Distinguishing Between Association and Causation (Practicing What We Preach), and the Interface Between Causal Inference and Psychosocial Measurement

Tyler J. VanderWeele
Harvard University

Plan of Presentation

(1) Association vs. Causation in Practice: Study Design

(2) Measurement and Causal Inference

Study Design

Different study designs allow for different levels of robustness to confounding; we can establish a certain hierarchy:

- VanderWeele, T.J. (2021). Can sophisticated study designs with regression analyses of observational data provide causal inferences? *JAMA Psychiatry*, 78(3):244-246.

Cross-sectional studies

Cohort / follow-up with adjustment for demographic covariates

Cohort / follow-up with adjustment for baseline outcome

Studies looking at change in exposure (religiousness/spirituality) i.e. which also allow for adjust for baseline R/S

Longitudinal studies allowing for time-varying exposures and outcomes and for feedback

Randomized controlled trial (often not possible with religion)

Too many of the studies, intended to assess causality, in the social sciences have been cross-sectional

Study Designs and Causal Inference

Restriction to longitudinal, experimental, quasi-experimental designs

Cross-sectional designs (data on all variables collected at the same time) are generally useless for assessing causality

- E.g. Marriage may cause happiness, but happy people are more likely to marry (Stutzer and Frey, 2006)
- E.g. Religious service attendance may protect against depression, but those who become depressed are more likely to stop attending (Li et al., 2016)

We cannot assess causal effects unless we have data over time

Ideally want longitudinal data controlling for baseline outcomes

Ideally evidence is robust to potential unmeasured confounding

Ideally evidence comes from multiple sources and meta-analyses of ***longitudinal*** studies

Sometimes almost all the studies in a given area are cross-sectional and actual evidence may only come from very few (e.g. as of 2017, 1 per 100 on religion and happiness/life satisfaction was longitudinal)

Part II: Causal Inference and Psychosocial Measurement

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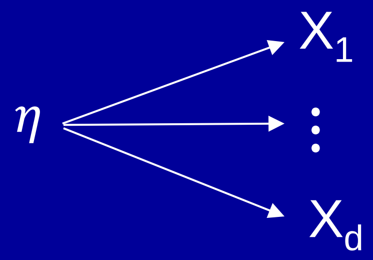
Harvard University

Measurement and Causal Inference

If there seems to be evidence for unidimensionality of the shared variance of indicators $\mathbf{X}=(X_1,\ldots, X_d)$ (often using techniques of factor analysis) then it is frequently assumed that some underlying unidimensional continuous latent variable η that gives rise to the indicators



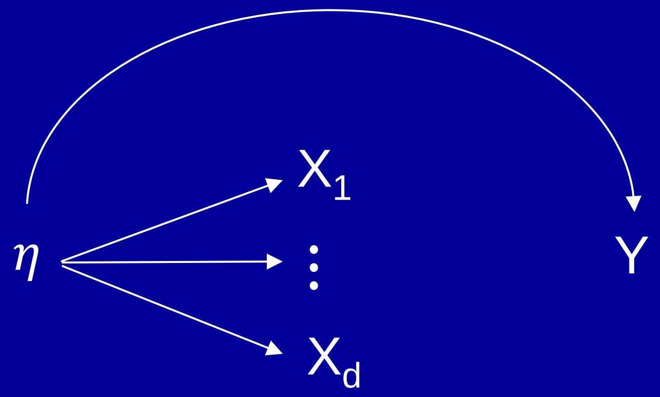
Often it is assumed that the latent variable η exists and is causally efficacious for various outcomes and the indicators $(X_1,\ldots, X_d)$ are just imprecise assessments of η

Measurement and Causal Inference

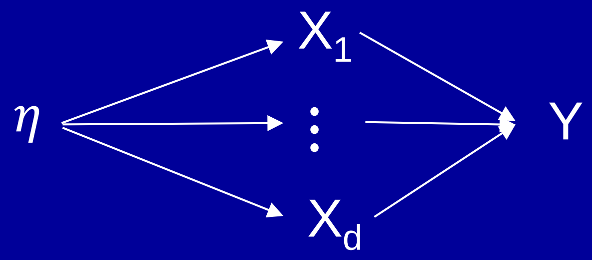
However the basic statistical factor model

$$X_i = \lambda_i \eta + \varepsilon_i \tag{1}$$

is consistent with η being causally efficacious:



But it is also alternatively entirely consistent with the indicators being causally efficacious:



Example: Satisfaction with Life Scale

One of the most widely used subjective well-being scales is Diener et al.'s (1985) Satisfaction with Life Scale (>40,000 citations)

Item number	Item content[a]
1	In most ways my life is close to my ideal
2	The conditions in my life are excellent
3	I am satisfied with my life
4	So far I have gotten the important things I want in life
5	If I could live my life over, I would change almost nothing

[a]Individuals are asked to rate their level of agreement to each item from "strongly disagree" (1) to "strongly agree" (7)

- Good psychometric properties: Cronbach's alpha is high and a single factor seems to explain a considerable proportion of the variance across item responses (Diener et al., 1985; Pavot and Diener, 1993).

Satisfaction with Life Scale

Kim et al. (2021) examine associations with all-cause mortality with Health and Retirement Study (HRS) Data (N=12,998, mean age = 66):

- Examined associations of tertiles of life satisfaction in 2010/2012 with 4-year mortality
- Controlled for sociodemographic characteristics (age, sex, race/ethnicity, marital status, annual household income, total wealth, level of education, employment status, health insurance, geographic region), childhood abuse, religious service attendance, health conditions and behaviors (diabetes, hypertension, stroke, cancer, heart disease, lung disease, arthritis, overweight/obesity, chronic pain, binge drinking, current smoking status, physical activity, sleep problems), various other aspects of psychological well-being (positive affect, optimism, purpose in life, mastery, depressive symptoms, hopelessness, negative affect, loneliness, social integration), and personality factors (openness, conscientiousness, extraversion, agreeableness, neuroticism).

Those in the top tertile of life-satisfaction were 0.74 (95%: 0.64, 0.87) times less likely to die during the four years of follow-up than those in the bottom tertile

Satisfaction with Life Scale

Supplementary analyses examined associations by indicator:

“In most ways my life is close to my ideal”	(RR=0.75; 95% CI: 0·61, 0·91)
“The conditions of my life are excellent”	(RR=0.79; 95% CI: 0·66, 0·95)
“I am satisfied with my life”	(RR=0.72; 95% CI: 0·62, 0·84)
“So far I have gotten the important things I want in life”	(RR=0.85; 95% CI: 0·73, 0·99)
“If I could live my life over, I would change almost nothing”	(RR=0.98; 95% CI: 0·83, 1·16)

Structural Factors

Structural Factors: We will say that a factor model

$$X_i = \lambda_i \eta + \varepsilon_i$$

is structural if the indicators, $(X_1, \ldots, X_d)$, do not have causal effects on anything subsequent, and if they are themselves only affected by antecedents through the latent variable η.

Causal Diagrams: On a causal diagram, a factor η would be structural if there are no arrows going out of $(X_1, \ldots, X_d)$ and no arrows going into $(X_1, \ldots, X_d)$ except from η.

Independence: On a causal diagram this also implies for other variables Z on the diagram, Z will be independent of $(X_1, \ldots, X_d)$ conditional on η.

This is what is assumed in most SEMs with latent variables (Bollen, 1989)

Empirical Implications

The assumption that a factor is structural is so strong that it has empirically testable implications even though the latent factor η is never observed

Theorem 1. *Suppose that Z is independent of $(X_1, \ldots, X_d)$ conditional on η and that the basic latent factor model in Equation (1) holds, then for any i and j, and any values z and z^*, we must have* $\lambda_i \left\{E(X_j|Z = z) - E\left(X_j|Z = z^*\right)\right\} = \lambda_j \{E(X_i|Z = z) - E(X_i|Z = z^*)\}$.

Corollary: For a randomized treatment T, a structural factor implies:

$$\{E[X_j|T = 1] - E[X_j|T = 0]\}/\lambda_j = \{E[X_i|T = 1] - \{E[X_i|T = 0]\}/\lambda_i.$$

Corollary: For any outcome Y, a structural factor implies:

$$\{E(X_j|Y = 1) - E(X_j|Y = 0)\}/\lambda_j = \{E(X_i|Y = 1) - \{E(X_i|Y = 0)\}/\lambda_i$$

Statistical Test for Structural Latents (VanderWeele and Vansteelandt, 2022)

We can use these empirical implications to develop a statistical test to evaluate the null of a structural latent factor model if we…

define $\gamma_i = E(X_i|Z=1)$ and $\beta_w = \{E(X_1|Z=w) - E(X_1|Z=1)\}$ then under the null hypothesis we can parameterize $E(X_i|Z=z)$ as:

$$E(X_i|Z=z) = \gamma_i + \frac{\lambda_i}{\lambda_1}\sum_{w=2}^{p}\beta_w I(z=w) \tag{2}$$

for $i=1,\ldots,d$, where $\gamma_i, \mathrm{i}=1,\ldots,\mathrm{d}$ and $\beta_w, w=2,\ldots,p$ are unknown. Let U_k be a $(p\times d)$-dimensional vector with elements $I(Z_k=z)\left\{X_{ik} - \gamma_i - \frac{\lambda_i}{\lambda_1}\sum_{w=2}^{p}\beta_w I(z=w)\right\}$ for $z=1,\ldots,p$.

We can construct a generalized methods of moments estimator (Newey and McFadden, 1994) under the null by minimizing

$$T_0 = N\left(\frac{1}{N}\sum_{k=1}^{N} U_k^T\right)\Sigma^{-1}\left(\frac{1}{N}\sum_{k=1}^{N} U_k\right),$$

With respect to $\boldsymbol{\gamma}_i$ and $\boldsymbol{\beta}_w$ where $\boldsymbol{\Sigma}$ is the empirical covariance matrix of U_k, or a modification if $\boldsymbol{\lambda}_i$ are estimated (as is usually the case)

The minima will follow a $\boldsymbol{\chi}^2$ with (d-1) x (p-1) degrees of freedom

We can also construct alternative tests without estimating $\boldsymbol{\lambda}_I$, and relying on weaker distributional assumptions, if Z has more than 2 levels

Satisfaction with Life Scale

Supplementary analyses examined associations by indicator:

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Applying the likelihood ratio test with Z= 4-year mortality:
X^2=57.25 with df=(5-1)(2-1)=4; strong evidence against the null ($p=1.1\times10^{-11}$)

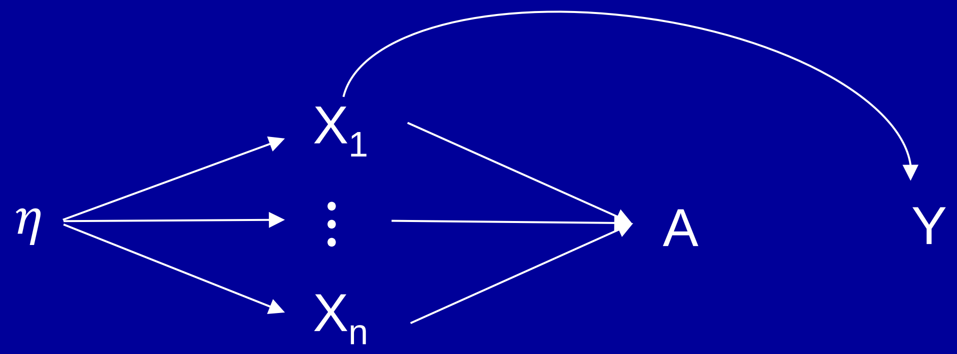
There is no underlying continuous univariate "life satisfaction" latent η to which these indicators correspond with uniform effects on mortality:

- This does not mean the "Satisfaction with Life Scale" is bad
- It may be a perfectly reasonable summary outcome
- But there is no underlying <u>univariate</u> "latent construct"

Implications

Factor analytic models can completely obscure relevant causal distinctions

It may be that only a single indicator is causally relevant for the outcome even if a single factor seems to statistically fit the data well



<u>Implications</u>:

Evidence for a single structural factor needs to be established not presumed

Without such evidence, indicator-by-indicator analyses may be preferable

Caution: Most psycho-social constructs are likely inherently multi-dimensional

❖ VanderWeele, T.J. (2022). Constructed measures and causal inference: towards a new model of measurement for psychosocial constructs. Epidemiology, 33:141-151.