

Use of Artificial Intelligence to understand adults' thoughts and behaviours relating to COVID-19

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Abstract

Aims: The outbreak of severe acute respiratory syndrome coronavirus 2 (COVID-19) is a global pandemic that has had substantial impact across societies. An attempt to reduce infection and spread of the disease, for most nations, has led to a lockdown period, where people's movement has been restricted resulting in a consequential impact on employment, lifestyle behaviours and wellbeing. As such, this study aimed to explore adults' thoughts and behaviours in response to the outbreak and resulting lockdown measures.

Methods: Using an online survey, 1126 adults responded to invitations to participate in the study. Participants, all aged 18 years or older, were recruited using social media, email distribution lists, website advertisement and word of mouth. Sentiment and personality features extracted from free-text responses using Artificial Intelligence methods were used to cluster participants.

Results: Findings demonstrated that there was varied knowledge of the symptoms of COVID-19 and high concern about infection, severe illness and death, spread to others, the impact on the health service and on the economy. Higher concerns about infection, illness and death were reported by people identified at high risk of severe illness from COVID-19. Behavioural clusters, identified using Artificial Intelligence methods, differed significantly in sentiment and personality traits, as well as concerns about COVID-19, actions, lifestyle behaviours and wellbeing during the COVID-19 lockdown.

Conclusions: This time-sensitive study provides important insights into adults' perceptions and behaviours in response to the COVID-19 pandemic and associated lockdown. The use of Artificial Intelligence has identified that there are two behavioural clusters that can predict people's responses during the COVID-19 pandemic, which goes beyond simple demographic groupings. Considering these insights may improve the effectiveness of communication, actions to reduce the direct and indirect impact of the COVID-19 pandemic and to support community recovery.

INTRODUCTION

On 11 March 2020, the World Health Organization (WHO) announced that coronavirus disease 2019 (COVID-19) was a global pandemic.¹ The disease is caused by a virus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The actual and estimated infection rate suggests that for many people the disease is not life-threatening. However, the severity of illness and mortality risk varies between countries, regions and population subgroups. For instance, in May 2020, it was reported that age, male sex, obesity and

underlying illness had emerged as risk factors for severe COVID-19 or death.²

Governments across the world have taken a range of actions to reduce the risk of infection and spread including the introduction of new legislation and policy, as well as public health messages, and the closing of their borders. In many countries, governments have enforced a period of lockdown that has typically included a requirement for people to stay at home unless they are key workers or have other essential reasons for leaving their home.^{3,4}

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Understanding the attitudinal and behavioural responses to COVID-19 and the associated lockdown is critical in building evidence to inform current and future communication and messaging, public policy, and the development of interventions to support risk mitigation efforts. This evidence can also provide insights to identify and support subgroups of a population who may be at greater risk of infection, and the unintended consequences of COVID-19 lockdown. As such, we have delivered a time-sensitive study of adults' thoughts and behaviours relating to COVID-19 to better understand the response and potential impact of the pandemic.

METHODS

Participants

The original sample comprised of 1126 respondents from the general population. Twenty participants were removed for either reporting an age < 18 years or an infeasible age. Of the remaining sample, there were 845 females, 249 males, 8 reported other for gender and 4 preferred not to say.

Measures

An online survey was developed to explore adults' thoughts and behaviours relating to COVID-19. The survey comprised eight sections utilising a combination of closed and open questions: (1) demographics; (2) thoughts and behaviours relating to COVID-19 including knowledge of symptoms, actions to reduce infection and spread; (3) impact on employment such as working from home and the perceived impact on work productivity; (4) impact of home schooling on work and health; (5) impact on health and lifestyle behaviours such as sleep, alcohol, diet, physical activity; (6) wellbeing, which was measured using the Warwick-Edinburgh Wellbeing Measure;⁵ (7) sources of information about COVID-19; and (8) additional comments. Please see Supplementary Table 1 for an overview of the online survey. Prior to launching the survey, a pilot study was conducted with a diverse sample of adults.

Procedure

Between 8 April and 15 May, the survey was disseminated using social media, email distribution lists, website advertisement and word of mouth. The survey was hosted by Qualtrics LLC; a third-party online survey administration platform. Inclusion criterion was age \geq 18 years.

The study was granted ethical approval by the School of Psychology Research Ethics Committee at University of Leeds (REC number PSYC-20).

Statistical analysis

Due to the insufficient number of participants reporting 'other' or 'prefer not to say' when asked about their gender, these participants were removed. Thus, the final sample included in the statistical analysis was 1094 of which 72.6% (794) were from the United Kingdom and 27.4% (300) from the rest of the world; 77.2% (845) were female, the average age was 39.4 ± 12.7 and 29.6% (324) reported having children 18 years of age or younger. The average age of participants was 39.4 years; for men the average was 40.8 and for women 38.9. Eighty-six percent of respondents reported having at least one risk factor.

We fit generalised linear models with main effects for all statistical analysis described in the results section. Statistical analyses were performed using R⁶ (version 3.6.2) and the tidyverse (version 1.3.0),⁷ and VGAM (version 1.1-2) packages.⁸ Wellbeing was treated as a continuous outcome. Risk mitigation was defined as the sum of the number of measures a respondent indicated taking and treated as a Poisson random variable; this assumption appears reasonable in our data. Knowledge of symptoms of COVID-19 and concerns about COVID-19 were modelled using logistic regression. Because 'none of the above' was not a possible option, failing to select any choice on these questions was treated as a negative response for that option. Likert-type scale questions regarding the impact of COVID-19 were modelled with Adjacent Category Logit models assuming proportional odds. Statistical significance was defined as a $p < .05$.

All responses were modelled as a function of age as a numeric covariate, gender (male or female), Index of Multiple Deprivation (IMD; numeric: 1–10 as identified using the English Indices of Deprivation,⁹ whether the person had children aged 0–4, 5–11, and 12–18 years (three separate binary variables), whether respondents were in the high risk categories for severe illness from COVID-19 infection as identified by the UK Government,³ and reported income. Income was treated as a numeric variable with the highest income in the selected bracket (see Supplementary Table 1).

RESULTS

Descriptive statistics

Table 1 provides an overview of participants' demographic characteristics and Supplementary Table 2 provides an overview of participants' income, perceptions of the impact of COVID-19 on finance, change in employment due to COVID-19 and, where parents are home schooling, the impact it has on job productivity, ability to perform their job role, and on sleep and relaxation.

We found that concerns about infection, illness or death, spreading COVID-19 to others, the impact on health services, the economy and employment were high, with significantly higher concerns for subgroups including people identified as at high risk from COVID-19 infection and people reporting a lower income (see supplementary materials).

Impact of COVID-19 on lifestyle behaviours

Figure 1 displays the impact of COVID-19 on lifestyle behaviours. People who are older were more likely to report a more negative impact of COVID-19 on their ability to make financial ends meet ($OR = 0.985, p = .0022$), whereas people with a higher income were more likely to report a more positive impact ($OR = 1.21, p < .0001$). People with a higher income were less likely to indicate that they are cutting back on their spending ($OR = 0.9201, p = .0037$).

People who are older were less likely to report more change in their diet compared to pre-COVID-19 ($OR =$

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Table 1

Demographics summary of participant age, gender, country, pregnancy status, parents with children under 18 years, parents with children aged 0–4, 5–11, 12–18 years, and high risk group

Participant characteristics

Age ^{a,b}	39.4 ± 12.7
Gender	
Male	22.8% (249)
Female	77.2% (845)
Country	
United Kingdom	72.6% (794)
Other	27.4% (300)
Pregnant (<i>n</i> = 834)	
Yes	0.7% (8)
No	75.5% (826)
Children (<i>n</i> = 1082)	
Yes	29.6% (324)
No	69.3% (758)
Children 0–4 years	
No	92.0% (1006)
Yes	8.0% (88)
Children 5–11 years	
No	86.2% (943)
Yes	13.8% (151)
Children 12–18 years	
No	87.6% (958)
Yes	12.4% (136)
High risk group ^c	
None listed	78.6% (860)
At least one	21.4% (234)

^aMean and standard deviation.

^b*n* = 1094 except where otherwise specified.

^cHigh Risk Group = people identified as at high risk of severe illness from COVID-19 by UK Government.

0.991, *p* = .013); people with risk factors were more likely to report more change in their diet and a change in their sleep compared to pre-COVID-19 (OR = 1.39 and 1.31, *p* = .00051 and .00035, respectively). People who are older, women, and people with children aged 5–11 years were more likely to report an increase in alcohol consumption (OR = 1.013, 1.25 and 1.47; *p* = .0017, .041 and .0091, respectively). There was no discernible difference among groups regarding change to the amount or type of physical activity that they are engaging in compared to pre-COVID-19.

Impact of COVID-19 on wellbeing

Supplementary Table 4 shows the percentage and participant counts for each of the items of the Warwick-Edinburgh Wellbeing Measure. The mean aggregate wellness score was 40.46; the standard deviation was 15.22. Across the items in the scale, large numbers of participants responded with 'not at all' or 'rarely'.

Although people who are older and people with children aged 12–18 years reported statistically higher wellbeing scores, the actual difference was small. Per additional year of age, people saw an average increase of 0.0800 (*p* = .0134); people with children aged 12–18 years reported an average wellbeing score 2.58 points higher than those without (*p* = .027), whereas the standard deviation of wellbeing was 15.2.

EXPLORATION AND PREDICTION USING TEXT-DERIVED FEATURES

Text data

Free text was collected across 14 questions which were distributed throughout the survey sections. As a pre-processing step all responses were concatenated for each participant and tokenised using spaCy's large English web model.ⁱ Tokenisation is the process of separating text into character sequences (words, numbers, punctuation). The length of the concatenated responses (i.e. the number of tokens) varied from 1 to 1934 (mean = 228, median = 173.5). The histogram of token counts is presented in Supplementary Figure 2.

The concatenated text for each participant was further processed to extract sentiment scores and personality scores. Sentiment scores were obtained using VADER Sentiment Analysis tool.¹⁰ All scores returned by the tool (positive, neutral, negative, compound sentiment) were used in the analysis. Personality scores were obtained using proprietary software by Scaled Insights. The software takes as input a language sample and produces 114 personality features. The machine learning models which underpin the software have been trained and evaluated on large samples of annotated text.

The 118 (114 personality, 4 sentiment) described previously were used as input in a number of machine learning models described below. Because the reliability of the personality modelling software depends on the number of words provided in the language sample, the following analysis was restricted to participants (*N* = 803) whose combined text response consisted of at least 100 tokens.

Machine learning was used in two settings: unsupervised (clustering) and supervised (classification or regression).

Clustering

The unsupervised setting used a clustering algorithm (*k*-means) to separate participants into groups based on their personality and sentiment scores. Since the *k*-means algorithm requires that the number of clusters be specified, we first experimented with different values of *k*. We used two heuristics (sum of squared distance and an elbow plot, and degree of separation between clusters and a silhouette plot) to check which *k* from a range between 2 and 10 resulted in most coherent and disparate clusters. Both heuristics indicated that two clusters was the optimal number. Subsequently, we applied the *k*-means algorithms with *k* = 2 to the personality and sentiment scores data. This resulted in two clusters of fairly equal size (Cluster_1: 436, Cluster_2: 367; see Figure 2 for a visualisation of the clusters). Table 2 lists the ten most differentiating features and the cluster centroid values. Cluster_1

Figure 1

Change in diet (panel a), alcohol (panel b), amount of physical activity (panel c), type of physical activity (panel d), and amount and quality of sleep (panel e), compared to pre-COVID-19

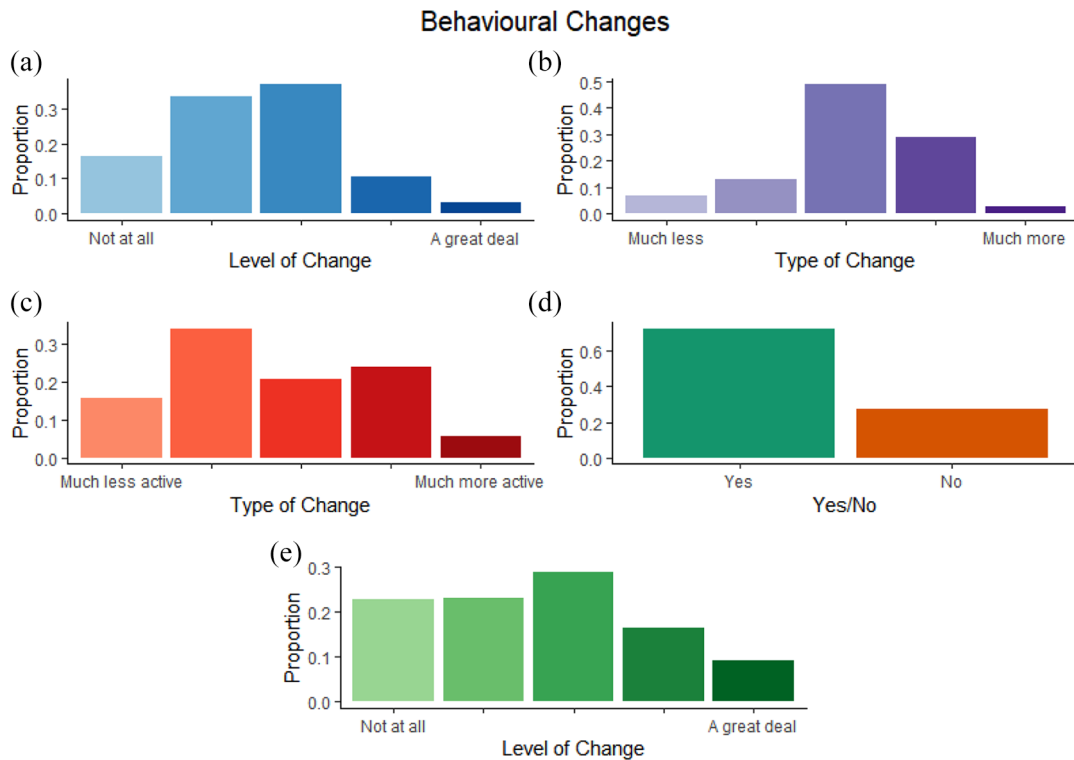
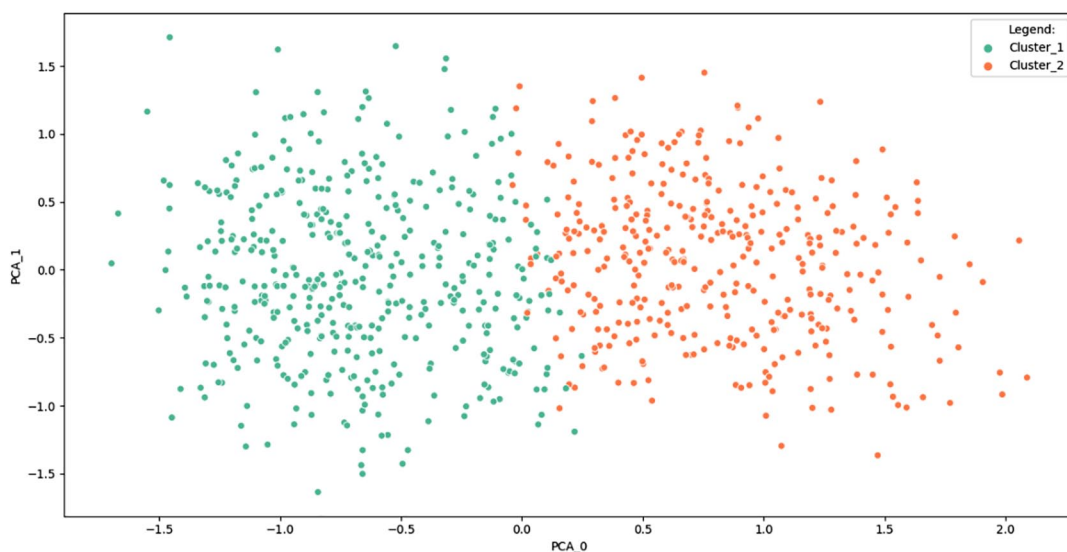


Figure 2

Visualisation of clusters using principal component analysis (PCA)



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Table 2

Ten features with largest scores differences between clusters (centroid values for each cluster given)

Feature	Cluster_1	Cluster_2
<i>Compound sentiment</i>	0.60	-0.70
<i>Neurotic</i>	0.56	0.79
<i>Insecure</i>	0.38	0.61
<i>Trust</i>	0.55	0.41
<i>Adventurous</i>	0.44	0.30
<i>Dutiful</i>	0.76	0.63
<i>Stressed</i>	0.64	0.76
<i>Happy</i>	0.32	0.20
<i>Depressed</i>	0.59	0.70
<i>Aggressive</i>	0.41	0.53

has positive compound sentiment and higher values for trust, adventurousness, dutifulness and happiness, while Cluster_2 has higher values for neuroticism, insecurity, stress, depression, aggression, and negative compound sentiment.

The responses of the two clusters was compared for concerns, mitigating actions, impact on lifestyle behaviours and wellbeing (Table 3). Three out of four lifestyle behaviours (diet, physical activity, sleep) and the wellbeing score had all statistically significant ($p < .05$) differences between the two clusters. Three out of six concerns (becoming infected, severe illness, and impact on employment) had a weaker result at $p < .1$. Participants in Cluster 2 (with more negative sentiment, more neurotic and insecure) have higher scores for concerns and impact on lifestyle behaviours. They also have a lower wellbeing score. A possible contributing factor to these findings might be the fact that the number of people identified as at high risk of severe illness from COVID-19 was significantly greater in Cluster_2 ($N = 126$) than Cluster_1 ($N = 96$) (two proportion z-test, $p = .0001$).

Prediction models

In addition to clustering participants based on their personality and sentiment scores, we investigated to what extent these features can be used for predicting concerns, mitigating actions, impact on lifestyle behaviours, and wellbeing score in the context of COVID-19. A model which predicts these attitudes and behaviours and requires only a language sample could be potentially used within a digital environment to better identify people who might be more likely to be negatively impacted and offer them preventive support. The aim of the current study is to assess to what extent only these features (personality and sentiment) are predictive.

General prediction set-up

For each attitude or behaviour, we trained a separate binary or multi-class classifier. We first explored a range of different classifiers (logistic regression, support vector machine, stochastic gradient descent classifier, and random forest). Across all classifiers we found that Random Forest achieved the best results and was chosen for further tuning. The algorithm parameters were tuned on a training set (shuffled and stratified 75% of the original data). The tuned parameters

were then used to train the final classifiers using 10-fold cross-validation.

Concerns about COVID-19

The responses relating to concerns were all expressed on a 1–10 scale. To form classes, the values were split into 'low' (1–3), 'medium' (4–7) and 'high' (8–10). Area Under the Receiver Operating Characteristics (AUROC) is used to evaluate the multiclass problem.

Overall, the classifiers for COVID-19 related concerns are performing only slightly better than random (AUROC = 0.5). The highest performance is achieved when predicting the concern for spreading the virus (AUROC = 0.58); see Supplementary Table 5.

Mitigating COVID-19

The mitigating actions each formed a binary class (i.e. someone either used particular mitigation method or not). Accuracy score is used for evaluation.

The two highly skewed mitigating actions (social distancing and taking all possible actions) achieved the highest accuracy scores. The scores are expected due to highly skewed class distribution. Among the other actions, predicting the use of protective apparel and increased shopping achieved highest scores (Acc. = 0.65 and 0.69 respectively); see Supplementary Table 6.

Impact of COVID-19 on lifestyle behaviours

The responses on the impact of COVID-19 on lifestyle behaviours used scales which were converted to classes as follows. Scale -2–2 (used for alcohol consumption and physical activity) was converted to 'Decrease' (-2, -1), 'No Change' (0), 'Increase' (1, 2). Scale 0–4 (used for diet and sleep) was converted to 'No or little impact' (0, 1), 'Some impact' (2), 'Significant impact' (3, 4). Area Under the Receiver Operating Characteristics (AUROC) is used to evaluate the multiclass problem.

Overall, the classifiers performed slightly better than random, with highest scores achieved by classifiers for alcohol consumption (AUROC = 0.61) and sleep (AUROC = 0.6); see Supplementary Table 7.

Table 3

Differences between clusters in mean scores for concerns, mitigating, actions, impact on lifestyle, and wellbeing score

	Cluster 1	Cluster 2	Result	p-value
Concern: becoming infected	5.87	6.21	-1.91	.06
Concern: severe illness or death	5.44	5.8	-1.66	.1
Concern: spreading to others	7.9	7.88	0.15	.88
Concern: impact on the health service	8.03	8.1	-0.42	.68
Concern: impact on the economy	7.44	7.42	0.15	.88
Concern: impact on employment	5.43	5.82	-1.8	.07
Actions: social distancing	425	357	0.18	.86
Actions: self-isolation	185	192	-2.8	.01
Actions: wearing protective apparel	148	131	-0.52	.6
Actions: shopping online	212	201	-1.74	.08
Actions: increased shopping	139	114	0.25	.8
Actions: all above	22	20	-0.26	.8
Lifestyle: diet	1.47	1.66	-2.73	.01
Lifestyle: alcohol	0.1	0.03	1.06	.29
Lifestyle: physical activity	-0.2	-0.51	3.76	<.01
Lifestyle: sleep	1.58	2	-4.92	<.01
Wellbeing score	45.79	41.15	6.84	<.01

t-test used for numeric variables (concerns, lifestyle, wellbeing), two proportion z-test used for binary variables (actions). All results rounded to two decimal places.

Impact of COVID-19 on wellbeing

The numeric Warwick-Edinburgh Wellbeing Measure (with a range of possible scores between 14 and 70) was used directly as a target variable. Participants with incomplete responses were removed from analysis and $N=794$ responses were used in the prediction model. Mean absolute error and explained variance were used for evaluation.

The best prediction model had a mean absolute error of 6.43 and explained variance score of 0.12.

DISCUSSION

This study aimed to explore adults' thoughts and behaviours about COVID-19,

and in doing so, provide insights about how people have responded to the global pandemic. Our study findings demonstrate a relationship between concern about infection and illness and death, where concern of both increases as age increases. Likewise, people who identify within one of the high-risk groups for severe illness from COVID-19 reported greater concern about being infected, and severe illness and death. This may reflect the public health messages that younger people have a lower risk of severe illness and death from COVID-19, and the increased risk for people aged 70 years and above, and identified as at high risk.

Our findings demonstrate that adults' physical activity, diet, sleep and alcohol consumption have been impacted – for some more than others. Greater changes in diet and sleep were reported by people in the groups identified as at high risk of severe illness from COVID-19 which may reflect the greater restrictions on daily life compared to people without a high risk status. This greater restriction on daily life and thus, likely greater change for people in the high risk groups, may explain the increased change in sleep amount and quality among this group compared to people without a high risk status. As such, given the importance

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of sleep and potential impact of a reduced amount and quality of sleep, it is likely that COVID-19 and the associated restrictive measures will have greater direct and indirect impact on people identified as at high risk of severe illness from COVID-19.

Our study also investigated the potential usefulness of features derived from participants' language sample to gain further insights about people's personality attributes and sentiment. Using those features, we were able to cluster participants based on their personality and sentiment – one of the clusters could be characterised as more neurotic and insecure, with more negative sentiment. That same cluster showed several higher scores for concerns about COVID-19, a greater impact on lifestyle, as well as a lower wellbeing score. The clustering approach is preferable, because it does not require that a categorisation is imposed ahead of analysis (as it would be with a classification approach). Instead, the grouping of individuals is derived from the data. Furthermore, cluster membership for any new individual can easily be determined by using similarity between the individual's inferred features and the cluster centroids.

This link between personality traits and concerns, and impact on lifestyle and wellbeing provides additional insights for public health institutions and other organisations that goes beyond demographic information. In particular, within the context of interventions delivered in digital environments, the use of personality modelling from text could enable the use of more personalised advice and support. As the second cluster shows higher scores for depression, stress, and anxiety, this approach could be especially helpful for identifying people who might benefit from extra support. Furthermore, communications tailored using personality traits have been shown to be perceived as more effective.¹¹ For example, someone who is dutiful (one of the characteristics of Cluster 1) can be motivated to follow social distancing by highlighting guidelines set by authorities. This opens the possibility of

using digital channels to personalise public health communications using readers' personality traits. Since personalised interventions and personality modelling from text remains an active research domain, it is key to carefully and thoroughly consider the appropriate design and implementation of such a system within the public health context.

This study is not without limitations. First, this article represents a cross-sectional analysis of the impact of COVID-19 on adults' thoughts and behaviours, and as such informs about a period that for most represents lockdown. The data do, however, provide much needed findings of the impact of lockdown resulting from COVID-19, and with further data collection through follow-up collections post-lockdown, the longer-term impact can be assessed. Second, the methods of dissemination meant that we were unable to control for a representative sample and as such we would suggest caution in suggesting that our findings provide a representative picture of how the general population have been impacted by the COVID-19 outbreak. This includes the high proportion of females who completed the survey compared to males, which is commonly reported in online survey-based research. Finally, for some of the survey questions relating to lifestyle behaviours, we have identified the extent of change during COVID-19 but have not indicated direction. Further exploration of the corresponding open-ended answers will provide details regarding the direction of change.

CONCLUSION

Our study provided insights into adults' thoughts and behaviours relating to the COVID-19 pandemic during a time period that was for most, a lockdown. Our findings demonstrate high concern relating to infection, severe illness or death, and in particular spreading infection to others. Across the board, lifestyle behaviours have changed compared to pre-COVID-19, in particular, the amount and quality of sleep.

People identified as at high risk of severe illness from COVID-19 were impacted the most. This, coupled with

the greater restrictions on daily life as directed by government guidance, may have a substantial impact on both mental and physical health of this subpopulation. National and local governments must consider the short- and longer-term direct and indirect impacts of the COVID-19 pandemic, where, as the current study findings demonstrate, restrictions such as national and local lockdowns have a substantial effect on population health. It is imperative that these impacts are considered within recovery strategies, and that every effort is made to learn from the unique challenges of a global pandemic so that these learnings can be implemented in the future. Our findings provide additional insights for stakeholders working in the area of population health, and efforts to support those most affected warrants attention. In particular, public health communication and risk mitigation planning that both addresses high concern and builds confidence given the current context of a gradual release from lockdown and the likely associated impact, is needed. Use of Artificial Intelligence such as the methods used in the current study could provide a mechanism of personalising communication which may, for instance, support public adherence to risk mitigating behaviours.

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CONFLICT OF INTEREST

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: SWF & AP are employed by Scaled Insights.

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SUPPLEMENTAL MATERIAL

Supplemental material for this article is available online.

NOTE

i. https://spacy.io/models/en#en_core_web_lg

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