondents' burden. Our design allows us to estimate non-linear effects of attributes. Scenario attributes will be presented using visual aids to ease comprehension (Table 1). Figure 2 shows an example choice task.

Questionnaire design

The online survey platform enables us to explain attributes using pop-ups of additional information and animated images. We will include questions to gauge understanding of the attributes' levels. We also include an additional repeated choice task as a consistency check, and we will ask respondents how likely they are to comply with the chosen scenario.

We include the Moral Foundation Questionnaire (MFQ) 20 to assess the role of moral attitudes in predicting preferences.[29] This instrument is based on Moral Foundations Theory, which evaluates the normative attitudes on which people base their moral thinking across five[5] dimensions (or foundations). The MFQ20 consists of 20 questions and statements for which respondents indicate their agreement or disagreement on a 6-point Likert Scale. The questionnaire includes 5 questions or statements for each moral foundation. Based on their responses, respondents are assigned score values for each dimension running from 0-20. The internal and external validity of the questionnaire has been demonstrated.[29]

The survey instrument will also collect information on respondents' socio-demographic characteristics (age, education, economic insecurity, health status), country of residence and experience of COVID-19. These observable characteristics will be used to characterise preference heterogeneity. To ensure comparability of our sample with the UK general population, where applicable questions will be based on questions underlying existing national statistics (e.g., the UK census, Office for National Statistics-Labour Force Survey).

[5] Moral Foundations Theory divides these five categories into 'individualising foundations' (Care/Harm and Fairness/Reciprocity) and 'binding foundations' (In-group/Loyalty; Authority/Respect; and Purity/Sanctity).[30]

Preliminary Developmental Work

We have conducted opportunistic developmental work. Virtual think-aloud interviews were conducted using MS Teams with colleagues (n=10) and members of our Stakeholder Advisory Group (SAG, n=3). Whilst think-aloud studies have been shown to be informative when understanding responses to DCEs[31] and interpreting the descriptors for attributes and levels,[32] their virtual application is novel. Participants were asked to share their computer screen with the interviewers and to think aloud whilst responding to the survey. Based on these interviews, we made a number of adjustments to attribute wording, ordering and the format of attribute levels. See OSM-2 for more information.

Identifying and recruiting participants for developing the questionnaire

We will further test the DCE survey with members of the general population, using think-aloud video interviews. Participants will be recruited using social media adverts, using Facebook (see OSM-3). We will target as wide an audience in the UK as possible to minimise selection bias. Participants who express an interest will be sent an invitation email with information about the think-aloud interview and, if still interested, can arrange an interview. Participants will be sent the survey link and asked to think aloud as they complete the survey while the researcher listens and takes notes. Participants will be encouraged to express their thoughts on the survey clarity, length, and structure and the format of the questions. Verbal consent will be taken prior to the start of the interview. Participants will be compensated with a £20 Amazon voucher for their time, which will be sent to them electronically after the interview. The survey text and layout will be changed iteratively during the think aloud phase to improve understanding of the task.[6]

Identifying and recruiting participants for the quantitative pilot and main survey

The pilot study will assess if parameter estimates are in line with a priori expectations. Should the data suggest face validity problems we will make further amendments to the questionnaire and conduct further piloting. Participants for the pilot and main DCE study will be identified and recruited by the survey company Qualtrics. The questionnaire will be administered as an online survey to the general public recruited from the UK (England, Scotland, Wales, and Northern Ireland) with quotas based on age and gender to ensure a representative sample. Qualtrics[7] will also arrange compensation to participants.

Sample size

Sample size for the think aloud virtual interviews will be determined by saturation point; this is expected to require approximately 15-20 interviews.[33]

The sample size for the DCE survey is calculated using Louviere's formula for choice proportions to approximate the minimum sample size.[34] Given a baseline choice probability of 50%, an accuracy level of 90%, a confidence level of 95% and 8 choice tasks per respondent, we require a minimum of 49 respondents. We will recruit 50 individuals from each of the four UK countries to pilot the DCE questionnaire and statistical model. Given we aim to explore heterogeneity of preferences in the main study, we thus decide to be conservative and to have a total of 1000 respondents per nation (n=4000 in total).

[6] We will seek approval for all amendments from the University of Aberdeen's College Ethics Research Board (CERB).

[7] More information of further consent related terms and conditions for Qualtrics can be found in the link: https://www.qualtrics.com/privacy-statement/.

Data analysis

The choice data will be analysed using variants of the multinomial logit (MNL) model.[35] From the DCE questions we observe that respondents will choose one intervention scenario from two scenarios presented in each choice task. We assume that, in each choice task, respondents choose the alternative that provides them with the highest utility. The link between observed choices and changes in the attributes is made possible by the random utility maximisation (RUM) framework.[36] The utility, U, that respondent n obtains from choosing intervention j in a choice task t can be decomposed into two parts: a deterministic part, V, which is observable to the researcher (i.e. based on the attributes included in the DCE), and a random component, ε, which is unobserved.

In mathematical terms, the RUM framework is described as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \quad (1)$$
$$V_{njt} = \sum_k \beta_k X_{kjt} \quad (2)$$

Where *n, j, t, and k* are subscripts respectively for the respondents (n=1,…,N), the pandemic response interventions/alternatives (j=1,…,i, …, J), the choice tasks (t=1,…,T), and the attributes (k=1,…,K). The systematic part (V) is typically described as a linear combination of both respondent's preferences (β_k) and attributes' levels (X_k). The stochastic part is unobserved, and assumptions should be made about its nature. The probability that respondents will choose scenario A over scenario B in the choice task can be calculated if the distribution of ε is specified. The typical assumption about ε is that it is identically and independently distributed (IID) as Type 1 extreme (EV1). Under this assumption, the respondents' choices can be analysed using logit-based models such as multinomial logit (MNL) model. In the MNL model, the probability of choosing an alternative (P_{njt}) depends on its relative utility (i.e. the larger the utility compared to the other pandemic response strategies on offer the more likely the alternative is to be selected).

In DCEs, the systematic component (V) is a function (typically linear and additive) of the attributes and levels included in the study design. The regression coefficients (and their associated t statistics) provide information on whether a change in an attribute's level has a significant effect on an intervention's utility, and the direction of any effect. The ratio of the regression coefficients, known as the Marginal Rate of Substitution (MRS), shows the trade-offs that respondents make between any two attributes e.g. how much household spending are respondents willing to forgo to reduce excess deaths or what increase in job losses they are willing to accept for a decrease in the infection rate. Trade-offs (MRS) will be estimated for all relevant attributes' levels and confidence intervals calculated.[37]

We will explore observed heterogeneity according to moral attitudes (using MFQ 20) and socio-economic characteristics e.g. age, gender, health status, economic insecurity, country of residence and experience with the COVID-19 pandemic. We will use mixed logit (MXL) models to test for unobserved preference heterogeneity, treating responses as a function of choice alternatives and individual characteristics. Choice of the final model will be determined using measures of goodness of fit e.g. log-likelihood, McFadden's R^2, Ben-Akiva-Lerman R^2, the Akaike and Bayesian Information Criteria.

ENSURING IMPACT

We have established a Stakeholder Advisory Group (SAG) to advise on the development of the survey instrument and dissemination and to maximise the policy contribution of this research. Our SAG has representation from the four devolved nations: Neil Craig, Acting Team Head Evaluation, Public Health Scotland; Professor Mark Bellis, Director of Policy, Public Health Wales; Professor Hugo van Woerden, Director of Public Health and Medical Director, Belfast and Brian Ferguson Chief Economist, Public Health England; Shona Christie, Scottish Government Chief Scientist Office Public Engagement Group. This group will be consulted throughout the project. Virtual sessions will be organised when developing the survey to ensure policy relevance and to discuss our findings with the aim of translating the findings into messages for policy.

PATIENT AND PUBLIC INVOLVEMENT

We have a public representative on our Stakeholder Advisory Group, Shona Christie. Shona is a member of the Scottish Government Chief Scientist Office Public Engagement Group. She will advise on the development of the DCE survey and reporting of results. We will work with the Public Engagement in Research Unit (PERU) at the University of Aberdeen to disseminate results to the public. PERU has a dedicated programme for the active engagement of researchers with the public. Our research will be registered with the Research Registry – this is a publicly accessible database.

ETHICS AND DISSEMINATION

Ethical approval was obtained from the University of Aberdeen's College Ethics Research Board (CERB) (Reference CERB/2020/6/1974). Following the developmental work, the research team will seek CERB approval for all amendments to the Protocol, questionnaire or other study documents. Results will be disseminated via webinars to the public health community (informed by our Stakeholder Group) and to the academic community (via journals). Project information will be reported on the publicly available HERU website, and we will use HERU's Blog and social media accounts to disseminate key findings. Findings from the study will be presented at national/international conferences and peer-reviewed journals. Authorship policy will follow the recommendations of International Committee of Medical Journal Editors; http://www.icmje.org/recommendations/browse/roles-and-responsibilities/defining-the-role-of-authors-and-contributors.html

CONSENT

For the questionnaire development, the researcher will confirm eligibility and take verbal consent before starting the interview. Qualtrics will confirm eligibility for the main study. Consent for participants will be sought as part of the survey prior to the data collection questions.

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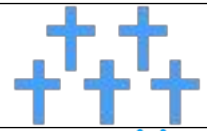
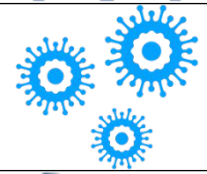
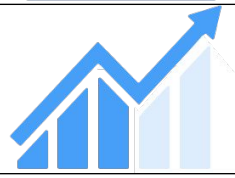
Table 1. Attributes and levels included in the DCE

	Attribute	Short Description	Levels	Visual for Choice Card
1	Type of lockdown	How restrictive the lockdown is (Refer to Figure 1).	Green Yellow Amber Red	
2	Lockdown length	How long the lockdown is in place	3 weeks 6 weeks 10 weeks 16 weeks	
3	Postponement of usual non-urgent medical care	Whether non-pandemic medical care is postponed.	All non-urgent care is postponed. Some non-urgent care is postponed. No urgent care is postponed.	
4	Excess deaths	Number of excess deaths in absolute numbers (% annual increase).	6,000 deaths (1% more) 30,000 deaths (5% more) 60,000 deaths (10% more) 90,000 deaths (15% more)	
5	Number of infections+	Number of infections as a percentage of population	1 in 100 people infected 6 in 100 people infected 13 in 100 people infected 20 in 100 people infected	
6	Ability to buy things	How much of the same amount of goods that respondents buy today (represented by a shopping trolley) will they be able to buy in a year's time.	100% of basket 90% of basket 80% of basket 70% of basket	
7	Job losses	Proportion of people who lose their job.	0 in 100 loses job 4 in 100 loses job 15 in 100 loses job 25 in 100 loses job	

Note: +Number of infections is linked to the excess deaths.

Table 2. COVID-19 response across European countries

Lockdown measures	UK		France		Italy		Spain		Sweden		Netherlands	
		Date		Date		Date		Date		Date		Date
Educational facilities closed	Yes	Mar 23-Aug 4	Yes	Mar 13-Aug 4	Yes	Mar 1-Aug 4	Yes	Mar 11-Aug 4	No	-	Yes	Ma 15-Aug 4
Any gathering restrictions	Yes	Mar 23-Aug 4	Yes	Mar 4-Aug 4	Yes	Feb 22-Aug 4	Yes	Mar 15-Aug 4	Yes	Mar 11-Aug 4	Yes	Mar 10-Aug 4
Stay at home order	Yes	Mar 23-Aug 4	Yes	Mar 18-Aug 4	Yes	Mar 8-Aug 4	Yes	Mar 15-Aug 4	No	-	No	-
Any business closure	Yes	Mar 20-Aug 4	Yes	Mar 15-Aug 4	Yes	Feb 22-Aug 4	Yes	Mar 13-Aug 4	No	-	Yes	Mar 12-Aug 4
All non-essential businesses closed	Yes	Mar 24-Aug 4	Yes	Mar 15-Aug 4	Yes	Mar 8-Apr 14	Yes	Mar 13-Apr 13	No	-	No	-
Travel severely limited	No	-	Yes	Mar 17-Aug 4	Yes	Mar 8-May 4	No	-	No	-	No	-
Average duration		4 months		4 months		5 months		4 months		-		4 months

Table 3. Colour coding for Type of Lockdown Attribute Levels

	Green	Yellow	Amber	Red
Stay at home (shelter in place)	Everyone (including vulnerable individuals) can interact with others.	Vulnerable individuals should stay home (shelter in place).	Vulnerable individuals should stay at home (shelter in place) and must have no visitors.	Everyone must stay at home (shelter in place).
Socialising group	Gatherings of up to 100 people.	Gatherings of up to 50 people.	Gatherings of up to 10 people.	No gatherings beyond own household (own bubble).
Non-essential (other than groceries and work-related) trips	Non-essential trips are allowed.	Non-essential trips are allowed.	Non-essential trips should be minimised	Non-essential trips are not allowed.
Schools & youth activities:	Open	Open	Closed	Closed
Businesses (e.g. shops) can operate under:	Limited social distancing	Moderate social distancing, operate at reduced capacity	Strict social distancing, operate at minimal capacity	Closed
Outdoor activities	Allowed	Allowed	Allowed	Not allowed

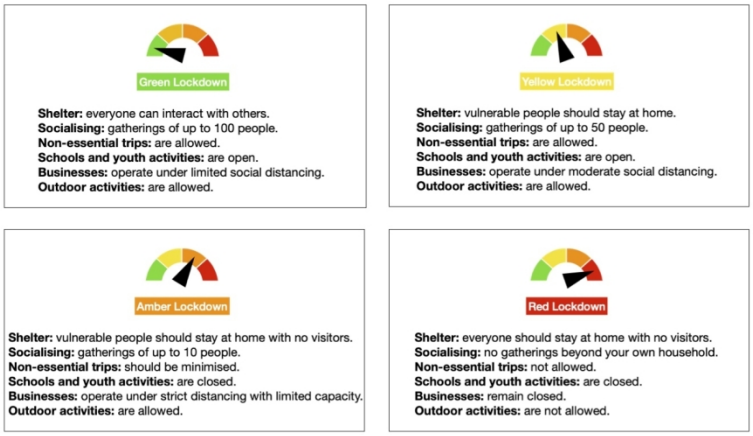


Figure 1: Lockdown levels for DCE

297x209mm (150 x 150 DPI)

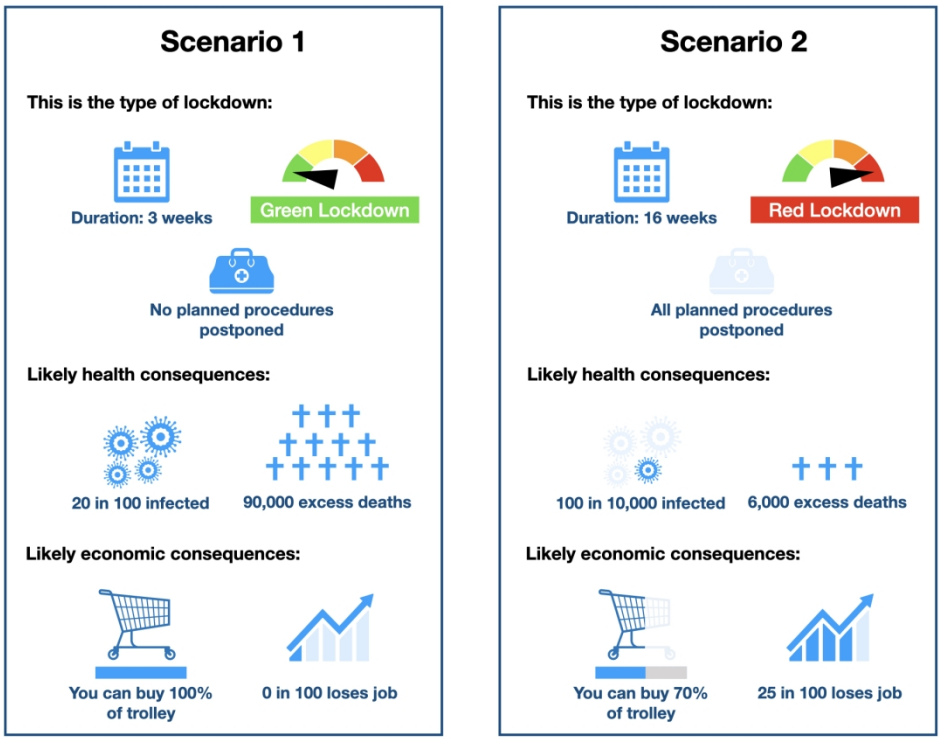


Figure 2: An example of a choice task

705x529mm (72 x 72 DPI)

OSM-1: Social Media (Twitter) Analysis[1]

Attributes were selected based on policy discussions and government guidance observed globally. To look more into the chosen attributes, we conducted a social media analysis. We extracted attributes-related tweets between 15th February 2020, and 19th May 2020, using the Twitter standard search application programming interface (API) consisting of a set of predefined expressions (see below), which are the most widely used news media terms relating to the novel coronavirus (COVID-19). 15,000 tweets with expressions related to the attributes were extracted for our social media analysis. Only English language tweets were extracted. We analysed the extracted tweets using **world cloud** and **sentiment analysis,** which are standard procedures in text mining literature.[1, 2, 3]

Word cloud: shows that the bigger the word, the maximum times it has been used. This gives us a sense of how the online community reacts to some expressions/attributes related to the COVID-19 pandemic.

Sentiment analysis[2]: this is the process of computationally identifying and categorising opinions expressed in a piece of text, especially to determine whether the tweeter's attitude towards a particular topic, product, etc. is positive, negative, or neutral.

[1] Date of Tweets Extraction: 19th May 2020 (Tweets from 15th February 2020-19th May 2020).

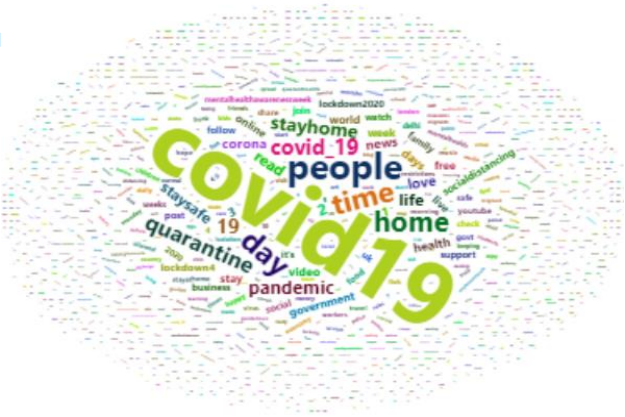
[2] Sentiment Scale: 0-Neutral >0-Positive <0-Negative

Type of lockdown: this refers to how strict the lockdown measures are. To construct a word cloud for this attribute, we used different related terms/expressions in our twitter search (lockdown rules, lockdown policy, and lockdown restrictions). We first present the word cloud for these related terms.

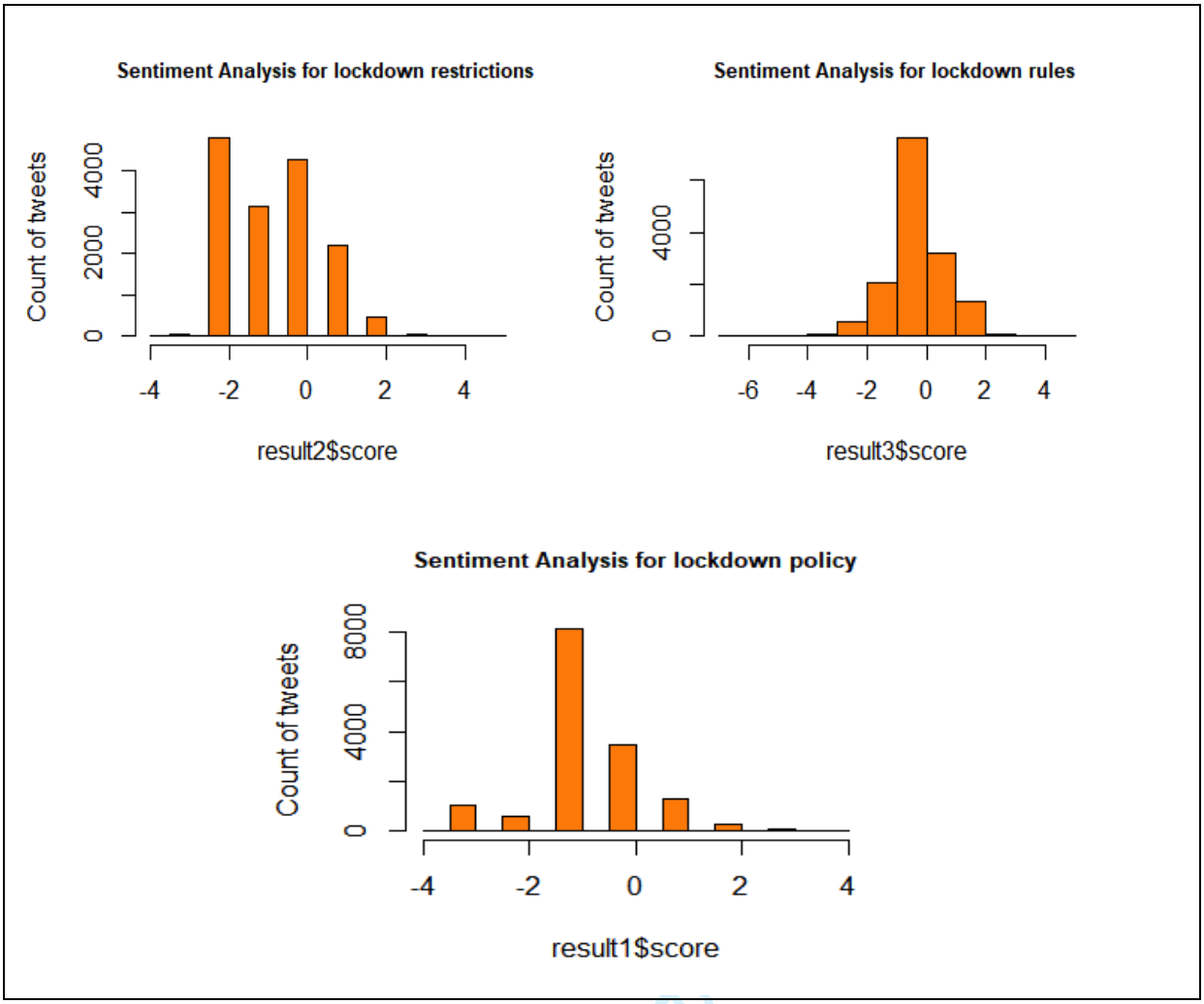
Lockdown restrictions

Lockdown rules

Lockdown policy



#Lockdown



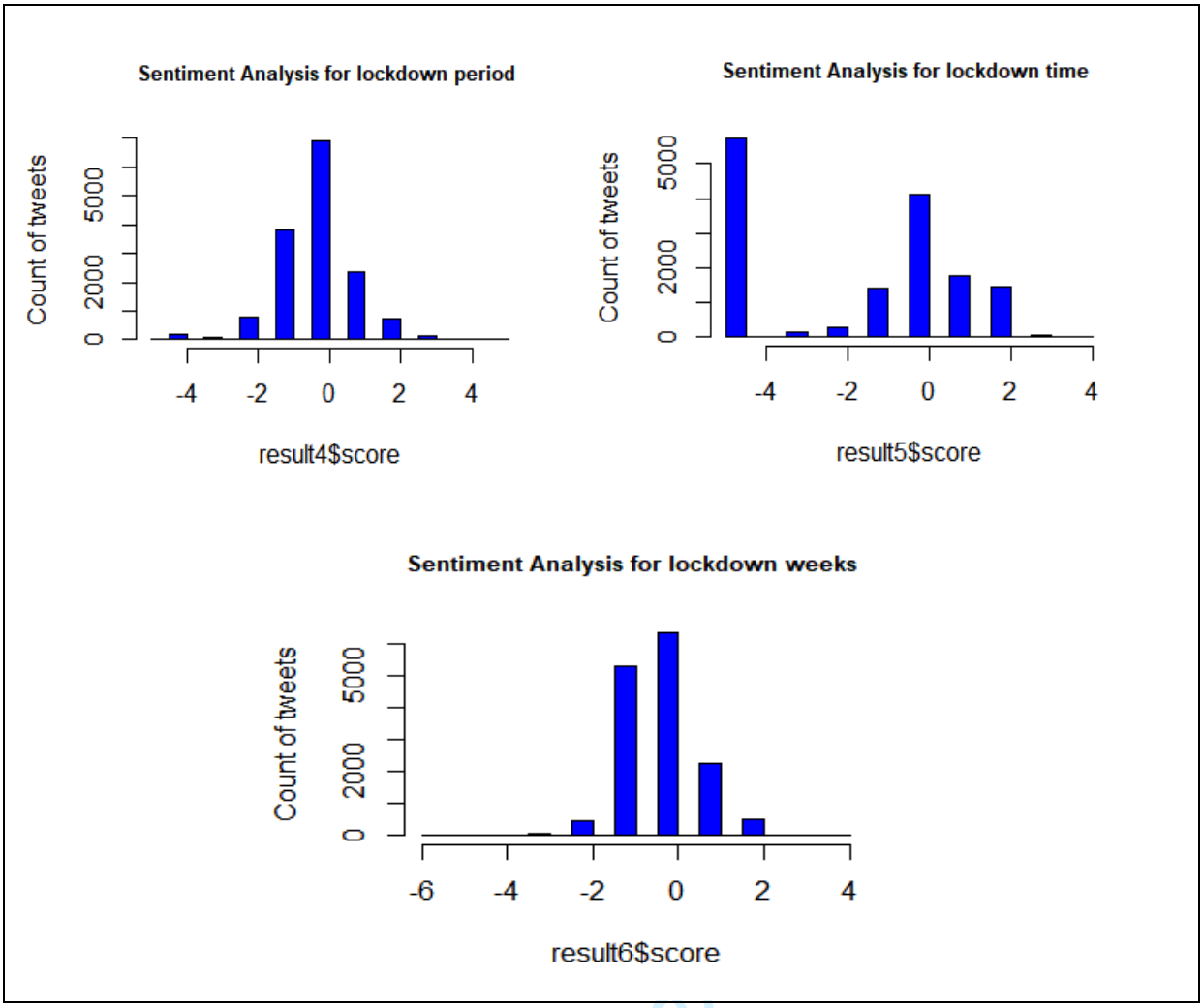
Sentiment types	Lockdown restrictions	Lockdown rules	Lockdown policy
Negative	53%	18%	65%
Neutral	28%	51%	23%
Positive	19%	31%	12%

Lockdown length: this refers to the number of months the lockdown will be in effect. We used related terms such as lockdown period, lockdown weeks, and lockdown duration.

Lockdown period

Lockdown time

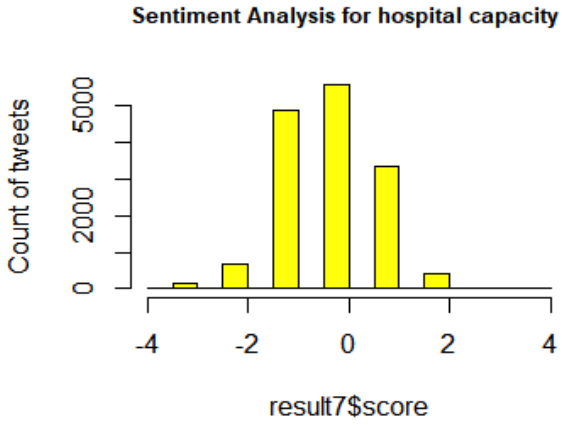
Lockdown weeks



Sentiment types	Lockdown period	Lockdown time	Lockdown weeks
Negative	33%	51%	39%
Neutral	46%	27%	42%
Positive	21%	22%	19%

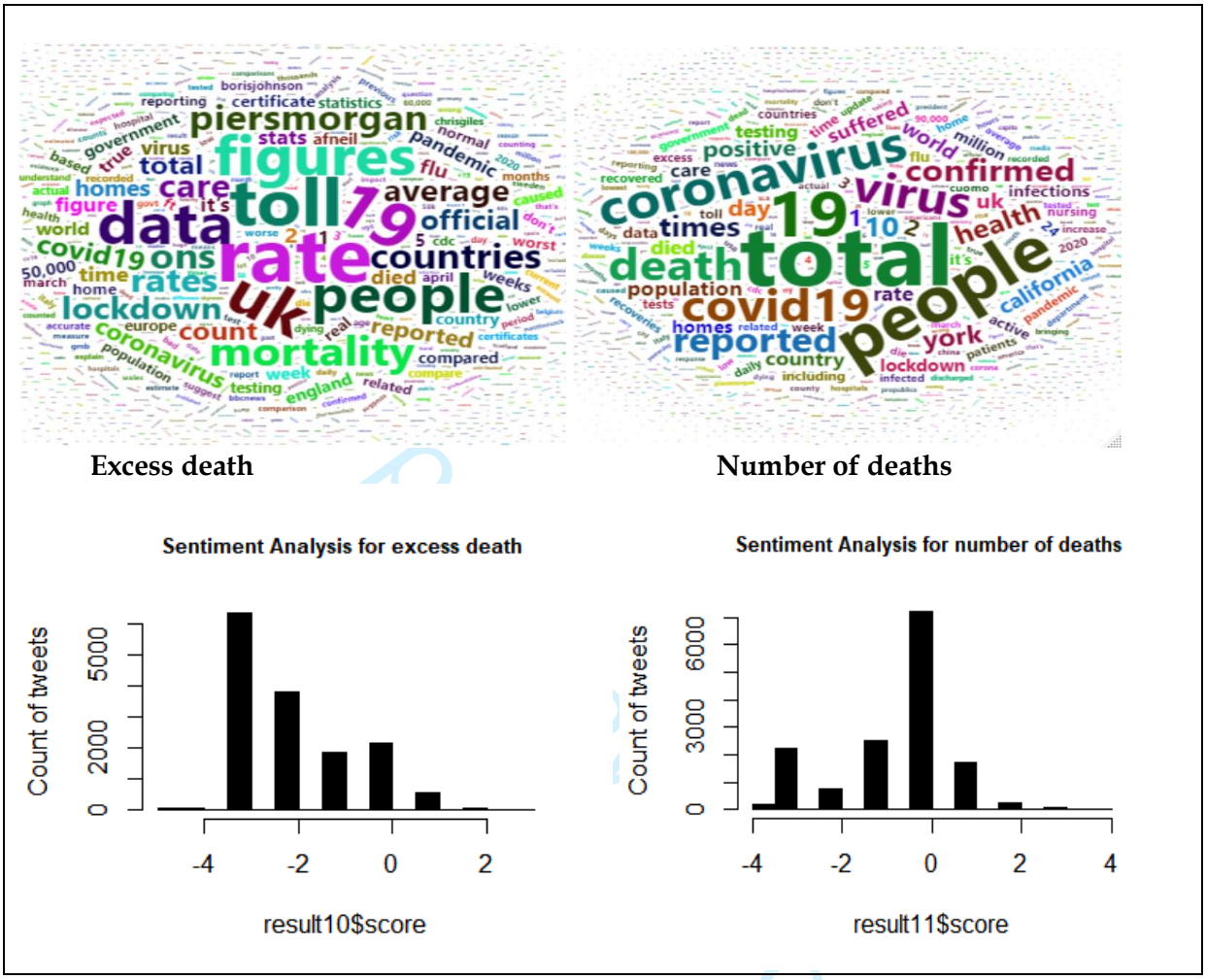
Postponement of usual non-urgent medical care: this refers to whether hospitals will postpone non-pandemic related medical procedures. Related terms to this attribute in our twitter search include hospital capacity, delay medical procedures.

Hospital capacity



Negative sentiment (38%), neutral (37%), positive (25)

Excess deaths: this refers to the difference between the number of people who die during the pandemic, and the historical average for the same place and time of the year. To construct the word cloud related to this attribute, we used terms such as 'excess death' and 'number of deaths' in the tweet searches.



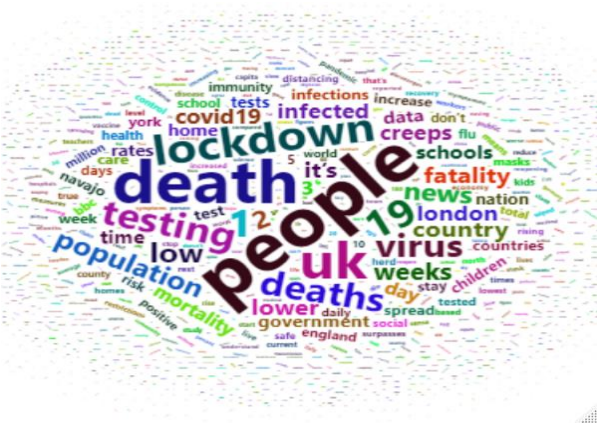
People use 'excess death' in their tweets. Most of the tweets indicate negative sentiment: 81% of the sentiment lies in the negative domain. Therefore, people's sentiment towards 'excess death' is largely negative. From the word cloud for the attribute 'excess death', it appears that terms like toll, mortality, rate, figures etc. are used several times in the tweets that were extracted. Words like 'rates,' 'total,' 'toll' give us a glimpse at their attitude.

Sentiment types	Excess death	Number of deaths
Negative	81%	38%
Neutral	15%	48%
Positive	4%	14%

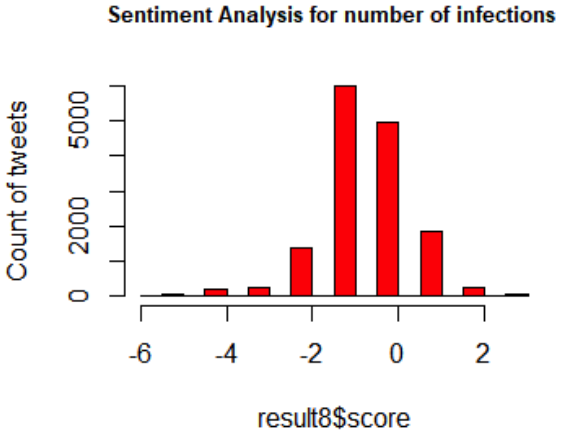
People are more concerned about excess death than the number of deaths.

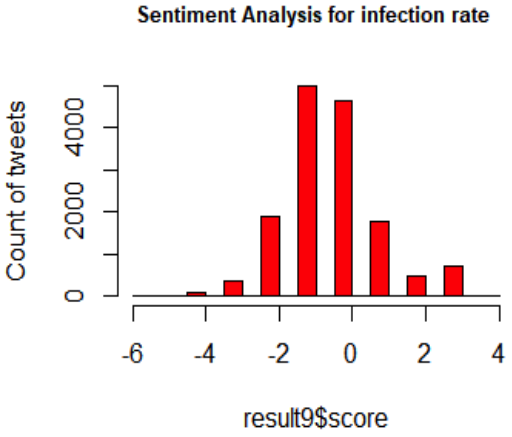
The number of infections: the number of people who will be infected. We used 'number of infections' and 'infection rate' in our tweet search.

Number of infections



Infection rate

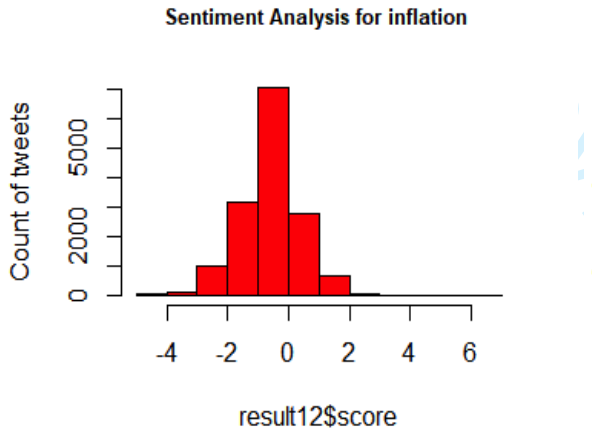


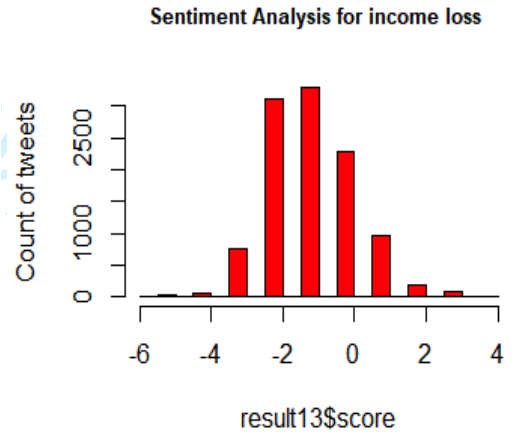


Sentiment types	Number of infections	Infection rate
Negative	53%	49%
Neutral	33%	31%
Positive	14%	20%

Ability to buy things: this refers to how much you will be able to afford one year from now compared to how much you would be able to afford normally. To build the word cloud for this attribute, we extracted tweets using related terms such as inflation and income loss.

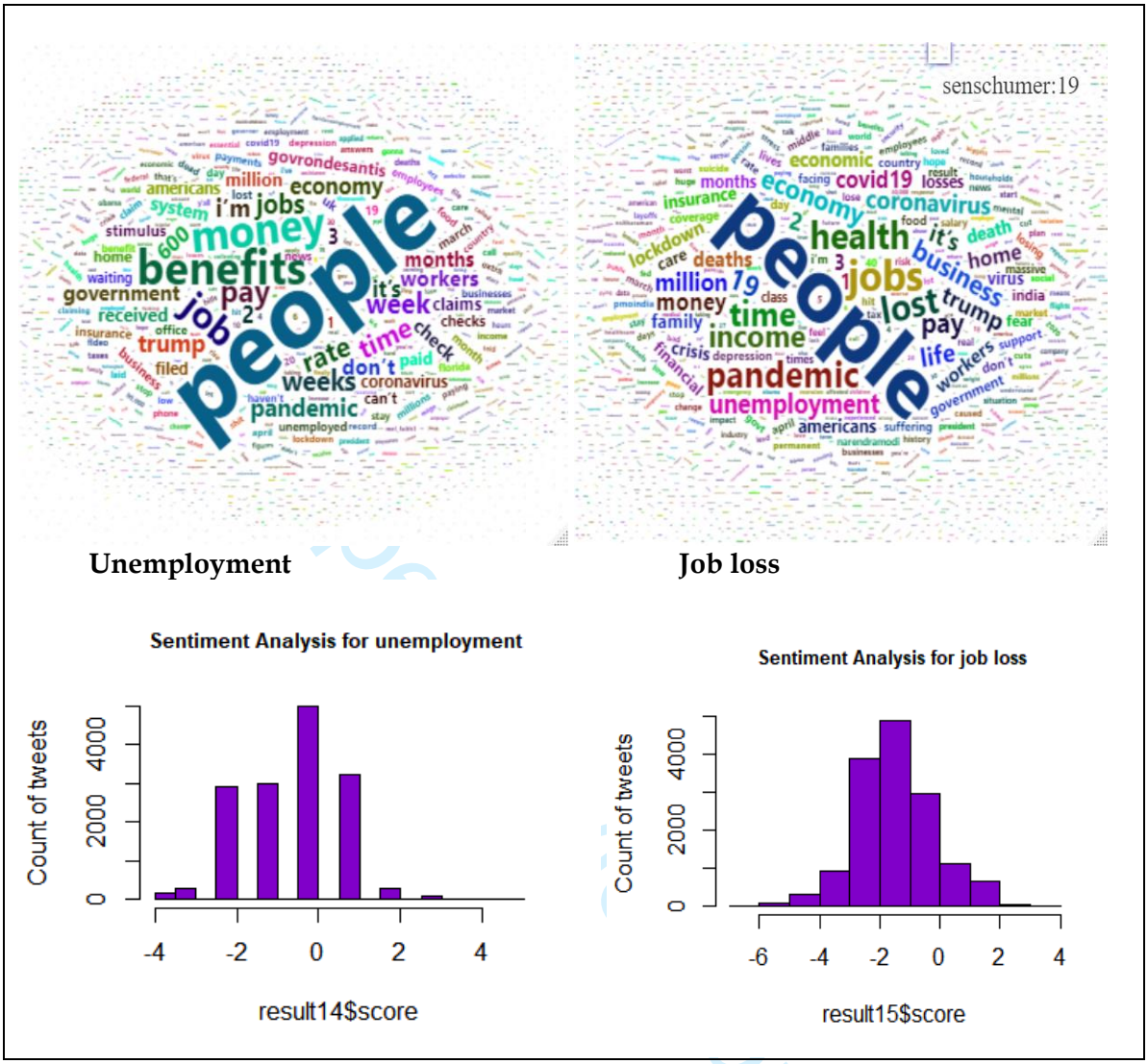
Inflation **Income loss**





Sentiment types	Inflation	Income loss
Negative	30%	67%
Neutral	47%	21%
Positive	23%	12%

Job losses: this refers to the proportion of people who will lose their jobs as a result of the lockdown. We used terms like unemployment and job loss in our tweet search.



Sentiment types	Unemployment	Job loss
Negative	43%	68%
Neutral	33%	20%
Positive	24%	12%

Additional References

1. Saif, H., He, Y., & Alani, H. (2012, November). Semantic sentiment analysis of twitter. In *International semantic web conference* (pp. 508-524). Springer, Berlin, Heidelberg.
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OSM-2: Opportunistic Think-Aloud Interviews

Virtual think-aloud (TA) interviews were conducted using MS Teams with colleagues from the University of Aberdeen (n=10) and members of our Stakeholder Advisory Group (SAG, n=3). Participants were asked to share their computer screen with the interviewers and to verbalise their thought processes whilst responding to the survey. As a warm-up, they were asked to think aloud whilst responding to the question: "*How many windows are there in your house?"* Respondents were told to consider the interviewer as a silent observer of their thought process. Interviewers did, however, encourage respondents to verbalise their thoughts if they were silent for a short period. Respondents were told there were no right or wrong answers. The interviews lasted between 45 and 90 minutes.

A number of changes were made to the DCE survey.

1. **Presentation of the excess death, number of infections, and job loss attributes**

In the TA interview used for internal testing, the attributes for excess death, number of infections, and job losses were presented differently. The number of jobs lost, and the number of people infected were presented as fractions of 100. In contrast, the excess death attribute was presented as absolute numbers of additional people dying over the expected figure during a normal year. This led to the excess death attribute dominating the choices of a significant number of participants, with some participants stating that they ignored all other attributes and considered the lower number of excess deaths presented in the choice task.

While this might be an expression of a valid preference, the feedback we received included evidence that the presentation of the excess death attribute in absolute numbers inflated its importance relative to other attributes. One participant stated that, while they recognised that job losses were presented as fractions, in their mind they ignored the denominator of the job loss attribute and directly compared its numerator to the absolute figures presented for the excess death attribute.

We changed the presentation of the excess death and number of infections attributes to be uniform across the choice task. The number of infections and excess deaths are now presented as fractions of 10,000.

2. **Presentation and placement of lockdown type attribute**

In the TA interview for internal testing, the colour-coded visual for the lockdown type attribute was prominently presented at the top of each choice option. Some participants interpreted the visual as a summary of the choice option rather than as an independent attribute.

We changed the position of the visual for the lockdown type attribute to make it appear next to the visual for the lockdown duration attribute.

3. **Visual presentation of the number of infections attribute**

The TA for internal testing displayed a *static* visual for the number of infections attribute that did not change according to the attribute level presented. Several participants stated that a changing visual would help them make better sense of the attribute level. We changed the visual to change with an increasing number of infections.

4. Presentation of the shopping trolley attribute

Initially, the text under the visual for the 'shopping trolley' attribute read "X% of the trolley." Some participants interpreted this to mean the economic impact on society rather than the economic impact on themselves. We changed the text to read "You can buy X% of the trolley."

5. Explanation of the shopping trolley attribute

Some participants were concerned that the initial explanation of the shopping trolley focused on consumption rather than the general cost of living. One participant expressed concerns that this might not accurately reflect the experiences of impoverished respondents. We expanded the explanation of the shopping trolley attribute to include housing costs and utility bills.

6. MFQ20: Likert scale anchors

The initial presentation of the MFQ20 presented the anchors for different points on a 6-point Likert scale ("not at all relevant" to "extremely relevant" and "strongly disagree to "strongly agree") at the top of the page. For the selection matrix, points on the scale were labelled with numbers running from 0-5 to mimic the presentation of the paper-based MFQ 20.

We observed that the top of the page was not visible for participants while they were answering the questions, leading them to spend a lot of time scrolling up and down on the page. We amended the selection matrix to display the anchors next to the numbered points on the Likert scale.

7. Ease-of-use updates

To make the survey more engaging, we made various improvements to the interface and presentation formats. This included a progress bar at the top of the screen, mouse-hover explanations for different selection options, and input prompts.

OSM-3: Social Media Ad for Think Aloud

1495 UNIVERSITY OF ABERDEEN

HERU
HEALTH ECONOMICS RESEARCH UNIT
Promoting Excellence in Health Economics

Want to take part in a survey development about interventions to control a future pandemic?

Participate in our study!

- **We are trying to understand public preferences for interventions to control a future pandemic.**
- **We are asking for volunteers who are willing to support the design of a questionnaire using a process called "Think Aloud".**
- **A small gratuity (£20) will be offered for your participation.**

Where? Over Video Call
How long? 30-40 minutes
Who? 18 years or over living in the UK

If you are interested in supporting this research project in this way, please email heru@abdn.ac.uk to arrange a suitable time for this to take place.

BMJ Open

Understanding public preferences and trade-offs for government responses during a pandemic: A protocol for a discrete choice experiment in the United Kingdom

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Primary Subject Heading:	Health economics
Secondary Subject Heading:	Public health
Keywords:	COVID-19, HEALTH ECONOMICS, INFECTIOUS DISEASES, PUBLIC HEALTH

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Understanding public preferences and trade-offs for government responses during a pandemic: A protocol for a discrete choice experiment in the United Kingdom

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ABSTRACT

Introduction: Social distancing and lockdown measures are among the main government responses to the COVID-19 pandemic. These measures aim to limit the COVID-19 infection rate and reduce the mortality rate of COVID-19. Given we are likely to see local lockdowns until a treatment or vaccine for COVID-19 is available, and their effectiveness depends on public acceptability, it is important to understand public preference for government responses.

Methods and analysis: Using a discrete choice experiment (DCE), this study will investigate the public's preferences for pandemic responses in the UK. Attributes (and levels) are based on: (i) lockdown measures described in policy documents; (ii) literature on preferences for lockdown measures; and (iii) a social media analysis. Attributes include: lockdown type; lockdown duration; impact on the health service; number of excess deaths; number of infections; impact on household spending; and job losses. We will pre-pilot the DCE using virtual think aloud interviews with respondents recruited via Facebook. We will collect preference data using an online survey of 4000 individuals from across the four UK countries (1000 per country). We will estimate the relative importance of the attributes, and the trade-offs individuals are willing to make between attributes. We will test if respondents' preferences differ based on moral attitudes (using the Moral Foundation Questionnaire), socioeconomic circumstances (age, education, economic insecurity, health status), country of residence and experience of COVID-19.

Ethics and dissemination: The University of Aberdeen's College Ethics Research Board (CERB) have approved the study (Reference: CERB/2020/6/1974). We will seek CERB approval for all amendments from the developmental and pilot work. Peer-reviewed papers will be submitted, and results will be presented at public health and health economic conferences nationally and internationally. A lay-summary will be published on the Health Economics Research Unit blog.

Strengths and limitations of this study

- The study will be the first discrete choice experiment (DCE) conducted to provide information on the public preferences and trade-offs for government responses during a pandemic in the UK.
- We will explore preference heterogeneity according to the respondents' socio-demographic characteristics.
- This is the first study to combine a DCE with Moral Foundation Theory (MFT) to understand how people's moral values shape preferences for government pandemic responses.
- It is not feasible to incorporate all factors that may affect the public preferences (e.g. effect on children through school closures; impact on mental health, impacts on inequalities).
- This study will be undertaken in the UK and may not be generalisable to other countries.

INTRODUCTION

The public health response of governments to the COVID-19 pandemic has differed across countries. Responses have mostly involved lockdown measure that encourages social distancing[2] to slow the spread of the disease.[1,2] The timing and strictness of these measures has differed across countries. Italy and Spain introduced early strict lockdown measures,[3,4] while restrictions in Sweden and the Netherlands were less severe.[5,6] Responses in China and Vietnam were more stringent [7,8] due to prior experiences of responding to outbreaks of other infectious diseases, including SARS, MERS, measles and dengue.[9,10] Policies in the UK shifted from a more relaxed initial approach towards stricter measures as the pandemic progressed.[11] As lockdowns have eased (as of 27th of July 2020), we have seen local lockdowns introduced to deal with spikes in infection rates (e.g. Leicester (England), Melbourne (Australia) and Barcelona (Spain).[12,13,14]

The pandemic and the subsequent public health response affect both public health and the economy.[15] Supressing infections has required stringent physical distancing measures, which has had a range of direct and indirect impacts on health as well as the wider determinants of physical and mental health.[16,17] Economic impacts include increased unemployment rates and decreased household income,[18] with certain groups more likely to experience economic hardship.[19,20,21] When lockdown measures are implemented the interests of different people may be in conflict. Public health responses must then balance protecting the population and health care system with the impact on the economy and personal freedoms. A better understanding of public preferences and how they differ across communities may help policy makers decide which interventions to deploy.

Very little is known about public preferences for lockdown policies. Previous research in Singapore and Australia conducted before the COVID-19 outbreak suggests considerable variation in preferences. Cook et al[22] used a Discrete Choice Experiment (DCE) to investigate public preferences for pandemic interventions for emerging infectious disease in Singapore. Whilst respondents preferred more intense interventions, fewer deaths and lower taxes to fund public health measures, the number of infections did not affect their preferences. Respondents were willing to accept a loss of S$370 million at the societal level for the full set of interventions considered and a personal cost of up to S$34 to prevent 30 deaths, S$70 to prevent 80, S$71 to prevent 120 and S$98 to prevent 180-at a national level. The value placed on a strong response (mandatory isolation and quarantine, cancelling all mass gatherings, and island-wide screening), S$74, corresponded to the value placed on preventing 100 deaths. Johnson et al[23] used a DCE to explore public preferences for attributes associated with One Health strategies for emerging infectious disease prevention and control in Australia. They examined trade-offs between risk attributes (zoonotic risk or mortality) and other attributes, expressed as 'willingness to accept' extra cases of severe disease or extra deaths, to avoid compromises in other attributes. Food security was valued most highly, with respondents willing to accept the highest number of additional cases of disease, or deaths, to avoid compromising food security. The next most highly valued attributes were: animal welfare; economic development; environmental health; community cohesion; personal autonomy; and free trade and travel.

[2] Social distancing, also called "physical distancing," means keeping a safe space between yourself and other people who are not from your household.[24]

More recent work has used the DCE method to understand preferences and trade-offs for responses to the COVID-19 pandemic. Chorus et al[25] elicited preferences of the Dutch adult public for relaxing lockdown. The DCE included attributes related to health, the economy, education, and personal income. They found that, compared to younger people, older people are less willing to sacrifice (per fatality avoided): people with mental health problems; children at an educational disadvantage and households with an income loss. Reed et al[26] explored the extent to which US adults are willing to accept a greater risk spread of COVID-19 to lift social-distancing restrictions and limit the economic impact of the pandemic. They identified 4 preference patterns: risk minimizers who are reluctant to accept any increases in risk (37%); those primarily concerned with time required for economic recovery, accepting increases in COVID-19 risk levels up to 16% to shorten recovery from 3 to 2 years (26%); those who preferred delaying reopening (26%); and those accepting COVID-19 risks beyond 20% to avoid a delay in reopening (13%). Political affiliation, race, household income and employment status predicted preference patterns, with political affiliation being the most important predictor.

AIMS

Building upon these studies, we use the DCE method to estimate how people in the UK make trade-offs between features of lockdown interventions. Specifically, we explore:

- the relative importance of pandemic response features
- trade-offs respondents make between these features e.g. how much household spending are respondents willing to forgo to reduce excess deaths or what increase in job losses they are willing to accept for a decrease in the infection rate?
- the impact of moral attitudes on preferences
- preference heterogeneity based on individuals' circumstances e.g. age, gender, health status, economic security, country/region of residence, experience with COVID-19.
- intended compliance for defined lockdown interventions and consequences

METHODS AND ANALYSIS

Overview of approach and methods

We use an online DCE survey to elicit preferences and combine it with moral attitude data and socio-economic characteristics to model heterogeneity. The DCE is a choice-based survey that quantifies preferences for attributes of goods or services. It assumes that goods or services (in this case pandemic responses) can be described by attributes and the levels of these attributes.[27] Each respondent faces a series of hypothetical scenarios (choice sets) composed of two or more alternatives.[28] In each choice set, respondents are asked to choose their preferred scenario. A DCE enables researchers to gain insight into the relative importance of each attribute and the trade-offs between these.

Development of attributes and levels for the DCE

The first stage of a DCE defines the attributes and levels. Attributes describe different lockdown scenarios (Table 1) and are based on: (i) current and possible future lockdown measures from policy documents e.g. Scientific Advisory Group for Emergencies (SAGE) guidance, government guidance and interventions that have been observed globally in

response to the COVID-19 pandemic (see Table 2); (ii) current literature[3] on preferences for lockdown measures;[22,23] and (iii) a social media analysis (see Online Supplementary Material (OSM-1)).

We chose attributes based on (i) and (ii) that described the health and wider economic context of the COVID-19 pandemic and lockdown measures. Then we used social media analysis to gain insight into how these attributes were discussed in the public domain. We conducted localised searches for *tweets* that contained phrases or words that could be used to describe the attributes. We generated a sentiment analysis[29,30] from the *tweets* to illustrate how people were construing these words when related to the attributes. This provided insight as to what was important to the general public and how it was being talked about. We informed the attribute levels using estimates and, if available, evidence of the effects from the pandemic and lockdown across different countries.

The attributes and levels are:

1. Type of lockdown: Lockdowns comprise measures across a number of dimensions (business operation, travel, stay at home orders, etc.). We compile these into types of lockdown that vary in the strictness of restrictions. We describe these using colour coding (Table 3). We include four lockdown types (from least to most restrictive): green, yellow, amber and red (Figure 1). Each level is based on on-going policy discussion during the COVID-19 pandemic and is analogous to the phased approach used in several countries (e.g. England, Scotland, USA, New Zealand).

2. Lockdown length: The number of weeks the lockdown will be in effect. This attribute had four levels: 3 weeks; 6 weeks; 10 weeks; and 16 weeks.

3. Postponement of usual non-urgent medical care: Governments around the world have cancelled usual medical care to deal with staff shortages and help the healthcare system respond to an expected increase in patients. This attribute is particularly relevant in the UK context and is under the scope of the government. For example, the Scottish government cancelled routine procedures in 2020.[31] Further, nearly a million appointments for mammograms have been missed in the UK due to the COVID-19 pandemic.[32] This, along with the extra capacity built (e.g. Nightingale around England and Louisa Jordan in Glasgow), make this attribute particularly relevant for providing policy advice. This attribute has three levels: all non-urgent, non-pandemic-related procedures postponed; some non-urgent procedures postponed, and all procedures continue as scheduled.

4. Excess deaths: Refers to the number of excess deaths that occur in a pandemic year compared to historical annual averages; this includes both pandemic and non-pandemic related deaths. Approximately 600,000 people die in the UK each year. It is expected at least 50,000 more people in the UK will die in 2020 than in previous years (an 8% increase (50,000/600,000))[4]. This attribute has four levels, increases of: 1% (1 in 10,000 additional people die), 5% (4 in 10,000 additional people die), 10% (9 in 10,000 additional people die) and 15% (13 in 10,000 additional people die) in the annual expected UK deaths.

[3] From May-June 2020, we searched Google (Scholar), using the following terms and combinations of them: 'covid-19', 'coronavirus', 'discrete choice experiment', 'pandemic', and 'infectious disease'.

[4] The expected increases in historical annual deaths for other European countries are Germany 1%, Sweden 4%, France 5% and Spain 8%.

We also report the **number of infections** as a complement to the excess deaths, which refers to the number of people infected as a fraction of 10,000 people. To avoid unrealistic combinations for each excess death level we infer a corresponding infection rate, using an Infection Fatality Rate range of 0.6-0.7%[5].[33]

5. Ability to buy things: It is expected that many people will be able to afford less after the pandemic, with the OECD predicting a return in real income per capita to 2016 levels by the end of 2021 in the majority of OECD countries.[34] The lockdown measures may reduce household income because of wage cuts or the shutdown of businesses. The lockdown measures may reduce the supply of goods, and fiscal stimulus may cause inflation in both cases the prices people face will increase.[35] We proxy the impact of the pandemic and lockdown measures on income by referring to how much participants would be able to afford one year after the pandemic began. We illustrate this using a basket of goods that represents the amount of goods the respondent was able to buy prior to the pandemic. Levels represent the percentage of the basket of goods respondents will be able to purchase a year after the start of the pandemic. The attribute has four levels of ability to afford of: 70%, 80%, 90%, and 100% of income.

6. Job losses: OECD projections indicate that the COVID-19 crisis will result in the highest peak in unemployment across OECD economies since the Great Depression, with the unemployment rate forecast to be at 9.4% across OECD countries at the end of 2020 in the most optimistic scenario, and still at 7.7% the year after.[34] This attribute refers to the proportion of people who will lose their jobs as a result of the lockdown. The attribute has four levels: 0 in 100 loses job, 4 in 100 loses job, 15 in 100 loses job, and 25 in 100 loses job.

Experimental design and construction of choice sets

These attributes and levels are combined to create **lockdown scenarios** and paired into choice sets of two scenarios. We used NGENE software (ChoiceMetrics) to generate a 24 choice tasks D-efficient design with non-informative (null) priors and allowing estimation of non-linear effects of attributes.[36] Respondents will be allocated to one of three blocks, so they will neither all face the same choice tasks, nor in the same order. The design was based on the main effects only (i.e. without interactions). The 24 choice sets were blocked into three sets of eight choice tasks to reduce respondents' burden. The order of choice tasks within each block will be randomised. Scenario attributes will be presented using visual aids to ease comprehension. Figure 2 shows an example choice task.

Questionnaire design

The online survey platform enables us to explain attributes using pop-ups of additional information and animated images. We will include questions to gauge understanding of the attributes' levels. We also include an additional repeated choice task as a consistency check, and we will ask respondents how likely they are to comply with the chosen scenario. The compliance information will be used to understand whether people's moral attitudes affect compliance with the chosen scenario. There is some evidence of a positive correlation between high scores in the binding moral foundations and an intent to defy social distancing rules.[37] Further, the compliance data will be used to explore whether respondents who are more likely to comply with the selected scenario have a specific pattern of preferences. We will also

[5] Given not all excess deaths are attributable to COVID-19, estimating the infection rate from total excess deaths is likely to cause an overestimation. Moreover, at the same there is uncertainty of the IFR. In the absence of surveillance testing, it is very difficult to know what is the IFR. We then propose to use a conservative IFR to compensate for the overestimation in infection numbers.

explore the impact of socio-economic characteristics, experiences with COVID-19 and views on government handling on compliance.

We include the Moral Foundation Questionnaire (MFQ) 20 to assess the role of moral attitudes in predicting preferences.[38] This instrument is based on Moral Foundations Theory, which evaluates the normative attitudes on which people base their moral thinking across five[6] dimensions (or foundations). The MFQ20 consists of 20 questions and statements for which respondents indicate their agreement or disagreement on a 6-point Likert Scale. The questionnaire includes 5 questions or statements for each moral foundation. Based on their responses, respondents are assigned score values for each dimension running from 0-20. The internal and external validity of the questionnaire has been demonstrated.[38]

The survey instrument will also collect information on respondents' socio-demographic characteristics (age, sex, education, ethnicity, economic insecurity, health status), country of residence and experience of COVID-19. These observable characteristics will be used to characterise preference heterogeneity. To ensure comparability of our sample with the UK general population, where applicable questions will be based on questions underlying existing national statistics (e.g., the UK census, Office for National Statistics-Labour Force Survey).

Preliminary Developmental Work

We have conducted opportunistic developmental work. Virtual think-aloud interviews were conducted using MS Teams with colleagues (n=10) and members of our Stakeholder Advisory Group (SAG, n=3). Whilst think-aloud studies have been shown to be informative when understanding responses to DCEs[39] and interpreting the descriptors for attributes and levels,[40] their virtual application is novel. Participants were asked to share their computer screen with the interviewers and to think aloud whilst responding to the survey. Based on these interviews, we made a number of adjustments to attribute wording, ordering and the format of attribute levels. See OSM-2 for more information.

Identifying and recruiting participants for developing the questionnaire

We will further test the DCE survey with members of the general population, using think-aloud video interviews. Participants will be recruited using social media adverts, using Facebook (see OSM-3). We will target as wide an audience in the UK as possible to minimise selection bias. Participants who express an interest will be sent an invitation email with information about the think-aloud interview and, if still interested, can arrange an interview. Participants will be sent the survey link and asked to think aloud as they complete the survey while the researcher listens and takes notes. Participants will be encouraged to express their thoughts on the survey clarity, length, and structure and the format of the questions. Verbal consent will be taken prior to the start of the interview. Participants will be compensated with a £20 Amazon voucher for their time, which will be sent to them electronically after the interview. The survey text and layout will be changed iteratively during the think aloud phase to improve understanding of the task.[7]

[6] Moral Foundations Theory divides these five categories into 'individualising foundations' (Care/Harm and Fairness/Reciprocity) and 'binding foundations' (In-group/Loyalty; Authority/Respect; and Purity/Sanctity).[41]

[7] We will seek approval for all amendments from the University of Aberdeen's College Ethics Research Board (CERB).

Identifying and recruiting participants for the quantitative pilot and main survey

The pilot study will assess if parameter estimates are in line with a priori expectations. Should the data suggest face validity problems we will make further amendments to the questionnaire and conduct further piloting. Participants for the pilot and main DCE study will be identified and recruited by the survey company Qualtrics. The questionnaire will be administered as an online survey to the general public recruited from the UK (England, Scotland, Wales, and Northern Ireland) with quotas based on age and gender to ensure a representative sample. Qualtrics[8] will also arrange compensation to participants.

Sample size

Sample size for the think aloud virtual interviews will be determined by saturation point; this is expected to require approximately 15-20 interviews.[42]

The sample size for the DCE survey is calculated using Louviere's formula for choice proportions to approximate the minimum sample size.[43] Given a baseline choice probability of 50%, an accuracy level of 90%, a confidence level of 95% and 8 choice tasks per respondent, we require a minimum of 49 respondents. We will recruit 50 individuals from each of the four UK countries to pilot the DCE questionnaire and statistical model. Given we aim to explore heterogeneity of preferences in the main study, we thus decide to be conservative and to have a total of 1000 respondents per nation (n=4000 in total).

Data analysis

The choice data will be analysed using variants of the multinomial logit (MNL) model.[44] From the DCE questions we observe that respondents will choose one intervention scenario from two scenarios presented in each choice task. We assume that, in each choice task, respondents choose the alternative that provides them with the highest utility. The link between observed choices and changes in the attributes is made possible by the random utility maximisation (RUM) framework.[45] The utility, U, that respondent n obtains from choosing intervention j in a choice task t can be decomposed into two parts: a deterministic part, V, which is observable to the researcher (i.e. based on the attributes included in the DCE), and a random component, ε, which is unobserved.

In mathematical terms, the RUM framework is described as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \quad (1)$$

$$V_{njt} = \sum_k \beta_k X_{kjt} \quad (2)$$

where n, j, t, *and* k are subscripts respectively for the respondents (n=1,…,N), the pandemic response interventions/alternatives (j=1,…,I, …, J), the choice tasks (t=1,…,T), and the attributes (k=1,…,K). The systematic part (V) is typically described as a linear combination of both respondent's preferences (β_k) and attributes' levels (X_k). The stochastic part is unobserved, and assumptions should be made about its nature. The probability that respondents will choose scenario A over scenario B in the choice task can be calculated if the distribution of ε is specified. The typical assumption about ε is that it is identically and independently distributed (IID) as Type 1 extreme (EV1). Under this assumption, the respondents' choices can be analysed using logit-based models such as multinomial logit (MNL) model. In the MNL model, the probability of choosing an alternative (P_{njt}) depends on

[8] More information of further consent related terms and conditions for Qualtrics can be found in the link: https://www.qualtrics.com/privacy-statement/.

its relative utility (i.e. the larger the utility compared to the other pandemic response strategies on offer the more likely the alternative is to be selected).

In DCEs, the systematic component (V) is a function (typically linear and additive) of the attributes and levels included in the study design. The regression coefficients (and their associated *t* statistics) provide information on whether a change in an attribute's level has a significant effect on an intervention's utility, and the direction of any effect. The ratio of the regression coefficients, known as the Marginal Rate of Substitution (MRS), shows the trade-offs that respondents make between any two attributes e.g. how much household spending are respondents willing to forgo to reduce excess deaths or what increase in job losses they are willing to accept for a decrease in the infection rate. Trade-offs (MRS) will be estimated for all relevant attributes' levels and confidence intervals calculated.[46]

We will explore observed heterogeneity according to moral attitudes (using MFQ 20) and socio-economic characteristics e.g. age, gender, health status, economic insecurity, country of residence and experience with the COVID-19 pandemic. Whilst some covariates such as sex, ethnicity, country of residence, education, and income will be included as categorical variables, others such as age, household size, etc. will be included either as continuous or categorical. We will use mixed logit (MXL) models to test for unobserved preference heterogeneity, treating responses as a function of choice alternatives and individual characteristics.

The socio-economic characteristics will be analysed by interacting them with the attributes in the multinomial logit and mixed logit model specifications. We will start from the multinomial logit model, interacting socio-economic variables with the attributes to account for observed preference heterogeneity. We will then interact the socio-economic variables with the mean of the random parameters in the mixed logit framework to account for both observed and unobserved preference heterogeneity. We will also test latent class models, using socio-economic characteristics as covariates of class membership. Given we cannot observe individuals' moral attitudes, but rather indicators of moral attitudes, we will treat them as latent variables. To explore differences in preferences between the five dimensions of moral values, we will use a hybrid choice model with each of the parameters interacting with each of the dimensions in turn. Choice of the final parsimonious model will be determined using measures of goodness of fit e.g. log-likelihood, McFadden's R^2, Ben-Akiva-Lerman R^2, the Akaike and Bayesian Information Criteria.

ENSURING IMPACT

We have established a Stakeholder Advisory Group (SAG) to advise on the development of the survey instrument and dissemination and to maximise the policy contribution of this research. Our SAG has representation from the four devolved nations: Neil Craig, Acting Team Head Evaluation, Public Health Scotland; Professor Mark Bellis, Director of Policy and International Health, Wales; Professor Hugo van Woerden, Director of Public Health and Medical Director, Belfast and Brian Ferguson Chief Economist, Public Health England; Shona Christie, Scottish Government Chief Scientist Office Public Engagement Group. This group will be consulted throughout the project. Virtual sessions will be organised when developing the survey to ensure policy relevance and to discuss our findings with the aim of translating the findings into messages for policy.

PATIENT AND PUBLIC INVOLVEMENT

We have a public representative on our Stakeholder Advisory Group, Shona Christie. Shona is a member of the Scottish Government Chief Scientist Office Public Engagement Group. She will advise on the development of the DCE survey and reporting of results. We will work with the Public Engagement in Research Unit (PERU) at the University of Aberdeen to disseminate results to the public. PERU has a dedicated programme for the active engagement of researchers with the public. Our research will be registered with the Research Registry – this is a publicly accessible database.

ETHICS AND DISSEMINATION

Ethical approval was obtained from the University of Aberdeen's College Ethics Research Board (CERB) (Reference CERB/2020/6/1974). Following the developmental work, the research team will seek CERB approval for all amendments to the Protocol, questionnaire or other study documents. Results will be disseminated via webinars to the public health community (informed by our Stakeholder Group) and to the academic community (via journals). Project information will be reported on the publicly available HERU website, and we will use HERU's Blog and social media accounts to disseminate key findings. Findings from the study will be presented at national/international conferences and peer-reviewed journals. Authorship policy will follow the recommendations of International Committee of Medical Journal Editors; http://www.icmje.org/recommendations/browse/roles-and-responsibilities/defining-the-role-of-authors-and-contributors.html

CONSENT

For the questionnaire development, the researcher will confirm eligibility and take verbal consent before starting the interview. Qualtrics will confirm eligibility for the main study. Consent for participants will be sought as part of the survey prior to the data collection questions.

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Figure legends

Figure 1. Lockdown levels for DCE
Figure 2. An example of a choice task

Table 1. Attributes and levels included in the DCE

	Attribute	Short Description	Levels
1	Type of lockdown*	How restrictive the lockdown is (Refer to Figure 1).	Green Yellow Amber Red
2	Lockdown length	How long the lockdown is in place	3 weeks 6 weeks 10 weeks 16 weeks
3	Postponement of usual non-urgent medical care	Whether non-pandemic medical care is postponed.	All non-urgent care is postponed. Some non-urgent care is postponed. No urgent care is postponed.
4	Excess deaths	Number of excess deaths as a fraction of 10,000.	1 in 10,000 additional people die 4 in 10,000 additional people die 9 in 10,000 additional people die 13 in 10,000 additional people die
5	Number of infections+	Number of infections as a fraction of 10,000.	100 in 10,000 people infected 600 in 10,000 people infected 1,300 in 10,000 people infected 2,000 in 10,000 people infected
6	Ability to buy things	How much of the same amount of goods that respondents buy today (represented by a shopping trolley) will they be able to buy in a year's time.	You can buy 100% of trolley You can buy 90% of trolley You can buy 80% of trolley You can buy 70% of trolley
7	Job losses	Proportion of people who lose their job.	0 in 100 loses job 4 in 100 loses job 15 in 100 loses job 25 in 100 loses job

Note: +Number of infections is linked to the excess deaths. *Descriptors for each type of lockdown are presented in Figure 1.

Table 2. COVID-19 response across European countries

Lockdown measures	UK		France		Italy		Spain		Sweden		Netherlands	
		Date		Date		Date		Date		Date		Date
Educational facilities closed	Yes	Mar 23-Aug 4	Yes	Mar 13-Aug 4	Yes	Mar 1-Aug 4	Yes	Mar 11-Aug 4	No	-	Yes	Ma 15-Aug 4
Any gathering restrictions	Yes	Mar 23-Aug 4	Yes	Mar 4-Aug 4	Yes	Feb 22-Aug 4	Yes	Mar 15-Aug 4	Yes	Mar 11-Aug 4	Yes	Mar 10-Aug 4
Stay at home order	Yes	Mar 23-Aug 4	Yes	Mar 18-Aug 4	Yes	Mar 8-Aug 4	Yes	Mar 15-Aug 4	No	-	No	-
Any business closure	Yes	Mar 20-Aug 4	Yes	Mar 15-Aug 4	Yes	Feb 22-Aug 4	Yes	Mar 13-Aug 4	No	-	Yes	Mar 12-Aug 4
All non-essential businesses closed	Yes	Mar 24-Aug 4	Yes	Mar 15-Aug 4	Yes	Mar 8-Apr 14	Yes	Mar 13-Apr 13	No	-	No	-
Travel severely limited	No	-	Yes	Mar 17-Aug 4	Yes	Mar 8-May 4	No	-	No	-	No	-
Average duration		4 months		4 months		5 months		4 months		-		4 months

Table 3. Colour coding for Type of Lockdown Attribute Levels

	Green	Yellow	Amber	Red
Stay at home (shelter in place)	Everyone (including vulnerable individuals) can interact with others.	Vulnerable individuals should stay home (shelter in place).	Vulnerable individuals should stay at home (shelter in place) and must have no visitors.	Everyone must stay at home (shelter in place).
Socialising group	Gatherings of up to 100 people.	Gatherings of up to 50 people.	Gatherings of up to 10 people.	No gatherings beyond own household (own bubble).
Non-essential (other than groceries and work-related) trips	Non-essential trips are allowed.	Non-essential trips are allowed.	Non-essential trips should be minimised	Non-essential trips are not allowed.
Schools & youth activities:	Open	Open	Closed	Closed
Businesses (e.g. shops) can operate under:	Limited social distancing	Moderate social distancing, operate at reduced capacity	Strict social distancing, operate at minimal capacity	Closed
Outdoor activities	Allowed	Allowed	Allowed	Not allowed

Figure 1. Lockdown levels for DCE

297x209mm (150 x 150 DPI)

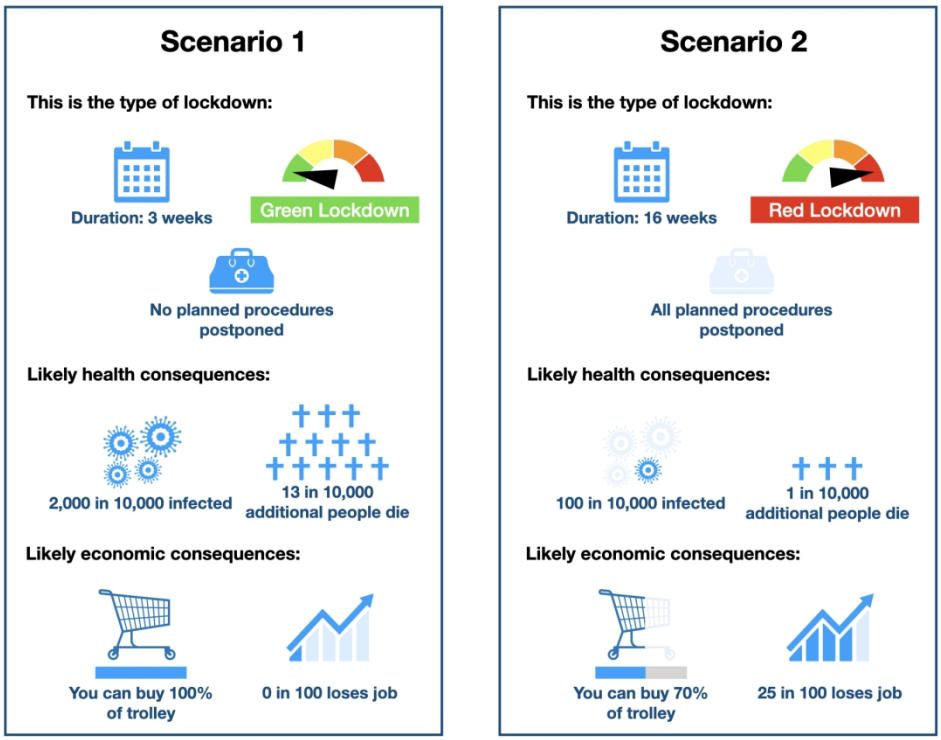


Figure 2. An example of a choice task

705x529mm (72 x 72 DPI)

OSM-1: Social Media (Twitter) Analysis[1]

Attributes were selected based on policy discussions and government guidance observed in European countries where the infection waves were concentrated. To look more into the chosen attributes, we conducted a social media analysis. We extracted attributes-related tweets between 15th February 2020, and 19th May 2020, using the Twitter standard search application programming interface (API) consisting of a set of predefined expressions (see below), which are the most widely used news media terms relating to the novel coronavirus (COVID-19). 15,000 tweets with expressions related to the attributes were extracted for our social media analysis. Only English language tweets were extracted.

We analysed the extracted tweets using **sentiment analysis,** which is a standard procedure in text mining literature.[1,2,3] **Sentiment analysis**[2] is the process of computationally identifying and categorising opinions expressed in a piece of text, especially to determine whether the tweeter's attitude towards a particular topic, product, etc. is positive, negative, or neutral. The key objective of sentiment analysis is to gauge opinions, identify hidden sentiments and finally to classify their polarity into positive, negative or neutral.[4]

Although we selected attributes based on policy discussions and government guidance observed globally and previous DCE studies on preferences to control emerging infectious diseases, we used the twitter analysis to gain insights into how the selected attributes are discussed on social media. We used the sentiment analysis to categorise opinions in the text related to our attributes. We identified sentiments that people have when talking about the attributes of interest. For example, do people use the term "excess death" in their tweets? What sentiments do people have when talking about excess death? Should we use excess death or number of deaths as an attribute? Are people more concerned about excess death or the number of deaths? The sentiment scores helped us to gain insights into these questions. They allowed us to identify what attitudes or sentiments people have when communicating about the attributes we selected (lockdown restrictions, number of infections, excess death, hospital capacity, income loss and job loss) on social media.

The x-axis in all the histogram plots shows the sentiment score as a negative and positive integer or zero. The sentiment score is the sum of sentiment values assigned to parts of the sentence (or textual field) and can be less than -1 or more than 1, as shown in all the histogram plots. A positive score represents positive or good sentiments associated with a tweet. In contrast, a negative score represents negative or bad sentiments associated with that tweet. A score of zero indicates neutral sentiment. The more negative the score, the more negative the sentiments of the person tweeting and vice-versa.

[1] Date of Tweets Extraction: 19th May 2020 (Tweets from 15th February 2020-19th May 2020).
[2] Sentiment Scale: 0-Neutral >0-Positive <0-Negative

Type of lockdown: this refers to how strict the lockdown measures are. The sentiment score of each term related to the attribute 'lockdown type' (lockdown restrictions, lockdown rules, and lockdown policy) is presented in Figure 1 and Table 1. It can be seen that the significant portion of tweets of 'lockdown restrictions' and 'lockdown policy' fall in negative sentiment category. The 'lockdown restrictions' tweets displayed 53% of negative sentiment, 19% of positive sentiment, and 28% of neutral sentiment (Table 1). In the think-aloud (TA) interviews, the lockdown attribute was initially presented as "lockdown type". The group of attributes representing policy choices (lockdown severity, lockdown length, and postponed procedures) was described in a very similar way as "type of lockdown". Following the insights we get from the sentiment analysis and the TA interviews, we renamed the attribute to "lockdown restrictions".

Figure 1. Histogram of tweets about lockdown restrictions and lockdown policy

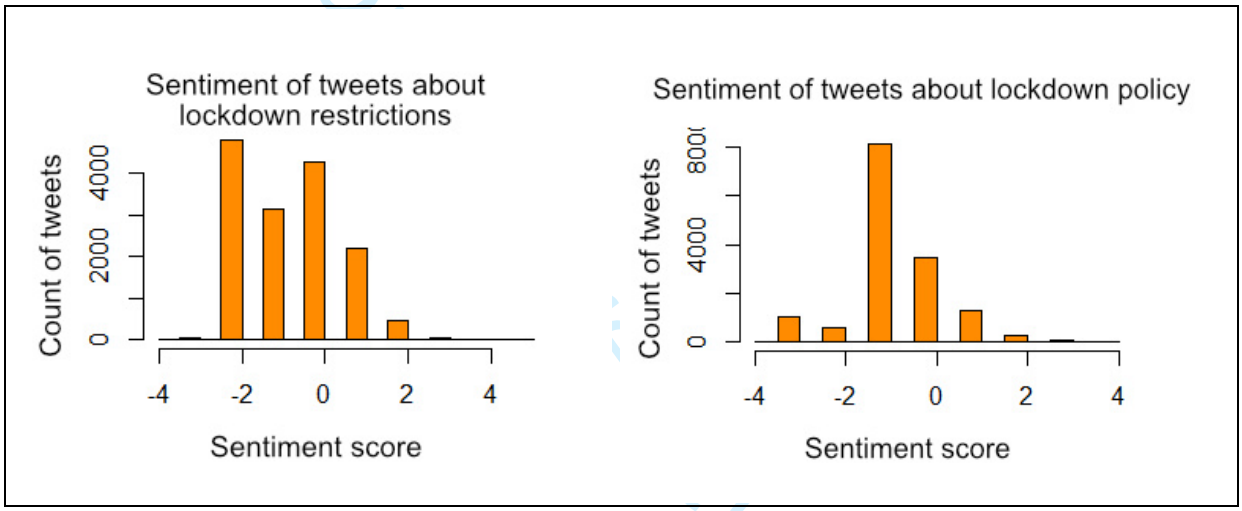


Table 1. Percentage of sentiment scores of tweets about lockdown restrictions and lockdown policy

Sentiment types	Lockdown restrictions	Lockdown policy
Negative	53%	65%
Neutral	28%	23%
Positive	19%	12%

Lockdown length: this refers to the number of months the lockdown will be in effect. For the sentiment analysis, we used related terms such as lockdown period and lockdown weeks. For the terms 'lockdown period' and 'lockdown weeks', the major portion of the tweets fall in the neutral sentiment category (Figure 2 and Table 2).

Figure 2. Histogram of tweets about lockdown period and lockdown weeks

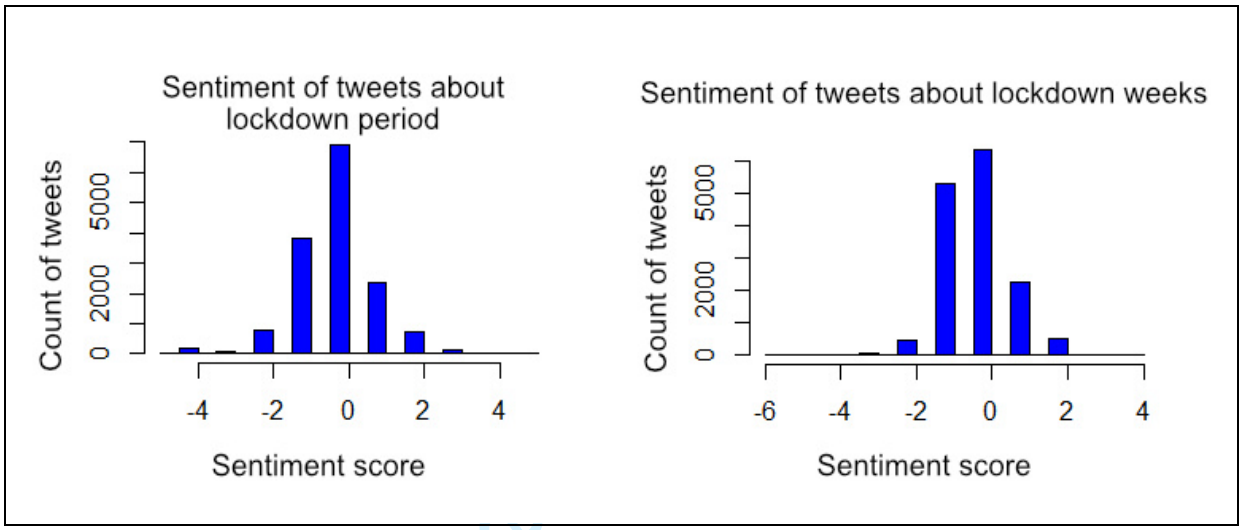
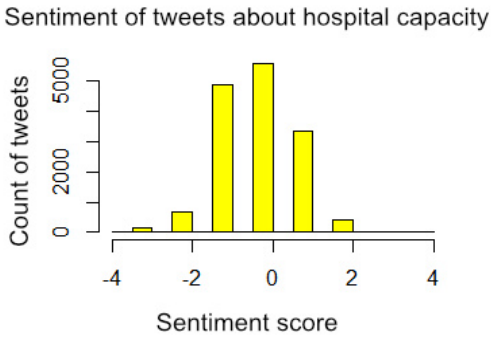


Table 2. Percentage of sentiment scores of tweets about lockdown period and lockdown weeks

Sentiment types	Lockdown period	Lockdown weeks
Negative	33%	39%
Neutral	46%	42%
Positive	21%	19%

Postponement of usual non-urgent medical care: this refers to whether hospitals will postpone non-pandemic related medical procedures. We used the expression 'hospital capacity' in our twitter search. The sentiment score for tweets of hospital capacity is fairly symmetric (Figure 3), with 38% of the tweets generating a negative sentiment, 37% a neutral sentiment and 25% positive sentiment.

Figure 3. Histogram of tweets about hospital capacity



Negative sentiment (38%), neutral (37%), positive (25)

Excess deaths: this refers to the difference between the number of people who die during the pandemic, and the historical average for the same place and time of the year. An analysis of the 'excess death' tweets displayed 81% of negative sentiment, 4% of positive sentiment 15% of neutral sentiment (Table 3). It can be seen that the major portion of tweets about excess death fall in negative sentiment category (Figure 4). As the 'excess death' attribute displayed 81% negative sentiment, we were careful in the framing of the excess death attribute levels. Initially, we tested the presentation of 'excess death' attribute in absolute numbers, but this inflated its importance relative to other attributes. Therefore, we changed the presentation of excess death as fractions of 10,000.

Figure 4. Histogram of tweets about excess death and number of deaths

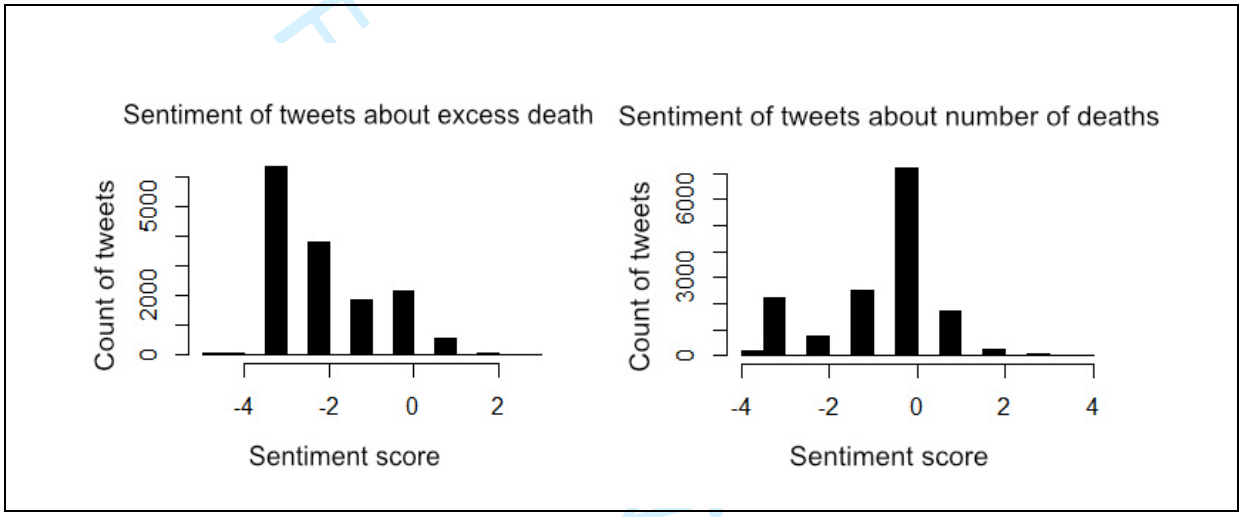


Table 3. Percentage of sentiment scores of tweets about excess death and number of deaths

Sentiment types	Excess death	Number of deaths
Negative	81%	38%
Neutral	15%	48%
Positive	4%	14%

The number of infections: the number of people who will be infected. We used the 'number of infections' and 'infection rate' in our tweet search. Tweets about the 'number of infections' displayed 53% of negative sentiment, 14% of positive sentiment, and 33% of neutral sentiment (Table 4). A major portion of tweets about 'excess death' fall in negative sentiment category (Figure 5). Initially, we tested the presentation of 'number of infections' attribute in absolute numbers, but this attribute, like the 'excess death' attribute, inflated its importance relative to other attributes. Therefore, we changed the presentation of the number of infections as fractions of 10,000.

Figure 5. Histogram of tweets about infection rate and number of infections

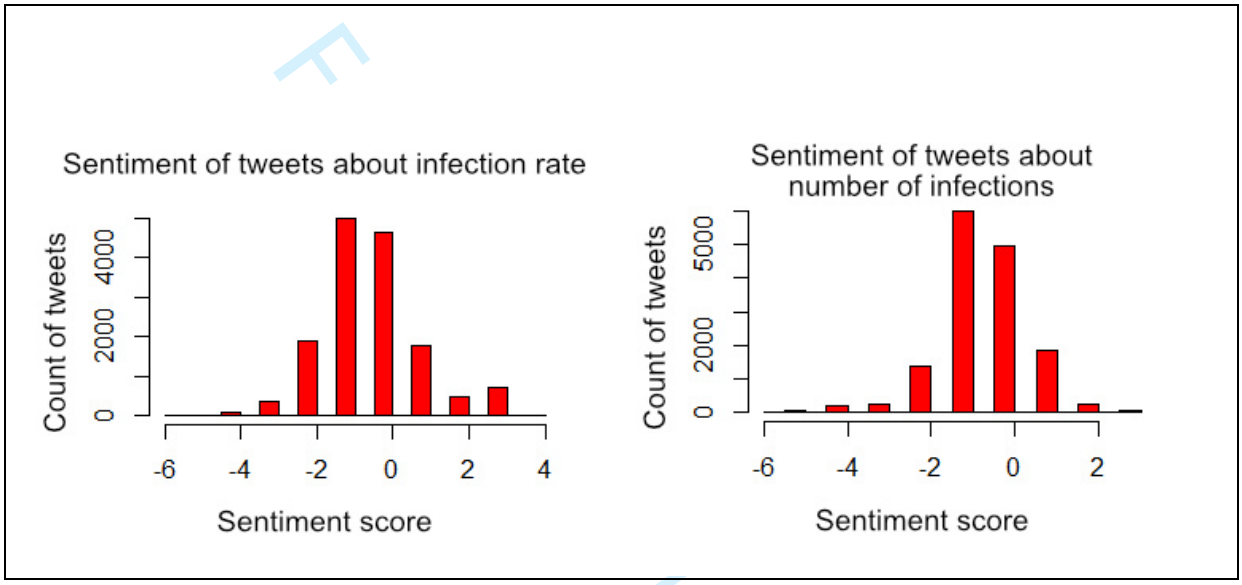


Table 4. Percentage of sentiment scores of tweets about the number of infection attribute

Sentiment types	Number of infections	Infection rate
Negative	53%	49%
Neutral	33%	31%
Positive	14%	20%

Ability to buy things: this refers to how much you will be able to afford one year from now compared to how much you would be able to afford normally. For this attribute, we used terms like 'inflation' and 'income loss' in our tweet search. A significant portion of (67%) of 'income loss' tweets generate negative sentiments. In comparison, a very small portion (12%) of tweets about 'income loss' suggested positive sentiments, while the remaining 21% are categorised as neutral tweets (Figure 6 and Table 5).

Figure 6. Histogram of tweets about inflation and income loss

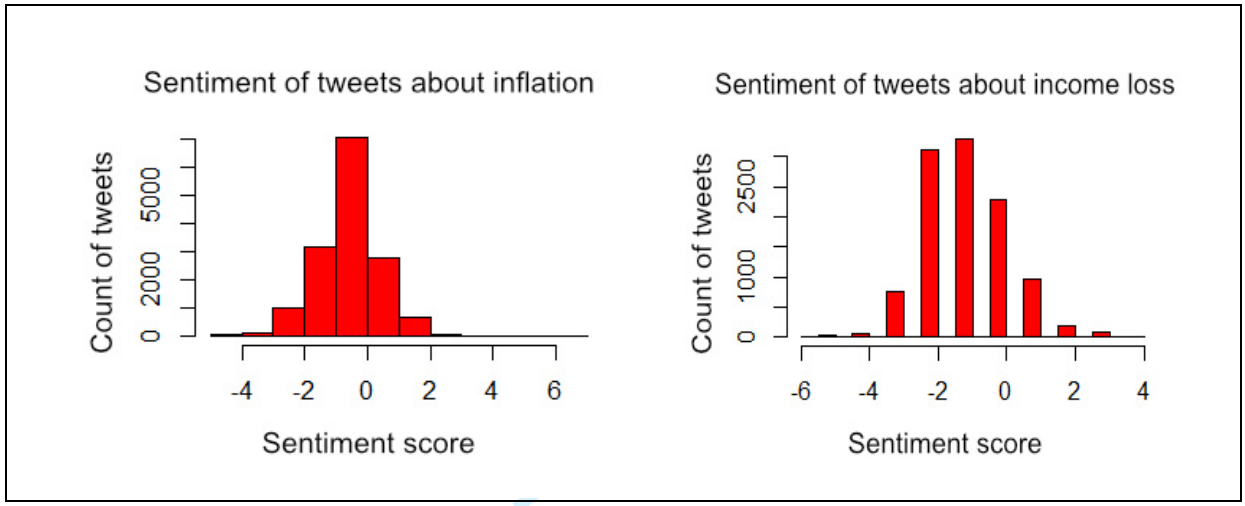


Table 5. Percentage of sentiment scores of tweets about inflation and income loss

Sentiment types	Inflation	Income loss
Negative	30%	67%
Neutral	47%	21%
Positive	23%	12%

Job losses: this refers to the proportion of people who will lose their jobs as a result of the lockdown. We used terms like unemployment and job loss in our tweet search. A major portion of the 'job loss' attribute (68%) generate negative sentiments (Figure 7 and Table 6). To make this attribute easier to understand, we used job loss instead of unemployment. Further, the higher sentiment attached to the job loss attribute would make the attribute easier to be traded-off when combined with other attributes.

Figure 7. Histogram of tweets about job loss and unemployment

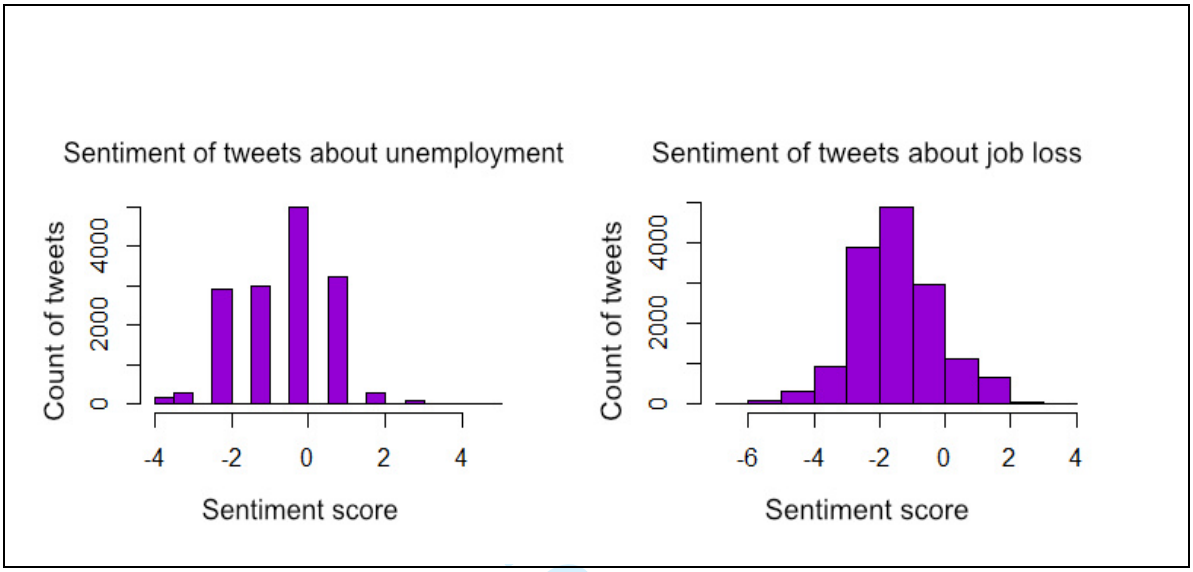


Table 6. Percentage of sentiment scores for the job loss attribute

Sentiment types	Unemployment	Job loss
Negative	43%	68%
Neutral	33%	20%
Positive	24%	12%

Additional References

1. Saif, H., He, Y., & Alani, H. (2012, November). Semantic sentiment analysis of twitter. In *International semantic web conference* (pp. 508-524). Springer, Berlin, Heidelberg.
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OSM-2: Opportunistic Think-Aloud Interviews

Virtual think-aloud (TA) interviews were conducted using MS Teams with colleagues from the University of Aberdeen (n=10) and members of our Stakeholder Advisory Group (SAG, n=3). Participants were asked to share their computer screen with the interviewers and to verbalise their thought processes whilst responding to the survey. As a warm-up, they were asked to think aloud whilst responding to the question: "*How many windows are there in your house?*" Respondents were told to consider the interviewer as a silent observer of their thought process. Interviewers did, however, encourage respondents to verbalise their thoughts if they were silent for a short period. Respondents were told there were no right or wrong answers. The interviews lasted between 45 and 90 minutes.

A number of changes were made to the DCE survey.

1. **Presentation of the excess death, number of infections, and job loss attributes**

In the TA interview used for internal testing, the attributes for excess death, number of infections, and job losses were presented differently. The number of jobs lost, and the number of people infected were presented as fractions of 100. In contrast, the excess death attribute was presented as absolute numbers of additional people dying over the expected figure during a normal year. This led to the excess death attribute dominating the choices of a significant number of participants, with some participants stating that they ignored all other attributes and considered the lower number of excess deaths presented in the choice task.

While this might be an expression of a valid preference, the feedback we received included evidence that the presentation of the excess death attribute in absolute numbers inflated its importance relative to other attributes. One participant stated that, while they recognised that job losses were presented as fractions, in their mind they ignored the denominator of the job loss attribute and directly compared its numerator to the absolute figures presented for the excess death attribute.

We changed the presentation of the excess death and number of infections attributes to be uniform across the choice task. The number of infections and excess deaths are now presented as fractions of 10,000.

2. **Presentation and placement of lockdown type attribute**

In the TA interview for internal testing, the colour-coded visual for the lockdown type attribute was prominently presented at the top of each choice option. Some participants interpreted the visual as a summary of the choice option rather than as an independent attribute.

We changed the position of the visual for the lockdown type attribute to make it appear next to the visual for the lockdown duration attribute.

3. **Visual presentation of the number of infections attribute**

The TA for internal testing displayed a *static* visual for the number of infections attribute that did not change according to the attribute level presented. Several participants stated that a changing visual would help them make better sense of the attribute level. We changed the visual to change with an increasing number of infections.

4. **Presentation of the shopping trolley attribute**

Initially, the text under the visual for the 'shopping trolley' attribute read "X% of the trolley." Some participants interpreted this to mean the economic impact on society rather than the economic impact on themselves. We changed the text to read "You can buy X% of the trolley."

5. Explanation of the shopping trolley attribute

Some participants were concerned that the initial explanation of the shopping trolley focused on consumption rather than the general cost of living. One participant expressed concerns that this might not accurately reflect the experiences of impoverished respondents. We expanded the explanation of the shopping trolley attribute to include housing costs and utility bills.

6. MFQ20: Likert scale anchors

The initial presentation of the MFQ20 presented the anchors for different points on a 6-point Likert scale ("not at all relevant" to "extremely relevant" and "strongly disagree to "strongly agree") at the top of the page. For the selection matrix, points on the scale were labelled with numbers running from 0-5 to mimic the presentation of the paper-based MFQ 20.

We observed that the top of the page was not visible for participants while they were answering the questions, leading them to spend a lot of time scrolling up and down on the page. We amended the selection matrix to display the anchors next to the numbered points on the Likert scale.

7. Ease-of-use updates

To make the survey more engaging, we made various improvements to the interface and presentation formats. This included a progress bar at the top of the screen, mouse-hover explanations for different selection options, and input prompts.

OSM-3: Social Media Ad for Think Aloud

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HEALTH ECONOMICS RESEARCH UNIT
Promoting Excellence in Health Economics

Want to take part in a survey development about interventions to control a future pandemic?

Participate in our study!

- **We are trying to understand public preferences for interventions to control a future pandemic.**
- **We are asking for volunteers who are willing to support the design of a questionnaire using a process called "Think Aloud".**
- **A small gratuity (£20) will be offered for your participation.**

Where? Over Video Call
How long? 30-40 minutes
Who? 18 years or over living in the UK

If you are interested in supporting this research project in this way, please email heru@abdn.ac.uk to arrange a suitable time for this to take place.