Construct Relationships

PSY 600K

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Agenda

- Construct relationships
  - The multitrait-multimethod matrix
    - Traditional approach
    - Modern CFA approach
  - Other strategies

Assessing Convergent & Discriminant Validity

- Easiest approach: look at the correlations!
  - Is the magnitude of the correlation consistent with predictions about the strength of the relationship?
- No magic cutoffs here, no rules of thumb.
  - Remember the continuum idea…
  - If you are arguing that two constructs are distinct, the correlation between the two should be less than the reliability of either measure.
- Some people will test for a significant difference between convergent and discriminant correlations.
  - Why is this probably a bad idea?

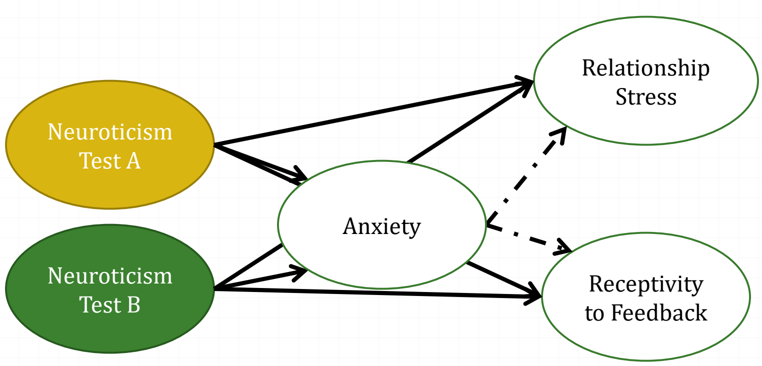
CFA for Discriminant Validity

- To establish whether two measures are really distinct:
  - Do all the items load onto one common factor? Or do we need "scale" factors to differentiate the two?
  - Test a one-factor vs. two-factor CFA model & evaluate fit.
- Need to be careful here – if our two-factor model fits better, is it for a substantive or a trivial reason?
  - E.g., response scale differences, frame of reference differences.
- Look at the **factor** correlations.
  - These are the relationships among our latent constructs, after accounting for error.
  - Confidence intervals around these can be helpful (do they exclude 1.0?). Again, **no** magic cutoffs.

Convergent & Discriminant Validity in the Nomological Net

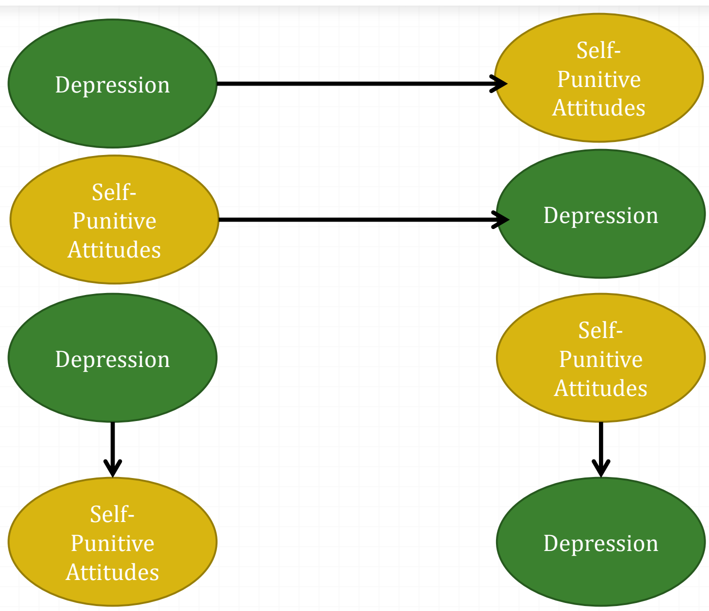
- Stronger argument: Constructs that are similar should have similar nomological nets. Constructs that are different should not.
  - Compared to another measure, does your test predict outcomes in a similar (convergent) or different (discriminant) way?
  - Does it have similar (convergent) or different (discriminant) relationships with other variables?
  - Does your test have **incremental** (discriminant) validity over another measure in predicting an outcome?

For Example



Be Careful!

- McDonald (1999) gives an example of a nomological net relating depression and self-punitive attitudes.
- There are four possible models for the relationship between the two:
  - Depression causes self-punitive attitudes.
  - Self-punitive attitudes cause depression.
  - Depression is a subdomain of self-punitive attitudes.
  - Self-punitive attitudes are a subdomain of depression.
- We can draw all four of these…



- In SEM, these models are **mathematically indistinguishable.**

SEM & the Nomological Net

- The causal argument (1st 2 models) is one important issue... but not the only one.
- The latter 2 models are just as problematic from a convergent/discriminant validity perspective.
  - Are we measuring 2 different constructs? Or one subdomain of a broader construct?
- If we just test one SEM model and find it fits well, we haven't answered this question.
  - And comparing these models doesn't help – they will yield **identical** fit indices.
- So what's the solution? What other evidence can you use to support your choice of model?

The MTMM Approach

- Formally, the **multitrait-multimethod matrix**.
- Proposed in 1959 by Campbell & Fiske.
- Rule out method bias or method similarities as an alternative explanation for observed relationships among constructs.
- Logic:
  - If we are measuring something real, we should be able to measure it in different ways and get consistent results.
  - If we get high correlations across different things using the same method, maybe we're measuring the method and not the construct.

The MTMM

		Method 1			Method 2			Method 3		
		A	B	C	A	B	C	A	B	C
	A	(.89)								
Method 1	B	.51	(.89)							
	C	.38	.37	(.76)						
	A	.57	.22	.09	(.93)					
Method 2	B	.22	.57	.10	.68	(.94)				
	C	.11	.11	.46	.59	.58	(.84)			
	A	.56	.22	.11	.67	.42	.33	(.94)		
Method 3	B	.23	.25	.12	.43	.66	.34	.67	(.92)	
	C	.11	.11	.45	.34	.32	.58	.58	.60	(.85)

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Correlations of the SAME TRAIT across DIFFERENT METHODS indicate CONVERGENCE . Called MONOTRAIT – HETEROMETHOD (MTHM) correlations. They should be **HIGH**.

		Method 1			Method 2			Method 3		
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Correlations of DIFFERENT TRAITS across the SAME METHOD indicate METHOD BIAS. Called HETEROTRAIT-MONOMETHOD (HTMM) correlations. They should be **LOW**.

		Method 1			Method 2			Method 3		
		A	B	C	A	B	C	A	B	C
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Correlations of DIFFERENT TRAITS by DIFFERENT METHODS indicate error or a general crud factor. Called heterotrait-heteromethod (HTHM) correlations. They should be **LOW!**

Evaluating the MTMM

- Old approach: look at the correlations!
  - MTHM > HTMM > HTHM
- More modern approach: CFA
  - Test a model of trait factors against a model of method factors.
  - Can use **correlated errors** – that is, error terms within the same method are likely to be correlated.

Evaluating the MTMM

- Very popular idea for a long time.
  - For many, the MTMM ***is*** construct validity.
- Empirically very difficult to obtain.
  - Humphreys (1960), Cronbach (1989)
  - Why?
- Sometimes it just doesn't make sense.
  - Not all characteristics can be measured using all methods!
- Sometimes it's a wild goose chase.
  - Exhibit A: assessment centers

More Ways to Get Evidence About Construct Relationships

- **Known-groups validity**: does your measure yield different scores for people who are known to differ on the construct?
  - Challenge: how do you **know** they differ?
  - Ex: prisoners vs. nuns, mental patients vs. "normals"
- **Experimental manipulation:** if a manipulation should induce change in a variable, does it induce change in your measure?
  - Appropriate for state or malleable measures.

Bottom Line

- If your test looks like your construct, walks like your construct, sounds like your construct…
  - … it's probably reasonable to proceed as if it really is measuring your construct.
- Accumulation of evidence is important here.
  - Construct validation is never "done."
- Testing alternative explanations is also important.
  - Just providing **convergent** evidence is not enough!
  - Focus on the most relevant alternative explanations first – use judgment.

Questions?

For next time: Consequences of testing
(specifically: test bias, precision of individual test scores).

Read: DeVellis pp. 110-114; Drasgow & Kang (1984)
Reading Response #11