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LSE GROUPS takes place during the final fortnight of the LSE summer term. Undergraduate students are placed in small groups; these are cross-year, interdisciplinary, and group members do not know one another in advance. Each group must then devise its own research question, and carry out every stage of a small-scale research project in less than two weeks.

LSE GROUPS is part of the LSE commitment to students learning through enquiry, and developing the skills for knowledge creation.

The overall theme of LSE GROUPS 2022 was *Resilience and the 'New Normal'*.

This paper was submitted on the final Thursday afternoon of the project. Students then presented their work at a conference, on the closing Friday.

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ShutdownLockdown:

A mixed method investigation of decreasing tendencies to comply with lockdown restrictions in the UK

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Abstract

In light of the recent COVID-19 health crisis, the question of whether or not compliance towards lockdowns wanes, and if so for what reasons, is of burgeoning importance to health policy now and in the future in order to guide better policy decisions for future health crises. In this research we discover that people's tendencies or willingness to comply with COVID-19 lockdown restrictions decreased as the pandemic progressed due to their attitudes towards government, their personality traits, and psychological factors. These indicators were analysed through two methods which utilised a mixed approach of applying sentiment analysis to tweets followed by analysing a secondary dataset on compliance and non-compliance throughout the first lockdown. The key results from our research indicate that the underlying reasons for a gradual decline in compliance tendencies can be summarised under two broad themes; *institutional factors* and *psychological factors* which we use to conclude that worsening mental health and distrust in the government can translate into less compliance. Additionally, certain personality traits such as extraversion affects one's propensity for non-compliance. Increasing non-compliance is also found to simultaneously occur alongside rising negative sentiment in tweets towards lockdown restrictions across the duration of the pandemic. These findings complement existing research where a comparative analysis of compliance between lockdowns emphasises focus on how compliance can be better ensured through increasing trust in governments which lead to a better protected society in the face of future public health crises.

Keywords: Compliance, Coronavirus pandemic, Government, Lockdowns, Policy

Introduction

In response to the COVID-19 pandemic first identified in December 2019, the UK government imposed three successive national lockdowns between March 2020 and March 2021 (Baker et al., 2021). This entailed protective measures to increase social distancing, namely implementing 'stay-at-home' orders, restricting non-essential activities, and limiting public group gatherings. Whilst compelling, these measures required long-term compliance to see effective results (Wright and Fancourt, 2021). Initially, there was a compliance rate of over 80% (Figure 1.2) regarding the first lockdowns measures. However, anti-lockdown protests, among other things, occurred nation-wide as the pandemic progressed, indicating a declining compliance rate which decreased to approximately 60% overall (figure 1.2).

We investigate some underpinning factors of why London based populations become less willing to comply with government lockdown regulations and quantify the extent to which different factors correlate with the non-adherence and suggest recommendations for future policy. In attempting to investigate this, we employ a mixed approach of analysing quantitative secondary data to address why non-compliance occurred and how frequently it did throughout the pandemic. In addition, we utilise sentiment analysis on tweets related to UK lockdowns to gauge public emotion towards lockdown guidelines. These methods will enable us to answer the following research question:

"Why did the London-based population become less compliant to lockdown regulations as the pandemic progressed? How can we reflect on this for future health related pandemics?"

In an attempt to shed light on such questions, the remainder of this paper starts with a reflective overview of previous research on the topic, an explanation of our methodology, the findings derived from our analysis, and a final discussion as to how our results can assist in future policymaking.

Literature Review

The literature primarily focuses on the arguments as to why compliance and non-compliance occurred throughout the pandemic. We first briefly discuss the secondary data obtained from the Office for National Statistics (ONS) to support our initial assumption that compliance reduces overtime. We also identify and discuss prominent themes in the literature namely barriers to compliance, factors facilitating compliance, and anti-establishment ideologies.

Secondary Data

Figures 1.1 and 1.2 exhibit a decreasing trend where self-isolation decreases between the first and second lockdown from May 2020 to January 2021. It further illustrates that the overall tendencies to leave home for non-essential activities were significantly greater in the second lockdown than in the first. This supports our assumption that the progression of the pandemic was accompanied by a reduction in compliance.

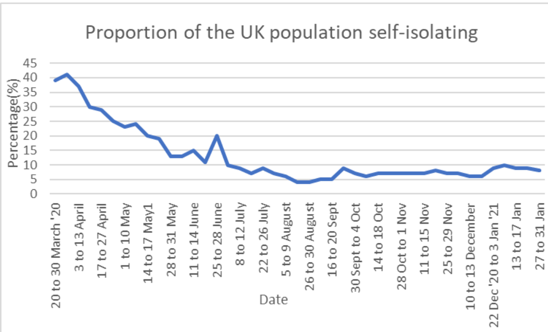

Figure 1.1: Proportion of the UK population self-isolating

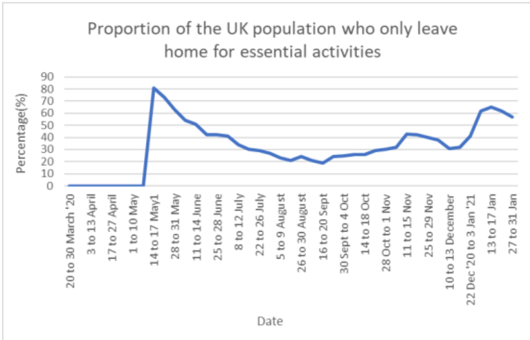

Figure 1.2: Proportion of the UK population who only leave for essential activities

Barriers

The barriers in the pandemic were factors that increasingly inhibited compliance due to the rise of inconvenience caused by covid policies. The first of such barriers were financial difficulties that arose during lockdown. Unemployed or part-time workers tended to be less willing to comply with lockdown regulations due to higher financial pressure (Ganslmeier et al., 2021). Mental health problems due to high stress and uncertainty also raised non-adherence to governmental recommendations. (Constantinou et al., 2021). Finally, complex, and obscure guidelines also instilled confusion in the public. Clearer guidance could have provided intelligible information on self-isolation rules, which would have reduced confusion in the public (Gorna et al., 2021).

Facilitators

The majority of the UK public felt a strong obligation to comply for their family's safety (76%) and for the safety of NHS workers (78%). However, 52% claimed compliance would be harder if rules became stricter or if a second lockdown was to occur (32%) (Halliday et al., 2020). Compliance was further motivated by an urge for a quicker return to normalcy, the reduction of risk and the spread of COVID-19. This was supplemented by the ease brought by being able to work from home and the technological means utilised to contact social networks (Wright et al., 2022).

Anti-establishment Sentiments

Covid lockdowns were viewed as a violation of individual freedom leading to a reduction in compliance. Dissent against the preventive measures were framed as efforts to prevent tyrannical government control. The infringements of freedom through lockdowns were believed to be a greater threat than COVID-19 (Bratich, 2021). Medical misinformation, especially on social media also played a role in reducing compliance. As a result, this put doubt on the effectiveness of lockdown measures and the severity of the pandemic. Therefore, as supported by protection motivation theory, we can infer that when people doubt the effectiveness of measures, they are less likely to engage in them (Kim, Tandoc, 2022).

In reviewing the literature, a noticeable gap appears where there is a lack of quantitative comparative analysis between levels of compliance across the three lockdowns and the reasons that affected the changes. Our research aims to fill this gap by comparing compliance levels across each lockdown using sentiment analysis and secondary data to understand the following hypotheses:

1. *A reduction in compliance is associated with decreasing trust in the UK government.*
2. *Individuals with less emotional support systems are more compliant to following lockdown restrictions.*

Research Design

To understand the underlying factors which contributed to a decreasing willingness to comply with lockdown restrictions in the UK, we designed two separate, but complementing studies, each using different datasets and analyses. Study 1 focuses on exploring people's subjective feelings and sentiments towards lockdown restrictions expressed through tweets. Study 2 utilises secondary survey data to investigate which factors strongly correlated with the high compliance rates of the first COVID-19 lockdown in the UK. We then integrated the results of both studies and discussed the findings in light of the research questions (see Discussion).

Methodology

Study 1: Sentiment Analysis of Tweets

To investigate our research question, understanding people's underlying sentiments regarding lockdowns and the changing dynamics of those sentiments across the first, second and third lockdowns was critical. As such we utilised the method of sentiment analysis using data we gathered from Twitter. This is chiefly because of the power of sentiment analysis in understanding emotions and behaviour, as well as Twitter as a platform where people express their emotions, perceptions, and experiences regarding the lockdowns.

We conduct the sentiment analysis based on relevant tweets posted by London Twitter users to reveal attitudes towards lockdown restrictions and facilitators of adherence. We utilise BERTweet (Nguyen et al., 2020), a RoBERTa based language model for English tweets, as our Natural Language Processing (NLP) model. This is trained on 845 million (M) tweets gathered from 01/2012 to 08/2019 and additionally 5M Tweets related to the COVID-19 pandemic. We then gather a data base of 37,499 tweets classified on a weekly basis from the first, second and third lockdown, and constrict users to those who consist only in London. Secondly, we proceed to use our language model to classify each tweet based on sentiment defined as 'negative', 'positive' and 'neutral'. For purposes regarding data robustness, we discard all 'neutral' tweets. Finally, we perform text analysis on our classified tweets by creating word clouds and time-series graphs based on frequency of words.

BERTweet was specifically chosen as the language model because of the large data set that it was trained on and because it was explicitly trained using tweets from the pandemic. This ensures robustness in our analysis, namely, that the tweets are classified in an accurate manner, as evidenced through the measures of accuracy presented by Nguyen et al., 2020. Nonetheless, there are limitations in our analysis. The primary limitation is that, like all NLP models, we have difficulty classifying sarcastic and ironic tweets. This is, however, less of a problem as the majority of sarcastic tweets were classified as 'neutral' which did not come into our analysis.

Study 2: Survey Data Analysis

Secondly, we employ a regression analysis using datasets from Kleitman et al., (2021) with 366 observations from the UK to find the extent to which each factor was associated with non-compliance behaviours. In doing so we use the following model:

$$Y = \alpha + \beta 1 + \beta 2 + \ldots \varepsilon$$

Where:

Y = dependent variable (compliance/non-compliance)

β = independent variable i.e., $\beta 1$'s ceteris paribus relationship with Y

ε = error term

Using a secondary dataset, our outcome variables were 'compliance' and 'non-compliance' whilst our independent variables included several personality traits such as extraversion and categorical variables such as gender and people's attitudes towards government's level of trust (see Appendix D for full list of variables).

We employ a multiple regression analysis to find the relationship between compliance and personality traits, finding that conscientiousness, agreeableness, and intellect are positively associated with compliance whilst neuroticism and extraversion are negatively associated. We find that extraversion and agreeableness are statistically significant at the 5% level (Table 2.1) and finding that compliance is associated with a 0.1 percentage point increase following an increase in one percentage point in agreeableness and a decrease of 0.07 percentage points if extraversion were to go up by percentage point.

When regressed by gender, we can see that females are shown to be more compliant than males as shown by tables 2.2 and 2.3 (see Appendix D) where compliance is positively associated with the Female beta coefficient but negatively associated with the Male beta coefficient.

Additionally, when regressed to gauge people's attitudes towards government, a government with high trust is positively associated with compliance but interestingly, satisfaction with the government's COVID response is negatively associated with compliance (see Appendix D for table 2.4).

Compliance	**Coef.**	**t**	**P>|t|**
Agreeableness	0.0128	3.05	0.002** (0.004)
Conscientious	0.000	0.06	0.955 (0.004)
Extraversion	-0.007	-2.05	0.041* (0.003)
Intellect	0.007	1.64	0.103 (0.004)
Neuroticism	-0.001	-0.44	0.661 (0.003)
_cons	0.736	7.15	0.000 (0.103)

Table 2.1 - regression model between personality traits against Compliance

Standard error in parentheses

R-squared = 0.0364; *Adjusted R-squared = 0.0230*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our methodology was primarily chosen based on the premise of allowing accessibility to a large sample population within a limited timeframe. Furthermore, the data sets also portray how different variables of government trustworthiness and emotional support influence compliance rates which further aids in justifying our hypothesis. Nonetheless there are limitations.

Firstly, there was a lack of data regarding the rates of compliance during the second and third lockdown. This was due to both a lack of quantitative studies on the compliance in the latter lockdowns and a lack of access to the limited data sets available in a two-week time period.

This leaves room for further research that can be conducted comparatively with data from the second and third lockdowns. Secondly, in the data sets that were available from the first lockdown the variables that were used in the surveys did not directly provide the factors that influence individual compliance. Thirdly, the secondary data overwhelmingly consisted of those who were compliant which limited our ability to find factors which promoted non-compliance. However, after reviewing these limitations, our results have proved robustness in contributing towards the existing literature in addressing how institutional and psychological factors have an adverse effect on compliance as will be further discussed in the following section

Discussion

Our findings are categorised into two themes: institutional and psychological. The findings from the sentiment analysis applied to tweets and our secondary data analysis supports the arguments made in the literature that protection motivation theory affects the compliance of individuals with regards to preventive measures.

Psychological Factors

The regression analysis of the Emotsupp (emotional support) variable against class exhibits how those providing less emotional support were more compliant with lockdown measures as shown by Figure 3.2 and Table 2.5 where increased emotional support is negatively associated with compliance. This may be due to individuals requiring emotional support from friends and family, thereby making adherence to lockdown measures easier whilst those requiring further contact with their social networks to gain emotional support were less compliant. The burden on one's mental health is also implied by the escalating frequency of negative tweets by the third lockdown where tweets included words such as mental health and stress (refer to figure 3.1).

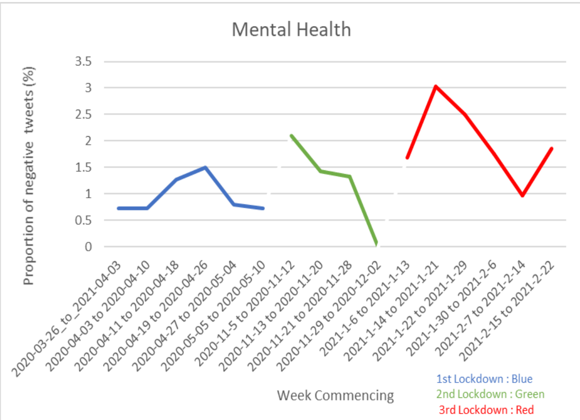

Figure 3.1 Proportion of negative tweets to do with mental health

This is emphasised by our word cloud analysis where during the latter end of the first lockdown, the frequency of words like 'cramped' and 'isolation' increased, showing already a decline in the mental health and dissatisfaction of those in lockdown. This is further supported by the research conducted by Wright et al., (2022) who argues that worsening mental health impacts the compliance rate with lockdown measures.

Compliance	Coef.	t	P>|t|
Emotsupp	-0.005	-0.74	0.460
			(0.007)
Conservatism	0.003	0.64	0.522
			(0.005)
Prosocial	-0.014	-1.09	0.276
			(0.013)
Reactance	-0.003	-1.90	0.050*
			(0.002)
_cons	1.053	14.94	0.000

Table 2.5 – regression model between compliance and actions and attitude variables

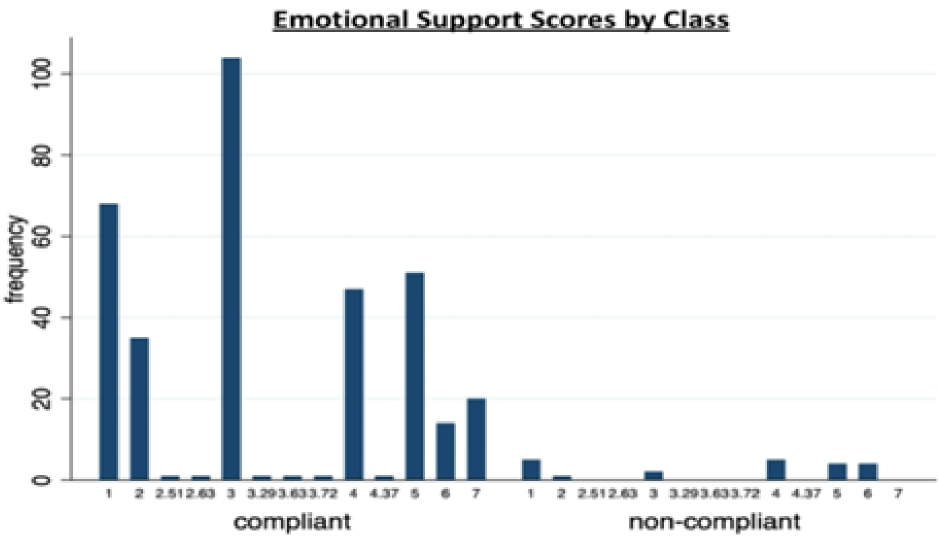

Figure 3.2 Emotional support by class

On the contrary, the word 'life' was the most frequent positive word used in tweets throughout the three lockdowns. We can interpret some reasons for this increased positive outlook on life since the start of the lockdown. First, it could be the increased time spent with close family members which improved the life of those in lockdown. Second, it could be a greater appreciation for one's life where COVID-19 is a public health crisis.

Institutional Factors

Ever since the outbreak of the COVID- 19 pandemic, questions about whom and what to trust became paramount. Using regression analysis, we conclude that those who believed that the government were more truthful about the COVID-19 outbreak, were more willing to comply with lockdown measures. Among those who do not trust government decisions we can infer they are also distrustful about the effectiveness of government decisions (Davies et al., 2021). This is illustrated by Figure 3.5 where the highest frequency of respondents to be compliant also scored high in the government truth score implying that they trust the government. This finding is also reinforced by protection motivation theory which argues that individuals are more likely to follow preventive measures when they have a belief that the measures are more effective. From the sentiment analysis applied to tweets from the London population, we can also conclude that there is an increase in negative sentiment amongst Twitter users relating to the government during the progression of the three lockdowns which highlights a lack of trust in government guidance which is showcased by figure 3.3.

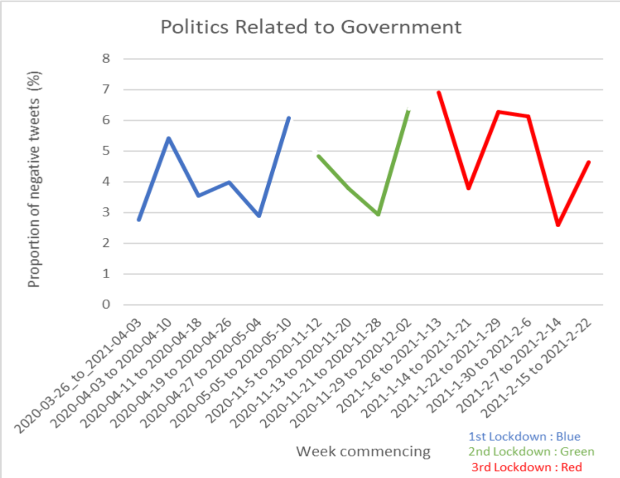

Figure 3.3 Proportion of negative tweets about Politics Related to Government

Most notably, an increasing trend of tweets was also visible where negative connotations were made in association with “Boris Johnson ”, the UK’s prime minister as shown in the figure 3.4. This could be due to an increased focus on the actions of individual government officials such as Boris Johnson and how they follow the preventive measures. When such officials break lockdown measures it breeds mistrust and cynicism regarding preventive policies which leads to a reduction in overall compliance (Williams, 2021).

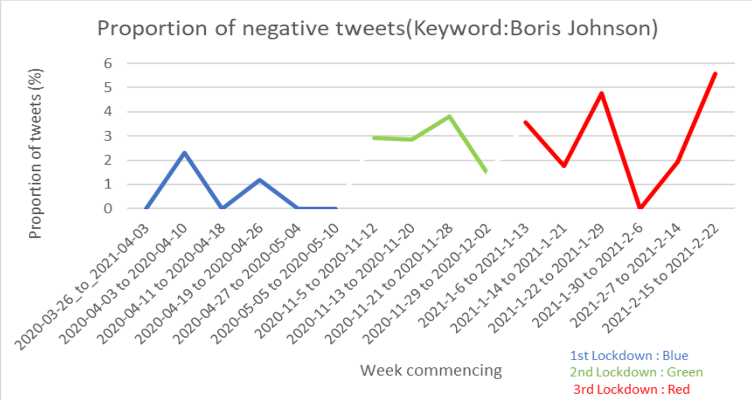

Figure 3.4 Proportion of negative tweets about Boris Johnson (Prime Minister)

This further portrays the increasing dissatisfaction towards governmental response to COVID-19 as the pandemic progressed where trust in government decreased, exacerbating non-compliance and negative sentiment towards lockdown restrictions. The following table showcases that those who had greater trust in the government were more compliant with regards to lockdown measures.

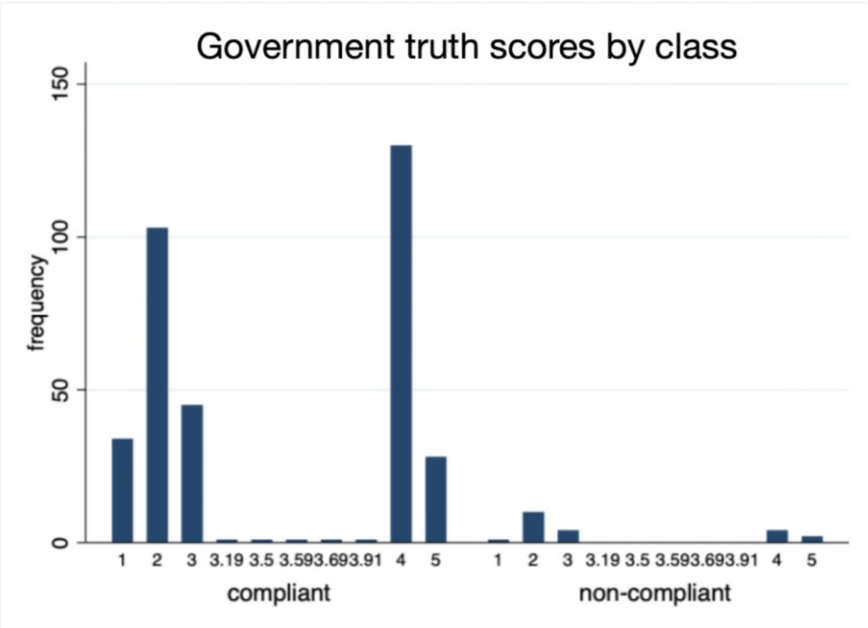

Figure 3.5 Government Truth Scores by Class

Conclusion

We find that government trust and the prevalence of emotional support systems are important factors that contribute to the compliance of COVID-19 lockdowns. While individual personality traits show differences in compliance, they were unable to give a complete picture because it did not include external factors which also impacted compliance. Our findings support our hypothesis that government trust has a positive relationship with the compliance rate of preventive measures. These findings highlight the need for governments to invest in enhancing public trust in health care institutions by improving the quality of the health care services provided and the speed of responsiveness to health crises (OECD, 2021). Future research on which specific governmental decisions are viewed most favourably by the public and greater focus on those policies could ensure increased compliance rates in future health related pandemics. While there is already a large body of research on individual characteristics which influence preventive behaviour (Kleitman et al, 2021) our research focuses on the public's sentiments regarding governmental decisions which provides a wider contextual picture regarding the influence of external factors on compliance.

We find in our secondary data analysis that those who had less emotional support networks were more compliant. This is in line with our second hypothesis regarding the impact of emotional support systems on compliance rates. The sentiment analysis of tweets also shows that tweets relating to mental health are primarily negatively classified tweets. This supports already existing literature by Constantinou, Closter and Karekla (2021) which highlight mental health issues which are a barrier to compliance. As a result, we further argue that future health related policy should have a focus on the impacts on mental health and how those issues can be addressed by governmental policies such as wider helpline and listening services (Brulhart et al, 2021).

We conclude that a reduction in government trust and mental health amongst the populations could explain the reduction in compliance in lockdown measures. Hence, during health pandemics governments should be mindful not only in building trust in the policies they are enacting but also addressing mental health concerns as they are both prerequisites for effective implementation of preventive measures.

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Appendices

Appendix A: Sentiment analysis of Tweets

The following is the results of the analysis of the Twitter data we have gathered. We analysed the proportion of both position and negative discourses and sentiments expressed by relevant tweets under 6 hashtags and topics (healthcare-related, trust, education, government policies, employment synonyms, and mental health), over weeks and across the three lockdowns. We also summarised the changes in the words and phrases used by Twitter users in London and their tendency to express their feelings about the lockdowns throughout.

	Healthcare related (Negative)	Healthcare related (Positive)
First Lockdown		
2020.3.26 – 2021.4.2	2.410%	5.780%
2020.4.3 – 2020.4.10	2.190%	3.581%
2020.4.11 – 2020.4.18	3.633%	3.535%
2020.4.19 – 2020.4.26	4.279%	4.709%
2020.4.27 – 2020.5.4	2.480%	3.474%
2020.5.5 – 2020.5.10	1.861%	2.736%
Second Lockdown		
2020.11.5 – 2020.11.12	2.908%	6.012%
2020.11.13 – 2020.11.20	3.555%	4.982%
2020.11.21 – 2020.11.28	2.133%	1.646%
2020.11.29 – 2020.12.2	0%	2.913%
Third Lockdown		
2021.1.6 – 2021.1.13	2.804%	6.464%
2021.1.14 – 2021.1.21	3.275%	4.348%
2021.1.22 – 2021.1.29	3.008%	5.128%
2021.1.30 – 2021.2.6	2.339%	6.103%
2021.2.7 – 2021.2.14	1.942%	6.222%
2021.2.15 – 2021.2.22	3.096%	3.960%

Fig.1 The proportion of the health-related word in both negative and positive tweets

	Trust	Education	Politics Related	Job	Mental Health	Boris Johnson/ Prime Minister
First Lockdown						
2020.3.26 – 2021.4.2	2.410%	5.780%	2.771%	6.897%	0.723%	2.169%
2020.4.3 – 2020.4.10	2.190%	3.581%	5.422%	7.925%	0.730%	2.294%
2020.4.11 – 2020.4.18	3.633%	3.535%	3.542%	8.447%	1.272%	0.636%
2020.4.19 – 2020.4.26	4.279%	4.709%	3.980%	6.866%	1.493%	1.194%
2020.4.27 – 2020.5.4	2.480%	3.474%	2.877%	8.631%	0.794%	1.687%
2020.5.5 – 2020.5.10	1.861%	2.736%	6.068%	7.362%	0.728%	4.935%
Second Lockdown						
2020.11.5 – 2020.11.12	2.908%	6.012%	4.847%	11.309%	2.100%	2.908%
2020.11.13 – 2020.11.20	3.555%	4.982%	3.791%	11.611%	1.422%	2.844%
2020.11.21 – 2020.11.28	2.133%	1.646%	2.933%	8.533%	1.333%	3.801%
2020.11.29 – 2020.12.2	0%	2.913%	6.383%	10.638%	0%	1.418%
Third Lockdown						
2021.1.6 – 2021.1.13	2.804%	6.464%	6.916%	14.206%	1.682%	3.551%
2021.1.14 – 2021.1.21	3.275%	4.348%	3.778%	9.572%	3.023%	1.763%
2021.1.22 – 2021.1.29	3.008%	5.128%	6.266%	10.526%	2.506%	4.762%
2021.1.30 – 2021.2.6	2.339%	6.103%	6.140%	7.310%	1.754%	2.339%
2021.2.7 – 2021.2.14	1.942%	6.222%	2.589%	6.472%	0.971%	1.941%
2021.2.15 – 2021.2.22	3.096%	3.960%	4.644%	7.121%	1.858%	5.5723%

Fig. 2 The proportion of six themes in negative tweets

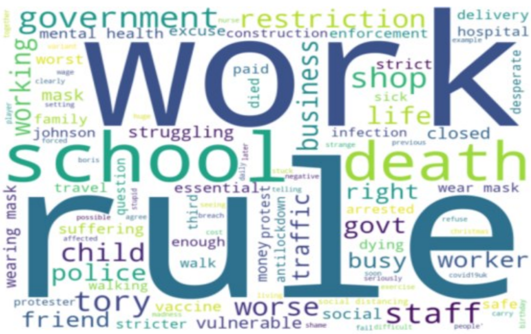
	Community
First Lockdown	
2020.3.26 – 2021.4.2	1.156%
2020.4.3 – 2020.4.10	2.204%
2020.4.11 – 2020.4.18	1.026%
2020.4.19 – 2020.4.26	0.897%
2020.4.27 – 2020.5.4	0.947%
2020.5.5 – 2020.5.10	0.912%
Second Lockdown	
2020.11.5 – 2020.11.12	1.202%
2020.11.13 – 2020.11.20	0.712%
2020.11.21 – 2020.11.28	0.823%
2020.11.29 – 2020.12.2	0%
Third Lockdown	
2021.1.6 – 2021.1.13	3.042%
2021.1.14 – 2021.1.21	2.899%
2021.1.22 – 2021.1.29	1.282%
2021.1.30 – 2021.2.6	0.469%
2021.2.7 – 2021.2.14	3.556%
2021.2.15 – 2021.2.22	0.990%

Fig. 3: The proportion of the keyword "community" in positive tweets

Appendix B: Frequency word clouds based on sentiment analysis of Tweets

Below are the word clouds showing twitter users' weekly keywords with positive and negative sentiments regarding the three lockdowns. The first lockdown started on 26 March 2020 and ended on 10 May 2020, while the second lockdown was a 4-week period from 5 November 2020 to 2 December 2020. As for the third lockdown, it began on 6 January 2021 and ended on 22 February 2021.

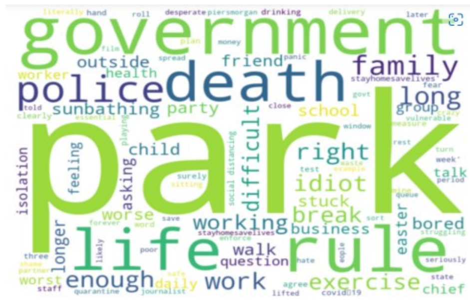
Meanwhile, the size of keywords in word clouds shows how frequently they are mentioned. For example, "rule" is the largest keyword in first lockdown week1 positive sentiment word cloud. This means the word "rule" is the most mentioned word with positive sentiment in week1 of the first lockdown.



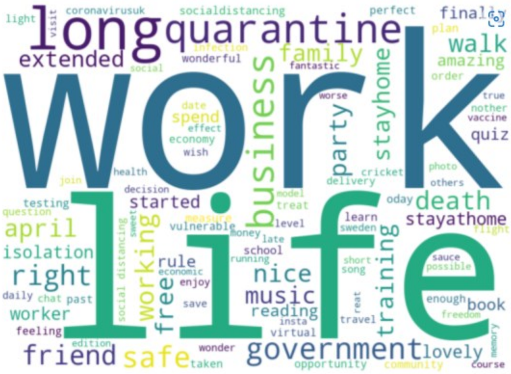
1st lockdown week1 positive

1st lockdown week1 negative

1st lockdown week2 positive

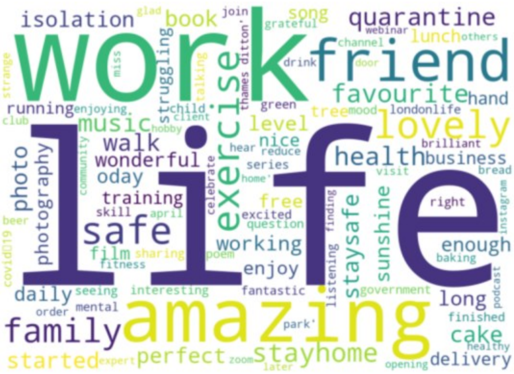


1st lockdown week2 negative



1st lockdown week3 positive

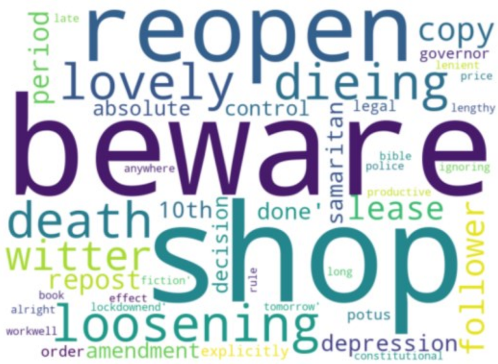
1st lockdown week3 negative



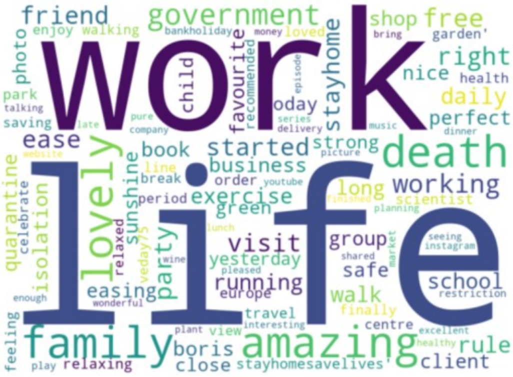
1st lockdown week 4 positive

1st lockdown week 4 negative

1st lockdown week 5 positive



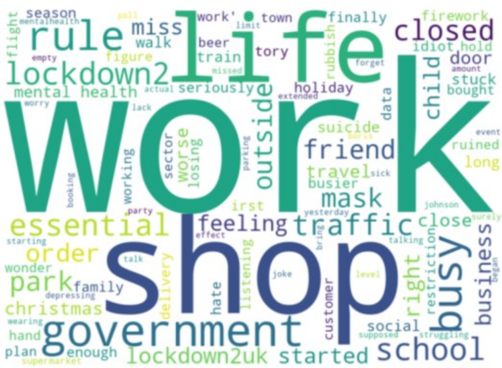
1st lockdown week 5 negative



1st lockdown week 6 positive

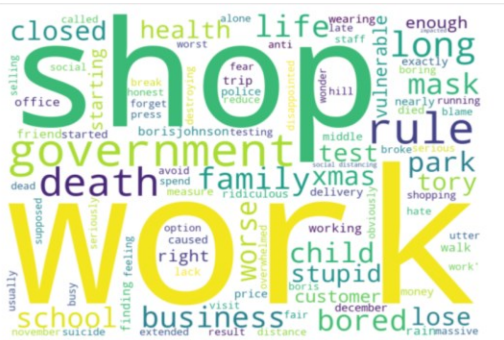
1st lockdown week 6 negative

2nd lockdown week1 positive



2nd lockdown week1 negative

2nd lockdown week 2 positive



2nd lockdown week 2 negative

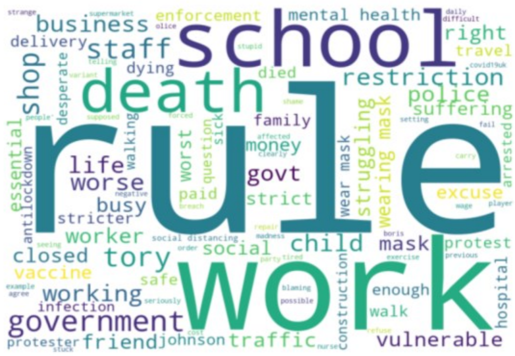
2nd lockdown week 3 positive

2nd lockdown week 3 negative

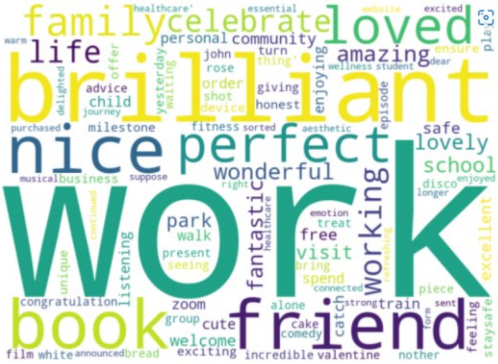
2nd lockdown week 4 positive

2nd lockdown week 4 negative

3rd lockdown week 1 positive



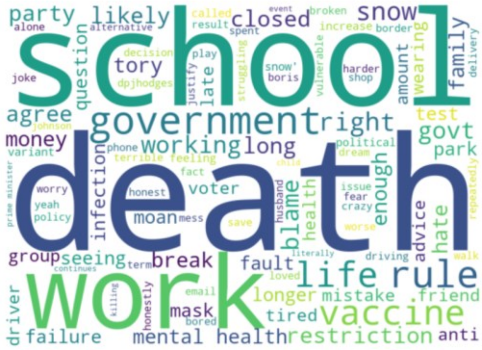
3rd lockdown week 1 negative



3rd lockdown week 2 positive

3rd lockdown week 2 negative

3rd lockdown week 3 positive



3rd lockdown week 3 negative

3rd lockdown week 4 positive

3rd lockdown week 4 negative

3rd lockdown week 5 positive

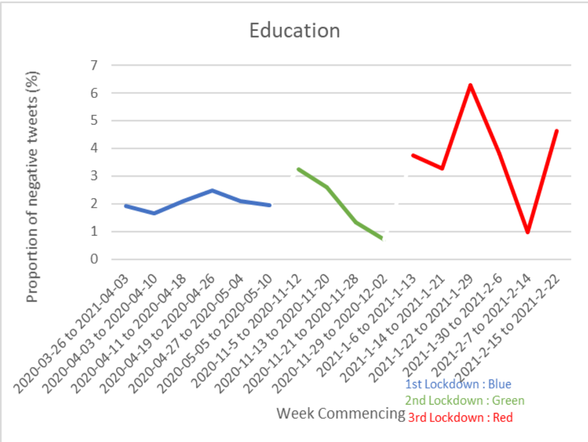
3rd lockdown week 5 negative

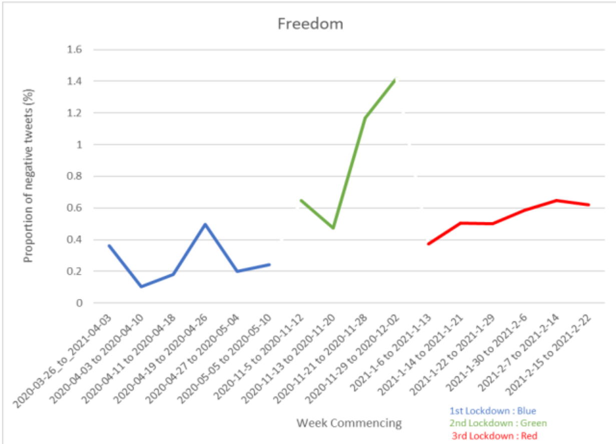
3rd lockdown week 6 positive

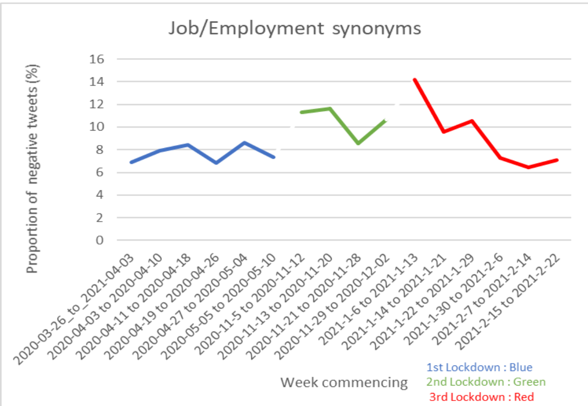
3rd lockdown week 6 negative

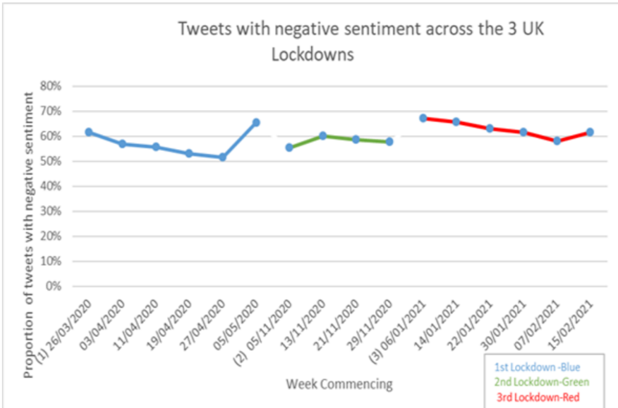
Appendix C: Trend graphs based on word frequency in sentiment analysis of Tweets

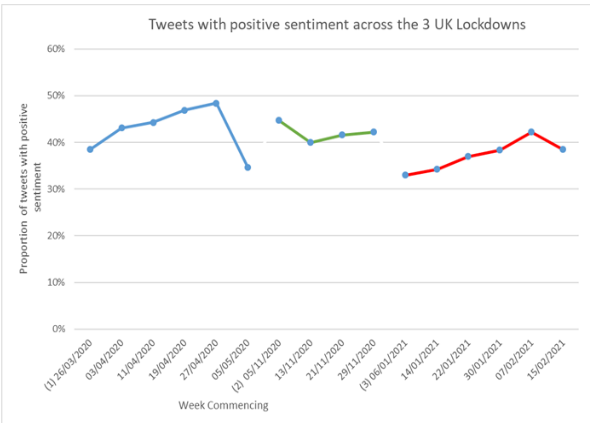
The graphs below show factors (e.g.such as Education, employment, government policies, freedom, Economy,,healthcare, and trust) we found to have contributed to non-compliance by the London-based population during the three lockdowns. The blue line represents the first lockdown, the green line represents the second and the red line represents the third. They show the changing tendencies over time.

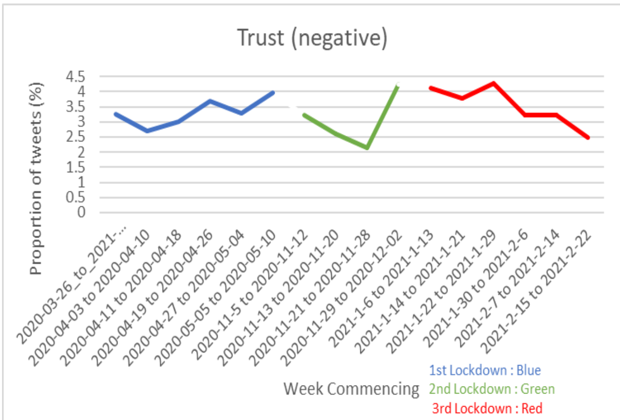


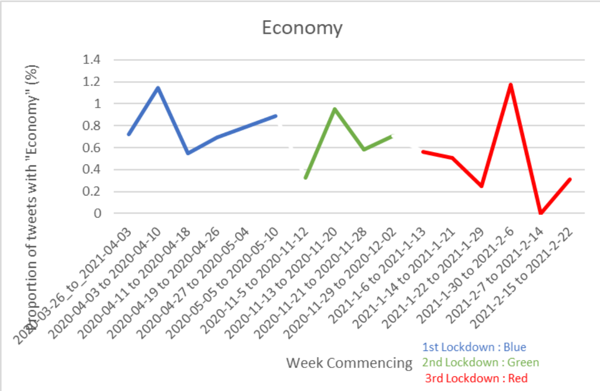


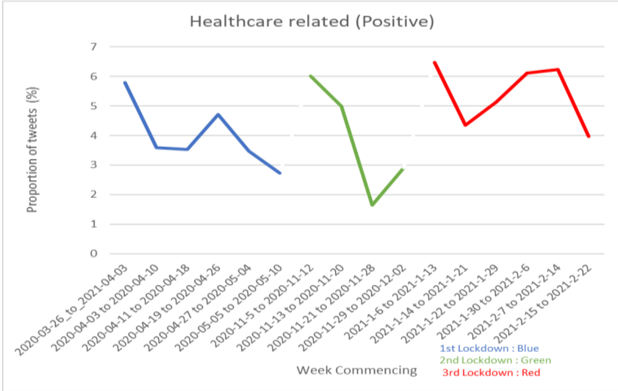




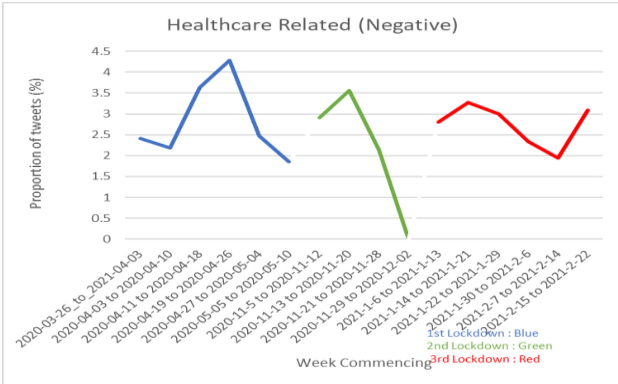


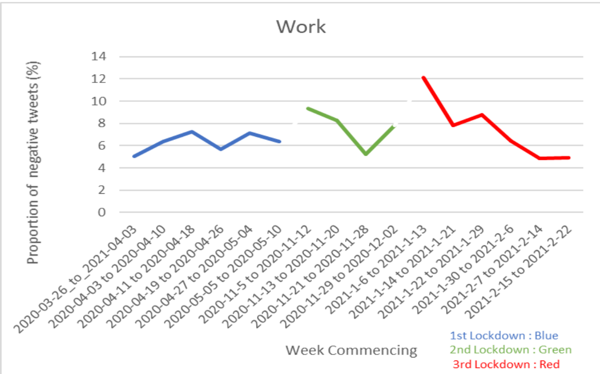


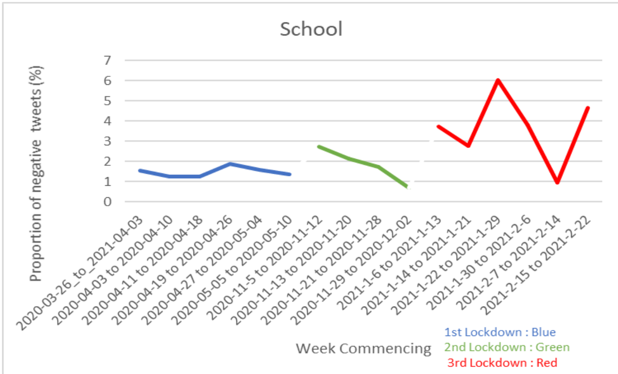

Economy
Proportion of tweets with "Economy" (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red

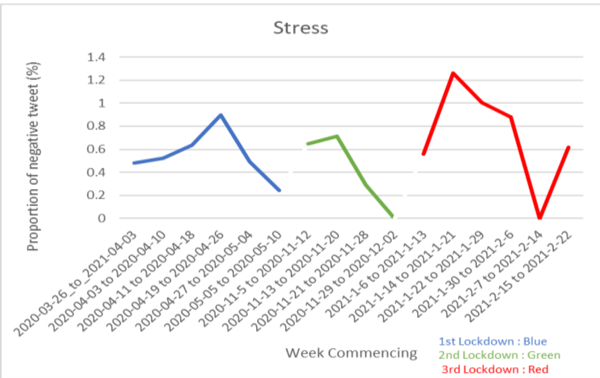

Healthcare related (Positive)
Proportion of tweets (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red


Money
Proportion of negative tweets (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red


Healthcare Related (Negative)
Proportion of tweets (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red


Work
Proportion of negative tweets (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red


School
Proportion of negative tweets (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red


Stress
Proportion of negative tweet (%)
Week Commencing
1st Lockdown : Blue
2nd Lockdown : Green
3rd Lockdown : Red

Appendix D: Raw Statistical Data

The tables below illustrate the regression model between compliance behaviours and a variety of variables, as well as the mean values of compliance and non-compliance against each variable with percentage difference.

Class	**Freq.**	**Percent**	**Cum.**
Compliance	345	94.26	94.26
Non-compliance	25	5.74	100.00
Total	366	100.00	

Table 2 – Tabulation of class variable

Compliance	**Coef.**	**t**	**P>|t|**
Agreeableness	0.0128	3.05	0.002** (0.004)
Conscientious	0.000	0.06	0.955 (0.004)
Extraversion	-0.007	-2.05	0.041* (0.003)
Intellect	0.007	1.64	0.103 (0.004)
Neuroticism	-0.001	-0.44	0.661 (0.003)
_cons	0.736	7.15	0.000 (0.103)

Table 2.1 – regression model between compliance and personality traits

Compliance	Coef.	t	P>ltl
Female	0.048	1.88	0.061 (0.026)
_cons	0.911	43.51	0.000 (0.021)

Table 2.2 – regression model between compliance and female variable

Compliance	Coef.	t	P>ltl
Male	-0.043	-1.88	0.061 (0.026)
_cons	0.959	64.41	0.000 (0.015)

Table 2.3 – regression model between compliance and male variable

Compliance	Coef.	t	P>ltl
govt_truth	0.018	1.42	0.158 (0.013)
govt_satisfaction	-0.015	-1.16	0.245 (0.012)
_cons	0.929	25.83	0.276 (0.036)

Table 2.4 – regression model between compliance and attitude to government

Variable	Mean Compliance	Mean Non-Compliance	Percentage Difference
Emotsupp	3.296	3.667	10.1%
Govt_truth	3.052	2.81	8.6%
Govt_satisfaction	2.743	2.857	3.9%
Reactance	26.838	30.088	10.8%
Conservatism	8.075	7.657	5.6%
Prosocial	2.565	2.82	9.0%
Agreeableness	12.777	10.861	17.63%
Conscientious	10.734	10.563	1.62%
Extraversion	8.157	8.71	6.35%
Intellect	10.705	9.466	13.1%
Neuroticism	11.766	11.8	0.3%

Table 2.5 – Mean values of compliance and non-compliance against each variable with percentage differences

Label	Description	Mean	Minimum	Maximum
Emotsupp	Asking respondents if they had provided emotional support to family/friends or strangers during lockdown (Asked under the ProSocial section of survey) answer on a scale from 0 (does not apply to you at all) to 100 (applies very much to you)	3.317	1	7
govt_truth	How truthful people felt their government had been about the lockdown on a scale of 1 to 5 (e.g., very untruthful (1) to very truthful (5))	3.038	1	5
govt_satisfaction	How satisfied people felt about their government's response to the COVID-19 outbreak on a scale of 1 to 5 (e.g., very dissatisfied (1) to very satisfied (5))	2.749	1	5
Conservatism	If people agreed with the political ideology of conservatism measured using a scale of 1 to 5(e.g., fully disagree (1) to fully agree (5))	8.051	1	13
ProSocial	Was measured by using 8 statements to do with how social people thought their behaviour was in lockdown which were provided to respondents to answer on a scale from 0 (does not apply to you at all) to 100 (applies very much to you)	2.579	1	6.74
Reactance	Reactance is when people feel restricted, they tend to resist control and get back their freedom. This was measured by asking respondents how much a provided statement applied to them on a scale from 1(strongly disagree) to 6 (strongly agree)	27.025	1	50

Table 4: Independent variables

Label	Description	Mean	Minimum	Maximum
Intellect	Respondents' intellect was identified by asking how open they were to dealing with change. Measured by respondents answering on a scale of 1 (very inaccurate) to 5 (very accurate) if a provided response applied to them	10.634	1	16
Extraversion	How much of an extrovert people are. Personality measure that was carried out by asking respondents how much a provided statement to do with extraversion applied to them on a scale from 1(very inaccurate) to 5 (very accurate)	8.188	1	17
Agreeableness	How agreeable or sympathetic people were. Personality measure that was carried out by asking respondents how much a provided statement to do with agreeableness applied to them on a scale from 1(very inaccurate) to 5 (very accurate)	12.667	1	17
Conscientious	How diligent people are when carrying out tasks. Personality measure that was carried out by asking respondents how much a provided statement to do with how conscientious they were with certain tasks applied to them on a scale from 1(very inaccurate) to 5 (very accurate)	10.724	1	17
Neuroticism	When people have negative emotions and may experience mood swings. Personality measure that was carried out by asking respondents how much a provided statement to do with neuroticism applied to them on a scale from 1(very inaccurate) to 5 (very accurate)	8.768	1	17

Table 5: Independent Variables – Personality Traits