The Alan Turing Institute

Understanding vulnerability to online misinformation

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Bertie Vidgen, Harry Taylor,
Myrto Pantazi, Zoe Anastasiou,
Becky Inkster and Helen Margetts

Contents

About

The research team

Dr Bertie Vidgen is a research fellow in online harms within the Public Policy Programme at The Alan Turing Institute and a research associate at the University of Oxford.[1] He is the corresponding author, bvidgen@turing.ac.uk.

Harry Taylor is a research assistant at The Alan Turing Institute, a research associate at the Centre on Dynamics of Ethnicity, and a PhD candidate at the University of Manchester.

Dr Myrto Pantazi is a post-doctoral researcher at the University of Oxford.

Zoe Anastasiou is a research assistant at The Alan Turing Institute.

Dr Becky Inkster is a visiting researcher and advisor at The Alan Turing Institute and an honorary fellow at the University of Cambridge's Department of Psychiatry.

Professor Helen Margetts OBE FBA is the Director of the Public Policy Programme at The Alan Turing Institute and Professor of Society and the Internet at the Oxford Internet Institute, University of Oxford.

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The Alan Turing Institute

The Alan Turing Institute is the UK's national institute for data science and artificial intelligence. It was founded in 2015 and undertakes research to tackle some of the biggest challenges in science, society and the economy. It collaborates with universities, businesses and public and third sector organisations, including its 13 partner universities. The Turing aims to help to make the UK the best place in the world for data science and AI research, collaboration, and business.

The Public Policy Programme was established in 2018. It works with policy makers to develop data-driven tools and methodologies to foster government innovation, improve public services, solve policy problems, and to develop ethical foundations for data science and AI policy-making and regulation.[2]

1 "Bertie Vidgen," The Alan Turing Institute. Accessed December 4, 2020, https://www.turing.ac.uk/people/researchers/bertie-vidgen.
2 "Public policy programme", The Alan Turing Institute. Accessed December 4 2020, https://www.turing.ac.uk/research/research-programmes/public-policy.

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Overview

Health-related misinformation risks exacerbating the COVID-19 public health crisis if it leads the public to refuse treatment when needed, not follow official guidance, such as policies on social distancing and mask-wearing, or even to use harmful ‘miracle’ cures. If left unchecked, misinformation could seriously undermine the vaccine rollout and heighten people’s anxiety and mistrust during this time of national stress.

Several large-scale research projects have started during the crisis with the aim of understanding the nature, prevalence and spread of health-related misinformation online. However, relatively little is known about who is vulnerable to believing false information and why. This is crucial for developing more targeted and effective interventions which tackle the root causes of misinformation rather than just its symptoms. To address this gap, researchers from The Alan Turing Institute’s public policy programme have conducted original research using a survey and assessments to understand (1) which individuals are most vulnerable to believing health-related falsities and (2) the role played by the content that individuals are exposed to.

Key findings

1. Individuals with **higher digital literacy**, **numerical literacy**, **health literacy** and **cognitive skills** are better at assessing the veracity of health-related statements. Their years of education do not make a difference.

2. Individuals who are at risk of COVID-19 are slightly better at assessing health-related statements than those who are not. Individuals who are afraid of COVID-19 are slightly worse and being diagnosed with COVID-19 does not have an effect.

3. Unexpectedly, most sociodemographic, socioeconomic and political factors make little or no difference at all. However, age did matter and we find that **older people are slightly better at assessing health-related statements**.

4. The **content that we showed participants affected how well they assessed health-related statements**. When we showed them true content they were better at assessing health-related statements, compared with when we showed them false content.

5. **Giving participants warnings about misinformation** before they made any assessments had only a very small effect on how accurate they were.

6. Finally, **people have inconsistent knowledge about health**. There is a lot of variation within individuals’ responses.

We also asked participants about their views on a range of COVID-19 related issues and found that they are **concerned about public health, prioritising it over the economy.** Most people say they are following UK government guidelines closely and have very high levels of trust in the NHS. **Social media is the least trusted source of information**.

Recommendations

A range of strategies have already been deployed to address health-related misinformation during the COVID-19 pandemic. Many platforms have started to demote, remove or apply warnings to misleading or false content, and provided links to verified information (Facebook 2020; Twitter 2020; YouTube 2020). The UK Government has created the SHARE checklist to encourage the public to be more careful when viewing online content and has launched dedicated units to tackle misinformation (UK Government 2020). Many civil society organisations have provided manuals and guides for identifying and countering misinformation, as well as databases of validated information (First Draft 2020; Full Fact 2020; The Center for Countering Digital Hate 2020). Nonetheless, despite these efforts, there is a pressing need for more to be done to tackle the harmful effects of misinformation.

Based on our original research we provide the following recommendations, aimed primarily at policymakers and online platforms.

1. **Address the factors that make people susceptible to misinformation as well as the supply of misinformation.** Everyone has 'room to improve' and policies should aim to enable people to better recognise, scrutinise and combat misinformation.

2. **Digital literacy should be explored as a powerful tool for combating misinformation**. Our analyses show an association between digital literacy and lower susceptibility to misinformation, even after controlling for sociodemographic and socioeconomic traits. This should be explored as an immediate priority, especially as increasing digital literacy has other pro-social benefits.

3. **New strategies for communicating the severity of misinformation to the public must be developed**. Our results show that simple warnings may not be enough to reduce people's susceptibility to misinformation. Nonetheless, it remains important that the public is made aware of the harm that misinformation can cause.

1. Background

The first case of COVID-19 was reported in Wuhan, China in late December 2019. The UK reported its first death on 6th March 2020 and on 11th March the World Health Organization formally recognised the worldwide COVID-19 pandemic (The New York Times 2020). Within 10 months more than 1.8 million people have died from the virus globally and in the UK there have been 2.8 million confirmed cases and 77,000 recorded deaths (John Hopkins Unversity 2021). Concerningly, the true death toll may be even higher given that different diagnostic tools have been used during the pandemic and in many countries more accurate tools are still not widely available (Maria 2020). The substantial resources devoted to tackling COVID-19 has itself created additional public health crises, such as people with mental and physical health issues having reduced access to vital treatment (Charlesworth 2020; Sergeant et al. 2020). COVID-19 has also had profound social and economic consequences, causing unemployment, reducing GDP and necessitating unprecedented government intervention in the economy (Hensher 2020; HM Government 2020). As the UN put it in April 2020, “The COVID-19 pandemic is far more than a health crisis: it is affecting societies and economies at their core.” (United Nations 2020).

Vulnerability to COVID-19 is affected by a range of factors. In the UK, people who are designated as ‘clinically vulnerable’ and ‘clinically extremely vulnerable’ include those with underlying health conditions, such as having a serious heart condition or being recipient of an organ transplant (NHS 2020). Numerous studies show that elderly people have a far higher risk of hospitalisation and death, especially over 65s (Amber L. Mueller, Maeve S.McNamara, and David A. Sinclair 2020; Davies et al. 2020; Mahase 2020). The June 2020 COVID-19 review by Public Health England outlined a number of disparities in which groups suffer the highest mortality rates from COVID-19 (Public Health England 2020). It is higher amongst males than females; those living in more deprived areas; and those in BAME rather than white ethnic groups. The review summarised that, “the impact of COVID-19 has replicated existing health inequalities and, in some cases, has increased them.” (Ibid.)

1.1 Health-related misinformation

The provision of high-quality and up-to-date information during health crises is crucial for maintaining trust between the government and the public and for ensuring compliance with policies (Covello 2003). Misinformation, which can be understood as "information that is contrary to the epistemic consensus of the scientific community regarding a phenomenon" (Swire-Thompson and Lazer 2019), risks undermining the public's understanding of health-related issues (Bessi et al. 2015; Swire-Thompson and Lazer 2019). Studies suggest that false information has contributed towards elevated levels of tooth decay in children (Cashmore, Phelan, and Blinkhorn 2010), the re-emergence of measles in the USA (Benecke and DeYoung 2019) and unnecessary deaths during the Ebola outbreak (Allgaier and Svalastog 2015). Conspiracy theories and false information about health often weaponise scientific uncertainty, exploiting areas where there is less consensus, weaker evidence or even genuine mistakes (Scheufele and Krause 2019). Infamously, a 1998 article in the Lancet incorrectly suggested that there was an association between vaccines and autism spectrum disorders. It was subsequently retracted due to misrepresentation of data by the lead author and has been widely discredited (The Lancet 2010). Nonetheless, it is still used by 'anti-vax' movements, which have gained substantial support over the past two decades.

The spread of misinformation has become a major concern during COVID-19. It has been described as an "infodemic" by the WHO Director-General Tedros Adhanom Ghebreyesus (UN News 2020) and a "second pandemic" by some academics (Valika, Maurrasse, and Reichert 2020). A report by KCL in December 2020 found that one in three people had been exposed to anti-vax messages (Duffy 2020) and an Ofcom study found that 46% of people had come across misleading stories about COVID-19 in the first week of lockdown (Ofcom 2020a). Misinformation has been linked to the deaths of over 700 people in Iran who were led to believe that gurgling or drinking alcohol can stop COVID-19 (Shokoohi et al. 2020). It can also have more diffuse but wide-ranging effects; a working paper by KCL found that those who believe COVID-19 related conspiracy theories are less likely to engage in social distancing (Allington and Dhavan 2020). In particular, misinformation may jeopardise the implementation of vaccination programmes. A survey by YouGov conducted in November 2020 found that one in five people in Britain are unlikely to take a COVID-19 vaccine (McDonnell 2020). Indeed, even before COVID-19, hesitancy to vaccinate was named as one of the top ten threats to global health by the World Health Organization in 2019 (World Health Organization 2019).

Misinformation varies in terms of what is claimed, and how it is framed and communicated. Wardle offers a working typology of mis- and disinformation with seven distinct types of problematic content, which she arranges "loosely" by "intent to deceive" (Wardle 2017). The scale starts with content which has no intention to deceive but could still be misleading, such as satire, and finishes with content that is entirely fabricated and is explicitly designed to be deceptive. These distinctions are important because it is likely that most of the 'misinformation' that people encounter online is not entirely false but, rather, misleading or taken out-of-context. A sample of 225 items of misinformation fact-checked by the University of Oxford during the first months of 2020 showed that 59% was 'misconfigured' rather than explicitly false (Brennen et al. 2020).

1.2 Individual-level factors associated with misinformation

Previous research identifies a range of factors associated with individuals who are susceptible to misinformation (Vicol 2020). One note of caution is that the landscape of misinformation is fast-moving, especially during COVID-19. New strategies and means of persuasion are appearing and, as a result, the individuals affected by misinformation could be different.

1. **Age**: A 2014 meta-analysis shows that older people were more vulnerable to misinformation (Wylie et al. 2014) and a 2019 study showed that people aged 65+ were more likely to share misinformation on social media (Guess, Nagler, and Tucker 2019). One theory suggests that older adults tend to rely on existing knowledge when confronted by new information and are particularly susceptible to misinformation when they do not have any pre-existing knowledge on the subject (Brashier et al. 2019). However, more research is needed to confirm this hypothesis, as well as any association between age and misinformation.

2. **Gender**: Laato et al. found that during COVID-19 men were more likely to share health information without fact checking it (Laato et al. 2020) and Roozenbeek et al. report that women are slightly less susceptible to believing misinformation in some countries (Spain and USA) although the relationship was not significant for others (Ireland, Mexico and the UK). A study in October 2020 reported that women over 50 are the demographic which is most likely to share pandemic-related stories on Twitter from websites that contain fake news (Lazer et al. 2020). However several analyses report that gender makes no difference to misinformation vulnerability (Xinran Chen and Sin 2013; Fernandez and Alani 2018) and, overall, the evidence on gender is mixed.

3. **Education**: Several studies show that higher levels of education are associated with decreased belief in conspiracy theories (Douglas et al. 2016; Georgiou, Delfabbro, and Balzan 2020; van Prooijen 2017; van Prooijen, Krouwel, and Pollet 2015). A Pew Research Centre report found that college-educated adults were better at discerning political fact from opinion (Pew Research 2018). However, in a detailed follow-up analysis van Prooijen argues that education is “multifaceted” and must be assessed by “multiple independent psychological processes”, including cognitive complexity and feeling of control, rather than just years of schooling (van Prooijen 2017). Overall, the evidence suggests that people with more education will be susceptible to misinformation, although the precise causal mechanism is unclear and strength of association identified may vary depending upon the research design.

4. **Cognitive skills**: Several studies show that people with higher cognitive ability are less susceptible to misinformation (Keersmaecker and Roets 2017; Lommen, Engelhard, and van den Hout 2013). Cognitive abilities can also be measured in terms of how individuals think. Two studies from Pennycook & Rand show that individuals who engage in more analytical reasoning are less susceptible to misinformation (Pennycook and Rand 2018, 2019b) and in a recent preprint they show that individuals who are susceptible to misinformation have less "cognitive sophistication", which they define in relation to scientific knowledge, analytical reasoning and numeracy (Pennycook, McPhetres, Bago, et al. 2020). Similarly, Garrett and Weeks report that individuals who "put more faith in their ability to use intuition to assess factual claims" are more likely to support conspiracy theories (Garrett and Weeks 2017). Another preprint from Pennycook and Rand shows that being prompted to think about the accuracy of COVID-19 related headlines improved people's ability to discern false from true content (Pennycook, McPhetres, Zhang, et al. 2020).

5. **Health literacy**: Higher health literacy has been linked with being less susceptible to health-related misinformation (Chen et al. 2018; Jones-Jang and Noland 2020; Wojtowicz 2020). However, there is some countervailing evidence. In a meta review of vaccine hesitancy Lorini et al. argue that the causal direction of its relationship with health literacy unclear, which they argue is partly due to the lack of longitudinal research (Lorini et al. 2018). Similarly, Biasio describes the relationship between misinformation and health literacy as 'uneven' (Biasio 2019). Quinn et al. investigated online information seeking practices and found that 96% of their participants, including many health-literate individuals, used unaccredited sources to answer health-related questions (Quinn, Bond, and Nugent 2017).

6. **Numerical literacy**: In a study of susceptibility to health-related misinformation during COVID-19 Rozenbeek et al. find that higher trust in scientists and higher numeracy skills were associated with lower susceptibility to COVID-related misinformation (Roozenbeek et al. 2020). Research in other domains indicates the positive effect of numerical literacy, showing an association between numerical literacy and better comprehension of everyday risks (Cokely et al. 2012) and with not being influenced by irrelevant, affective arguments (Peters et al. 2006).

7. **Digital, media and information literacy**: Digital, media and information literacy are often proposed as a key way of addressing people's susceptibility to misinformation (Polizzi and Taylor 2019; Renwick and Palese 2019; Select Committee on Democracy and Digital Technologies 2020). A study published in 2020 showed that a media literacy intervention increased participants' ability to separate mainstream from false news, in both American and India (A. M. Guess et al. 2020). Researchers presented people with tips to help spot false news stories, which helped them to discern between low- and high-quality news. However, another study found that an hour of online misinformation-robustness training made little difference to people's vulnerability (Badrinathan 2020). Roozenbeek et al. show that individuals with lower digital literacy are more likely to believe false health-related content (Roozenbeek et al. 2020). It is important to note that different literacies often share core features and can overlap in terms of what they actually measure.

Jones-Jang et al. argue that information literacy rather than digital literacy may be a better explanation of misinformation susceptibility (Jones-Jang, Mortensen, and Liu 2019). Overall, more evidence is needed to better understand the relationship between literacies and misinformation.

8. **Political ideology**: van Prooijen et al. examined the relationship between political ideology and conspiracy theories, finding that they are more likely to be believed by people with more extreme views (van Prooijen et al. 2015; van Prooijen, Krouwel, and Pollet 2015). On the other hand, several studies show that conservative right-wing beliefs are associated with misinformation (Basol, Roozenbeek, and Van der Linden 2020; Grinberg et al. 2019; Rothgerber et al. 2020) and Piejka and Okruszek show that people with liberal views are less likely to accept claims that conflict with evidence-based science (Piejka and Okruszek 2020). Notably, a large-scale cross-country survey by YouGov and Cambridge University found that Brexit and Trump voters are more likely to believe in conspiracy theories (Waal 2018). However, the association between right-wing beliefs and misinformation may partly be an artefact of academic research and arguably left-wing false information needs further investigation (Freelon, Marwick, and Kreiss 2020).

9. **Personality traits**: Evidence on the link between misinformation and personality is mixed. Buchanan and Benson report that individuals who score lower on 'agreeableness' from the Big-5 personality traits are more likely to interact with online misinformation (Buchanan and Benson 2019). Akbar et al. suggest that individuals with the 'extraversion' characteristic are more likely to share misinformation (Akbar et al. 2018). Pennycook and Rand suggest that susceptibility to misinformation is associated with what they label "reflexive open-mindedness", which is the tendency to be overly accepting of weakly supported claims (Pennycook and Rand 2019a). Reliance on emotion may increase susceptibility to misinformation (Martel, Pennycook, and Rand 2020), as well as feeling anger and anxiety (Weeks 2015) and having higher levels of stress (Lommen, Engelhard, and van den Hout 2013).

10. **Trust in government**: Several studies link a lack of trust in government with greater belief in conspiracy theories (Brotherton, French, and Pickering 2013; Einstein and Glick 2015). Bargain and Aminjonov show that trust in the government is associated with greater adherence to COVID-related guidelines (Bargain and Aminjonov 2020). The association between misinformation and trust in institutions may have been disrupted by recent events and the changing political landscape; a study in the Harvard Kennedy School's Misinformation Review found that support for Donald Trump was strongly related to a belief that the threat of the virus had been exaggerated (Uscinski et al. 2020).

1.3 Content-level factors associated with misinformation

The nature, presentation and substance of content can affect whether individuals are likely to believe it. It is important to note that how the features of content impact susceptibility to misinformation has been less extensively researched than individual-level features.

1. **How content is presented**: Online content is often more ambiguous compared with traditional offline content (such as newspaper articles) because it can lack the same markers of quality and veracity. A report from First Draft News notes, "On social media, the heuristics (the mental shortcuts we use to make sense of the world) are missing. Unlike in a newspaper where you understand what section of the paper you are looking at and see visual cues which show you're in the opinion section or the cartoon section, this isn't the case online." (Wardle 2016) A range of content features can affect the perceived trustworthiness of content; Smelter and Calvillo show that attaching pictures to content increases perceived trustworthiness (Smelter and Calvillo 2020) and other studies report that information is more believable if it is printed in an easy-to-read font (Song and Schwarz 2008) and in high- rather than low- colour contrast (Reber and Schwarz 1999).

2. **Style and understandability**: The ease with which content is processed can affect its believability, with some suggesting that easy-to-understand information may be more believable because it is easier for individuals to process (Smelter and Calvillo 2020). Lewandowsky et al. argue, "In general, fluently processed information feels more familiar and is more likely to be accepted as true; conversely, disfluency elicits the impression that something doesn't quite "feel right" and prompts closer scrutiny of the message." (Lewandowsky et al. 2012) Similarly, Hameleers argues that misleading content is more likely to be accepted than content which is entirely fabricated (Hameleers 2020).

3. **The source of content**: Who creates content can affect its perceived veracity. Buchanan and Benson show that messages which are shared from sources which are perceived to be trustworthy are more likely to be shared by others (Buchanan and Benson 2019). Interestingly, there is evidence that during COVID-19 there has been increased traffic to traditionally-trusted outlets such as the BBC, NHS and WHO (Ofcom 2020a). Allington and Dhavan highlight the risk of misinformation shared by celebrities and politicians, given their reach and levels of audience trust (Allington and Dhavan 2020) and numerous commentators have debated the impact of misinformation shared by prominent politicians (McCarthy 2020). Overall, more research is needed to understand the impact of content's source.

4. **Warnings**: Attaching warnings to false and misleading content is an increasingly common practice used by social media platforms to address harmful content (Vidgen and Margetts 2019). This has a clear rationale; warning people about content should make them scrutinise it more closely. Several studies suggest that this can be effective in combatting harmful untruths (van der Linden, Leiserowitz, and Maibach 2018). However, other studies suggest that, in some cases, warnings can be inefficient (Pantazi, Kissine, and Klein 2018) or counter-effective and actually increase acceptance of false information (Berinsky 2017; Schaffner and Roche 2016). Pennycook et al. show that warnings may have other unexpected adverse effects; they report an 'implied truth effect', which is where false headlines that are not given warnings are considered implicitly validated and therefore accurate – even though in practice they may have just not been reviewed (Pennycook, Bear, et al. 2020). Overall, the effect of warnings remains unclear, although the evidence suggests that they reduce vulnerability to misinformation.

5. **Information overload**: Information overload is where people find it hard to understand and make decisions about issues when they are faced with too much information (Laato et al. 2020). Hall and Walton conducted a literature survey and showed that information overload can negatively affect people's ability to make decisions about health-related issues (Hall and Walton 2004). This is a substantial concern during COVID-19 given the large amount of information which is being communicated and the speed with which official guidance is being updated (Rathore and Farooq 2020).

2. Research questions

Building on findings from previous research, we address the following two research questions:

1. What factors are associated with **people** who are more likely to believe health-related misinformation?

2. What features are associated with false health-related **content** that people are (erroneously) more likely to believe is true?

3. Research design and data

Participants were recruited and paid via the survey platform Qualtrics. They were paid above the London living hourly wage. Participants participated in the study between 26th October and 17th November 2020. The target size of the sample was 1,700 participants, based on power calculations (see Appendix A). To meet the sampling criteria, 1,793 participants were recruited. Data quality was maintained through use of two attention checks and a review of the time they took to complete the study. Following these checks, 28 participants were excluded, leaving 1,765 participants in the sample.

The 1,765 participants are broadly representative of the UK in terms of age and gender. They also broadly reflect UK demographics in terms of ethnicity, income and region. The distribution of our sample compared with representative UK figures, based partly on ONS statistics, is shown in Figure 1.[3] The figures for income are harder to compare, and are shown in Table 1. Note that our sample contains more individuals who identify with a 'centre' political affiliation rather than a right-wing affiliation and more individuals who have a degree/professional qualification rather than no qualification.

Participants first completed a survey which contained a range of questions on their background, experiences, views and traits. They then completed an assessment in which they were shown vignettes (short 'headline' style social media posts) and associated statements that they had to assess. The veracity of the vignettes as manipulated (see below) A pilot study was conducted in August 2020, which involved 150 participants and simplified assessments and survey battery. Ethical approval is described in Appendix B.

3 Statistics on sex and region are available at: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland. Statistics on age are available at: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesanalysistool. Statistics on ethnicity are available at: https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/ethnicity/articles/ethnicityandnationalidentityinenglandandwales/2012-12-11. Statistics on income are available at: https://www.gov.uk/government/statistics/family-resources-survey-financial-year-201718. Statistics on political ideology are available at: https://www.ipsos.com/ipsos-mori/en-uk/political-alignment-left-wing-or-right-wing-trends. Statistics on education are available at: http://www.nomisweb.co.uk/census/2011/qs501ew. All sources were last accessed on 13 January 2021.

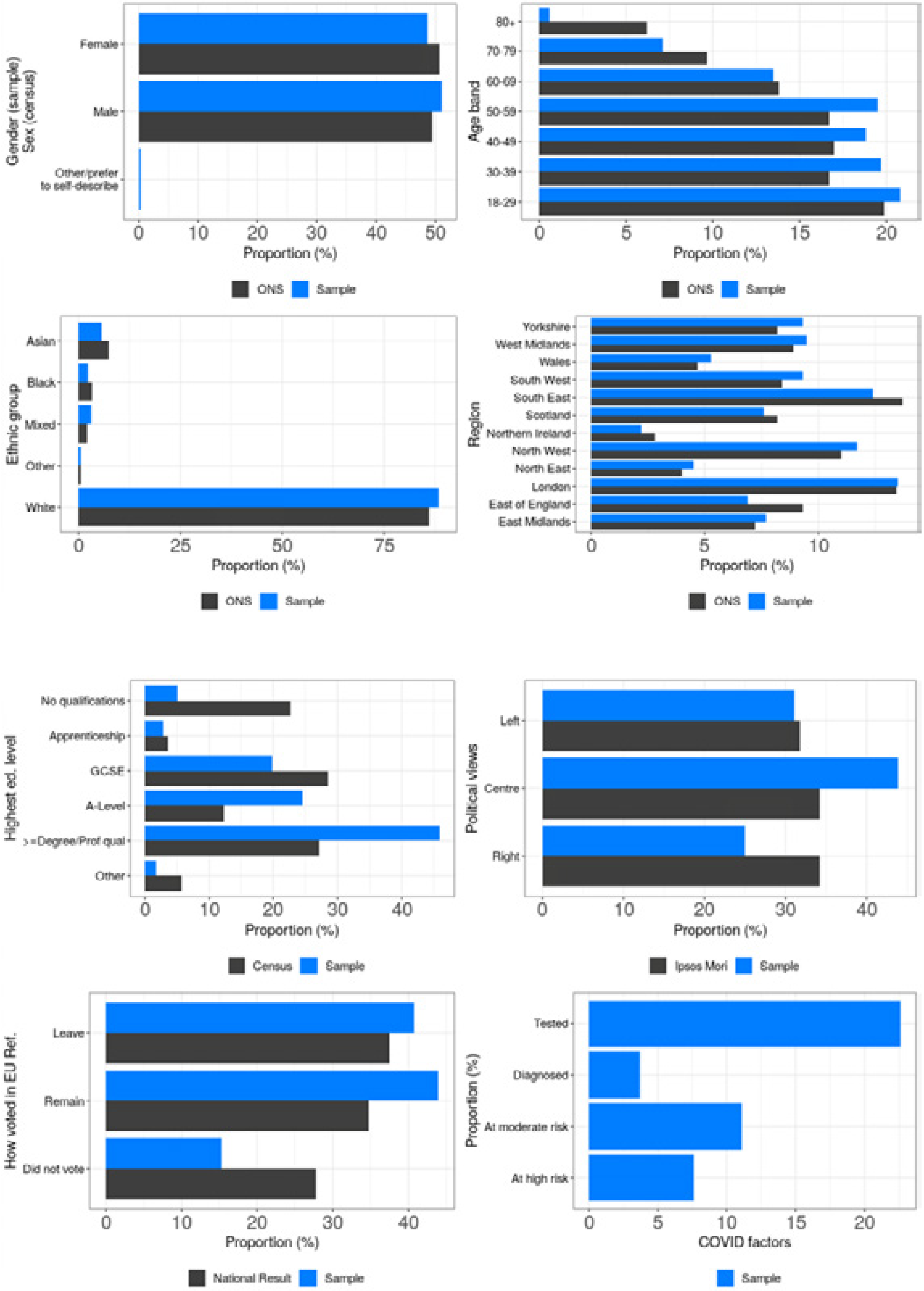


Figure 1: Comparison of our sample with representative UK figures.

Table 1: Comparison of our sample with representative UK figures for income.

Family resources survey		Sample in study	
Income band	Proportion	Income band	Proportion
< £10.4k	7%	<£12.5k	15%
£10.4k - £20.8k	21%	£12.5k-£20k	14%
£20.8k - £31.2k	20 %	£20k-30k	21%
£31.2k-£41.6k	14%	£30k-40k	17%
£41.6k-£52k	11%	£40k-50k	11%
£52k+	27%	£50k+	22%

Assessing the veracity of content

Participants were presented with vignettes which contained health-related claims relevant to COVID-19. These were formatted as headlines, akin to a social media post. They were adjusted from health-related misinformation identified in WHO 'Mythbusters', collated in August and September 2020.[4] An example is shown in Figure 2.

Figure 2: Example vignette shown to participants. This vignette is 'ambiguous'. The source is the Daily Mirror.

4 The WHO, "Coronavirus disease (COVID-19) advice for the public: Mythbusters". Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters. Last accessed on 21 January 2021.

The vignettes were split into three conditions:

- **True**: Headlines which contain a true claim relating to health and COVID-19. For example, “COVID-19 can spread through the air”.
- **False**: Headlines which contain a false claim relating to health and COVID-19. For example, “The COVID-19 virus can be treated by drinking lemonade”.
- **Ambiguous**: Headlines which contain a leading question relating to health and COVID-19. This is a so-called ‘Betteridge question’.[5] For example, “Does taking a hot bath prevent COVID-19?”.

Participants assessed statements that contained claims which related to the content of the vignettes. For instance, the vignette could contain a claim (or a leading question if ‘ambiguous’) about the use of garlic to treat COVID-19. The associated statement would then be a factual claim about the use of garlic to treat COVID-19 which the participant would assess. Assessments were made on a scale of 1 to 7, from ‘Not at all accurate’ (1) to ‘Completely accurate’ (7). The scale the participants used is shown in Figure 3. We adopted this two-step process because claims made in ambiguous vignettes were formulated as questions and so could not be directly assessed using the scale.

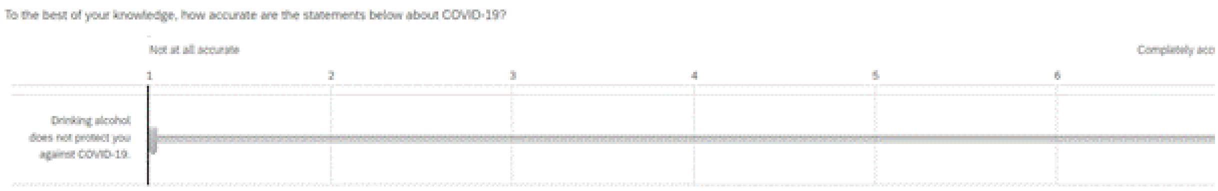


Figure 3: How participants assess the veracity of statements.

All participants assessed the same 24 statements, but they were associated with different vignettes (i.e., some participants were shown a true vignette and others a false or ambiguous vignette for the same statement). Participants were shown the 24 vignettes/statements in four blocks of six. Within each block, they were shown all six vignettes in one go and then assessed all six of the associated statements in one go.

Error score: measuring misinformation

For each assessment we calculated an error score. This is the difference between the correct assessment and the participants’ assessment. For instance, if participants rated a completely accurate statement as 7 then the error score would be 0 (i.e., 7 –7=0). If they rated it as a 5 then the error score would be 2 (i.e., 7–5=2). Equally, if participants rated an inaccurate statement as 1 then the error score would be 0 (i.e., 1–1=0) and if it was rated as a 4 then the error score would be 3 (i.e., 4–1=3).

5 For an overview, see the Wikipedia page: https://en.wikipedia.org/wiki/Betteridge%27s_law_of_headlines

Warning

Half of the participants were presented with a warning before they assessed any statements and half were not presented with a warning. The warning stated:

> "You are going to be shown content of varying accuracy. We are all vulnerable to misinformation and it's not always easy to distinguish between true and false information. Please be on the lookout for false information and make sure to evaluate the content carefully. This should take you about 10 minutes. Please make sure to take your time whilst viewing the content."

Source

Each vignette was associated with one of four different sources, as shown in Figure 2.

- A random person, who we named 'Alex Smith'.
- A newspaper. We selected six publishers, reflecting different ideologies and quality: The Times (broadsheet, right), The Guardian (broadsheet, left), The Sun (tabloid, right), The Daily Mirror (tabloid, left), Politicalite (alternative news, right), Vox Pol (alternative news, left).
- The UK Government.
- The World Health Organization (WHO).

For more information on the assessment design, see Appendix A.

4. Participants' outlooks on COVID-19, Government policies and misinformation

4.1 Most people say that they are closely following Government guidelines

We asked participants the extent to which they follow government guidelines on six safety practices, including whether they wash their hands, use hand sanitiser and practice social distancing. Results are shown in Figure 4. For all seven practices at least 50% of participants reported that they follow 'Very closely'. 95% of responses about following the guidelines were 'Fairly closely', 'Closely', or 'Very closely'. This indicates that the vast majority of the public is following the Government guidelines. However, one cautionary note is that a small number of people report following each of the guidelines 'not at all closely' (<5% in all cases). Given the severe impact of the public not following health guidance, this is still of concern. Our analyses also show that often the same individual score lowly across all six safety practices.

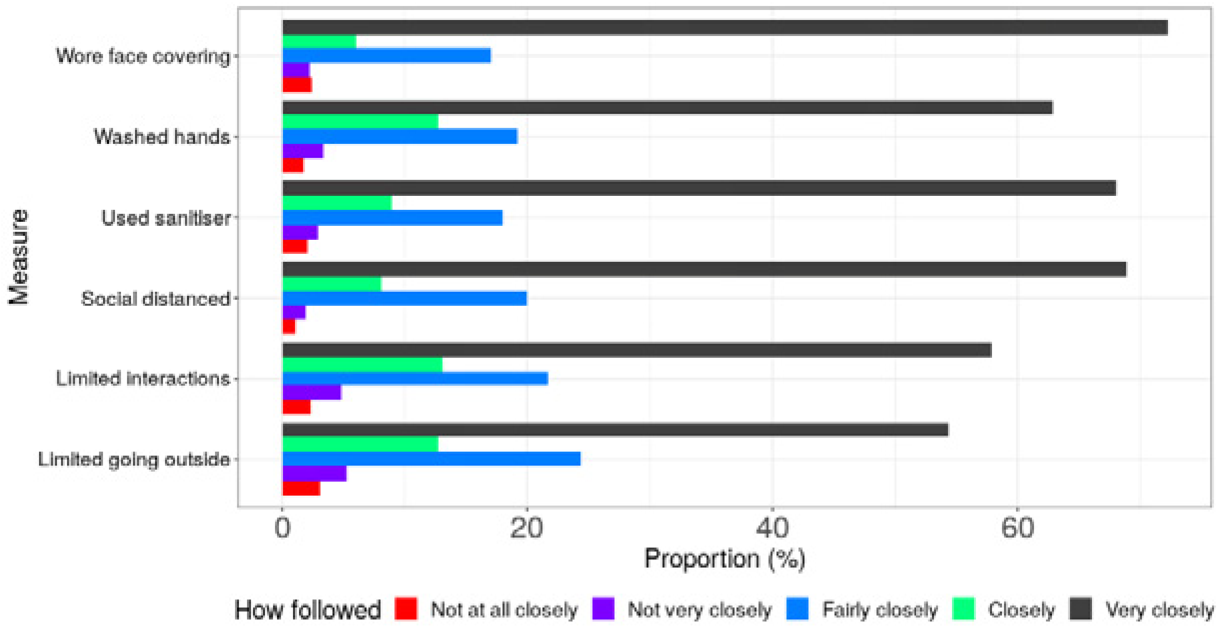


Figure 4: How closely participants followed the government guidelines on seven measures.

4.2 People favour protecting the health of the nation rather than the economy

We asked participants whether they favour protecting the health of the nation versus protecting the economy. They were asked to place themselves on a one to seven scale, with '1' indicating protecting public health and '7' indicating protecting the economy.[6] Results are shown in Figure 5. 51% of participants favour protecting health (i.e., they selected '1', '2' or '3') versus 28% for protecting the economy (i.e., they selected '5', '6' or '7') and the remainder undecided (i.e., they selected '4'). The changing nature of the pandemic threat, and the policy measures taken to address it, means that ours results should be treated with some caution.

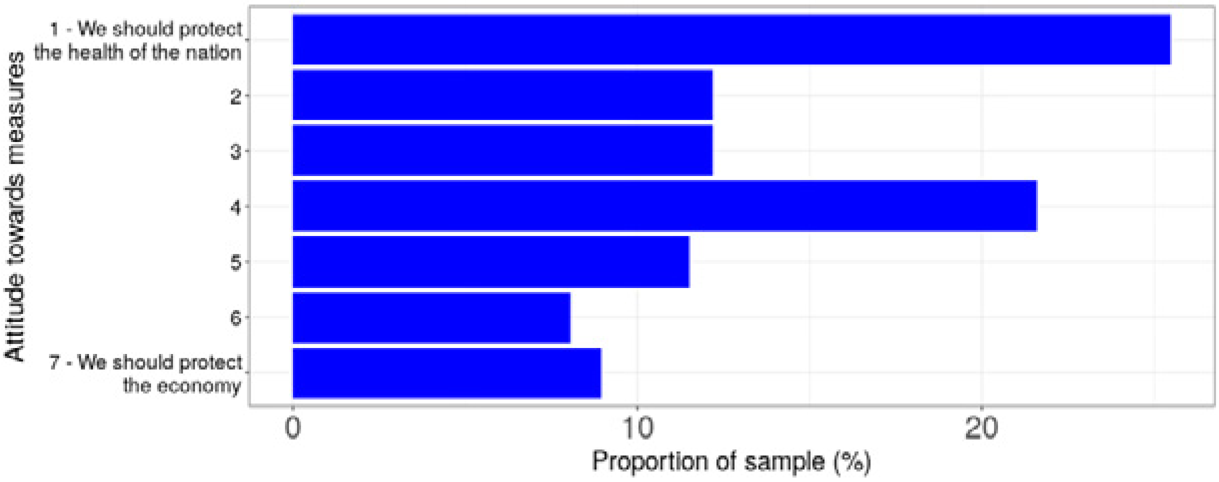


Figure 5: Participant attitudes towards health and the economy.

6 We asked participants similar questions about how worried they are that restrictions are being lifted (versus not being worried), whether they favour taking 'necessary' measures to controlling the virus of relaxing measures, and whether lifting lockdown poses a risk to peoples' lives (versus no risk). All results were in line questions about the economy versus public health and are not shown here for brevity.

4.3 People trust the NHS the most and the media the least

We asked participants how much they trust the NHS, the World Health Organization (WHO), the UK Government and the media on a one to nine scale. This is shown in Figure 6. Participants had highest levels of trust in the NHS (average = 7.2), followed by the WHO (average = 5.9) and then the UK Government, the EU and the Media. Over 50% of participants rated the NHS an 8 or 9, indicating extremely high levels of trust. This is unsurprising; even before COVID-19 a survey by the King's Fund in 2017 found that 77% of the public reported that 'the NHS is crucial to British society and we must do everything we can to maintain it' (Wellings 2017).

The lack of trust in the UK Government is concerning. It supports similar research from Ipsos MORI in early November 2020 which found that only 32% of the UK public believes the Government is doing a 'good' or 'very good' job of handling the pandemic (Ipsos MORI 2020).

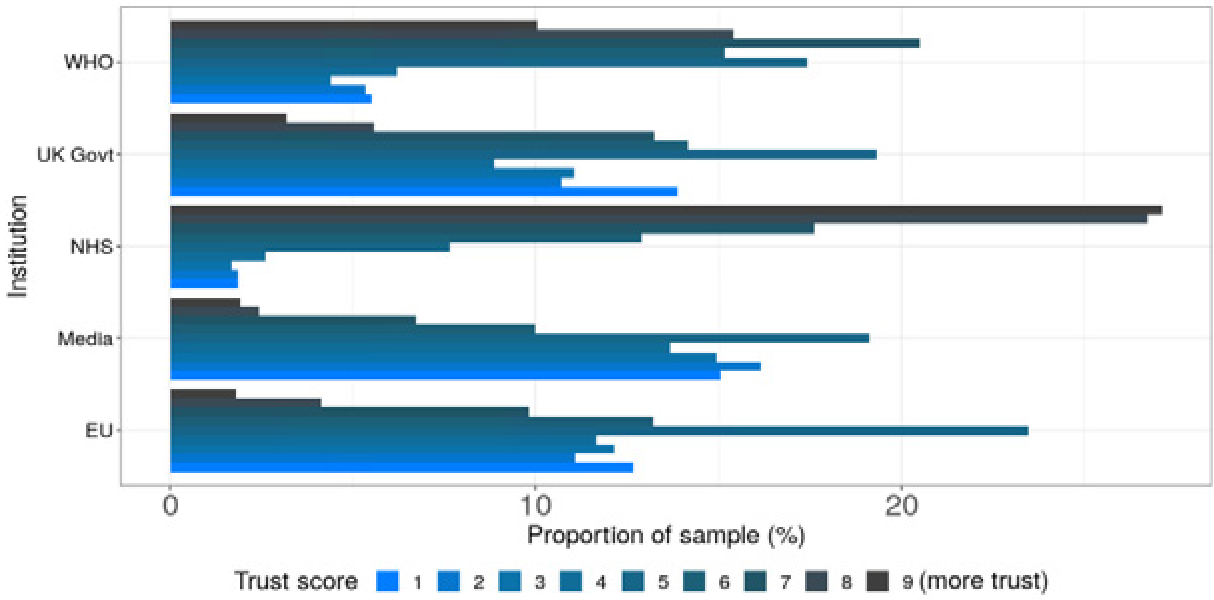


Figure 6: Participants' trust in different institutions.

We asked participants whether the UK government can be trusted to control the spread of COVID-19. 18% strongly disagreed that the government can be trusted to control the virus' spread, with 49% of participants disagreeing in total (combining 'strongly disagree', 'disagree' and 'somewhat disagree'). Notably, only ~5% of participants 'strongly agree' that the government can be trusted to handle COVID-19.

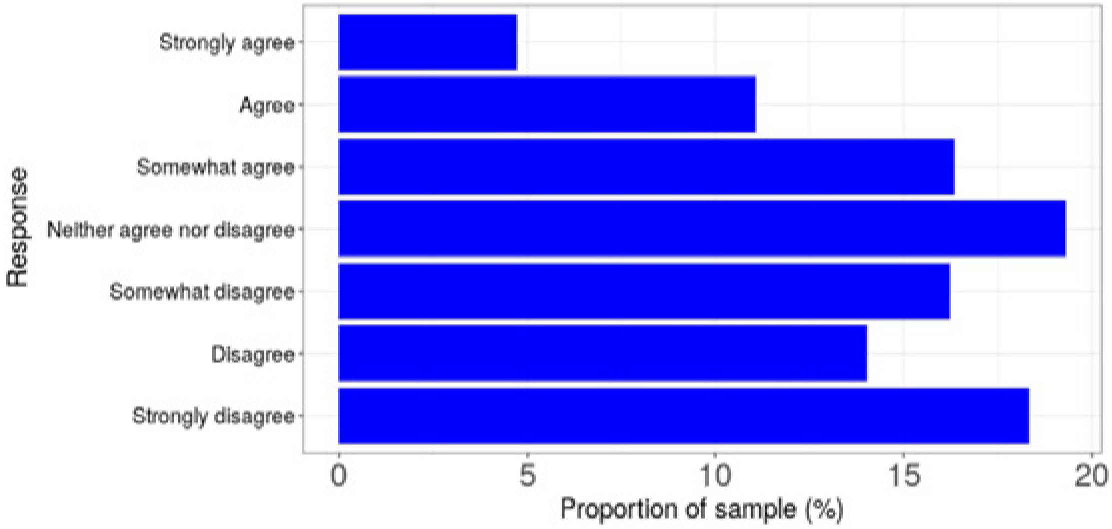


Figure 7: Participants' trust in the UK government to control the spread of COVID-19.

4.4 Social media is seen as the most untrustworthy source of information

Participants rated the trustworthiness of six sources of information (TV, radio, podcasts, newspapers (print), social media, family and friends) on a 5-point scale of 'Completely untrustworthy' to 'Completely trustworthy'. This is shown in Figure 8. Over half of participants reported that social media was untrustworthy ('Completely untrustworthy', 21% of participants, and 'Somewhat untrustworthy', 32% of participants). In contrast, family and friends were seen as the most trustworthy source.

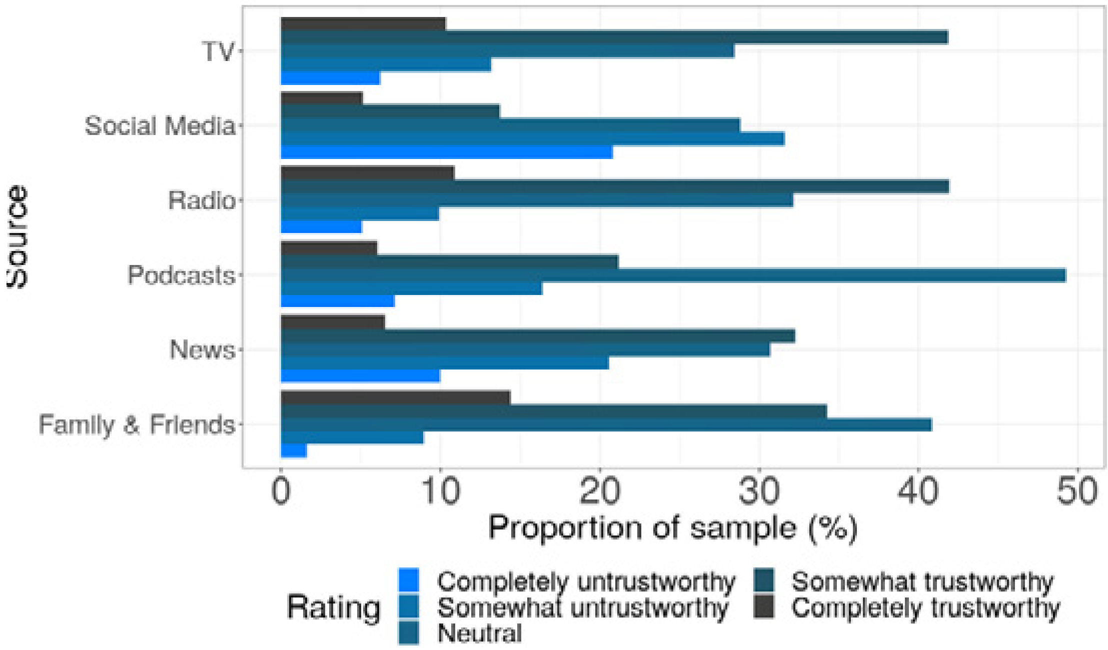


Figure 8: Participants' trust in sources of information

We asked participants whether they were concerned about misinformation from different sources, shown in Figure 9. Unsurprisingly, social media was identified as the most concerning with 87% of participants saying they were 'somewhat concerned' or 'very concerned'. Participants were the least concerned about misinformation from family and friends.

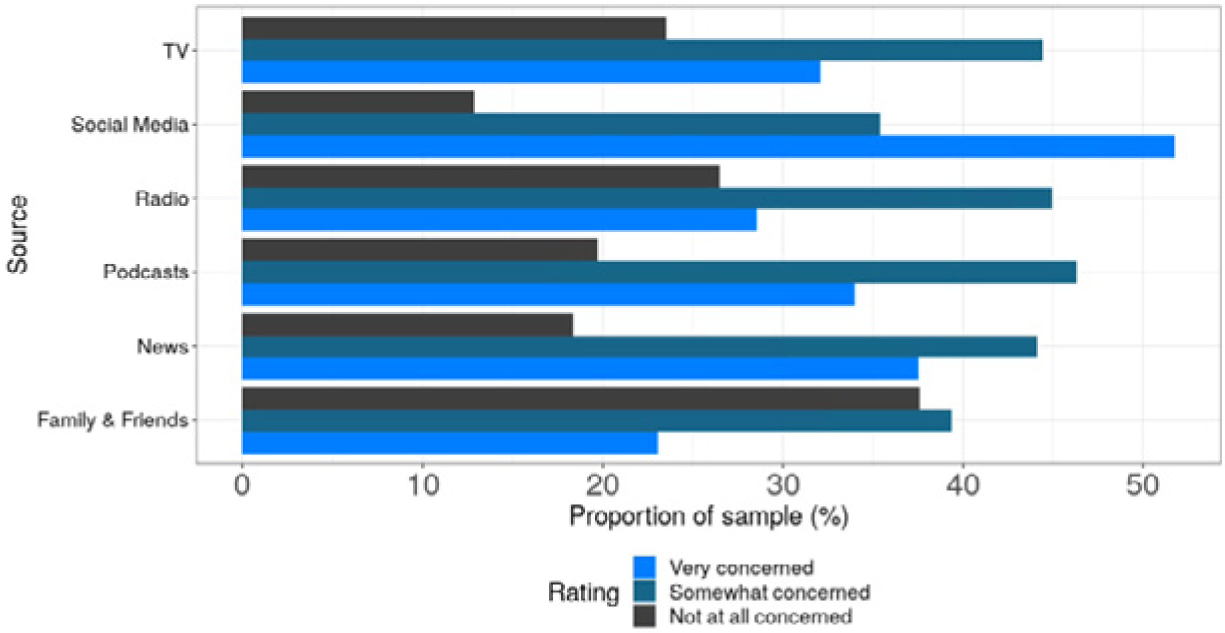


Figure 9: Participants' concern about misinformation from different sources

4.5 Most people did nothing when faced with misinformation

Participants were asked how they responded to misinformation online, selecting from at least one of seven responses, including 'Forward/shared it', 'Did nothing' and 'Checked it'. Results are shown in Figure 10. The majority of participants reported that they did nothing (51%). Otherwise, a range of strategies were pursued, including using a fact checking site (18%), asked the person who shared it (9%) and blocked/reported the person who shared it (17%). Our survey does not reveal how often participants deployed each strategy, which is likely to have varied. A previous survey by Ofcom found similar results, including 55% of people who report doing nothing on seeing information (Ofcom 2020b).

These responses can only be understood in relation to misinformation that participants identified. They will also have exposed to misinformation online that they failed to identify and may have responded to differently. This is a fundamental limitation of surveys which ask people about the content they have been exposed to; they can only report on the content they actually identified.

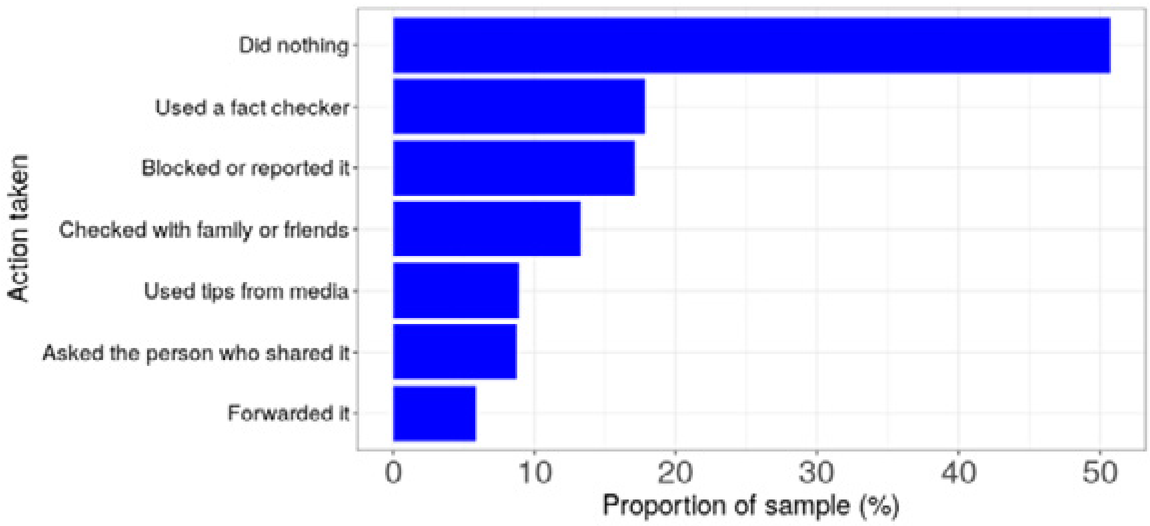


Figure 10: Participants' response on encountering misinformation online

5. Evidence of misinformation

When assessing health-related claims in statements (see ‘Research design and data’ above) participants were generally capable of making correct assessments. The average score participants gave to an inaccurate statement was 2.4 and the average score given to an accurate statement was 5.0. This is a statistically significant difference (Kruskal-Wallis test, $p<0.0001$). In 44% of cases participants gave a completely correct assessment, giving a 1 to inaccurate statements and a 7 to accurate statements. This is shown in Figure 11, which shows the error scores for all assessments and the percentage of assessments which are correct (i.e., a 1, 2 or 3 is given for inaccurate statements and a 5, 6 or 7 for accurate statements).

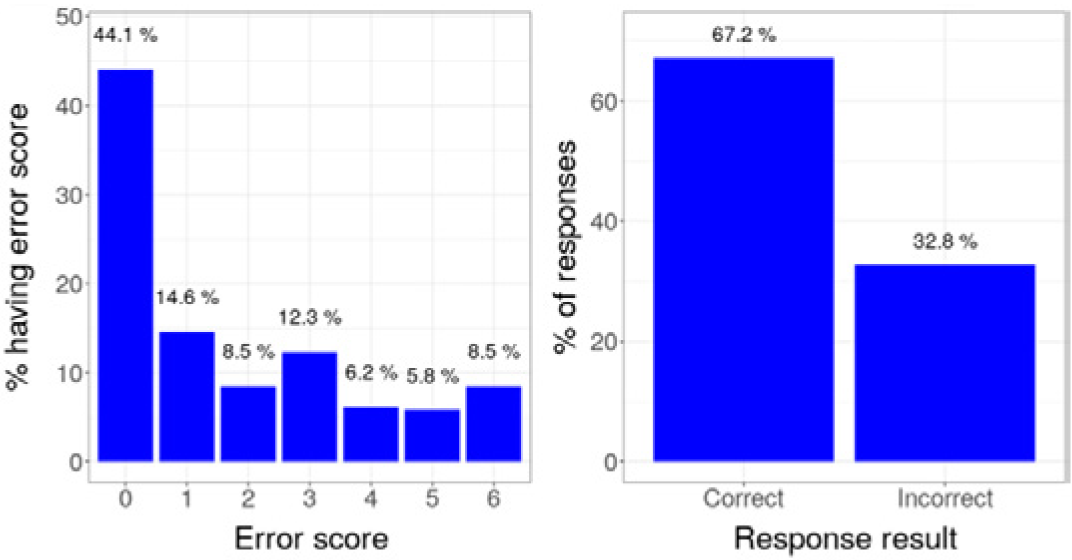


Figure 11: (a) Distribution of error scores and (b) Percentage of assessments which are correct.

We conduct bivariate and multivariable analyses to understand which traits are associated with greater vulnerability to misinformation. A linear regression model fit on the average error scores for each participant (i.e., taking the mean error across all 24 statements they assessed) achieves an R-squared of 0.456 (statistically significant to $p<0.0001$). This high R-Squared indicates that the model is highly explanative. However, a linear regression model fit on the average error score has two substantial limitations. First, it does not account for the impact of the vignettes, which are ignored when all 24 entries are averaged. Second, it does not account for the substantial variation within each individual’s assessments. This is a substantial source of variation and means that a linear regression model over-estimates the amount of certainty in individual’s responses and as such the amount of variation that the model can explain. The distribution of the standard deviation of error scores for each participant is shown in Figure 12. The average standard deviation is 1.8.

To analyse the data, we use a multi-level model (MLM), the results of which are reported in the remainder of the paper. Using a MLM allows us to specify the structure of the data; each individual is the grouping factor level 'one' and the assessments they make are nested within this level. This means that we can specify both variables which are associated with each statement that individuals assess (such as whether it is well-known or not) and which variables are associated with each individual (such as their gender and age). This structure cannot be taken into account with a standard linear regression model. Details on the multi-level model fitting are given in Appendix A, including imputation for missing data.

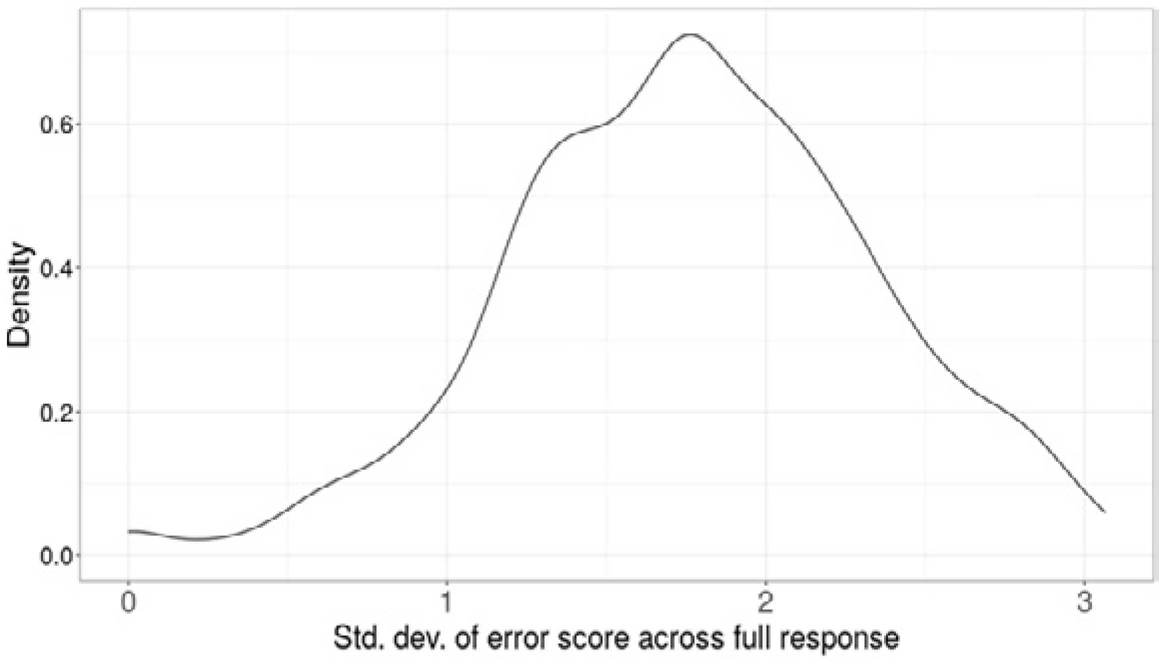


Figure 12: Distribution of standard deviation of each participants' error scores.

5.1 Content-level features associated with misinformation

Based on prior work we analysed a range of hypotheses to uncover the features of content associated with greater vulnerability to misinformation. These are given in Table 2.

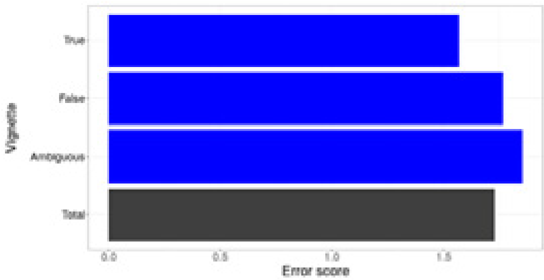
Table 2: Hypotheses for content-level features associated with greater vulnerability to misinformation.

Number	Type of hypothesis	Hypothesis	Outcome
1	Vignettes	The veracity of vignettes will affect participants' ability to accurately assess statements.	Evidence supports hypothesis
1a	Vignettes	When participants are exposed to true vignettes they will have less error when assessing statements.	Evidence supports hypothesis
1b	Vignettes	When participants are exposed to false vignettes they will have more error when assessing statements.	Evidence supports hypothesis
2	Source of vignettes	The source of vignettes will affect participants' ability to accurately assess statements.	Evidence does not support hypothesis
3	Warnings	Participants given the warning will have less error when assessing statements.	Evidence supports hypothesis
4	Statement notoriety	Participants will have less error when assessing statements which relate to a well-known claim.	Evidence supports hypothesis

The vignettes participants saw affected their assessments (Hypothesis 1, 1a and 1b)

The average error score after viewing an ambiguous vignette was 1.8, compared with 1.7 for a false vignette and 1.6 for a true vignette (Wilcoxon rank sum test, $p<.001$).[7] This means that the vignettes had the effect on participants we had anticipated, providing support for both hypothesis 1a and 1b. Exposure to a true vignette improved participant's ability to assess statements whereas exposure to a false or ambiguous vignette worsened their ability.

Surprisingly, ambiguous vignettes had the greatest effect on participants' ability to assess the veracity of statements. This reflects the harm that confusion and uncertainty can cause by undermining people's confidence in, and ability to assess, different statements.



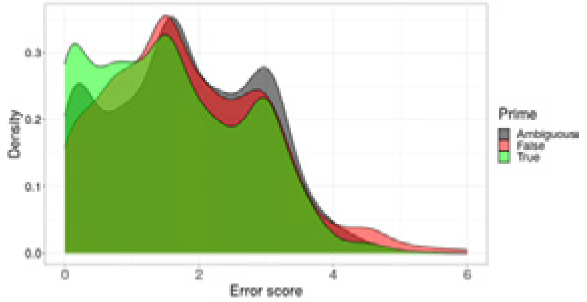


Figure 13: (a) Average error scores for statements after exposure to each vignette, (b) Distribution of error sores.

The suggestibility gap: Some participants are more susceptible to vignettes than others

The impact of the vignettes varied across individuals; some were highly affected by the vignettes and others were not affected at all. To evaluate the vignettes' impact we constructed a suggestibility gap metric. This is the difference between two scores: the amount of error in participants' assessments after seeing a false or ambiguous vignette and the amount of error after seeing a true vignette.[8]

Suggestibility gap = (Error | False and Ambiguous vignette) – (Error | True vignette)

Participants who have a large suggestibility gap have far less error after seeing a true vignette and far more after seeing a false vignette. This suggests that they are highly susceptible to the content of the vignettes as they had a large influence on their assessments; they make accurate assessments after seeing true vignettes and make inaccurate assessments after seeing false vignettes. In contrast, individuals with a small suggestibility gap are only slightly affected by the vignettes. Participants can also have a negative suggestibility gap. This is when they go against the prompt given by the vignettes, also indicating that the vignettes have no impact on them or that they actively mistrust them. The distribution of the suggestibility gap is shown in Figure 14.

7 Our multilevel model analysis, reported below, gives a very similar result. MLM uses false vignettes as the dummy and has a coefficient of 0.08 for ambiguous vignettes (indicating more error) and -0.10 for true vignettes (indicating less error).

8 For this calculation, we merge ambiguous and false vignettes together.

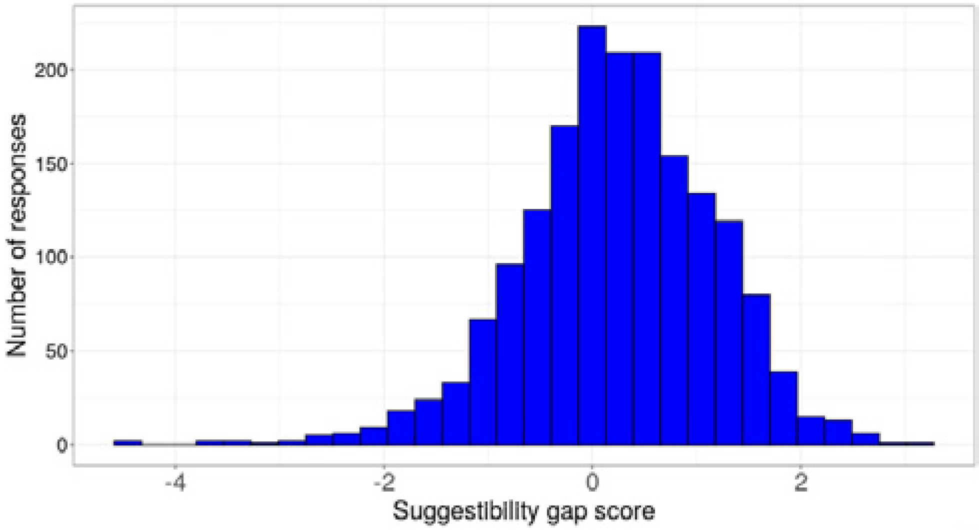


Figure 14: Distribution of participants' suggestibility gap scores.

As an exploratory analysis, we assessed the relationship between each participant's suggestibility gap and their average error in assessing statements. We found that there was a small positive relationship (correlation of 0.13), which weakly indicates that individuals who are more susceptible to vignettes tend to make more error. This is shown in Figure 15. We ran regression models to explore systematic explanations of the suggestibility gap. However, their explanative power was low and these models are not reported for brevity.

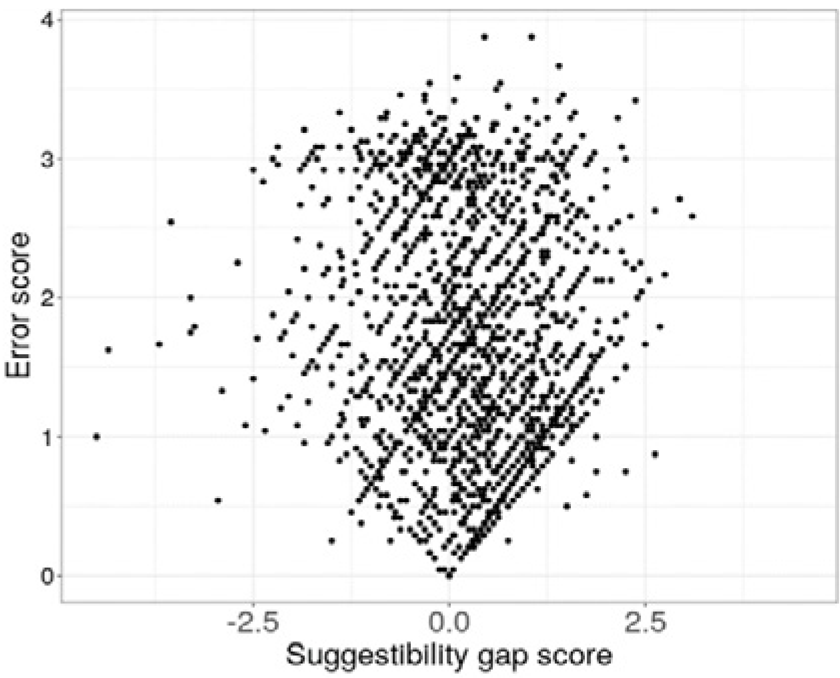


Figure 15: Association between participants' suggestibility gap scores and average error.

The source of content has little effect on participants' assessments (Hypothesis 2)

We had anticipated that the source of vignettes would affect the assessments that participants gave to their associated statements. However, the effect is small for all sources and the only significant difference in the MLM is an increase in the amount of error when participants see vignettes from the random person source ('Alex Smith').

Warnings about misinformation have very little effect (Hypothesis 3)

Half of participants were shown a warning and half were not. We anticipated that the warning would have made participants more aware of the risk of misinformation and so would encourage them to scrutinize all of the claims they were presented with, reducing the amount of error. Warnings had a significant but very small effect on participants, reducing the amount of error by 0.03 on average. The size of the effect varied by vignette but in all cases reduced error. As such, this provides evidence to accept Hypothesis 1, although the effect size is small.[9]

– Ambiguous vignettes: with a Warning, error reduced from 1.87 to 1.83.
– True vignettes: with a Warning, error reduced from 1.6 to 1.56.
– False vignettes: with a Warning, error reduced from 1.77 to 1.76.

It is plausible that warnings would reduce the average score that participants gave, irrespective of the vignette. This is because they would scrutinie everything more and be more likely to give a lower score, in effect being more likely to assess that content is 'not at all accurate'. In some cases, this would result in more error (i.e. because participants would give a lower score for accurate statements) but in other cases it would result in less error (i.e. because participants would give a lower score for inaccurate statements). As such, we conduct exploratory analysis on the warnings to assess whether they are associated with lower absolute scores, irrespective of the error. However, we do not find evidence of a difference, with participants shown a warning and those who are not given a warning both reporting an average score of 3.70.

Participants are best at assessing well-known statements (Hypothesis 4)

As anticipated, participants were far better at assessing well-known statements. The standardised coefficient in MLM is -0.94, which is the largest effect for any single variable. Details on how we identified which statements are considered 'well-known' is given in Appendix A.

9 Our multilevel model analysis, reported below, gives a very similar result. MLM uses false vignettes as the dummy and has a coefficient of 0.08 for ambiguous vignettes (indicating more error) and -0.10 for true vignettes (indicating less error).

5.2 Individual-level features associated with misinformation

We test eight hypotheses using the MLM. The results of our hypotheses are given in Table 3. For completeness we provide the full model, with all coefficients and significant scores, in Appendix C. To account for the fact that the units of the variables have very different ranges, we standardise them by dividing values by two times the standard deviation as recommended by Gelman (Gelman 2008). This means they can be interpreted generically as the mean plus/minus one standard deviation and can be more easily assessed alongside categorical variables. The standardised values are reported in Table 3. In all cases a negative coefficient indicates reduced error and therefore higher accuracy in assessing statements.

Table 3: Hypotheses for individual-level features associated with greater vulnerability to misinformation.

Number	Hypothesis	Outcome	Explanation (MLM)
5.1	Participants with low health literacy will have more error when assessing statements.	Evidence supports hypothesis	Subjective health literacy is not related to participants' error scores ($p=0.067$), with a standardised coefficient of -0.07. Objective health literacy is related to participants' error scores ($p<0.0001$) with a standardised coefficient of -0.29. This provides evidence for hypothesis 5.1.
5.1a	Among participants with low health literacy, participants who assess their own health literacy as high will have even more error when assessing statements.	Evidence does not support hypothesis	We specify an interaction effect between objective and subjective health literacy. It is not related to participants' error scores ($p=0.075$). This does not provide evidence for hypothesis 5.1a.
5.2	Participants with higher cognitive skills will have less error when assessing statements.	Evidence supports hypothesis	Cognitive ability is related to participants' error scores ($p<0.001$) with a standardised coefficient of -0.18. This provides evidence for hypothesis 5.2.

5.3	Participants with higher numerical literacy will have less error when assessing statements.	Evidence supports hypothesis	Numerical literacy is related to participants' error scores ($p<0.001$) with a standardised coefficient of -0.32. This provides evidence for hypothesis 5.3.
5.4	Participants with higher digital literacy will have less error when assessing statements.	Evidence supports hypothesis	Digital literacy is related to participants' error scores ($p<0.001$) with a standardised coefficient of -0.22. This provides evidence for hypothesis 5.4.
5.5	Participants with more years of education will have less error when assessing statements.	Evidence does not support hypothesis	Education is not related to participants' error scores. This does not provide evidence for hypothesis 5.5.
5.6	Degree of institutional trust will be related to participants' ability to assess the veracity of statements (non-directional).	Evidence supports hypothesis	Trust in Institutions [f] is related to participants' error scores ($p<0.001$) with a standardised coefficient of 0.15. Trust in UK Government [f] is also related ($p<0.001$) with a standardised coefficient of 0.13. Both variables are associated with more error. This provides evidence for hypothesis 5.6 and we can confirm that the direction of the association is negative.
5.7	Participants with greater personal vulnerability will have more error when assessing statements.	Evidence does not support hypothesis	Being "at risk" of COVID-19 is related to participants' error scores ($p=0.013$) with a standardised coefficient of -0.09. Being "afraid" of COVID-19 is also related ($p=0.0006$) with a standardised coefficient of 0.09. Being diagnosed with COVID-19 is not related ($p = 0.998$). Given this weak and mixed evidence there is not sufficient evidence to support hypothesis 5.7.

For variables where we did not establish hypotheses at the start of the research, we can only conduct exploratory analyses. These should be treated with caution given that there is a greater risk of false positives.

Personality (Big 5)

- **Agreeableness** has a standardized coefficient of -0.09 (p=0.001). This means that being more agreeable is associated with less error.
- **Conscientiousness** has a standardized coefficient of -0.09 (p=0.002). This means that being more conscientious is associated with less error.
- **Extraversion** has a standardized coefficient of 0.10 (p=0.003). This means that being more extraverted is associated with more error.
- **Neuroticism** and **openness** are not significant.

Socio-economic status, sociodemographics and politics

In addition to Education, for which we stipulated a hypothesis, we include control variables for Socio-economic status (Income), Sociodemographics (Gender, Ethnicity and Region) and Politics (Ideological position and position on Brexit). None of them are statistically significant.

Age is statistically significant, with a standardized coefficient of -0.18. This means that being older is associated with less error.

Internet use

Surprisingly, we find that decreased Internet use has one of the largest positive standardized coefficients (0.23), which suggests that it is associated with more misinformation. It is statistically significant (p=0.005). Increased Internet use does not have a statistically significant effect. Future research could investigate the association between Internet use and vulnerability to misinformation alongside digital literacy and other associated factors.

Conclusion

The causes of vulnerability to misinformation are complex and multi-factored. We have sought to shed light on this topic through a comprehensive research design, which takes into account both the traits of individuals and of the content they are exposed to. This has proven to be a promising approach, increasing the explanatory power of our models and enabling us to test a greater range of factors. It also shows the methodological and theoretical limits of work which only takes into account just one of these aspects. Our design includes a large number of measurements, with each participant assessing 24 statements. This is far more than most studies and its importance is demonstrated by the large amount of intra-individual variation we observe.

Our analyses of vulnerability to misinformation show that individuals with higher digital literacy, numerical literacy, health literacy and cognitive skills are better at assessing health-related statements. We also show that age, institutional trust and warnings have significant effects, as well as some personality traits. Our results also suggest that the public supports efforts to tackle COVID-19; when asked to compare, they favour tackling the public health crisis rather than protecting the economy, and most people are following government guidelines. However, we caution that our results are from late 2020 and that (as of January 2021) public opinion may have already changed somewhat.

This report is intended to provide up-to-date insight into health-related misinformation during COVID-19, informing the work of policymakers, social media platforms, civil society and academics. Our results are preliminary, and more sustained research is needed to fully understand who is vulnerable to false and misleading content, as well as to better understand how it impacts them. Future work should focus on (a) investigating what interventions are most effective for increasing the robustness of individuals to misinformation, (b) which types of health-related claims are most likely to be misbelieved and (c) creating more powerful and advanced models to explain the cognitive and social factors associated with misinformation.

Appendix A – Robustness checks

Statement formulation

For statistical robustness, we varied whether the statements that participants assessed were formulated as accurate or inaccurate. For instance, the same claim could be formulated as an accurate statement that participants could agree with and give a higher score to (e.g., "People should wear masks while exercising") or it could be formulated as an inaccurate statement that participants could disagree with and give a low score to (e.g., "People should not wear masks while exercising"). An equal number of statements were formulated as accurate and inaccurate. Note that statement formulation is different to the veracity of vignette: a true vignette could be associated with a statement formulated as either accurate or inaccurate and vice versa. Our results show the importance of this decision: participants were more likely to rate inaccurate statements with a '1' than accurate statements with a '7'. 49% of inaccurate statements were labelled '1' compared with 39% of accurate statements labelled as '7'. In MLM statement formulation has a standardised coefficient of 0.65 ($p<0.001$).

Assessing how well-known statements are

Assessing how 'well known' statements are is by nature a subjective evaluation. As noted above, all health-related claims used in this research were taken from the WHO Mythbusters website. By nature, they were all therefore likely to be somewhat 'well-known' given that they had been sufficiently concerning for the WHO to take action against them.

Two researchers on the project assessed how well known the statements are through group discussion and then validated our labels by asking three external researchers. The five assessments are given in Table 4.

Table 4: Statements shown to participants with relevant labels.

Assessment statements	Source	Type of claim	Is correct answer well-known?	Team assessment of well-known
People should wear masks while exercising	Press	Prevention	No	Y: 1, N: 4
The likelihood of shoes spreading COVID-19 is very low	Press	Spread & Infection	Yes	Y: 4, N: 1
The coronavirus disease (COVID-19) is caused by a virus, not by bacteria	Press	Spread & Infection	Yes	Y: 5, N: 0
The prolonged use of medical masks causes CO2 intoxication and oxygen deficiency, even when worn properly	Press	Prevention	No	Y: 1, N: 4

Most people who get COVID-19 recover from it	Press	Cure	Yes	Y: 4, N: 1
Drinking alcohol does not protect you against COVID-19	Press	Prevention	Yes	Y: 4, N: 0
Thermal scanners cannot detect COVID-19	WHO	Cure	No	Y: 2, N: 3
There are drugs licensed specifically for the treatment and prevention of COVID-19	WHO	Cure	No	Y: 1, N: 4
COVID-19 can be transmitted through houseflies	WHO	Spread & Infection	Yes	Y: 5, N:0
Spraying and introducing bleach or another disinfectant into your body will protect you against COVID-19	WHO	Prevention	Yes	Y: 5, N:0
Drinking methanol, ethanol or bleach does not prevent or cure COVID-19	WHO	Prevention	Yes	Y: 5, N:0
5G mobile networks spread COVID-19	WHO	Spread & Infection	Yes	Y; 5, N:0
Exposing yourself to the sun or temperatures higher than 25°C does not protect you from COVID-19	UK Govt	Prevention	Yes	Y: 5, N:0
Catching COVID-19 means you will have it for life	UK Govt	Cure	Yes	Y: 5, N:0
Being able to hold your breath for 10 seconds or more without coughing or feeling discomfort means you are free from COVID-19	UK Govt	Prevention	Yes	Y: 5, N:0
Taking a hot bath does not prevent COVID-19	UK Govt	Prevention	Yes	Y: 5, N:0
The COVID-19 virus cannot be spread through mosquito bites	UK Govt	Spread & Infection	No	Y: 2, N:3
Hand dryers can kill the COVID-19 virus	UK Govt	Prevention	Yes	Y: 5, N:0
Ultra-violet (UV) lamps should not be used to disinfect hands or other areas of your skin	Alex	Prevention	Yes	Y: 4, N: 1
Vaccines against pneumonia are proven to protect against the COVID-19 virus	Alex	Cure	Yes	Y: 5, N:0
Rinsing your nose with saline prevents COVID-19	Alex	Prevention	Yes	Y: 5, N:0

Eating garlic does not prevent COVID-19	Alex	Prevention	Yes	Y: 5, N:0
Only older people can be infected by the COVID-19 virus	Alex	Spread & Infection	Yes	Y: 5, N:0
Antibiotics cannot prevent or treat COVID-19	Alex	Cure	Yes	Y: 5, N:0

Multi-level model fitting

Using a multi-level model we create 8 models (m1 to m8), which increase in complexity. Their construction is based on our theoretical analysis of the causes of susceptibility to misinformation. For each subsequent model, we add new variables to the earlier models. For instance, m4 contains all of the variables in m3 plus additional variables (in m4, these relate to participants' COVID-19 risk status and behaviours). The models are described in Table 2. Note that some of the variables are factors constructed from other variables, where appropriate.. m7 has the lowest AIC and BIC and m8 has the highest log likelihood. Every subsequent model is significant compared with the previous one, evaluated using LRT.

We analyse m8 in the paper, which we refer to as MLM.

Table 5: Overview of MLMs.

Model	Description	Conditional R2 (total var)[10]	Marginal R2	Random R2	Remainder	AIC	BIC	LRT[11]
m0	No variables, only user IDs	0.155	0.000	0.155	0.845	175682	175708	/
m1	Content variables	0.213	0.056	0.157	0.787	172855	172959	Sig
m2	Socio-demographics	0.213	0.073	0.140	0.787	172733	172897	Sig
m3	Social economic status + political views	0.214	0.083	0.131	0.786	172691	172942	Sig
m4	COVID-19 risk status and behaviours	0.214	0.093	0.121	0.786	172611	172905	Sig

10 We use multiple imputation and as such the model coefficients are combined scores. We observed little variation in the estimated R2 values and report these based on just one randomly selected model.

11 AIC stands for 'Akaike information criterion'; BIC stands for 'Bayesian Information Criterion'; LRT stands for 'Likelihood Ratio Test'.

m5	Cognitive factors	0.214	0.144	0.071	0.786	171975	172329	Sig
m6	Non-cognitive factors	0.214	0.147	0.067	0.786	171970	172377	Sig
m7	Trust	0.215	0.154	0.061	0.785	171901	172360	Sig
m8 (MLM)	Online behaviours	0.215	0.155	0.060	0.785	171909	172411	Sig

The values for models shown in Table 2 can be interpreted as follows (Nakagawa and Schielzeth 2013):

1. Conditional R2 is the total variance accounted for by the MLM.
2. Marginal R2 is the total variance that is explained by the predictors in the MLM.
3. Random R2 is the unexplained variance that can be attributed to the MLM's group level (level 1).
4. Remainder is the variance not accounted for by the MLM.
5. The AIC and BIC are measures of model fit which assess whether adding more variables is parsimonious, given that the marginal gains in explanatory power from adding more variables can be positive but very small.
6. The LRT reports whether the increased explanation of each subsequent model is statistically significant compared with previous models.

In the null model (m0) the Random r2 is 0.155; this can be interpreted as the intra-class correlation (ICC) (Huang 2018). It measures how much of the total variation is apportioned to the grouping factor. A value of 0 indicates that none of the variance is apportioned to the grouping factor and a value of 1 indicates that all of the variance is apportioned to it. If the value is 0 then a multi-level model might not be justified (Musca et al. 2011). 0.155 supports our analysis of the simple linear regression model we created (see Above); individuals' performance is highly inconsistent across their assessments.

In m8 the total variance explained is 15.1%. A further 6.3% is accounted for by the group structure of the MLM but not apportioned to the variables. This means that the model has accounted for the variance through the structure that we stipulated (i.e., the inclusion of individuals as a level 1 grouping factor) but cannot identify which variables to apportion the variance to. m8 leaves ~80% of the total variance unexplained. A range of factors could explain this outstanding variance, such as measurement errors (e.g., variables might lack external validity and could not be measuring what we want them to or individuals might interpret them in unexpected ways) and random fluctuations and disturbances (such as factors that we have not measured or if the relationship

Missing data imputation

Comparisons of methods used to handle missing data have found that multiple imputation is generally less biased and more accurate than complete case analysis or mean substitution when the type of missingness is unknown (Ali et al. 2011; Cummings 2013). Missingness in our dataset varied between 0% and 7.5% across variables. The mice package in R was used to impute the data.[12] No dependent variable values were imputed, although the dependent variable was used to inform imputation of other variables. Data from 10 imputations (Stuart et al. 2009), each with 10 iterations was combined using Rubin's rules for calculating estimates and variances in multiply-imputed datasets (Rubin 1989).

Power analysis

Our target sample size was 1,700, which we exceeded (n = 1,765). This was driven primarily by budget and sample size used in previous research. We ran several sensitivity analyses in G*power (Erdfelder et al. 2009), which indicated that our sample was sufficient to detect even small effects. For instance, our study had the power to detect effects as small as f2 = .02 in a multiple regression analysis with 36 fixed predictors at the standard 0.05 alpha probability with β = .95 power. The mixed-effect models that we finally used, if anything, had even higher statistical power (Quené and van den Bergh 2008; Quené and Van Den Bergh 2004).

Factor analysis

Factor analyses were conducted in R using the factanal function in the FAiR package, with Varimax rotation.[13] We created factors for variables which had a large number of levels. In each case, the number of factors was increased until interpretable groups could be made. Interpretations were made based on loadings above 0.4, as recommended in prior work (Pituch and Stevens 2016).

Factor analysis – Trust

- Factor 1: Trust in UK Government
- Factor 2: Trust in traditional media
- Factor 3: Trust in new media
- Factor 4: Trust in institutions

12 Available at https://cran.r-project.org/web/packages/mice/mice.pdf.
13 Available at https://www.rdocumentation.org/packages/FAiR/versions/0.4-15.

Table 6: Factor analysis for trust.

Variable	Factor1	Factor2	Factor3	Factor4
Trust (UK Government)	0.73			
Trust (EU)				0.54
Trust (NHS)				0.56
Trust (WHO)				0.87
Trust (UK Government control of COVID-19)	0.87			
Trust (UK Government information about COVID-19)	0.84			
Trust (Content from TV)		0.79		
Trust (Content from Radio)		0.83		
Trust (Content from Podcasts)			0.61	
Trust (Content from News)		0.45	0.46	
Trust (Content from Social media)			0.82	
Trust (Content from family and friends)				
SS loadings	2.22	1.79	1.64	1.63
Proportion Var	0.18	0.15	0.14	0.14
Cumulative Var	0.18	0.33	0.47	0.61

Factor analysis – Concern about information sources

- Factor 1: Concern about misinformation from other media
- Factor 2: Concern about misinformation from social media

Table 7, Factor analysis for concern about information sources

Variable	**Factor1**	**Factor2**
Concern about information from TV	0.85	
Concern about information from Radio	0.90	
Concern about information from Podcasts	0.53	0.50
Concern about information from Newspapers	0.63	0.45
Concern about information from social media	0.87	0.85
Concern about information from family/friends	0.50	
SS loadings	2.50	1.32
Proportion Var	0.42	0.22
Cumulative Var	0.42	0.85

Factor analysis – Action on seeing misinformation

- Factor 1: Active reports
- Factor 2: Active checkers
- Factor 3: Spreaders of misinformation

Table 8, Factor analysis for action on seeing misinformation

Variable	Factor1	Factor2	Factor3
Factcheck	0.85		
Checkfam	0.90		
Block rep	0.53	0.50	
Used tips	0.63	0.45	
Did nothing	0.87	0.85	
Asked	0.50		
Forwarded			
SS loadings	1.10	0.83	0.47
Proportion Var	0.16	0.12	0.07
Cumulative Var	0.16	0.28	0.34

Appendix B – Ethical approval

Ethical approval was granted by The Alan Turing Institute on the 13th July 2020, before any research involving participants was conducted. We completed a GDPR compliance assessment and all data was analysed in anonymised form in a secure data safe haven. The Hawthorne effect is when participants modify their behaviour in response to the setting of the research and the involvement of the researchers. This is a particular concern when researching topics such as misinformation, where people may feel normative pressure and change their behaviour. To avoid magnifying the Hawthorne effect in an ethical way we took the following steps:

- Before participants started the survey and assessment, they were informed that they were taking part in research relating to online content interpretation – but details about the purpose of the research, specifically the focus on online misinformation, were not provided until afterwards. In the context of observtaional research, this can be seen as an 'equivocation' given that it does not involve being misleading but also does not fully explain to participants the purposes of the research. Once the surveys and assessments were completed, we informed participants of the true purpose of the research.
- The design of the research means that participants were shown false and misleading content. After participants completed making their assessments we required them to undertake a debriefing session. We explained to them the truth of each statement, which they had to click to formally acknowledge having read.

Participants gave their consent at the start of the research. Then, once they had completed the debrief session and were fully aware of the research purpose they were asked to give their informed consent. This strategy ensures that they give consent with full knowledge of the research goals and the use of their data and responses, without risking the study's validity. Participants were paid irrespective of whether they gave this final informed consent. If any participants had not given their informed consent at the end then they would have been excluded from the dataset.
Participants were given contact information to raise any concerns about the study and the use of their data. To our knowledge, no participants have made contact to raise such concerns.

Appendix C – Multi-level model details

For completeness, we provide all details of the fully specified MLM (referred to as m8 in Appendix B). We include both the original model estimates and the model estimates divided by two times the standard deviation, which are shown in the main body of the report.

Category	Variable	Predictors	Estimate (divided by 2*SD)	Estimate	Confi-dence interval	p-value
/	/	Intercept	2.16	3.34	2.93 – 3.74	<0.001
Content-level variables	Warning	Warning given	-0.03	-0.03	-0.05 – -0.01	<0.01
	Source	Source – UK Government	-0.01	-0.03	-0.06 – 0.04	0.754
		Source – Random person ('Alex')	0.21	0.21	0.16-0.25	<0.001
		Source – WHO	-0.06	-0.06	-0.11 – -0.01	0.031
	Vignette	Vignette – Ambiguous	0.08	0.08	0.04 – 0.13	<0.001
		Vignette – True	-0.10	-0.10	-0.14 – -0.05	<0.001
	Statement formula-tion	Statement formulation – True	0.65	0.65	0.61 – 0.68	<0.001
	Claim type	Claim type – Prevention	-0.02	-0.02	-0.06 – 0.03	0.489
		Claim type – Spread & Infection	-0.06	-0.06	-0.11 – -0.01	0.021
	Well-known	Well known – Yes	-0.94	-0.94	-0.98 – -0.89	<0.001

Individual-level variables	Socio-demo-graphics	Age	-0.18	-0.01	-0.01 – 0.00	<0.001
		Gender – Male	0.04	0.04	-0.02 – 0.11	0.186
		Gender – Other	-0.26	-0.33	-0.76 – 0.11	0.145
		Ethnicity – BME	-0.04	-0.04	-0.13 – 0.04	0.329
		Region – London	-0.01	-0.01	-0.10 – 0.09	0.866
		Region – North	-0.01	-0.01	-0.08 – 0.05	0.670
		Region – Wales/N. Ireland	-0.07	-0.07	-0.19 – 0.04	0.216
	Socioec-onomic status and politics	Education – Other	0.00	0.01	-0.13 – 0.15	0.862
		Education – Degree or higher	-0.04	-0.03	-0.18 – 0.12	0.671
		Income – Below median	-0.02	-0.02	-0.09 – 0.05	0.568
		Income – Below mini-mum wage	-0.07	-0.02	-0.11 – 0.08	0.728
		Politics – slightly/ fairly right or left	-0.08	-0.09	-0.15 – -0.02	0.010
		Politics – very left or right	-0.01	-0.02	-0.13 – 0.09	0.749
		Politics – prefer not to answer	-0.02	-0.05	-0.19 – 0.08	0.461
		Brexit – Leave	0.05	0.05	-0.05 – 0.15	0.307
		Brexit – Remain	0.02	0.02	-0.07 – 0.12	0.636

Individual-level variables	COVID-19 risk status and behaviours	COVID-19 risk	-0.09	-0.03	-0.05 – -0.01	0.013
		COVID-19 afraid	0.09	0.03	0.01 – 0.06	0.006
		COVID-19 diagnosed	-0.02	0.00	-0.16 – 0.16	0.998
		COVID-19 guidelines	0.01	0.00	-0.05 – 0.06	0.915
		Anti-lockdown outlook	0.09	0.03	0.01 – 0.05	0.012
	Cognitive factors	Subjective health literacy	-0.07	-0.04	-0.07 – 0.00	0.067
		Objective health literacy	-0.29	-0.01	-0.02 – -0.01	<0.001
		Subjective Health literacy / Objective health literacy [interaction]	-0.15	0.00	-0.001 – 0.00	0.075
		Cognitive ability test	-0.18	-0.07	-0.10 – -0.04	<0.001
		Numerical literacy	-0.32	-0.09	-0.11 – -0.07	<0.001
		Digital literacy	-0.22	-0.18	-0.25 – -0.12	<0.001
		Attention check	0.14	0.15	0.05 – 0.25	0.003
	Non-cognitive factors	Belief in conspiracy theories	0.09	0.02	0.01 – 0.04	0.002
		Big 5 (Extraversion)	0.10	0.02	0.01 – 0.03	0.003

Individual-level variables		Big 5 (Agreeableness)	-0.10	-0.03	-0.04 – -0.01	0.001
		Big 5 (Conscientiousness)	-0.10	-0.02	-0.04 – -0.01	0.002
		Big 5 (Emotional stability)	0.05	0.01	0.00 – 0.02	0.102
		Big 5 (Openness)	-0.05	-0.01	-0.03 – 0.00	0.137
	Trust	Trust in the UK government [f]	0.13	0.08	0.04 – 0.11	<0.001
		Trust in traditional media [f]	-0.05	-0.02	-0.06 – 0.01	0.201
		Trust in new media [f]	-0.09	-0.05	-0.08 – -0.01	<0.001
		Trust in institutions [f]	0.25	0.15	0.11 – 0.18	<0.001
		Concerned about social media [f]	0.02	0.00	-0.03 – 0.04	0.011
		Concerned about other media [f]	0.13	0.08	0.04 – 0.11	<0.001
	Online behaviours	Use of the Internet (Decreased)	0.23	0.23	0.07 – 0.39	0.005
		Use of the Internet (Increased)	0.02	0.01	-0.05 – 0.08	0.736
		ActiveChecker [f]	0.02	0.01	-0.03 – 0.05	0.567
		ActiveReporter [f]	0.08	0.05	-0.00 – 0.11	0.067
		ContentSpreader [f]	0.08	0.07	0.02 – 0.13	0.007

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