Viewing mode effects through the lens of causal directed acyclic graphs (DAGs)

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METHODS COLLABORATION

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Background

Many surveys have implemented or are transitioning to mixed-mode designs.

This brings two key challenges:

Mode effects

Mode selection

Mode effects

Differences in ***how*** people respond by each mode

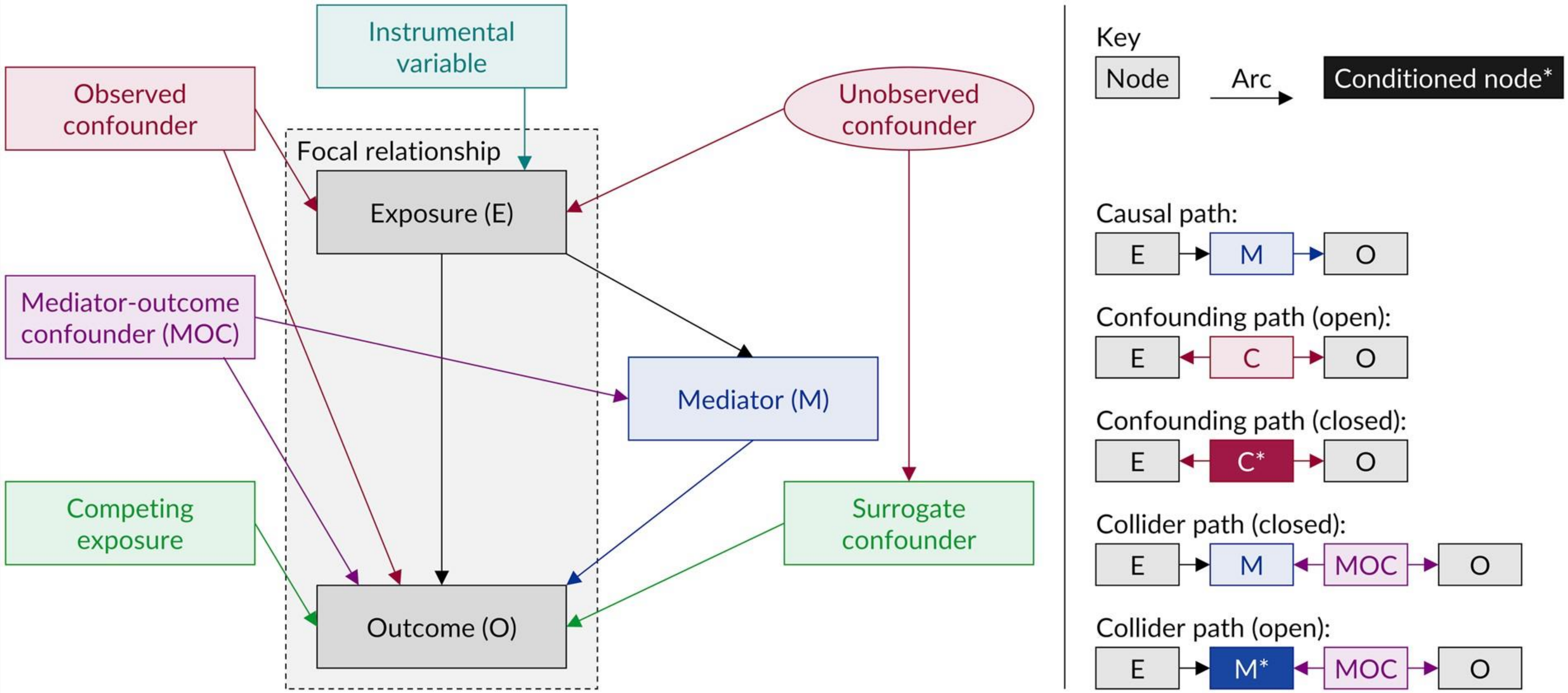
- a type of systematic measurement error
- can introduce error or bias in analyses

Mode selection

Differences in ***who*** responds by each mode

- does not automatically introduce bias in analyses
- but can introduce bias if handled inappropriately

Directed acyclic graphs (DAGs)



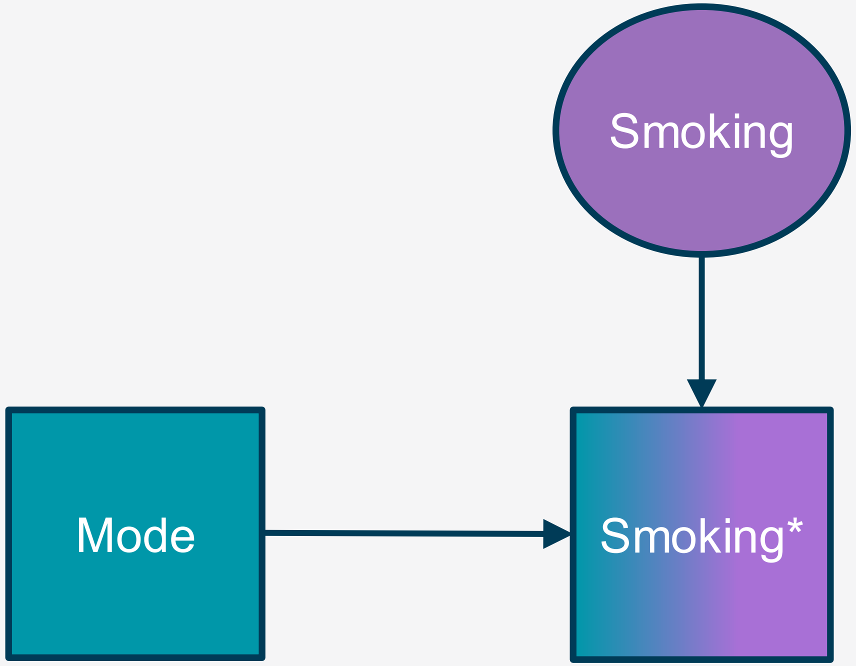
Tennant et al. 2020. *Int J Epidemiol*

Mode effects: descriptive statistics

example: prevalence of **smoking**

The measure will be a combination of:

- the true value of smoking
- variation introduced by **survey mode**

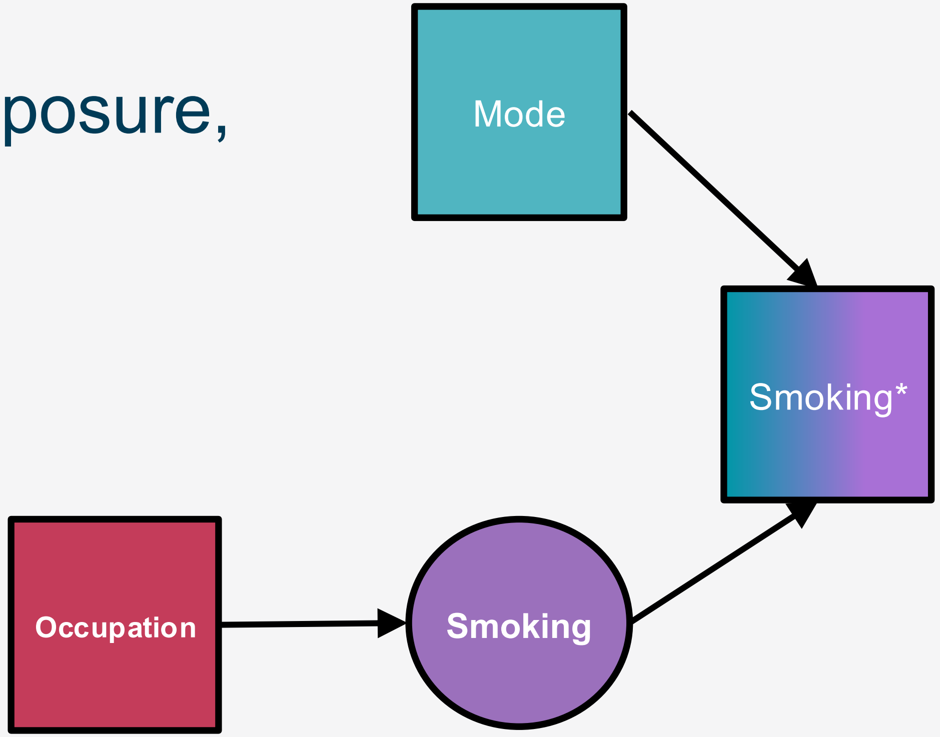


Mode effects: outcome

example: the effect of **occupation (the exposure)** on **smoking (the outcome)**

Mode causes the outcome, but not the exposure, i.e. it is a **competing exposure**

This introduces **error**, but not **bias**



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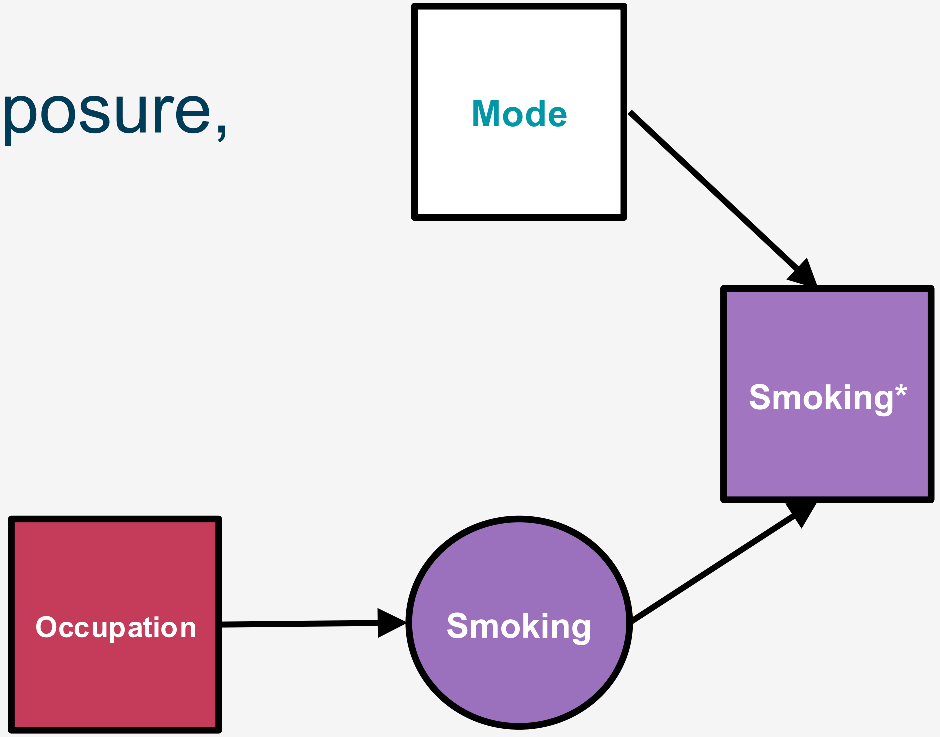
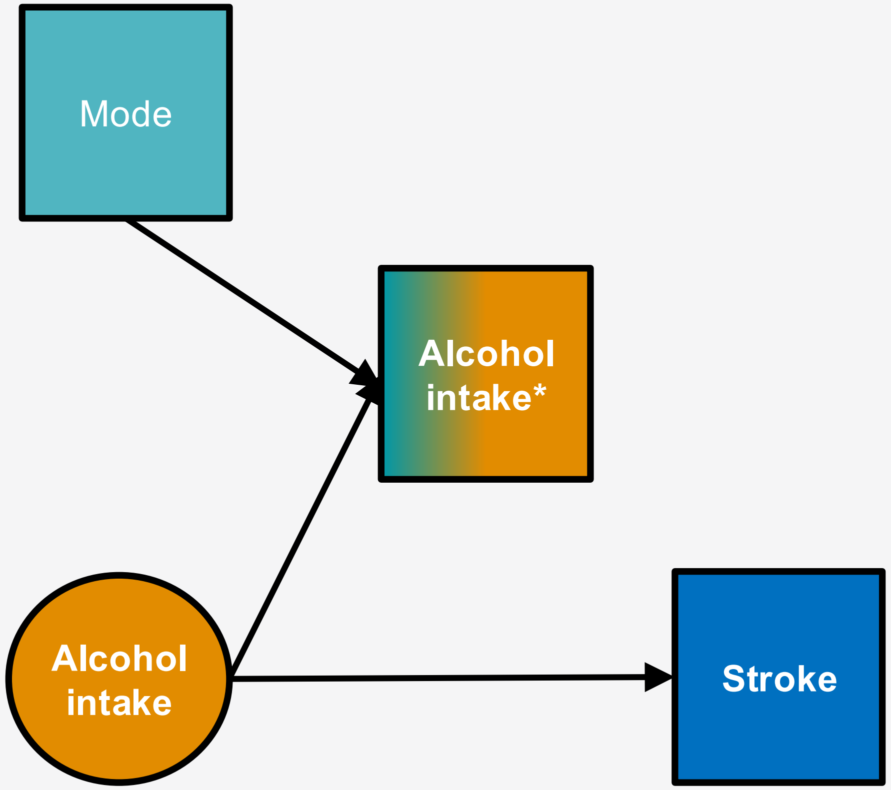
It can be resolved by conditioning



Mode effects: exposure

example: the effect of **alcohol intake (the exposure)** on **stroke (the outcome)**

Uncontrolled, this scenario can introduce **regression dilution (attenuation)**, biasing the relationship towards zero.



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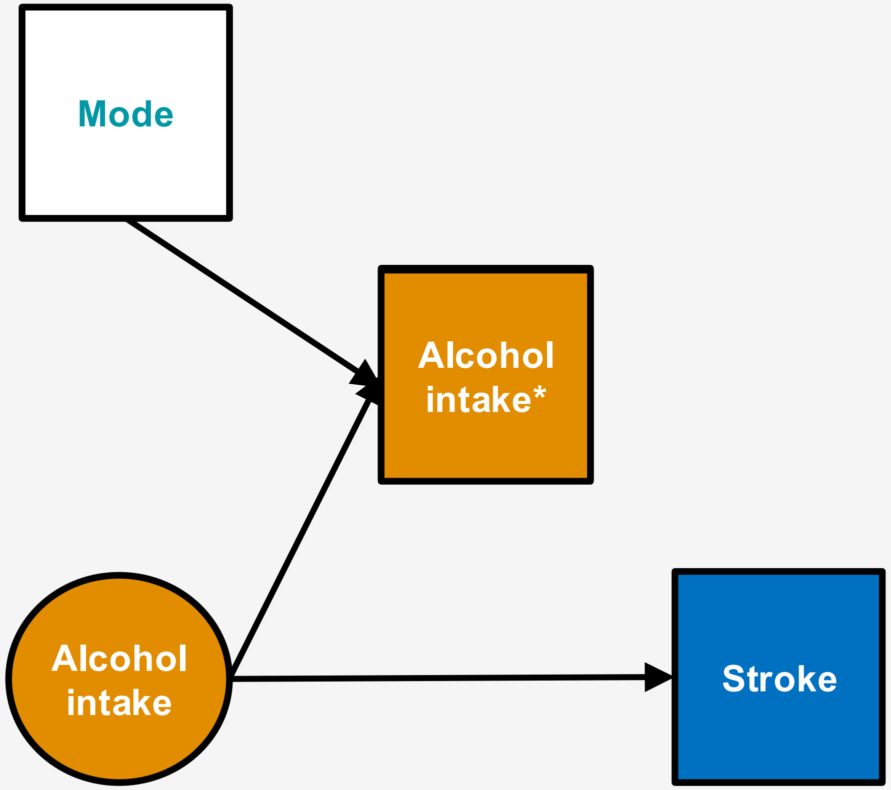
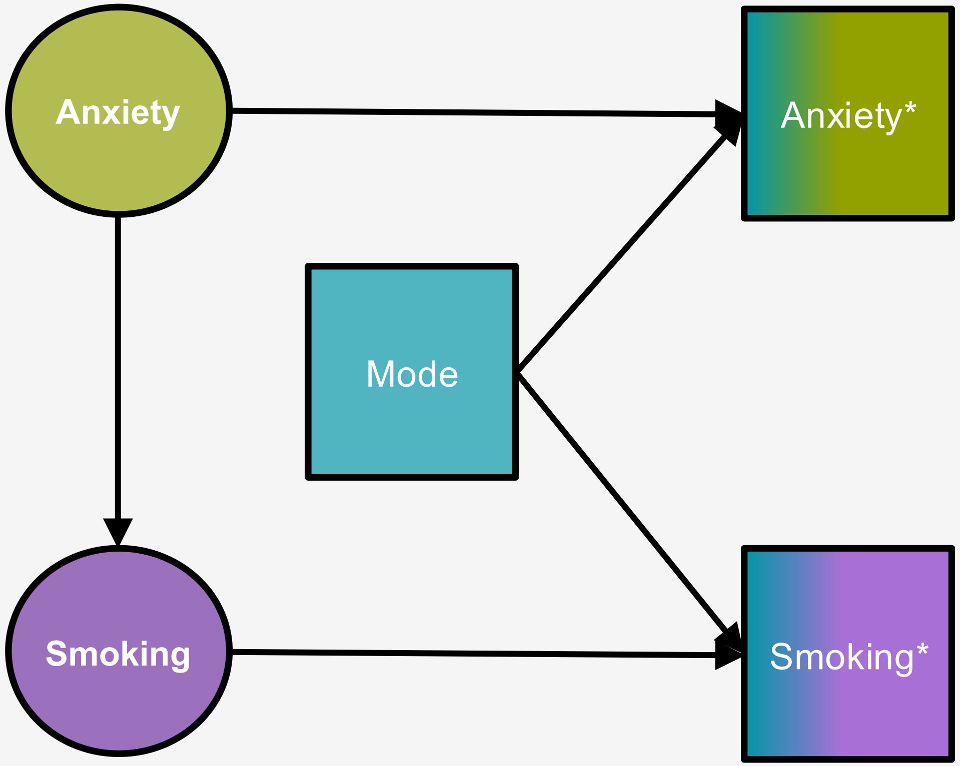


Mode effects: exposure and outcome

example: the effect of **anxiety** on **smoking**

We may expect both **anxiety** and **smoking** to be subject to mode effects **i.e. mode** is a **confounder**



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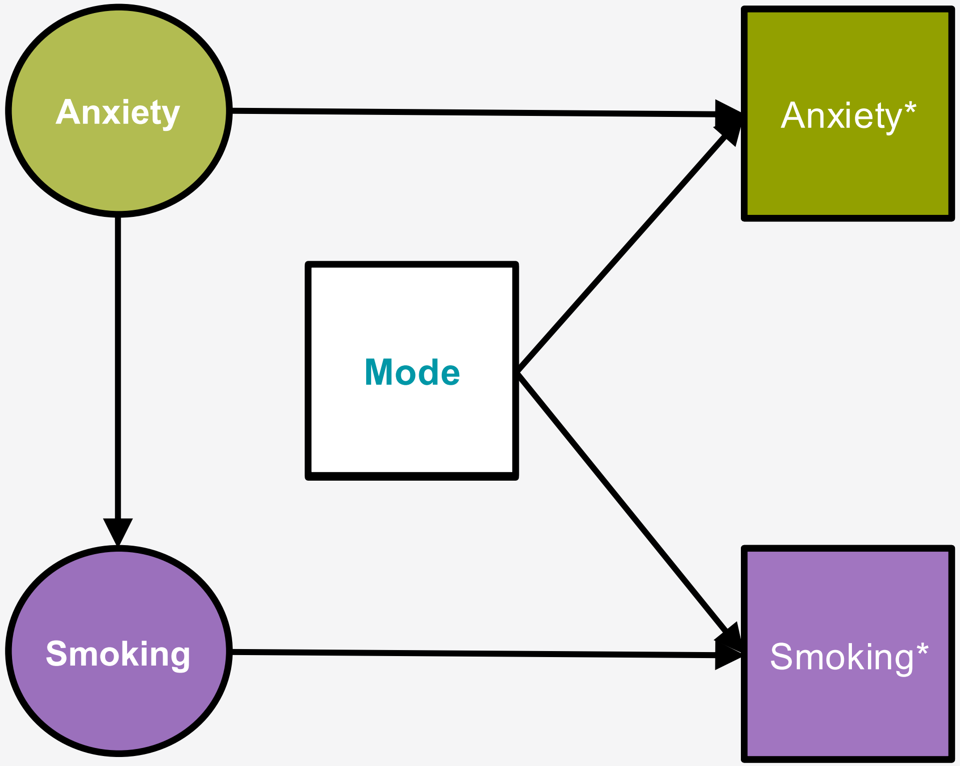
Conditioning on mode will remove the confounding

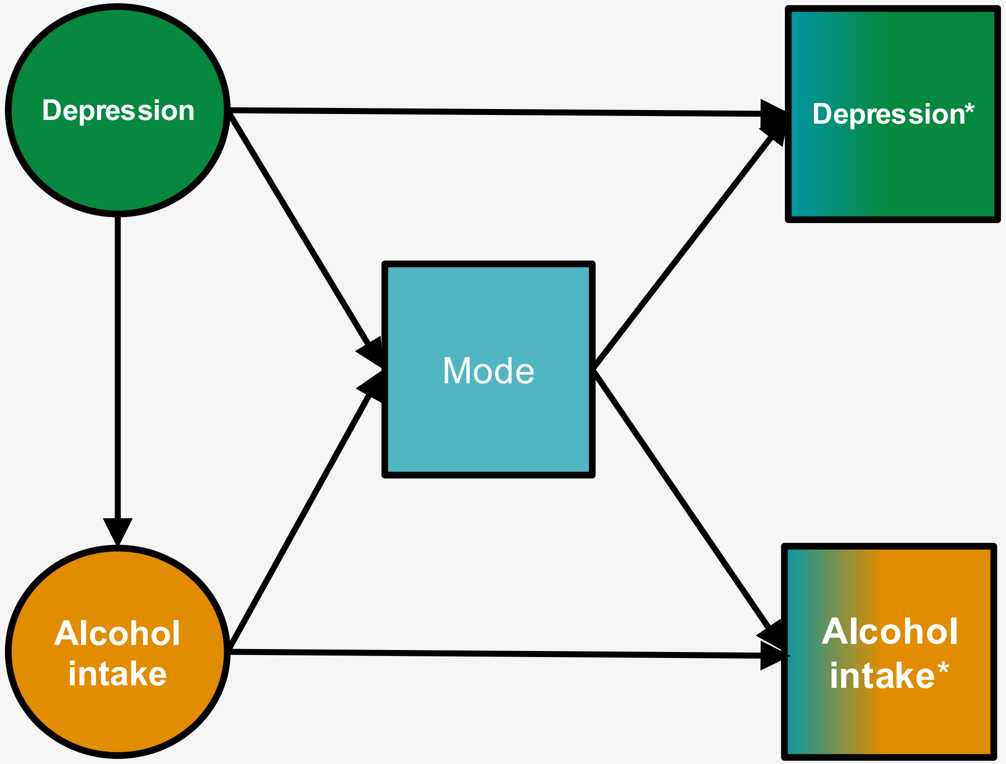


Mode effects and mode selection

example: the effect of **depression** on **alcohol intake**

Both may be subject to mode effects

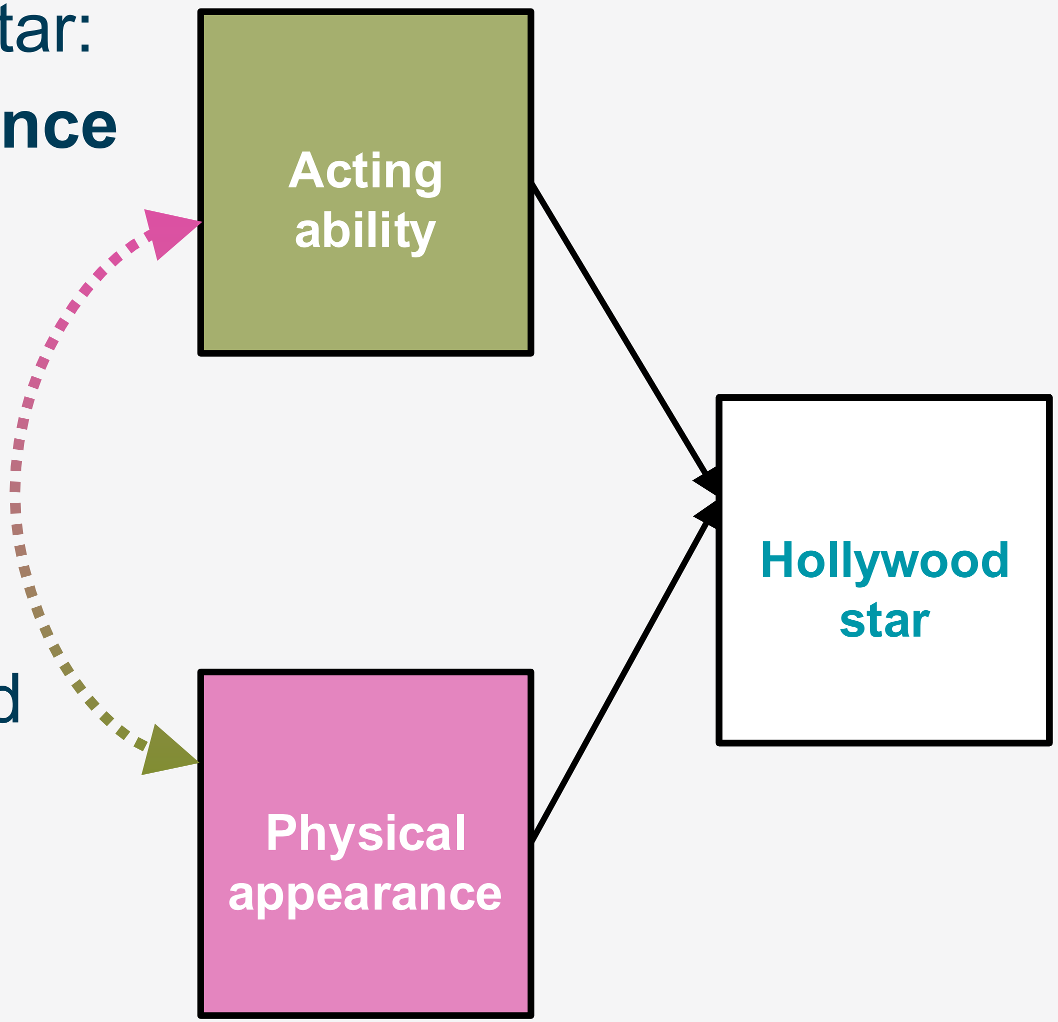
Both may be related to participation via a certain mode



Collider bias

Two reasons for being a Hollywood star:
acting ability and **physical appearance**

Conditional on being a Hollywood actor…
There will appear to be a negative association between acting ability and physical appearance…

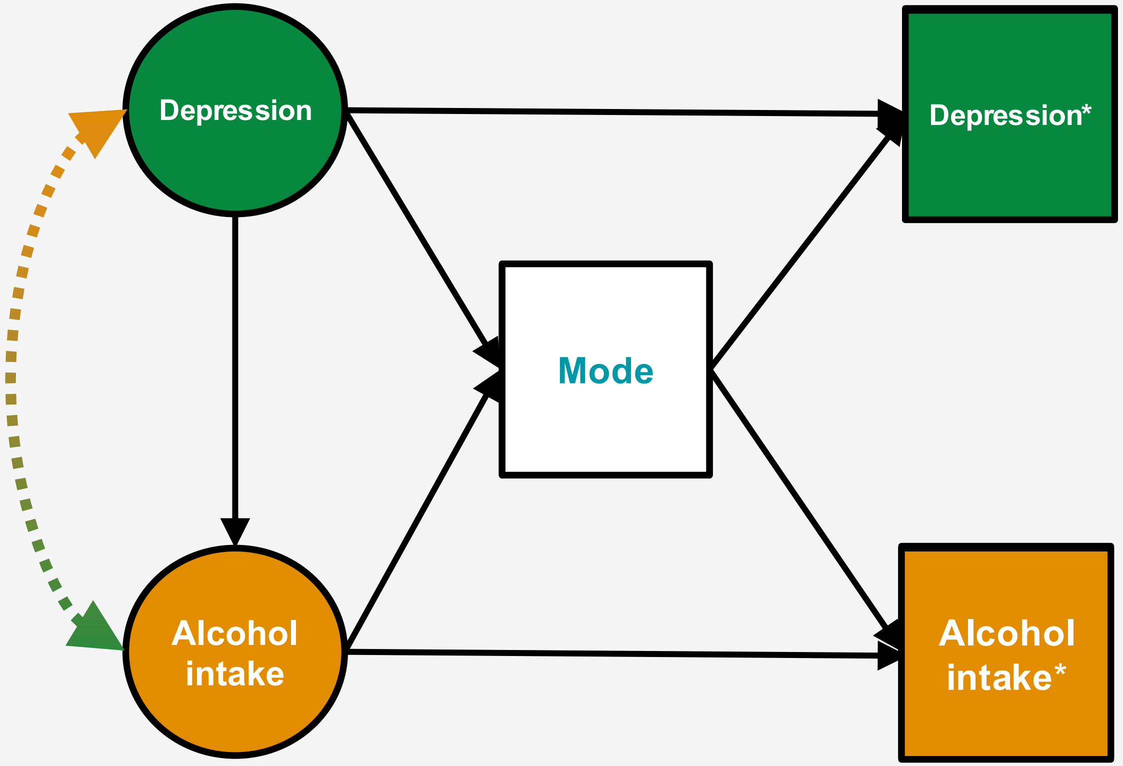


Mode effects and mode selection

example: the effect of **depression** on **alcohol intake**

Survey mode may be both a confounder and a collider

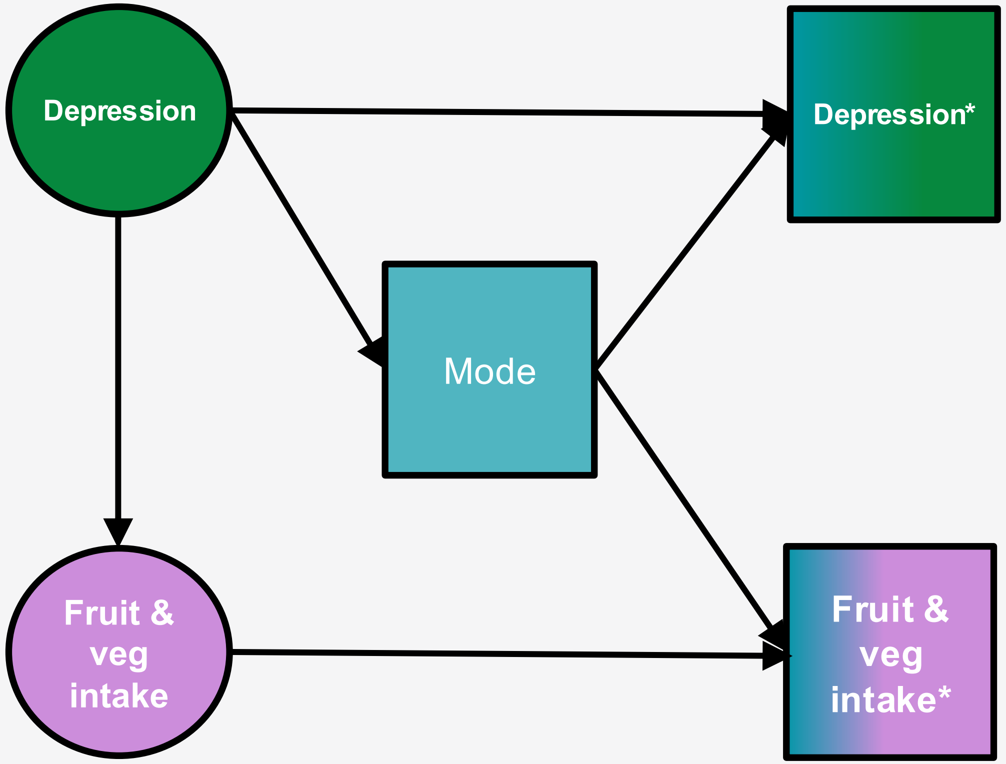
Conditioning will resolve one problem but introduce another…



Mode effects and mode selection

example: the effect of **depression** on **fruit & veg intake**

Fruit & veg unlikely to cause mode selection



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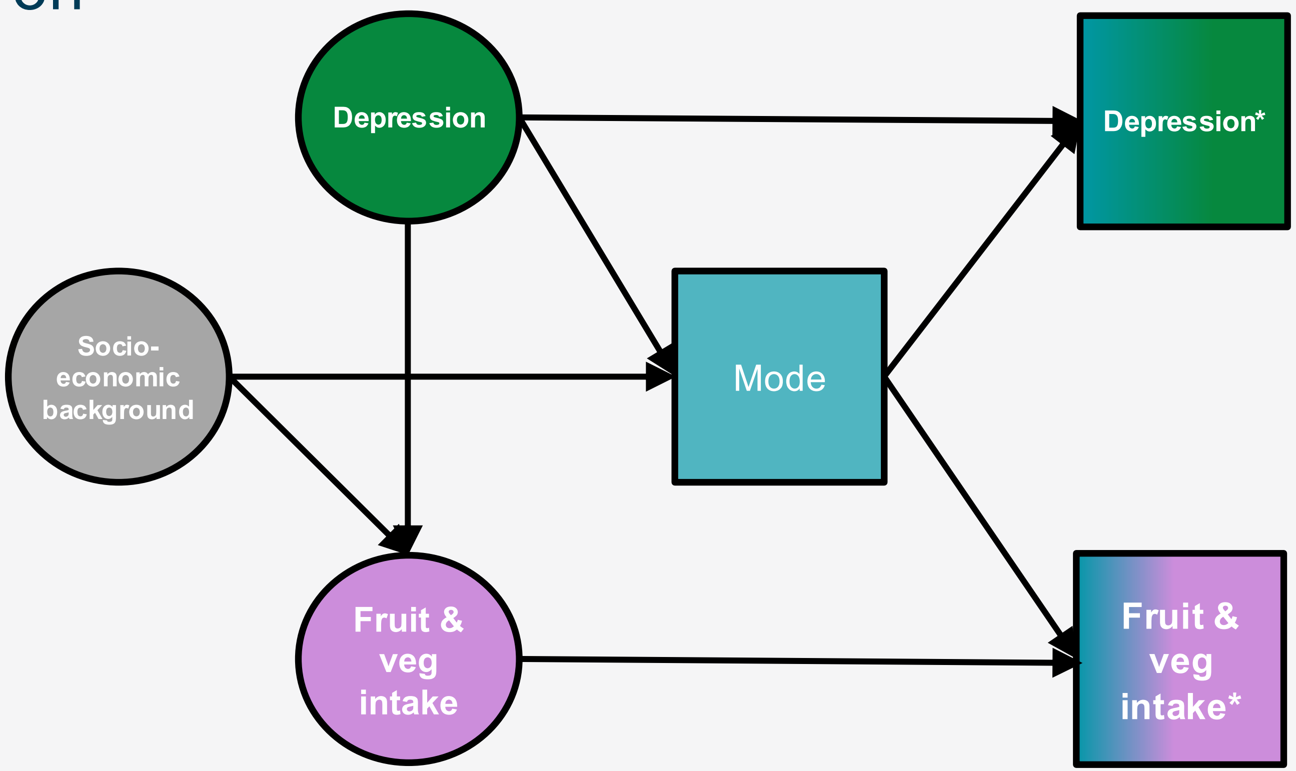
But naïve adjustment for mode will not be without problems…

Because other variables causing mode selection will exist



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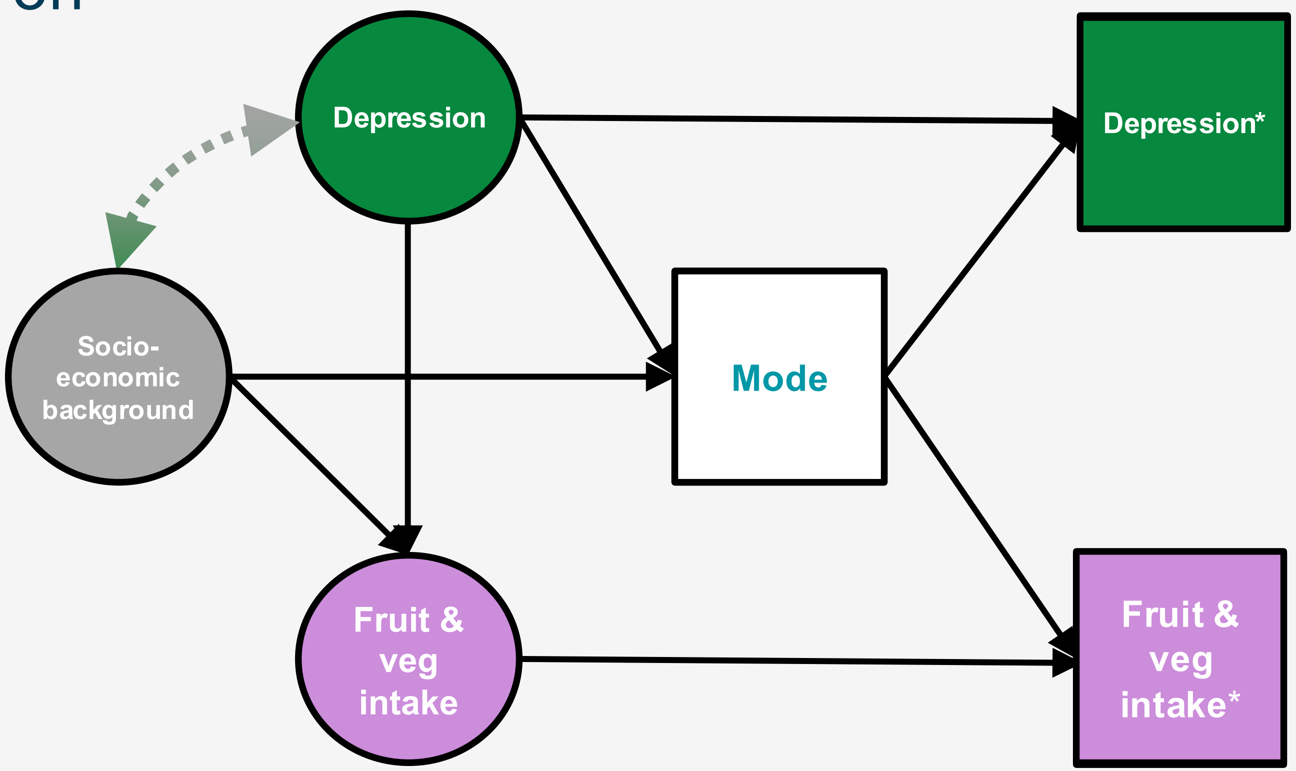


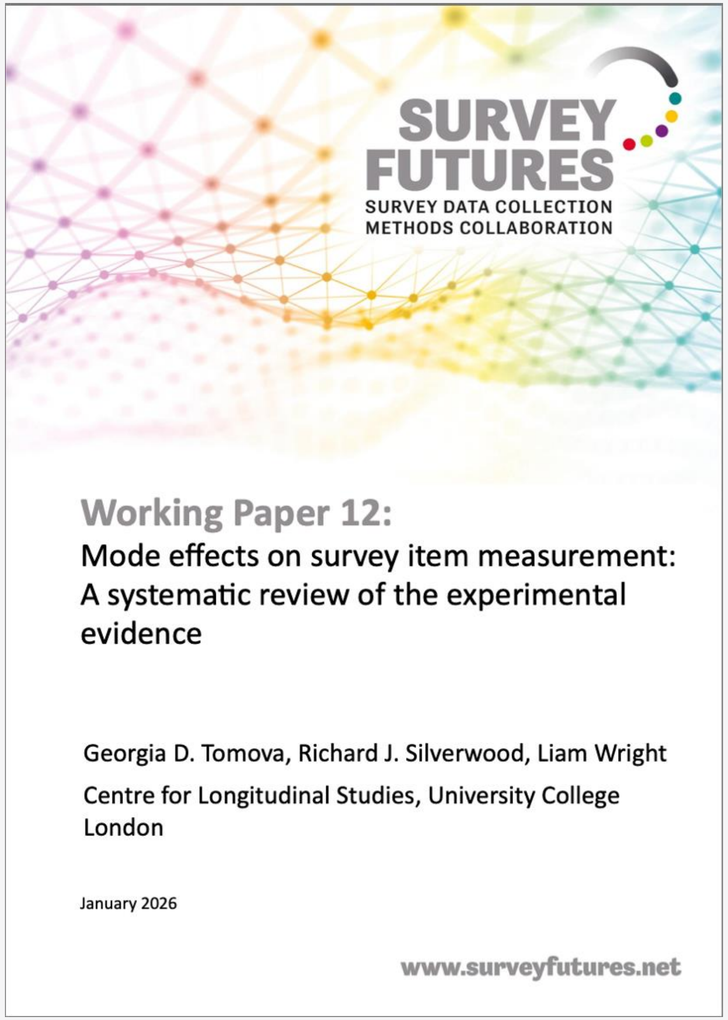
What can we do instead?
Quantitative bias analysis

- **Calibration**: use validation sub-sample or external information to calibrate estimates

- **Simple sensitivity analysis**: determine the size of mode effect required to explain away an association

- **Counterfactual simulation:** given the hypothesized size of a mode effect, simulate a counterfactual single-mode analysis

Systematic review


SURVEY FUTURES
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Working Paper 12:
Mode effects on survey item measurement: A systematic review of the experimental evidence

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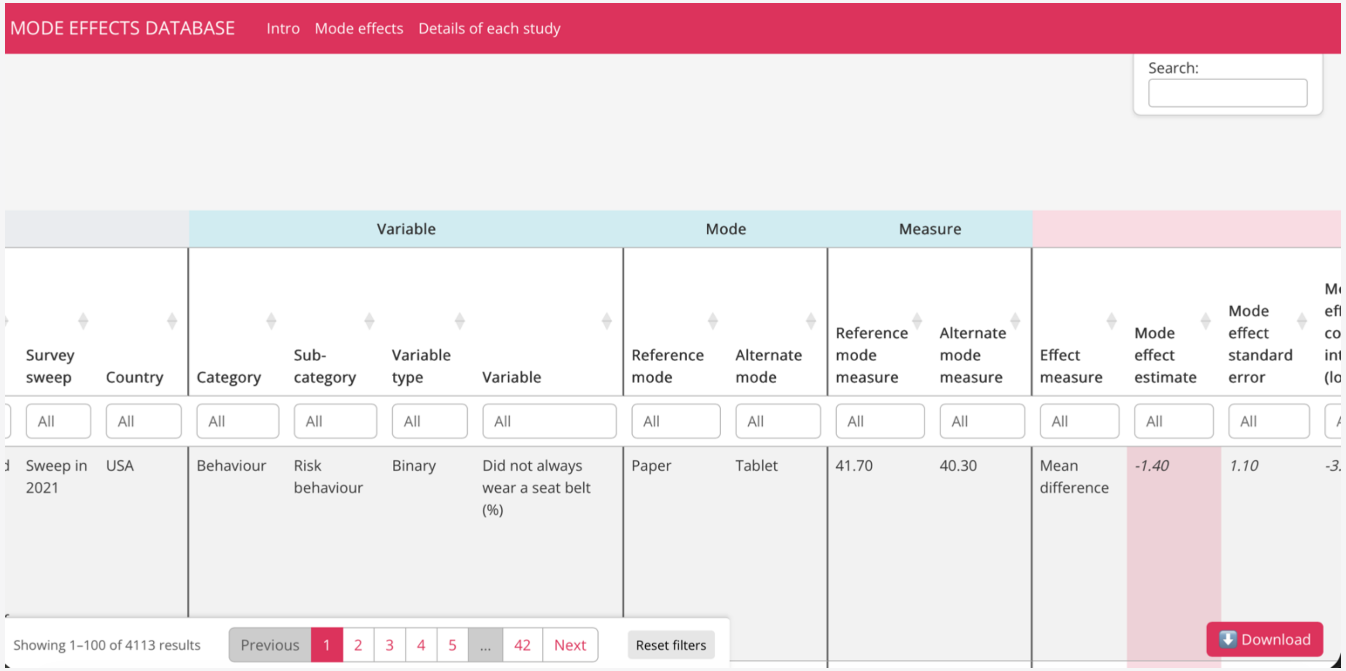
Centre for Longitudinal Studies, University College London

January 2026

www.surveyfutures.net

Database of mode effects



https://cls-data.github.io/mode-effects-database/

Publication

American Journal of EPIDEMIOLOGY

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JOURNAL ARTICLE ACCEPTED MANUSCRIPT

How can the use of different modes of survey data collection introduce bias? An introduction to mode effects using directed acyclic graphs (DAGs)

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Abstract

Survey data are self-reported data collected directly from respondents by a questionnaire or an interview and are commonly used in epidemiology. Such data are traditionally collected via a single mode (eg, face-to-face interview alone), but use of mixed-mode designs (eg, offering face-to-face interview or online survey) has become more common. This introduces two key challenges. First, individuals may respond differently to the same question depending on the mode; these differences due to measurement are known as “mode effects.” Second, different individuals may participate via different modes; these differences in sample composition between modes are known as “mode selection.” Where recognised, mode effects are often handled by straightforward approaches such as conditioning on survey mode. However, while reducing mode effects, this and other equivalent approaches may introduce collider bias in the presence of mode selection. The existence of mode effects and the consequences of naïve conditioning may be underappreciated in epidemiology. This paper offers a simple introduction to these challenges using directed acyclic graphs by exploring a range of possible data structures. We discuss the potential implications of using conditioning- or imputation-based approaches and outline the advantages of quantitative bias analyses for dealing with mode effects.

User guidance

IOE, Faculty of Education and Society

UCL

Handling Mode Effects in the CLS Cohort Studies

User Guide

November 2024

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Thank you

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