Understanding the quality of a quantitative paper 6: bias and confounding

KEY WORDS
- Quantitative
- Bias
- Error
- Systematic
- Confounding
- Stratify

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In the previous paper in this series, we considered the concept of research bias. We saw how bias can be introduced during study design, research execution, and analysis. We identified that some papers do not get published because they do not have statistically significant findings or are subject to publication bias, and so their learning may be lost to the wider research and health and social care practice communities.

We saw that bias is important because it has the potential to change the findings of a study such that it is not possible to place faith in what was found (Parahoo, 2014). We also discussed how bias cannot be managed at the analysis stage of a study and must therefore be thought about and designed out before a study is undertaken. Confounding is another form of error that can occur in the design and undertaking of a study that can be managed at the analysis stage.

This paper will identify and discuss some of the forms of bias that were not discussed in the previous papers in this series, as well as go on to discuss the nature of confounding in quantitative research and how this might be managed. Readers are reminded that considerations of bias are important when reviewing the quality of research, especially research that may be applied to clinical practice — this paper gives an indication of what the reader might therefore look for when reading a research paper.

THE HAWTHORNE EFFECT

This is a well-known and described form of bias that reflects the findings from a number of experiments undertaken in workplaces that suggest that when workers are enrolled in research studies, their productivity increases. This increase in productivity, essentially a change in behaviour, is thought to result from the fact that the workers are being subjected to increased attention (Polit and Beck, 2017).

Such an effect in a quantitative study might affect the behaviour of study subjects, both cases and controls, and could effectively change the outcome of a study. Like the workers, people involved in a study might choose, or inadvertently, change their behaviour because they are being observed and this might impact the size of the effect seen within a study.

The use of randomisation and blinding in randomised controlled trials (RCTs) may help negate such an effect because people are unaware as to which group they are assigned to, so any changes in behaviour are likely to be distributed evenly across the groups.

VOLUNTEER BIAS

People who volunteer, or 'self-select', to participate in research are by definition different to people who do not. Malone et al (2014) note that people who participate in research, regardless of whether they are in a treatment or control arm of an RCT for example, tend to do better than people who are subject to routine care. This is a concept that is broadly similar to the Hawthorne effect and is addressed in RCTs, for example, by having a treatment and control arm. The idea here is that if people in both groups randomly change their behaviour it is likely that the change in behaviour will be equally spread between the groups such that the effect of the change is negated in the analysis.

Volunteers, for example, might if enrolled in a study of a new wound dressing decide to exercise more, eat more healthily or stop or cut down on smoking, which might play a role in speeding up wound healing regardless of the dressing being studied. This would not matter in an RCT because the change in behaviour is just as likely to occur in the treatment arm as it is in the control arm of the study.

RECALL BIAS

This form of bias also results from the behaviours of people participating in a study that requires them to remember something. Recall bias is therefore associated with retrospective case-control studies

(studies that compare exposures to potentially disease-causing phenomena between people who have a disease (cases) and people who do not, controls (Ellis, 2015)). In such studies, people tend to underreport things that may be embarrassing or that they don't consider as being related to the study, e.g. their use of healthcare services, especially if their use was associated with a mental health issue (Khare and Vedel, 2019).

Another common example of recall bias is that people with lung cancer are more likely to provide a fuller smoking history than people without lung cancer because they are aware that there is an association and have had time to think about it.

The obvious strategy for overcoming recall bias is to use other sources of evidence for a study (Malone et al, 2014). Using the example above, this would mean accessing patient records to ascertain the actual number of visits a patient made to various healthcare facilities and checking visit records to see if the individual smokes.

PARTICIPANT REPORTING BIAS

In some studies, participants may be embarrassed to report a behaviour, such as illicit drug use, or a disease or illness, such as a sexually transmitted disease. Such underreporting can seriously skew the finding of a study and may indicate that some behaviours, e.g. sexual behaviour, may not be amenable to self-reporting in some forms of study (Gallo et al, 2011). A health or social care professional reading a research paper which covers a potentially sensitive topic would expect to see that the researchers have made some efforts to reassure participants about the way in which their information is handled or found some other mechanisms to ensure their data collection is of good quality.

CONTAMINATION BIAS

Stuckless and Parfrey (2021) identify contamination bias as a further source of bias that may affect RCT participants. Contamination occurs when the people in the control group of the RCT, those not getting the treatment that is being studied, are in some way exposed to the intervention, or a part of the intervention, that is being applied to the treatment group.

This might occur, for example where a wound care study involves the treatment group being given additional lifestyle advice that is not given to the control group, but which researchers inadvertently also apply in some part to those in the control group. A similar effect might be seen, as was the case in the falls in care homes (FinCH) study, where new falls prevention initiatives that had nothing to do with the study were introduced in the areas in which the study was taking place. The new initiatives may have reduced falls and therefore caused the impact of the FinCH initiative to be underestimated (Robinson et al, 2020).

In studies where there is a risk of contamination, the reader might expect to see that the researchers have separated the people providing the intervention from those who are providing usual care (controls); cluster randomisation, that is enrolment to the study not as individuals but as a collective group e.g. all patients in one GP practice are either cases or controls; ensuring clinicians in the locality are aware of the study and how they might contaminate it.

CONFOUNDING

Confounding is a special form of bias. A confounding variable is a variable which is independently associated both with the outcome of interest and the exposure (Stuckless and Parfrey, 2021). In RCTs, confounding is not so much of an issue as it is dealt with by the randomisation process, but in other forms of quantitative research, it can be ruinous for the study if not noted and dealt with (Vetter and Mascha, 2017).

Ellis (2022) gives a simple example of confounding as the development of coronary heart disease (CHD, the outcome) and its association with both smoking and drinking alcohol (both exposures). Both smoking and drinking alcohol are independent of each other and associated with the development of CHD. People who smoke are also known to, as a rule, drink more alcohol than other people, so drinking large amounts of alcohol and smoking are both associated with each other and with the development of CHD.

A study that fails to collect data on both exposures might therefore overestimate the effect of an exposure on causing the outcome of interest. That said, a study which collects data on both exposures can, in the analysis, deal with this by looking at the statistical strength of the association

between the development of CHD and people who, returning to our example, smoke and don't drink, people who drink and don't smoke and people who do both. This approach is called stratification and, like regression analysis and standardisation, can be used in the analysis to manage the effects of confounding on the results (Kahlert et al, 2017). Someone reading such research might expect to see the researchers identifying potential confounding variables and identifying how they have dealt with them.

CONCLUSION

In this paper, we have identified some further sources of bias that might impact quantitative studies. Such bias could mean that nurses and other health and social care professionals are unable to place faith in the findings of the research. It is therefore important that before undertaking a study, researchers must identify potential sources of bias and design around them.

We have seen that confounding is a special form of bias, in which a confounding variable is independently associated with both an exposure of interest and the potential outcome of interest. Unlike bias, we have seen that confounding can, when identified, be managed during the analysis phase of a study.

In these last few papers in this series, we have identified some of the ways in which the integrity of a research design, its undertaking and analysis can be affected by poor study design and how this might impact the faith that a reader may place on the findings and hence their applicability to practice.

In subsequent papers in this series, we will continue to look at quantitative research methodologies and methods and what healthcare professionals should look for before deciding whether the research is applicable to their practice.

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