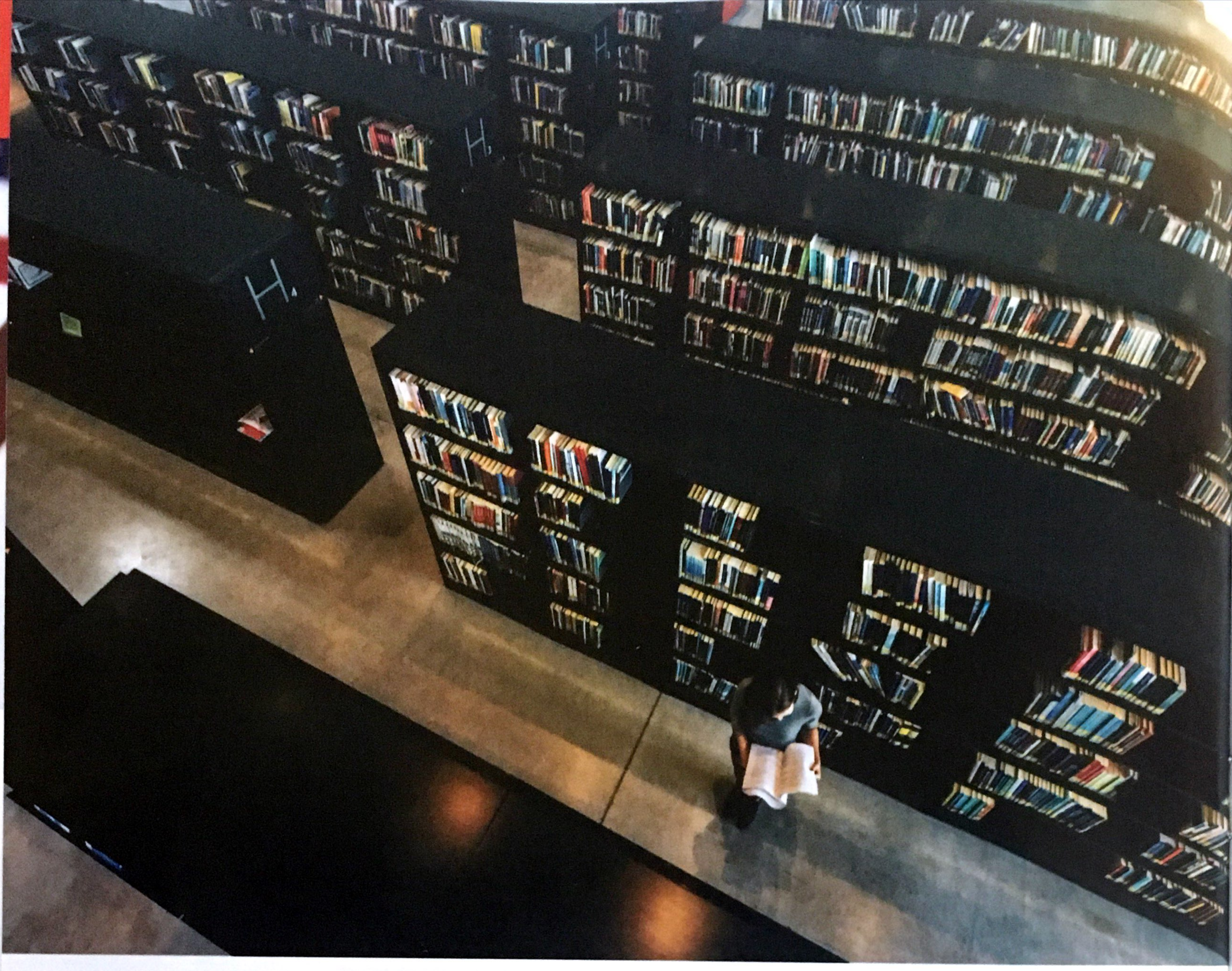

Mind your language

Attempts to explain the findings of observational studies might lead readers to confuse correlation with causation. **Dalmeet Singh Chawla** reports

Readers of scientific content often find it difficult to decipher simple correlations from causal relationships – but are researchers partly to blame? A new analysis suggests they may be.

The study, posted before peer review on the preprint server bioRxiv in November 2017 (bit.ly/2BXvgKY), suggests that readers are more likely to interpret inferential analyses as causal when authors attempt to explain their findings.

In January 2013, thousands of students with varying levels of statistical expertise – who had seen definitions of various relationships and study types as part of an online course – took a multiple-choice quiz. In one question, they were presented with an observational study claiming a link between smoking and lung cancer, and were asked to state what type of analysis this described.

The correct answer was "inferential", but students were also given incorrect answer choices, including "descriptive", "causal", "predictive" and "mechanistic".

Students were split into two groups. Before answering the question, both groups were presented with the following text: "We take a random sample of individuals in a population and identify whether they smoke and if they have cancer. We observe that there is a strong relationship between whether a person in the sample smoked or not and whether they have lung cancer.

The solution is not to avoid all arguments of causality, says mathematician Rebecca Goldin

We claim that the smoking is related to lung cancer in the larger population."

One group, however, saw this additional explanatory text: "We explain we think that the reason for this relationship is because cigarette smoke contains known carcinogens such as arsenic and benzene, which make cells in the lungs become cancerous."

In both groups, the majority of respondents correctly identified the analysis as "inferential". However, in the group presented with the explanatory text, 32% described it as "causal", compared with 17% in the group that did not see the additional text. The researchers later repeated the experiment with a second, smaller batch of students. Again, roughly twice as many described the analysis as "causal" in the group presented with the explanatory text.

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The implications for communications

Leah Jager, a biostatistician at Johns Hopkins University in Baltimore, Maryland, and co-author of the study, speculates that the results would hold up among a broader audience. She notes, however, that the wider public may have a different view of what can be called "causal", and may not know the difference between observational and experimental studies.

Within the statistics community, it is clear when one can start to make causal conclusions, says Jager. But this boundary may be more of a grey area for consumers of science and researchers from other fields who do not specialise in statistics, she says.

Jager does not believe scientists are deliberately including explanatory language as a way to deceive or mislead people, but she thinks it is important to be aware that the inclusion of certain phrases may have unintended consequences. Indeed, one possible extension of this study is to investigate whether different types of explanatory language have different effects.

Ron Wasserstein, executive director of the American Statistical Association (ASA), says: "It is quite natural to suggest a possible explanation for research results in inferential studies. This troubling outcome challenges us to rethink how we communicate results."

Evidence and opinions

Jager thinks some confusion might be avoided if researchers were to explicitly state that by including explanations they do not mean to imply there is necessarily a causal relationship between two phenomena. Another option, she says, is for journals to post warnings for authors to check wording before submitting papers.

But the solution is not to avoid all arguments of causality, says Rebecca Goldin, a mathematician at George Mason University in Fairfax, Virginia, "since such arguments are often put in scientific context, relying on other literature and often connecting to mechanistic explanations".

"It's important that the causal conclusions are framed as opinions and grounded in other scientific research," says Goldin, who also directs the non-profit statistical literacy initiative STATS (which is a collaboration between the ASA and Sense About Science USA).

Critiquing the study, Goldin notes that "the authors picked a topic that will exaggerate the effect they are measuring, as it is widely acknowledged that cigarette smoking does in fact cause lung cancer". The same point was made by Chris Hartgerink, a statistician at Tilburg University in the Netherlands, who reviewed the study publicly with colleagues after reading it at their preprint journal club (bit.ly/2BTyGbY).

Like Goldin, Hartgerink and colleagues think that the smoking and lung cancer example might "create stronger effects than other associations". However, in explaining why they think the study is relevant, they write: "Considering that humans seek order in the world, it seems plausible that this also happens in the interpretation of research findings, but that researchers might forget to keep these claims tentative. If such language affects the interpreted scope of the results, it is important as a self-reflection in order to adjust writing behavior in the future to better reflect the scope of the analysis." ■

Dalmeet Singh Chawla is a freelance science journalist based in London, UK, who has written for *Nature*, *Science*, *New Scientist* and *The Economist*, among others. In 2016, he spent a year as a reporter with *Retraction Watch*.

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