

## Mediated change in intervention studies

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Dear all,

I have previously discussed causality paradoxes, such as [Lord's paradox](#), Berkson's paradox, and [Simpson's paradox](#). Some of these paradoxes highlight issues of selection bias and some of confounding. Sometimes the paradox is simply a counterintuitive truth, while other times it is the product of fallacious reasoning.

The most well-known fallacy in statistics is that “correlation equals causation”, with web-pages dedicated to some of the [more humorous examples](#). Most researchers are aware that “**correlation does not imply causation**”. However, there is a lesser known counterpart to this, which is a paradox of concurrent change.

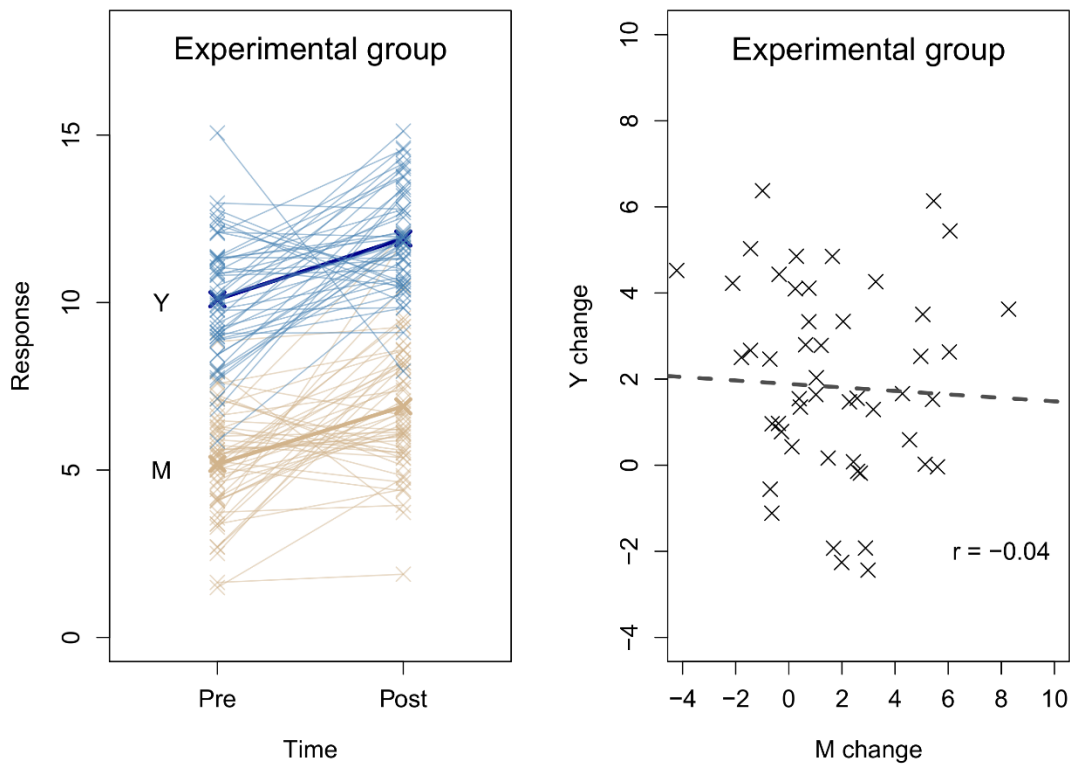


Figure 1. Observed changes in M and Y for the experimental group ( $X=1$ )

## Concurrent change paradox

Consider an intervention study with treatment groups  $X$  ( $0$ =Control,  $1$ =Experiment), and measurements  $M$  and  $Y$  taken at times  $T$  before ( $0$ = $T_1$ ) and after ( $1$ = $T_2$ ) the intervention.  $Y$  is the target outcome (e.g., well-being), while  $M$  is a mediating variable reflecting the mechanism of action of the treatment (e.g., emotion regulation).  $M$ -change is defined as  $\Delta M = M_{T_2} - M_{T_1}$ , and  $Y$ -change as  $\Delta Y = Y_{T_2} - Y_{T_1}$ .

In this scenario, significant change in both  $M$  and  $Y$  in the experimental group does not imply that the  $M$ -changes caused  $Y$ -changes, or even that they should be correlated. That is, just as correlation does not imply causation, **neither does concurrence imply correlation!** This may appear to be paradoxical, in that researchers would conclude that if both  $M$  and  $Y$  changed as a result of the intervention  $X$ , the two changes should also be correlated.

The attached graph shows an example for the experimental group. On the left, we see that both  $M$  and  $Y$  increased as a result of the intervention. On the right, however, we see that  $M$ -changes and  $Y$ -changes are not correlated. While we can conclude that the intervention significantly changed  $M$  and  $Y$  in the experimental group, there is no evidence for  $M$ -changes mediating  $Y$ -changes.

Several variations on the above scenario may occur, including ones that seem even more paradoxical. Each of the following effects may occur without the others' presence:

1. Significant or non-significant changes in  $M$  and  $Y$
2. Significant or non-significant mediation of  $Y$ -changes by  $M$ -changes
3. Significant or non-significant moderation of  $Y$ -changes by  $M$ -changes

This highlights three conceptual cautions that should be observed in intervention studies: **(a)** mediational or moderational analyses should be conditional on significant  $M$  and  $Y$  changes, and not explored otherwise, **(b)** the absence of mediation by  $M$ -changes does not exclude the possibility of moderation by  $M$ -changes, and **(c)** mediation or moderation should be absent in the control group to conclude that they are causal effects.

## Analyzing mediational change

The concurrent change paradox also requires caution at the analysis level. For wide-format data, the correct approach is relatively straightforward:

1. Establish a significant  $X \times T$  interaction on both  $M$  and  $Y$ , using a repeated measures ANOVA with  $X$  as between-subjects factor and  $T$  as within-subjects factor.
2. Calculate the change score variables  $\Delta M$  and  $\Delta Y$ .
3. Establish significant mediation (or moderation) on the  $X$ - $\Delta M$ - $\Delta Y$  path, using a mediational analysis (e.g., SEM).

ID	X	M <sub>T1</sub>	M <sub>T2</sub>	Y <sub>T1</sub>	Y <sub>T2</sub>	ΔM	ΔY
1	Ctrl	5	5	8	10	0	2
2	Inter	4	8	7	14	4	7
...	...	...	...	...	...	...	...
N	Inter	6	7	9	11	1	2

Table 1. Wide format intervention data.

For long-format data, step 1 can easily be accommodated in a multilevel regression, but step 3 is more complicated. That is, it may seem straightforward to fit:

$$Y \sim X + T + X:T + M$$

Or,

$$Y \sim X + T + X:T + X:M + T:M + X:T:M$$

But these models do not address the same hypothesis of mediational change as the wide-format model with change scores! In fact this model investigates if M either covaries with X × T changes, or if M moderates X × T changes, *regardless of the measurement time of M*. This is clearly different than hypothesizing that change in M mediates or moderates change in Y.

ID	X	T	M	Y
1	Ctrl	T1	5	8
1	Ctrl	T2	5	10
2	Inter	T1	4	7
2	Inter	T2	8	14
...	...		...	...
N	Inter	T1	6	9
N	Inter	T2	7	11

Table 2. Long format intervention data

For the multilevel regression to test the same hypothesis as the change mediation model, it would also need to use ΔM rather than M, and fit, e.g.:

$$Y \sim X + T + X:T + \Delta M$$

This highlights that, for time-varying data, there are multiple ways to format and analyze them, each addressing different hypotheses. Analysis models for intervention data have included change regression, ANCOVA, repeated measures ANOVA, multilevel regression, and SEM. Extreme caution is therefore advised in planning your analysis when designing an intervention study!

Best,  
Ben

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