Bias-aware design of interfaces to overcome junk science

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ABSTRACT

Science news is important since many people use it to make important decisions for diverse aspects of their lives. This paper analyses how cognitive biases affect the processes that produce scientific news, particularly those processes that contribute to the unintentional creation of junk science news. We present a stakeholder analysis for the processes involved in the dissemination and consumption of scientific results, identifying key cognitive biases that play a role in the dissemination of incorrect information. We then explore ways to augment interfaces used through those processes. We consider how to design interface elements to help people become aware of the cognitive biases that contribute to creation and dissemination of junk science. That awareness can be a foundation for each stakeholder group to avoid unintentional contributions to this problem. Our work provides a foundation for

CHI '20, April 25–30, 2020,, Honolulu, HI, USA

new research to create personalised interface mechanisms and elements at each stage in the news dissemination process, to help people contribute to improving the quality of scientific news and to recognise junk science news.

KEYWORDS

Truth decay, Fake news, Misinformation, Cognitive bias

INTRODUCTION

The widespread availability of Internet services enables people to exchange all sorts of information easily. Scientists have developed many techniques to preserve the integrity of transmitted bits across the Internet. But current technology falls short in detecting and limiting the spread of false content [8]. This paper considers dissemination of science from its source scientific publication to popular print and social media. We are particularly concerned with the broad public, the non-expert consumers of science news reports [50]. Misinformation and disinformation have existed well before the arrival of modern news dissemination technology [34] but the problem has become critically important as billions of people have gained access to so much political, science, and wellness news [3, 11, 12, 54]. This has resulted in what has been called Truth Decay [42]. We focus on the challenges people face in making important decisions about their health and lifestyle, believing that they are using scientific research findings [16, 17, 21, 30, 31].

Our work aims to create new ways to help people reduce the production and sharing of *junk science (also called pseudoscience)*. This has many causes. At the most basic level, there can be failures as academics do research and report it, especially when the results of a study require nuanced interpretation. Problems can also arise in the academic review process which should play a key role in quality control. The broader dissemination of science typically involves press releases, articles by journalists and social media reports and each of these can amplify an incomplete report of the actual scientific findings and its limitations [2, 13, 41]. With novelty trumping rigor, false news is particularly likely to be shared [50] and social media metrics may draw more attention to junk science reports [48]. This makes it hard for people to judge the credibility of reports they read of academic studies [18]. Adding to this, they are likely to miss retractions [43] and be deterred from reading the original papers if these are not open access [10].

To tackle this problem, we want to create interfaces that help people overcome cognitive biases that play a role in the *unintentional* creation and dissemination of junk science news. We take a broad definition of cognitive biases as methods, shortcuts or heuristics that a person uses to make a judgment that may be inaccurate or irrational [24, 25]. There is considerable evidence that cognitive biases have important roles in the creation and sharing of junk news: enhancing its distribution [39, 42, 50]; making dissemination decisions after considering too little information [25, 49], for example based on reading only a news headline, not going on to read the article [19, 40]; and hindering the correction of false beliefs, particularly if people are heavily invested in those false beliefs [23, 35]. We limit this paper to unintentional dissemination of junk science news, rather than the more intractable case of malicious dissemination activity. When cognitive biases do contribute to unintentional dissemination, suitable interfaces may help people become aware of the cognitive biases influencing them as well as strategies for overcoming them. Our analysis goes beyond the work that helps just the final user recognise junk science on social media [27, 52, 53] to consider the whole dissemination process described above.

In the next section, we conduct a bias-aware stakeholder analysis of the processes and checks involved in creating news that the public sees. We discuss how this currently makes it difficult for people to be aware of problems that they contribute to in this process. From this, we explore two stakeholder groups and the ways that new interfaces could help them become aware of these biases. We conclude by positioning these approaches, showing how they go beyond previous work.

STAKEHOLDER ANALYSIS

This section identifies a key set of stakeholders in the creation and dissemination of science news. For each stakeholder group, we consider the decisions they need to make and key cognitive biases that may influence those decisions. This is a foundation for the next section where we analyse the contexts where interfaces might help people become aware of the potential impact of their biases and how these affect their decisions and action.

Figure 1 characterises a typical process for creating and disseminating a scientific paper. On the left, we show the flow from the draft paper through to social media. The blue rectangles indicate information that is publicly available. On the right are the people associated with each part of the flow.

Our figure starts with the paper that authors submit for peer review. There are clearly many steps before this but our analysis begins with the creation of the paper because it is the first step towards dissemination. Authors are subject to several biases that may influence the ways they formulate hypotheses, frame the research and then analyse and report results. Nuzzo [33] distinguishes the following forms of confirmation biases that cause scientists to unintentionally "fool themselves".

- *Hypothesis myopia* favours collection and reporting of information supporting the author's hypotheses and failing to report dis-confirming evidence or alternative explanations.
- *Texas sharp shooter* influences people to see patterns that are not meaningful.
- *Asymmetric attention* where expected results are not rigorously checked and may be used to over-claim – by contrast, unexpected ones are down-played or scrutinised more carefully for reasons to omit them.

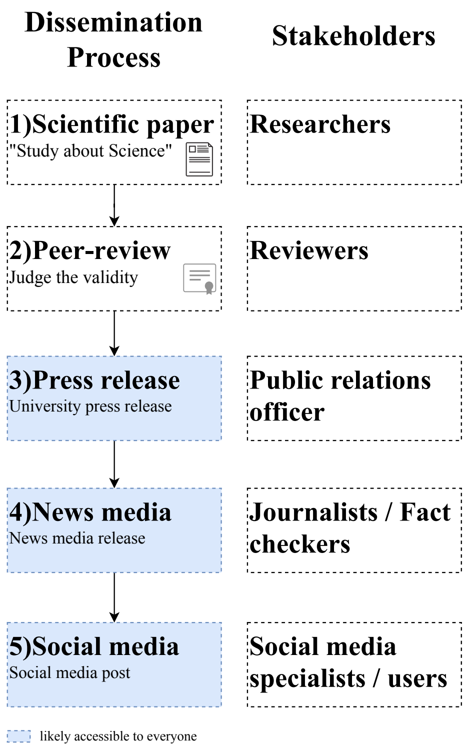

Figure 1: Characterisation of the key processes and stakeholders in a typical flow from a scientific paper submitted for review to news articles and social media posts.

Several factors drive these biases [42]; for example the pressure to publish and deadlines. In line with the dual-processing model of thinking, fast or slow, authors under pressure may fail to do the slow and deliberate thinking needed to avoid the above biases [24]. Another well-recognised driver can come from the funding source for the research or other conflicts of interest, such as potential financial benefits from commercialisation of the research. Many journals require declarations about these which can be used by readers further down the chain in Figure 1.

The second step in dissemination is peer review. This relies on experts [26] who carefully assess the paper on various criteria. For this analysis, the relevant ones are the validity of the research process, the analysis reported and claims based on the interpretations of the data, accounting for the limitations of the work. Reviewers have one key role as gate-keepers since they determine which papers are published. Another role is to provide quality reviews and to state required changes to improve the paper before it is accepted. The review process typically has three or more experts involved, in line with a form of social cognition amplification [1, 29].

Reviewers and editors are prone to all the biases listed above for authors. In addition, we can identify other key biases which may influence acceptance of invalid research papers (indicated with +) or rejection of valid work (marked −).

- +− *Stereotyping bias* may occur if the reviewer knows the identity or institution of the authors.
- +− *Framing effects* may mean reviewers are influenced by the paper’s framing or the reviewer’s ability to reason from a different frame from the authors.
- +− *Novelty bias* is a particular risk, especially as novelty may be a review criterion.
- − *Negative results bias* causes reviewers to more critical of papers reporting negative results [25].
- − *Over-confidence bias* may mean a reviewer over-estimates their ability to assess the quality of a paper and they may not seriously consider papers that present information that does not match their own views.

These are all well recognised problems. Review processes aim to reduce their impact. It is also well known that all such processes have limitations. Double blind reviewing may reduce the first of the biases above, although reviewers may be able to guess the authors and institutions. There may be opportunities to create interfaces that can help reviewers and editors consider the impact of more of these biases.

We now consider three groups, public relations staff who write press releases, journalists and social media specialists. We will refer to them all as science communicators [7]. They create a new piece of writing so that it is understandable for a very different audience from the target readers of an academic paper. We now identify the key differences in the writing:

- length: the public version is far shorter, requiring science communicators to select the aspects they consider most important, relevant and understandable;

- lexical difficulty [22]: means that new simpler text is created;
- sensationalism and novelty are important to engage the audience: these may compromise the academic paper's careful statements about uncertainty and limitations [32].
- independent fact-checking is one essential contribution that science communicators should make at this stage.

The science communicators in the dissemination process are subject to the following cognitive biases:

- Authority bias may occur during dissemination when a science communicator accepts the scientific claims without fact checking because they see the researchers as trusted authorities [4, 45]. These writers may also lack the expertise to judge the quality of science [6].
- Novelty bias occurs when science communicators overestimate the novelty of scientific findings, while disregarding the limitations.

Finally, we consider the non-expert, who consumes scientific news generated by other stakeholders. Users on social media may be susceptible to following set of cognitive biases.

- Availability bias can occur if users give more weight to information they recently saw in the media.
- Confirmation bias is particularly prevalent. Social media users are susceptible to an echo-chamber effect [37], being delivered personalised content that is aligned with what they previously read. They may not even realise this is the case. Beyond that, readers may seek and consume information that confirms their beliefs and reject or react negatively to content that causes discomfort [36, 52]. Subsequently, users tend to engage with (like, share, tweet, etc.) conforming content.
- Anchoring bias can influence non-experts decisions by giving disproportional importance to a piece of information that appears first. Similarly, causal imprinting [46] may mean that readers hold established beliefs about causal relationships.
- Novelty bias means they pay more attention to novel news and engage more with it [50].

Each stakeholder group performs a complex creative task that involves many decisions. Each is influenced by multiple cognitive biases, especially when the decisions are made under time pressure. The full process results in a ripple-down effect that multiples the impact of each decision making step.

TOWARDS INTERFACES TO HELP REDUCE JUNK SCIENCE

Having identified the stakeholders and key cognitive biases affecting each, we believe there is a particular opportunity to create interfaces that can help these people become aware of the impact of their biases. We explore how to create nudges that are biases aware. As an exploration of this approach, we now consider two stakeholders in this process, the reviewers and social media users.

Figure 2: User interface elements that could be generated to indicate the quality of scientific article based on information provided by various stakeholders.

For reviewers, we harness status-quo and regret aversion biases [9] to counter the biases identified above. We particularly consider challenges due to the nature of much research: where each paper typically makes a small contribution to science; with uncertainty being the norm in research results; and it is both difficult and important to clearly state "the strengths and weaknesses intrinsic to every study conducted and published" [14]. We propose three classes of support:

- *private interface elements* to help the reviewer pause and reflect on the potential effects of key biases affecting their reviewing;
- *confidential elements* that aid reflection but are also available to the whole review team, often the 3 reviewers and senior editors – we propose systematic new additions to the confidential comments that reviewers can already provide in many review processes;
- *shared interface elements* that provide information to the authors as well as the review team.

Stereotyping biases may mean that a reviewer tends to value work from prestigious institutions and well-known researchers (and discount the work of others). While double-blind reviewing aims to address this problem, it has limitations as reviewers may often be able to guess the identity of authors. Indeed this is especially likely when the reviewer is expert in a precise area of the paper. We propose that a private interface could invite reviewers to *reflect* on the possible impact of stereotyping. This might be as modest as a check box the reviewer click to indicate they did pause to consider this possibility.

Framing effects and negative results bias mean that a review may over-value work that is framed in ways that match their own views or that gives positive results. One growing trend is the pre-registration of studies [15] and pre-review of the research protocol. Beyond these measures, the reviewer interface could explicitly ask reviewers to consider whether the paper reports a negative result and to indicate how much this has influenced their assessment of the paper. For both framing effects and negative results bias, we propose new confidential elements that mean reviewers should comment on these. This gives reviewers the opportunity to reflect on them. It also makes them available to the whole review team, to discuss and take into account. For the case of negative results bias, the senior editors could then be alerted to take account of these signals from authors.

Over-confidence bias is partially accounted for in current review practices where reviewers rate their expertise or confidence in their assessment. In addition, it is supported when there is a discussion phase, where reviewers see all the reviews and are called to justify their reviews. We propose that new confidential interface elements could ask the reviewer to explicitly distinguish where their expertise matches the content of the paper and where it does not. With the growing appreciation of the importance of multi-disciplinary research, it can be expected that each reviewer's expertise matches only parts of the work.

We now consider interface elements to help readers of social media recognise the quality of science news and to distinguish junk science news. Figure 2 summarises several credibility indicators based on information validated and acquired through the dissemination process. There are many interface challenges in designing suitable interface elements for these. For example, since social media users consume each news item so quickly, any quality indicator needs to be noticeable and quick and easy to interpret. Beyond this, we consider it would be valuable to enable users to then drill down on these, in line with the visualisation principle of overview first and details on demand [44]. So we propose a small set of simple indicators, each with the option for a user to click on it to see a personalised interface that enables them to see more detail. We need research to gain understanding about the ways people respond to these, whether they will be noticed and used. This needs to be accompanied by a commitment to educate the public [14] to understand the uncertainty of science, to appreciate that it is a work in progress and that every study has strengths and weaknesses. We have the opportunity for this interface to make each news item offer a teachable moment about the reader's own biases.

We propose that the interface should present a confidence score indicating the strength and validity of claims in the study. These should reflect the fact that one scientific study alone does not have high strength even if the quality of the research is very high. By contrast, umbrella meta-reviews (when well done) bring together evidence from many studies, assessing their quality and the consistency of the evidence across them. To create such indicators, we need to provide ways for both authors and the reviewer process to contribute to the score. This could follow the approach that is common in meta-review papers which classify the quality of the results in the papers they analyse, describing the best as gold standard. This gives a simple score with a drill down option to see the descriptor of the way it was determined.

Since conflict of interest is such a well understood source of bias, we envisage a summary score for it and a drill down to its explanation. Many medical publications already include information about conflict of interest which could feed into the dissemination process. A similar approach could ensure that the review process provides evidence of the quality of a study in terms of reproducibility with key indicators being that data and code used in the study were disclosed and examined during the review process.

Another interface indicator should indicate the extent of information that became available after this paper was finalised, based on the date it was accepted for publication. The most important is a retraction which should have an alert level score. Lesser scores should indicate whether there are subsequent studies that cite this one. Drill down details could be based on citation information to indicate the influence of the paper and ideally, but more difficult, there could be details of the agreement with subsequent findings.

We propose another high level indicator of the ranking of the publication. This is not a straightforward process, as evidenced by the many publication ranking schemes. It could also be designed in light of the presentation approaches for rankings for news outlets, such as the one created by the American Council of Science and Health [5, 20].

The design of the user interface elements for social media users could both account for, and make use of, their underlying motivations and cognitive biases. For example, we could draw on techniques in community-based social marketing (CBSM) [23, 28]. In another example, availability, bandwagon and framing biases are play a role in helping social media users recognise junk news based on a very simple indicator of the assessment by fact-checkers [53]. That crowd-sourced study suggests that such a simple indicator can reduce sharing of news marked as unreliable, offering a promising way to reduce the dissemination of misinformation. We envisage that personalisation could also enhance such interface elements, for example by taking account of personality [47].

CONCLUSION

There are many ways to create junk news; our focus is on just one pathway to junk news, based on published scientific research. So, for example, we do not consider junk news that is entirely fabricated. There are also many drivers for each stakeholder group to create junk news, on a spectrum from malicious to completely unintended. Our work focuses on the unintended end of that spectrum, in the situations where people's cognitive biases enable the creation, consumption and dissemination of junk news. This paper focused on examples of miscommunication in science papers; similar processes apply in other domains.

This paper has argued that each stakeholder is important in the creation and amplification of misinformation [38, 51]. We have proposed that new user interface elements could help overcome this. We explored these in the case of reviewers, who are early in the process and play a critical role as gate-keepers and in their ability to influence revisions to the initial publication. We then explored the end-point of the process, the social media user. We have proposed a small set of quality indicators: overall confidence in the strength and quality of the claims; conflict-of-interest, reproducibility, ranking of the publication and updates. These need to be designed to account for the needs of *non-expert on social media* [9].

Our work reflects the spirit of initiatives led by Meta-fact[1] and Retraction Watch [2]. Our work is different from these in important ways: 1) consideration of the role of the range of stakeholders, notably the reviewer; 2) exploring the different nudging mechanism for different stakeholders; 3) recognising the important gulf between the social media user and updates such as retracted scientific findings [43]. We have mapped an approach to enable each stakeholder group to act as gatekeepers of the flow of science news. We hope this will enable them to limit the influence of junk science and to recognise quality science news in the digital world.

[1]Metafact is an expert crowdsource based platform to verify facts and claims **https://metafact.io/about_us**

[2]Retraction Watch is a website that keep tracks of paper retracted **https://retractionwatch.com/**

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