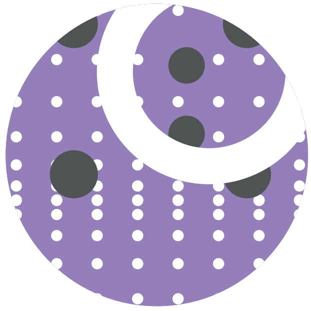
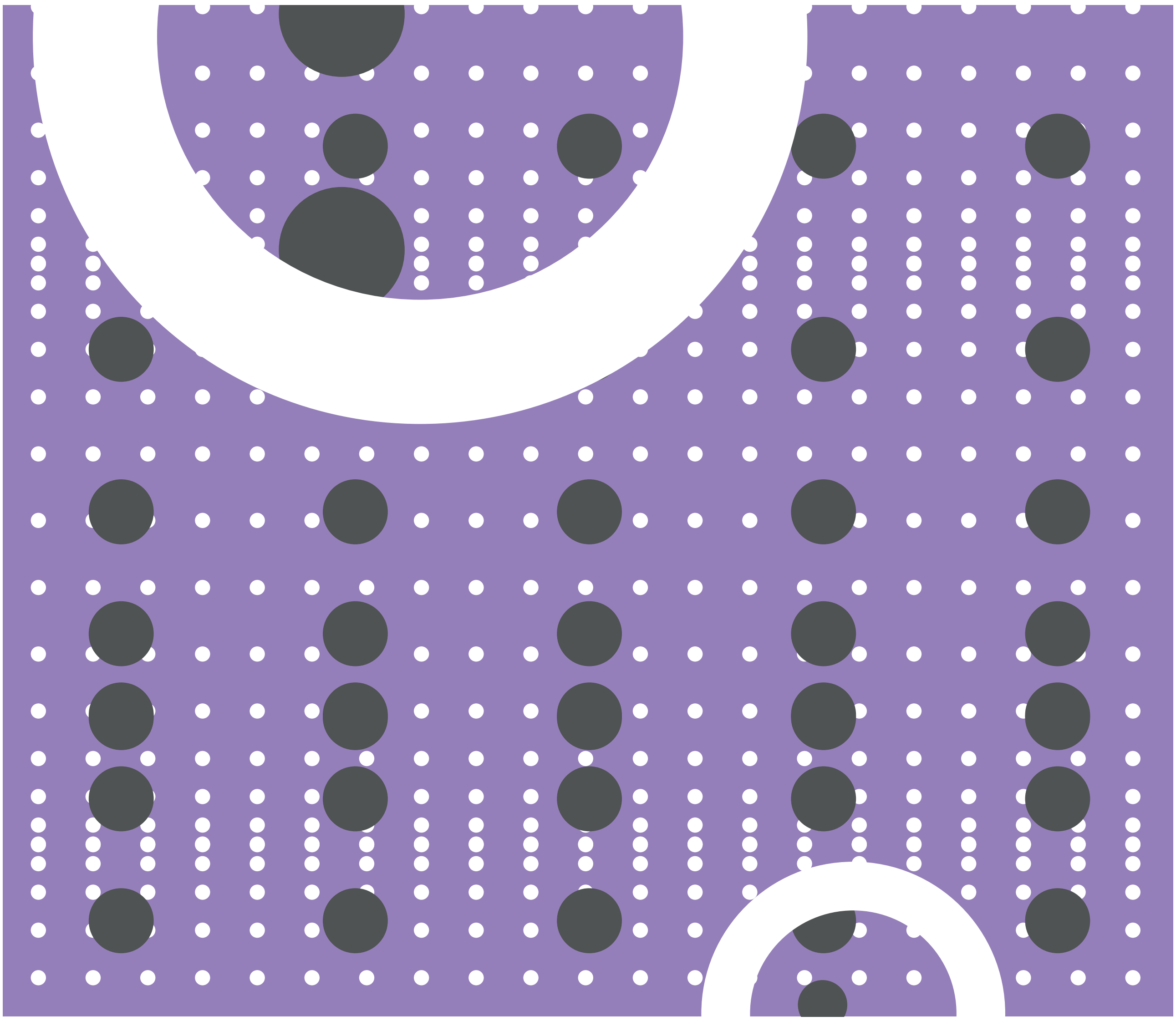
OCTOBER 2020

How to communicate uncertainty





A JOINT BRIEFING FROM: Africa Check (Sorting fact from fiction), Chequeado, Full Fact

About this briefing

Misinformation causes real harm to people's lives, health, finances and to democracy. We need good evidence on how to tackle it. This briefing is part of a research programme set up by Africa Check, Chequeado and Full Fact, to find that evidence and make it useful.

In this briefing Full Fact's researcher Dr. Dora-Olivia Vicol looks at how to communicate uncertainty to ensure that the public detect, and understand, evidence limitations. We thank Prof. Alexandra Freedman for her gracious feedback on earlier drafts.

We welcome feedback and comments at **research@fullfact.org**

Full Fact
2 Carlton Gardens
London
SW1Y 5AA

research@fullfact.org

@FullFact

fullfact.org

Africa Check
Johannesburg

africacheck.org

Chequeado
Buenos Aires

chequeado.com

This research was supported by a grant from Luminate.

Published by Africa Check, Chequeado and Full Fact, October 2020.

Luminate
Building stronger societies

Contents

Summary

Transparency about the knowledge we hold and lack is one of the cornerstones of fact checking.

As fact checkers, we encourage individuals and organisations to back up what they say with evidence, and to get their facts right. We help the public make sense of that evidence by summarising it and providing our judgement on where the weight of evidence lies. That involves a careful balance of being explicit about uncertainty and nuance where they exist, while also being clear where we think the evidence points in a particular direction. And yet, while acknowledging uncertainty is key to trustworthy fact checking, the way in which we communicate it also matters. It affects what the public understands, and it shapes trust in numbers and communicators themselves.

This briefing reviews mostly Anglo-American academic literature on uncertainty communication. Overall, we find that:

- The need to know is a widely prevalent feature of human psychology. Those of us studied by Western European and American researchers share an aversion towards ambiguity, and a preference for bets where the odds are known.
- And yet, there are limits to what can be known. A level of uncertainty is unavoidable, due to the limitations of measurements which characterise data about the past and future, or due to the simple fact that any prediction about the future is plotted on a probability spectrum.

The formats used to communicate uncertainty influence what audiences are able to understand and interpret.

- For the averagely literate population, numbers can be hard to grasp. Difficulties of calculus, jargon, or the sheer fact that large quantities like “billion” are hard to fathom can lead some members of the public to switch off when it comes to numerical communication.
- Verbal expressions of quantity also have their limitations. Simply adding words like “estimated” is not enough to get readers to understand that underneath a singular figure, such as unemployment growth, there is a range of possible scenarios. To communicate uncertainty clearly, we need to be explicit about ranges.
- When it comes to expressing the probability of future outcomes, words such as “likely” can be interpreted very differently, for example as a 60% chance by some readers, but a 30% chance by others.
- Notably, the public tends to cumulate verbal expressions of probability. Learning that something is “likely” from several sources leads some to erroneously interpret it as “very likely”.

The ways in which uncertainty is communicated also affects the public's trust – in numbers, and in the professionals who communicate them.

- Experiments have found that verbal expressions of uncertainty (through phrases such as "figures could be higher or lower"), slightly decreased readers' trust in the figures in question, as well as the trust they placed in the journalists doing the reporting.
- There is also evidence that trust is lowered when the outcome of a probability turns out to be different from the direction of the prediction, and when uncertainty is left unspecified.

However, these limitations can be mitigated. Being specific about our uncertainty as well as what we know, and where there is a level of disagreement, can fulfil our commitment to transparency, without casting a shadow of uncertainty over the entire message.

As with every briefing in this series, this marks the beginning, not the end, of a conversation about the communication of uncertainty. The evidence here pertains to the communication of uncertainty about unemployment, migration and climate change, and generally refers to cases of statistical uncertainty. We recognise the fact that the topics covered by fact checkers everyday are more diverse than those tested in experimental research, and that the vast majority of research in this direction is based on studies with Anglo-American audiences. This is why we see these conclusions as tentative, and we welcome input from practitioners.

The role of uncertainty in fact checking

Communicating the boundaries of what we do and do not know is a fundamental part of a fact checker's job. It is also fundamental to what we are asking others to do when they use evidence to make claims.

We can use statistical measures of uncertainty to provide an estimate of where the likely range of answers lie. Uncertainty in a fact check might also be indirect, and inherent in not being able to find credible evidence for a claim at all – where we might say the claim is "unsubstantiated", such as allegations that 5G networks are linked to coronavirus,[1] or that the Bill and Melinda Gates foundation were "kicked out of India".[2]

Most people have an aversion towards ambiguity

The need to know is a widely documented feature of human psychology. In a landmark experiment conducted at Harvard University and published in 1961, psychology PhD candidate Daniel Ellsberg designed a thought experiment with two urns. The first urn contained exactly 100 balls, half red and half black. The second also contained 100 balls, but the ratio between them was unknown. Asked to bet money on a colour being drawn, Ellsberg learnt that the vast majority of participants preferred the known odds in the first urn, and avoided the uncertain odds in the second. This came to be known as the Ellsberg paradox – or what is more commonly known as ambiguity aversion.[3]

Decades after the experiment, empirical research has confirmed time and again that we share a dislike for ambiguity. This isn't just the case in lab experiments. It also applies to real life scenarios. Ambiguity aversion leads people to avoid participating in the stock market, which has unknown risks,[4] as well as to avoid certain medical treatments when the risks are not fully known.[5] A study of medical students at an Irish university even found that an intolerance of uncertainty correlates with a feeling of distress.[6] Simply put, people naturally (and rationally) dislike making decisions when not all relevant information is available.

1 Grace Rahman, 'Here's Where Those 5G and Coronavirus Conspiracy Theories Came from', Full Fact, 2020, **fullfact.org/online/5g-and-coronavirus-conspiracy-theories-came**.

2 Abbas Panjwani, 'The Bill and Melinda Gates Foundation Wasn't Kicked out of India', Full Fact, 2020, **fullfact.org/online/gates-polio-vaccine**.

3 Mark Ratchford, 'The Ellsberg Paradox and the Ambiguity and Complexity of Decision-Making | USAPP', 2018, **blogs.lse.ac.uk/usappblog/2018/12/15/the-ellsberg-paradox-and-the-ambiguity-and-complexity-of-decision-making**.

4 David Easley and Maureen O'Hara, 'Ambiguity and Nonparticipation: The Role of Regulation', *The Review of Financial Studies* 22, no. 5 (2009): 1817–1843.

5 Loïc Berger, Han Bleichrodt, and Louis Eeckhoudt, 'Treatment Decisions under Ambiguity', *Journal of Health Economics* 32, no. 3 (2013): 559–569.

6 John Lally and Peter Cantillon, 'Uncertainty and Ambiguity and Their Association with Psychological Distress in Medical Students', *Academic Psychiatry: The Journal of the American Association of Directors of Psychiatric Residency Training and the Association for Academic Psychiatry* 38, no. 3 (June 2014): 339–44, **doi.org/10.1007/s40596-014-0100-4**.

Yet some things cannot be known for sure

Despite our psychological need to know, there are many things we cannot be sure of. Take the future, for instance. Predictions about whether it's likely to rain tomorrow or whether a medical treatment will work or not are not certainties, but a matter of probability. There may be a 30% chance of rain, or an 80% chance of recovery for the treatment, for example.

A degree of uncertainty can also characterise data about the past or present. Sampling errors, coverage, or even the possibility that respondents provide inaccurate responses can all lead to a degree of uncertainty in datasets. This is what scholars refer to as "epistemic uncertainty" – from the Greek word episteme, which means knowledge.[7] In contrast to psychological uncertainty, which refers to what we cannot know, epistemic uncertainty refers to situations where even the knowledge we do have is imprecise – due to the absence of evidence, the imperfect way of assessing evidence, or just the fact that they refer to future predictions.

7 Anne Marthe van der Bles et al., 'Communicating Uncertainty about Facts, Numbers and Science', *Royal Society Open Science* 6, no. 5 (2019): 181870.

The formats we use to communicate uncertainty shape comprehension and trust

On the simplest level, being transparent about what we don't know is a matter of ethics.

From national statistics which inform public debate, to medical information which affects decisions about personal health, communicators owe it to their public to be transparent about data sources, their limitations, and how they may be interpreted.[8]

But there are many ways of communicating uncertainty, with very different effects. Take something as simple as a claim about the weather. If you were told, "rain is unlikely", what would you consider to be the percentage chance of rain occurring: 5%, 10%, 30%? A numerical expression, such as "there is a 30% chance of rain" is very different from a verbal equivalent, such as "rain is unlikely". The format we choose to communicate uncertainty matters. Formats enable the public to understand what is communicated, and affect trust in communicators themselves. Let's start with understanding.

Numbers are tricky

Processing numerical uncertainty is hard. The UK's Royal Statistical Society examined this by surveying a sample of 1,000 UK adults. Most people could answer simple questions: for example 90% of people correctly answered the question, "what is 50 as a percentage of 200?", while 71% could correctly calculate the average of 5, 10, and 15. However, only 30% could answer a more complex question, such as the probability of getting two heads after spinning a coin twice.[9]

Interestingly, understanding numbers is not just a question of calculus, but also understanding of mathematical terminology. A qualitative investigation conducted with audiences of the British Broadcasting Corporation (BBC), with 97 respondents, found that only a minority of the public "think in numbers". The study doesn't specify how many. The averagely numerate majority can handle low levels of numbers with careful presentation, but too many numbers becomes overwhelming.[10] This gets particularly difficult with statistical terms such as "net" or "mean", or economic terms

8 Rebecca Hill, The Full Fact Report: Fighting the causes and consequences of bad information (London: Full Fact, 2020), **fullfact.org/media/uploads/fullfactreport2020.pdf**

9 John Pullinger, 'Margins of Error: Public Understanding of Statistics in an Era of Big…', Design (London: Royal Statistical Society, 2013), **slideshare.net/IpsosMORI/margins-of-error-public-understanding-of-statistics-in-an-era-of-big-data**.

10 BBC, 'Impartiality Review: BBC Reporting of Statistics', 2016, **downloads.bbc.co.uk/bbctrust/assets/files/pdf/our_work/stats_impartiality/audience_research.pdf**.

such as GDP, which are not familiar to non-specialist audiences – we explored this in depth in a separate briefing.[11]

Numerical comprehension also gets harder with high numbers such as "billion", which are difficult to imagine. Experiments with US participants (with non-representative samples) found that, when asked to plot numbers on a scale, nearly half of the participants placed 1 million halfway between the 1,000 and 1 billion mark, as though they believed that "thousand, million, billion, trillion" constitute a uniformly spaced count list.[12] This is an important finding. Participants who struggled to understand numerical magnitude also struggled to grasp the difference between large numbers, such as 980 million, and a much larger, more than double value of 2 billion. This is particularly important, given that so much policy communication is about numbers – for example election pledges proposing how to spend or increase a department's budget. In the experiment, participants who struggled with numerical magnitude also tended to offer optimistic evaluations of ineffective political strategies – for instance, where someone claims that planting 95 million trees is enough to fix a deficit of 1 billion (1,000 million) trees.

It is no wonder then, that the public's abilities to understand numerical expressions are also shaped by words. As anyone who did at least an hour of maths as school can attest, understanding numbers can feel easy or can feel completely off putting, depending in part on how they are communicated. In experiments conducted in the US, psychology professor David Landy found that the only way to make comparisons between large numbers clear was by using the same "label" – or unit of magnitude. The comparison between 980 million and 2 billion is much clearer when 2 billion is expressed as 2,000 million. Writing six or nine zeros, or powers-of-ten notations (106 for million, and 109 for billion) only caused more confusion – though this part of the work is unpublished and was only disclosed by the author in an interview with Nautilus.[13]

The fact that many of us struggle to comprehend large numbers adds an extra layer of complexity to the existing challenge of communicating numerical uncertainty.

Words are easier to understand than numbers, but less precise

If numbers are precise, but hard for some of us to comprehend, verbal expressions of quantity can offer a more accessible overview of a trend. One experiment tested three versions of Plain Language Summaries for Systematic Review articles, with a sample of 34 members of the public from Norway, Argentina, Canada, and Australia. It found that

11 Amy Sippitt, 'Understanding of Economic Terms' (London: Full Fact, 2018), **fullfact.org/media/uploads/understanding_the_economy_research_briefing.pdf**.

12 David Landy, Noah Silbert, and Aleah Goldin, 'Estimating Large Numbers', *Cognitive Science* 37, no. 5 (1 July 2013): 775–99, **doi.org/10.1111/cogs.12028**.

13 Elizabeth Landau, 'How to Understand Extreme Numbers', Nautilus, 2018, **nautil.us/blog/how-to-understand-extreme-numbers**.

participants preferred results presented as words supplemented by numbers in a table, compared to versions where results were presented in qualitative form only, which left them wanting more detail, or where numbers were included in text directly, which felt too complex to comprehend.[14]

However, even though words may feel like the simplest way to express quantity, when it comes to quantities which are uncertain, different people interpret things in very different ways.

Psychologists have learnt that verbal expressions of probability through words such as "likely", "unlikely", or "doubtful" can lead to a variety of interpretations. An experiment asked 233 students from the University of Illinois to read 13 sentences from an International Panel on Climate Change report (IPCC).[15] Each sentence presented a scientific affirmation which included a probabilistic pronouncement such as very likely, likely, unlikely and very unlikely, similar to what they would encounter in a report about climate change. For instance, participants read sentences such as: "It is very likely that hot weather extremes, heat waves, and heavy precipitation events will continue to become more frequent" (emphasis in original).

For each sentence, students were required to provide their best estimate of the probability intended by the authors of the report, including the lowest and highest values. The students were then assigned to one of four conditions. In the control group, they were given no instructions on how to interpret the phrases – simulating the experience of a reader who is unaware of the report's guidelines regarding interpretation and, we might add, the usual experience of reading reports which don't include a probability benchmark at all. Subjects in a translation group were shown the IPCC interpretation guidelines (as in Table 1) and were allowed to revisit them at any point – simulating the experience of a conscientious reader. In the verbal-numerical conditions, participants saw a range of numerical values next to each probability term, using either the wide ranges recommended by the IPCC in every sentence, or a narrower range.

Term	**Likelyhood of the outcome**
Virtually certain	99 - 100% probability
Very likely	90 - 100% probability
Likely	66 - 100% probability
About as likely as not	33 - 66% probability

14 Claire Glenton et al., 'Presenting the Results of Cochrane Systematic Reviews to a Consumer Audience: A Qualitative Study', *Medical Decision Making* 30, no. 5 (2010): 566–577.

15 David V. Budescu, Stephen Broomell, and Han-Hui Por, 'Improving Communication of Uncertainty in the Reports of the Intergovernmental Panel on Climate Change', *Psychological Science* 20, no. 3 (2009): 299–308.

Unlikely	0 - 33% probability
Very unlikely	0 - 10% probability
Exceptionally unlikely	0 - 1% probability

Table 1. Likelihood Scale. Source: International Panel on Climate Change (IPCC) guidance notes.

The analysis revealed that participants' interpretations of probability diverged widely from the guidelines of the IPCC. Only a small minority provided estimates consistent with the guidelines in the control group. Notably, this was even the case in the treatment group where participants were given the chance to read the guidelines – though inconsistencies here were smaller. While the IPCC uses "very likely" to indicate a probability of 90% or higher, the typical median response from participants was between 65-75%. Worryingly, qualifiers such as "most" or a "majority", such as "the majority of climate scientists have concluded that human-caused climate change is happening" are interpreted at around 60%, when the intention is in fact to reflect consensus of 90% to 100%.

People consistently misinterpret the intended meaning of verbal expressions of probability. These differences were not related to the sex and age of the respondents, nor to their overall attitudes toward climate change.

A similar level of variance applies to understanding medical data. A study conducted in the UK asked 120 patients who were taking medication after cardiac interventions to read two versions of side effects.[16] One was verbal, using words such as "rare" or "common". By EU regulations, these words reflect a probability of 0.01-0.1% and, respectively, 1-10%. The other version was numerical. The "rare" side effect in this case had a 0.04% chance of occurring, while the common one stood at 2.5%.

Patients' interpretations of verbal cues differed wildly from the intentions of communicators. On average, a side effect described as "common" was understood to occur 34% of the time, and a "rare" one 18% of the time.

It is interesting to note that a similar inflation of probability also applied to participants who had seen the exact figure. Despite being shown a specific incidence rate, the mean interpretation of the 0.04% chance of developing a side effect was 2%, while the average interpretation of 2.5% was 8%. Overall however, the verdict was clear. On their own, verbal expressions of probability led to interpretations which were several times higher than the intended rates.

16 Peter Knapp, D. K. Raynor, and Dianne C. Berry, 'Comparison of Two Methods of Presenting Risk Information to Patients about the Side Effects of Medicines', *BMJ Quality & Safety* 13, no. 3 (2004): 176–180.

Verbal expressions of probability are prone to cumulative interpretations, which tend towards unwarranted certainty

A series of seven studies with over 6,700 participants found that respondents "count" verbal probabilities.[17] Hearing that something is "likely" from several sources prompts them to move closer to certainty, and see it as "very likely", even though the sources don't necessarily reflect more data that would warrant stronger conclusions, but simply a plurality of voices about the same data. The study found this effect for probabilities above and below 50%, for hypothetical scenarios and real events, as well as when presenting forecasts simultaneously or sequentially.

Numbers, by contrast, are less prone to these interpretations. Research with participants exposed to numerical predictions found that people average the numbers presented to them, looking for the mean across the values, not their sum, as is the case with verbal expressions.[18]

Communicating uncertainty in words can decrease readers' trust in numbers and the people communicating them: but expressing uncertainty in numbers has no negative effect on trust

When it comes to the relationship between uncertainty and trust, opinion is divided. On the one hand, transparency about what we know, and what we don't know, is key to fact checkers and many other professions. In the UK, the Office for National Statistics describes uncertainty as no less than fundamental to official statistics. Its guidance notes make it clear that statisticians should provide sufficient information to allow users to judge whether estimates are fit for their purpose, but also to maintain and build users' confidence in estimates.

On the other hand, however, there are people who think that too much uncertainty diminishes trust in expertise. Starting from the premise that "as a rule, people dislike uncertainty [and] may attribute uncertainty to poor science", the National Academies of Sciences, Engineering, and Medicine note that "communicating uncertainty can diminish perceived scientific authority".[19] Some go as far as suggesting that "the drive to increase transparency on uncertainty of the scientific process specifically does more harm than good" – though evidence for this is elusive, at best.[20]

17 Robert Mislavsky and Celia Gaertig, 'Combining Probability Forecasts: 60% and 60% Is 60%, but Likely and Likely Is Very Likely', SSRN Scholarly Paper (Rochester, NY: Social Science Research Network, 16 September 2019), **papers.ssrn.com/abstract=3454796**.

18 David V. Budescu and Hsiu-Ting Yu, 'To Bayes or Not to Bayes? A Comparison of Two Classes of Models of Information Aggregation', *Decision Analysis* 3, no. 3 (1 September 2006): 145–62, **doi.org/10.1287/deca.1060.0074**.

19 Cited in Anne Marthe van der Bles et al., 'The Effects of Communicating Uncertainty on Public Trust in Facts and Numbers', Proceedings of the National Academy of Sciences 117, no. 14 (7 April 2020): 7672, **/doi.org/10.1073/pnas.1913678117**.

20 Bles et al., 2018:177.

Scientists at the Winton Centre for Risk and Evidence Communication at the University of Cambridge ran a series of five experiments to investigate how communicating uncertainty affects public trust in facts and numbers.[21] In the first experiment, over 1,000 participants were asked to read a short text which contained either no uncertainty (just a single value, known as "point estimate"), or variations of it. For instance, in a text about unemployment, participants read that an official report put the number of unemployed people in the United Kingdom at an estimated 1,484,000. Those in the control condition received no further information. In the treatment groups, some participants saw a numerical expression of uncertainty ("minimum 1,413,000 to maximum 1,555,000"), while others were presented with a verbal statement ("The report states that there is some uncertainty around the estimate, it could be somewhat higher or lower"). They were then asked to rate their trust in the numbers, and the writers of the report.

The analysis revealed that both numerical and verbal statement forms of communication were understood. Participants perceived the original numbers to be more uncertain after the treatment conditions – but especially so in the verbal condition. Asked how reliable they thought the numbers and sources were, the views of participants who had seen numerical ranges were no different from the control condition. In the verbal condition however, trust in the numbers and writers decreased slightly.

Further experiments by the same authors confirmed the finding in studies of other topics, including the more contested one of migration figures, as well as in a field experiment with a BBC article. Readers of a BBC news article about the economy were either shown an unemployment figure without any uncertainty, as is common in news reporting ("...unexpectedly rose to 3.9%"); with a verbal cue – "...rose to an estimated 3.9%"), or with a numeric range and verbal cue – which is uncommon in news reporting – "...rose to an estimated 3.9% (between 3.7% and 4.1%)" . Once again, uncertainty communicated in numerical form did not affect readers' trust in numbers, the statisticians, or the BBC journalists. One thing to note, however, is that numerical communication prompted a stronger perception of uncertainty. When readers were simply shown the figure accompanied by the word "estimated", perceptions of uncertainty did not differ significantly from either the control group, or the range group.[22]

Overall, after varying the topic, the magnitude, and the format and context of communication, the authors found little evidence that communicating uncertainty would backfire. First of all, readers are able to recognise uncertainty – except when only words such as "estimated" or "about" are used. When they do so, their level of trust varies with the format of communication. By and large, findings illustrate that

21 Bles et al., 'The Effects of Communicating Uncertainty on Public Trust in Facts and Numbers'.

22 Bles et al., 177.

the provision of numerical uncertainty, in particular as a range, does not substantially alter trust in either the numbers or the source of the message. However, lengthy verbal quantifiers do, such as "there is some uncertainty around the estimate, it could be somewhat higher or lower". These findings applied across topics, mode of communication, and magnitude of uncertainty.

Trust is also eroded when the outcome differs from the expectation

A level of uncertainty occurs almost every time we refer to future events. Transformations in the economy after a particular trade deal is adopted, or in personal health after following a treatment, are not definite outcomes, but points on a scale of likelihood which ranges from "exceptionally unlikely" (0-1%), as the IPCC put it, to "virtually certain" (99-100%). Studies which investigated expressions of probability have found that words such as "likely" or "unlikely" are not at all neutral. Unlike a numerical expression, words create a stronger sense of expectation of an outcome happening. This relationship between the direction of communication and outcome also affects what readers trust.

An experiment showed 436 participants a vignette about a flood ("the Wayston flood plain has a history of flooding due to its flat terrain and proximity to the east side of the River Wayston. The river is currently in flood, and flood water is expected" etc).[23] Depending on the group they were allocated to, participants read a statement which cast a level of verbal doubt over the prediction ("An expert has suggested that given the river's situation and recent weather, it is doubtful/not entirely definite/a small chance/a good chance that the floodwater will extend 7km"), or gave a numerical likelihood of it happening (10%-30%, or 70%-90%). Participants were asked to provide initial ratings of the geologist's expertise and trustworthiness. Next, they were informed that the flood happened or did not happen, depending on their group. Trust ratings in geologists' expertise were measured once again, as well as ratings of the correctness of the prediction, and their level of surprise.

As expected, the study found that participants sanctioned cases when the outcome differed from the prediction. But it is interesting to observe that their loss of trust depended on the format of the prediction. Participants who learnt that the flood happened after being told that this was "doubtful" were more critical of the geologist than those who had simply been told that "there was a 10-30% chance of flooding". Mathematically, at least in the authors' interpretations, they all saw the same prediction. But the verbal expression created a stronger sense of expectation of the outcome not happening.

23 Sarah C. Jenkins and Adam J. L. Harris, 'Maintaining Credibility When Communicating Uncertainty: The Role of Directionality', *Thinking & Reasoning* 0, no. 0 (9 February 2020): 1–27, **doi.org/10.1080/13546783.2020.1723694**.

Interestingly, the reverse applied when the flood occurred. Participants who were told that there was a 10-30% chance of flooding, but later learned that the flood did not occur, were more critical of the scientist than those who were told that flooding was “unlikely”. In other words, even when the probability is low, numbers create a stronger expectation of something happening.

Uncertainty particularly damages trust when it is left unspecified

Finally, it is important to remember that uncertainty also damages trust when left unspecified – as a shadow looming over an entire story. One study showed a representative sample of 1,174 American adults three versions of a prediction about rising sea levels. It found that participants trusted the version which included a best and worst case scenario more than those which only presented one possibility.[24] However, when participants were presented with an additional disclosure, which questioned the extent to which sea level rises could be measured at all due to unpredictable forces, such as storm surges, the number of those who reported high trust in scientists decreased (by 5%).

The findings held true regardless of educational levels and political party affiliation. They also chime with recommendations by statistical authorities. In the UK, the Government Statistical Service recommends quantifying the impact of uncertainty on statistics precisely, early on in the publication. Where this is not possible, they suggest making a reasoned judgement on the likely size and direction of uncertainty, and its potential impact on statistics.[25]

It is important to be specific, even about the things we do not know. The distinction between epistemic uncertainty, which applies to a particular fact, and psychological uncertainty, which refers to the anxiety-inducing state of not knowing, is artificial. It is not hard to imagine how imprecise debate about the certainty of a specific isolated fact can balloon into the stressful psychological state, where it appears that nothing can be known.

What about visual representations?

Uncertainty about a statistic can be communicated visually in a variety of ways. Error bar charts represent the variability of data (based on its standard deviation, confidence interval, or standard error). The top of the column represents the main estimate, while the top and bottom of the error bar mark other possible estimates, under conditions of variance (based on the confidence interval, for instance). Simply put, the longer an

24 Lauren C. Howe et al., ‘Acknowledging Uncertainty Impacts Public Acceptance of Climate Scientists’ Predictions’, *Nature Climate Change*, 2019, 1–5.

25 Government Statistical Service, ‘Communicating Uncertainty and Change. Guidance for Official Statistics Producers’ (Government Statistical Service, 2014), 5, **gss.civilservice.gov.uk/wp-content/uploads/2014/11/Communicating-uncertainty-and-change-v1.pdf**.

error bar is, the less precise the measurement. Other charts can achieve similar visual representations of uncertainty, by plotting different data scenarios in “fan shape”, where bands of decreasing colour saturation represent deviations from the central estimate, or by showing a full probability distribution as a “fuzzy” density plot, with increased saturation of colour representing increased likelihood of the true (central) value (see Fig 1).

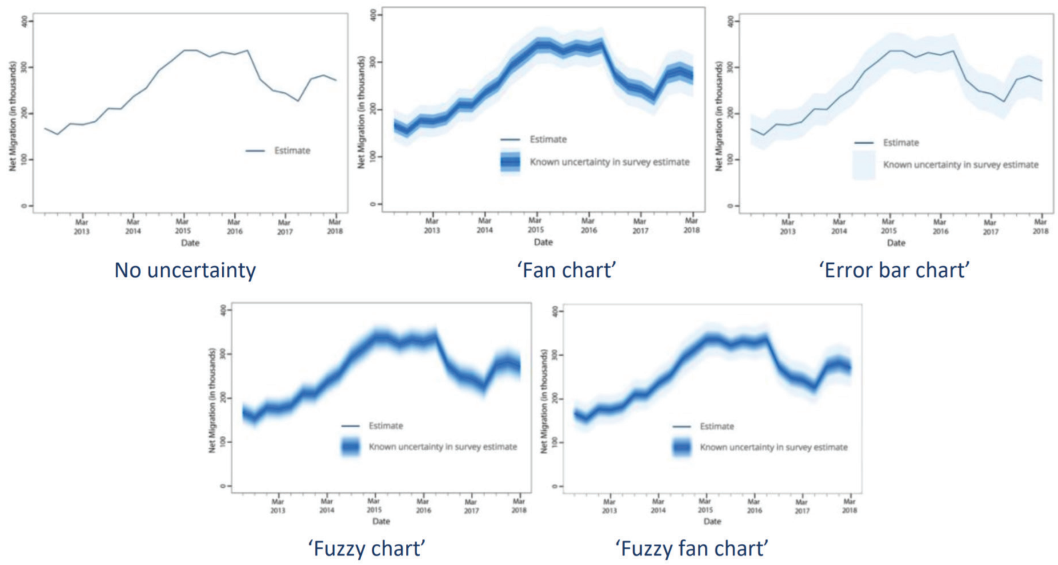


Fig 1. Visual representations of uncertainty. Source: van der Bles, A. M., et al. (2018), *Determining and facilitating the clearest ways to visualize uncertainty around estimates, time series and curves*. Working Paper, Cambridge University.

Two experiments conducted with samples of 1,000+ UK adults investigated the roles of four types of charts in communicating uncertainty about migration and unemployment data – this included an error bar chart, as well as a fan chart, fuzzy chart, and a fuzzy fan chart.[26] The study found that in general, presenting uncertainty visually did not affect respondents’ comprehension of the trends. The majority were correct in reading the upwards trajectory of net migration, and downward trend in unemployment – and this did not differ significantly between the control condition, which included no uncertainty, and the treatment groups. Their perception of the reliability and trustworthiness of the data and its producers were also largely unaffected. Encouragingly, error bars did help people assess the certainty of trends – though none of the presentation styles was successful in getting participants to realise that numbers closer to the midline of the distribution were more likely than those on the outside. Participants’ more positive feelings towards the state of the UK or about immigration were linked to their more positive perceptions of the accuracy, reliability and trustworthiness of the graphs they viewed – but effect sizes were small.

26 Anne Marthe van der Bles et al., ‘Determining and Facilitating the Clearest Ways to Visualize Uncertainty around Estimates, Time Series and Curves’ (University of Cambridge: Winton Centre for Risk and Evidence Communication, 2018).

Recommendations

Be transparent

Transparency about the quality and limitations of data is a duty owed by anyone putting information out to the public to inform individual decision making.

While some representations of uncertainty do have a small negative effect on trust in sources, this effect doesn't always occur, and it can be mitigated. Uncertainty is something to be managed and normalised, not hidden.[27] Do make it clear when there is a level of uncertainty about the data. Don't gloss over variance and evidence gaps.

Be specific about what exactly is uncertain

To manage ambiguity aversion and avoid casting a shadow of doubt over everything we say, it is important to localise where exactly there is a level of uncertainty. Be specific about whether it is due to incomplete understanding of a process, unreliability of measurements, insufficient data, or other sources. Don't leave readers with sweeping statements which make it sound like nothing can be trusted.

Indicate uncertainty in existing data using numerical ranges in brackets, after the main value

Using words like "estimated" and "around" once is not enough to show readers that there is a level of uncertainty in the data. This format also was not found to reduce perceived trust in either the number or the source of uncertainty. Do say, for instance, "unemployment is estimated at 3.9% (between 3.7% and 4.1%)" at least when you introduce the figure for the first time. Don't just say "unemployment is estimated at 3.9%" expecting readers to understand the underlying uncertainty.

In the case of future predictions, use verbal expressions to indicate the general direction of travel, but supplement these with numerical probability ranges, and wherever possible access to underlying data.

A common stem such as likely (or its variations), can make it easier to understand the general direction of an outcome. But this should be accompanied by underlying numbers and a clear reference to data sources, to avoid the variation in interpretation, and the danger that audiences sum a multitude of probabilities into certainty. Do say, for instance, "global warming is likely (66% chance) to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate".

27 Budescu, Broomell, and Por, 'Improving Communication of Uncertainty in the Reports of the Intergovernmental Panel on Climate Change'.

Take care when using large numbers and jargon

If jargon is necessary, remember to explain it. When using large numbers, remember that the difference between 1 million and 1 billion is clearer if the latter is expressed as 1,000 million.

We need to explore how we can help members of the public get better at processing uncertainty

Interpreting numerical variance is subject to technical difficulty and cognitive bias – perhaps even more so than interpreting other media content. A suggested area for further work is to consider how fact checkers, researchers and information literacy communities could raise awareness of common barriers to understanding and interpretation – such as the tendency to interpret terms such as “likely” as anything from 10% to 60% chance, or to cumulate verbal expressions of probability into certainty. Perhaps most importantly, we could explore how to get the public comfortable with the distinction between epistemic, and psychological, uncertainty. Most statistics are estimates, and most predictions about the future are probabilities. We would welcome more research about how to get audiences accustomed to processing statistical analysis, to ensure that the epistemic uncertainties which characterise everyday communication don’t balloon into the stressful state of psychological uncertainty.

How we selected the studies

This briefing is informed by two strands of literature: peer-reviewed academic research and reports produced by academics which are awaiting peer review. It is important to mention a few caveats.

This briefing is intended as an introduction to possible impacts of and interventions about uncertainty, rather than an exhaustive review. The distinction between psychological and epistemic uncertainty is designed to highlight why uncertainty about what we know can come to shape how we feel. Other frameworks propose more complex typologies of uncertainty which distinguish between several communicating actors, objects, forms and recipients of communication channels.[28] Similarly, authorities such as the IPCC, the UK Government Statistical Service, or the EU propose their own, much more detailed guides for uncertainty communication.

In the interests of brevity and keeping this briefing accessible, we have refrained from engaging more closely with these sources, focusing instead on the relation between uncertainty communication, understanding, and trust which is key to fact checkers. Technically literate communicators would benefit from consulting these sources in more depth.

Finally, there are a few other caveats.

The vast majority of research on uncertainty comes from UK and US audiences. This is not representative of audiences across the world and, even in this literature, student samples are not representative.

Perhaps most notably, fact checkers would benefit from field research which investigates the effects of uncertainty communication upon their readers, using real fact checks and local participants. The literature we consulted here, which included stories of unemployment, migration, and climate change, is arguably a good fit to the areas of debate covered by fact checkers. However, the format, tone, and experience of communicating and reading a fact check are distinct. Fact checking organisations and the academic community invested in uncertainty communication, would benefit from further field experiments.

Further field research could investigate, for instance, whether fact checks which specify numerical ranges for every “estimated” figure and “likely” outcome will be clearly understood by their readers – or conversely, whether readers will be put off by the multitude of numbers in brackets, and close the article completely. Similarly, it will be interesting to discover whether readers’ perceptions of uncertainty persist in time, a week or more after seeing a fact check. Experimental research provides a number

28 van der Bles et al., ‘Communicating Uncertainty about Facts, Numbers and Science’.

of possible interventions in uncertainty communication. Field research will be best placed to test their effectiveness in real life.

Bibliography

BBC. 'Impartiality Review: BBC Reporting of Statistics', 2016. **downloads.bbc.co.uk/bbctrust/assets/files/pdf/our_work/stats_impartiality/audience_research.pdf**.

Berger, Loïc, Han Bleichrodt, and Louis Eeckhoudt. 'Treatment Decisions under Ambiguity'. *Journal of Health Economics* 32, no. 3 (2013): 559–569.

Bles, Anne Marthe van der, Sander van der Linden, Alexandra L. J. Freeman, and David J. Spiegelhalter. 'The Effects of Communicating Uncertainty on Public Trust in Facts and Numbers'. *Proceedings of the National Academy of Sciences* 117, no. 14 (7 April 2020): 7672–83. **doi.org/10.1073/pnas.1913678117**.

Bles, Anne Marthe van der, Sander van der Linden, Alexandra LJ Freeman, James Mitchell, Ana B. Galvao, Lisa Zaval, and David J. Spiegelhalter. 'Communicating Uncertainty about Facts, Numbers and Science'. *Royal Society Open Science* 6, no. 5 (2019): 181870.

Bles, Anne Marthe van der, David J. Spiegelhalter, Sarah Dryhurst, Alexandra Freeman, and Jin Park. 'Determining and Facilitating the Clearest Ways to Visualize Uncertainty around Estimates, Time Series and Curves'. University of Cambridge: Winton Centre for Risk and Evidence Communication, 2018.

Budescu, David V., Stephen Broomell, and Han-Hui Por. 'Improving Communication of Uncertainty in the Reports of the Intergovernmental Panel on Climate Change'. *Psychological Science* 20, no. 3 (2009): 299–308.

Budescu, David V., and Hsiu-Ting Yu. 'To Bayes or Not to Bayes? A Comparison of Two Classes of Models of Information Aggregation'. *Decision Analysis* 3, no. 3 (1 September 2006): 145–62. **doi.org/10.1287/deca.1060.0074**.

Easley, David, and Maureen O'Hara. 'Ambiguity and Nonparticipation: The Role of Regulation'. *The Review of Financial Studies* 22, no. 5 (2009): 1817–1843.

Glenton, Claire, Nancy Santesso, Sarah Rosenbaum, Elin Strømme Nilsen, Tamara Rader, Agustin Ciapponi, and Helen Dilkes. 'Presenting the Results of Cochrane Systematic Reviews to a Consumer Audience: A Qualitative Study'. *Medical Decision Making* 30, no. 5 (2010): 566–577.

Government Statistical Service. 'Communicating Uncertainty and Change. Guidance for Official Statistics Producers'. Government Statistical Service, 2014. **gss.civilservice.gov.uk/wp-content/uploads/2014/11/Communicating-uncertainty-and-change-v1.pdf**.

Howe, Lauren C., Bo MacInnis, Jon A. Krosnick, Ezra M. Markowitz, and Robert Socolow. 'Acknowledging Uncertainty Impacts Public Acceptance of Climate Scientists' Predictions'. *Nature Climate Change*, 2019, 1–5.

Jenkins, Sarah, C. and Harris, Adam, J.L. 'Maintaining credibility when communicating uncertainty: the role of directionality'. *Thinking & Reasoning* 0, no. 0 (9 February 2020): 1–27, **doi.org/10.1080/13546783.2020.1723694**.

Knapp, Peter, D. K. Raynor, and Dianne C. Berry. 'Comparison of Two Methods of Presenting Risk Information to Patients about the Side Effects of Medicines'. *BMJ Quality & Safety* 13, no. 3 (2004): 176–180.

Lally, John, and Peter Cantillon. 'Uncertainty and Ambiguity and Their Association with Psychological Distress in Medical Students'. *Academic Psychiatry: The Journal of the American Association of Directors of Psychiatric Residency Training and the Association for Academic Psychiatry* 38, no. 3 (June 2014): 339–44. **doi.org/10.1007/s40596-014-0100-4**.

Landau, Elizabeth. 'How to Understand Extreme Numbers'. Nautilus, 2018. **nautil.us/blog/how-to-understand-extreme-numbers**.

Landy, David, Noah Silbert, and Aleah Goldin. 'Estimating Large Numbers'. *Cognitive Science* 37, no. 5 (1 July 2013): 775–99. **doi.org/10.1111/cogs.12028**.

Mislavsky, Robert, and Celia Gaertig. 'Combining Probability Forecasts: 60% and 60% Is 60%, but Likely and Likely Is Very Likely'. SSRN Scholarly Paper. Rochester, NY: Social Science Research Network, 16 September 2019. **papers.ssrn.com/abstract=3454796**.

Panjwani, Abbas. 'The Bill and Melinda Gates Foundation Wasn't Kicked out of India'. Full Fact, 2020. **fullfact.org/online/gates-polio-vaccine**.

Pullinger, John. 'Margins of Error: Public Understanding of Statistics in an Era of Big…'. Design. London: Royal Statistical Society, 2013. **slideshare.net/IpsosMORI/margins-of-error-public-understanding-of-statistics-in-an-era-of-big-data**.

Rahman, Grace. 'Here's Where Those 5G and Coronavirus Conspiracy Theories Came from'. Full Fact, 2020. **fullfact.org/online/5g-and-coronavirus-conspiracy-theories-came**.

Ratchford, Mark. 'The Ellsberg Paradox and the Ambiguity and Complexity of Decision-Making | USAPP', 2018. **blogs.lse.ac.uk/usappblog/2018/12/15/the-ellsberg-paradox-and-the-ambiguity-and-complexity-of-decision-making**.

Sippitt, Amy. 'Understanding of Economic Terms'. London: Full Fact, 2018. **fullfact.org/media/uploads/understanding_the_economy_research_briefing.pdf**.

Full Fact
2 Carlton Gardens
London
SW1Y 5AA

research@fullfact.org

@FullFact

fullfact.org

Africa Check
Johannesburg

africacheck.org

Chequeado
Buenos Aires

chequeado.com

This research was supported by a grant from Luminate.
Published by Africa Check, Chequeado and Full Fact, May 2020. Updated July 2020.