

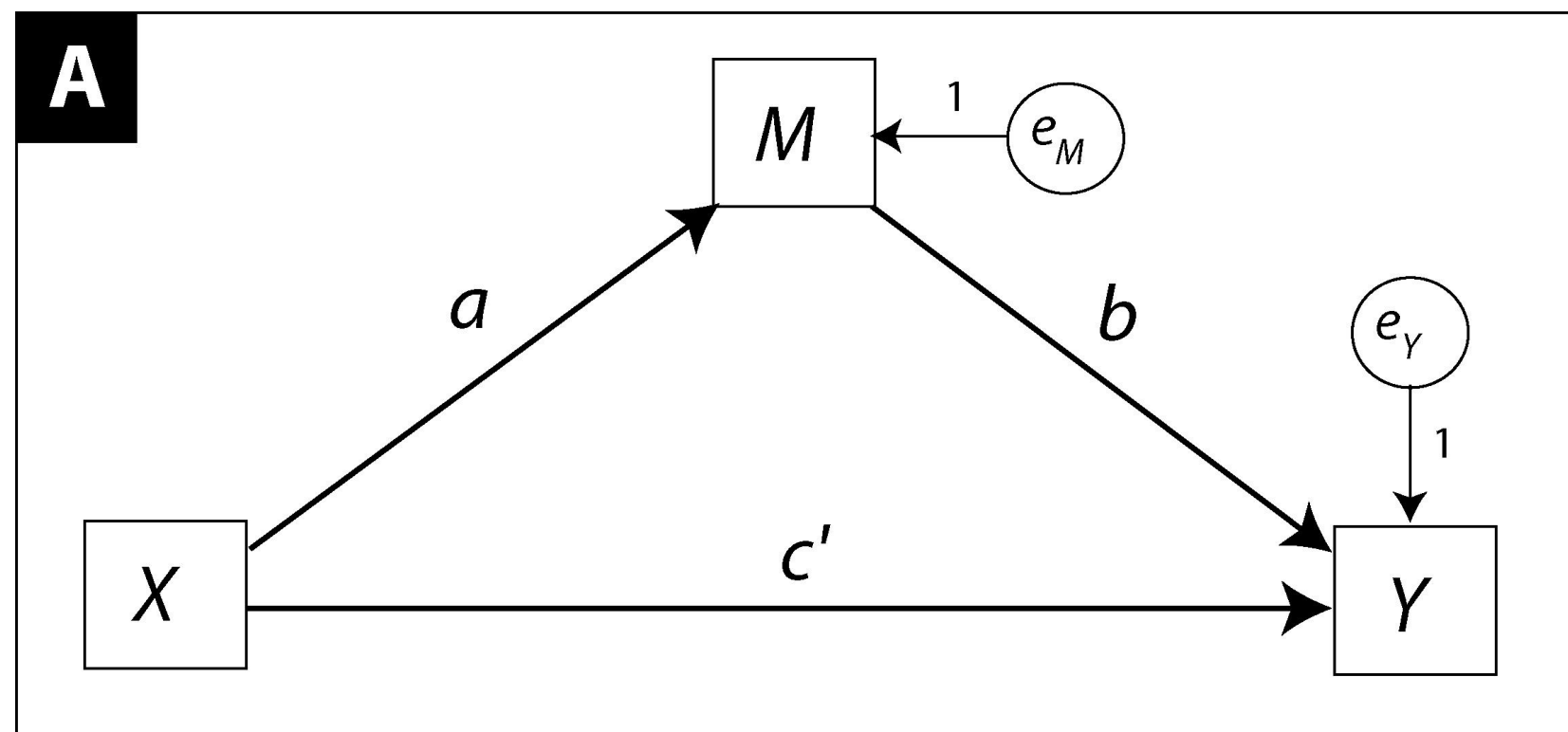
Consequences of and Remedies for Unaccounted-for Random Measurement Error in Mediation Analysis of Clinical Trials and Other Two-Group Comparisons

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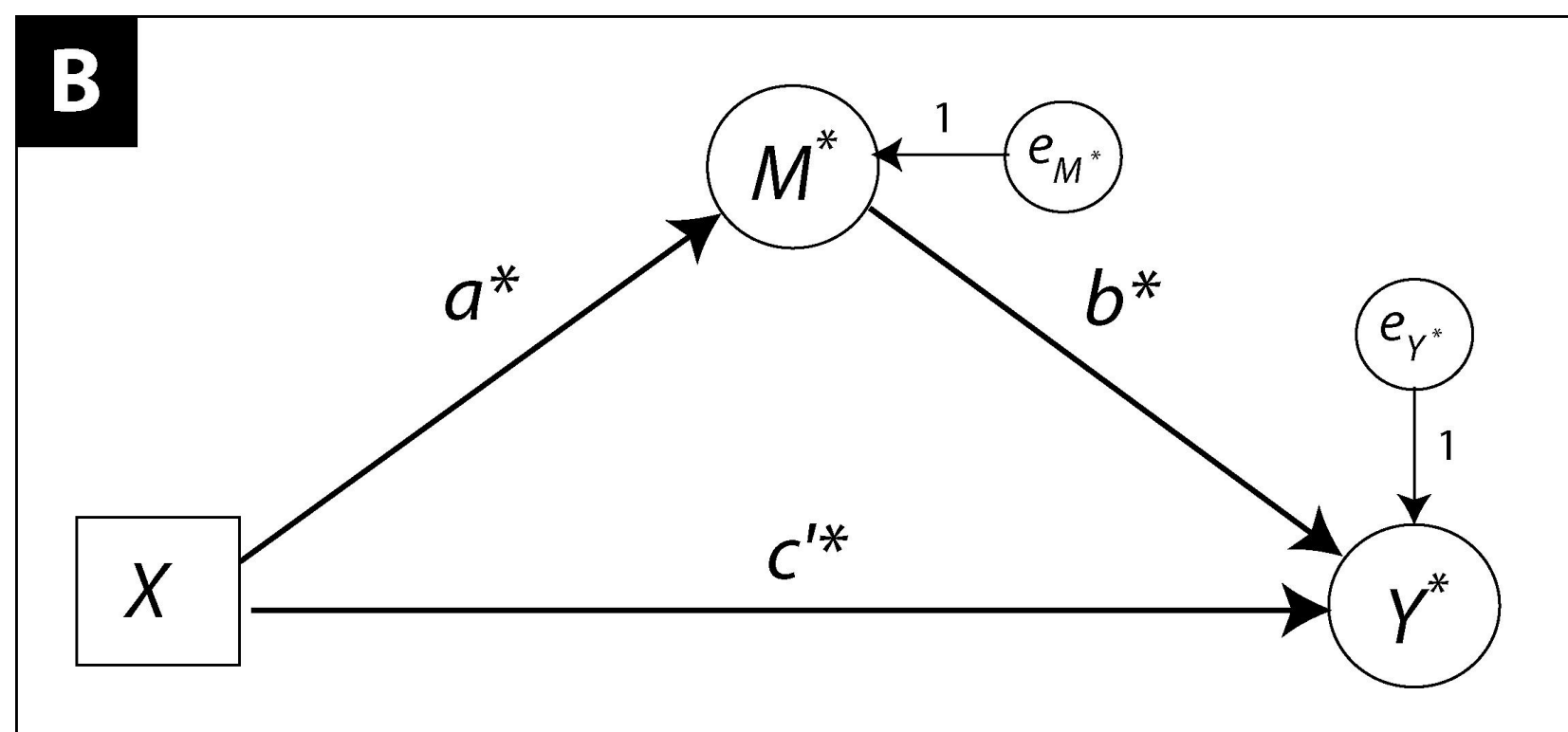
Indirect and direct effects are misestimated when random measurement error (RME) in the mediator is not acknowledged. PROCESS v5 can help.

Mediation analysis

In a mediation analysis, the investigator is interested in the direct, indirect, and total effects of X on Y . **In the typical clinical trial with X randomly assigned or known exactly, there is no measurement error in X** , but mediator M (and perhaps Y) are usually **observed scores** containing random measurement error (RME). The mediation model typically estimated is



But what we usually care about are the direct, indirect, and total effects of X on Y involving the **true scores** M^* and Y^* , had M and Y been measured perfectly without RME. In **B** below, b^* and c'^* are not the same as b and c' in **A** above when M in **A** contains RME.



Derivations and Implications

It can be shown that when estimating **A** instead of **B** with no measurement error in X but M measured with reliability ρ_M (and also making a few other assumptions people routinely make when conducting a mediation analysis)

$$E(a) = a^*$$

$$E(b) = b^*(\rho_M - r_{XM}^2)/(1 - r_{XM}^2)$$

$$E(ab) = a^*b^*(\rho_M - r_{XM}^2)/(1 - r_{XM}^2)$$

$$E(c') = c'^* + a^*b^*[(1 - \rho_M)/(1 - r_{XM}^2)]$$

$$E(c' + ab) = E(c') + E(ab) = c'^* + a^*b^*$$

This is all true
regardless of the
reliability of
measurement of Y

This means that ignoring measurement error in M in the analysis by estimating **A** will tend to result in...

- ...an estimate of the total effect of X that is correct. **GOOD**
- ...an estimate of the indirect effect of X that is typically closer to zero than reality. It will usually be attenuated toward zero. **NOT GOOD**
- ...an estimate of the direct effect of X that is under- or overestimated in magnitude, depending on the actual direct and indirect effects. **NOT GOOD**

Your estimate of the direct effect of X could be...

- ...opposite in sign of the actual direct effect of X .
- ...nonzero when the direct effect is actually zero.
- ...zero when the direct effect is actually nonzero.
- ...larger or smaller in magnitude than the actual direct effect.

MORAL: Expect that your estimates of direct and indirect effects of X in a mediation analysis will be wrong if you don't address random measurement error in the mediator.

Fixing the Problem

The hard way using structural equation modeling:

Here is an example program using lavaan in R that estimates a *single-indicator latent variable* model of the effect of cognitive behavioural therapy vs. therapy as usual ("cbt") on PTSD symptoms ("ptsd") through social support ("support"), with social support measured with reliability 0.7.

```

library(lavaan)
cbt<-read.table("cbt.csv", sep=",", header=TRUE)
library(lavaan)
model.silv<-"lsupport=~support
lsupport~a*cbt
ptsd~b*lsupport+cp*cbt
ab :=a*b
c := a*b+cp
support~~((1-0.70)*4.35)*support"
modelp<-sem(model.silv,data=cbt)
summary(modelp,rsquare=T)
set.seed(27654)
modelp<-sem(model.silv,data=cbt,se="bootstrap",bootstrap=5000)
parameterestimates(modelp,boot.ci.type="perc")
  
```

The easy way using the PROCESS macro, version 5

As of version 5, PROCESS for SPSS, SAS, and R implements **errors-in-variables regression** that fixes this problem with an accurate **estimate of the reliability of your measurements of the mediator**.

The PROCESS code below estimates the same model as the lavaan code above and generates (largely) identical results:

SPSS
process y=ptsd/x=cbt/m=support/**re1m=0.7**.

SAS:
%process (data=cbt,y=ptsd,x=cbt,m=support,**re1m=0.7**)

R
process (data=cbt,y="ptsd",x="cbt",m="support",**re1m=0.7**)