

Validity: Estimating and Evaluating Convergent and Discriminant Validity Evidence

- I. Estimating and Evaluating Convergent Validity
- II. Validity generalization
- III. Discriminant validity
- IV. Multitrait multimethod matrices
- V. Predictive validity
- VI. Validity Miscellaneous

# I. Estimating and Evaluating Convergent Validity

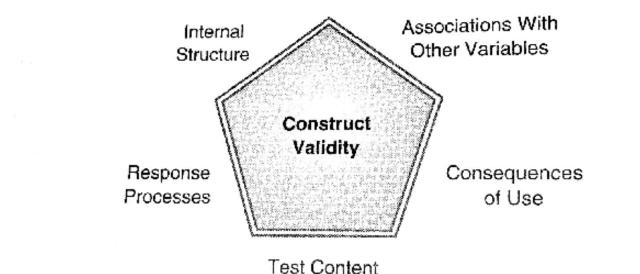


Figure 8.1 A Contemporary Perspective of Types of Information Relevant to Test Validity

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Newsom, Spring 2025, Psy 495 Psychological Measurement

# I. Estimating and Evaluating Convergent Validity

### Validity coefficients

- Common validation strategy is to estimate correlation of the new measure (*test*) with similar measures (*criterion* measures)
- Provides information about convergent validity
- Choose criterion measures based on theory
  - Example: a new measure of self-esteem should be expected to be related to the Rosenberg self-esteem scale (high correlation expected)
  - Example: self-esteem may be related physical self-image but should not be considered the same thing (smaller correlation expected)
- Validity of criterion measures also needs to be considered

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# I. Estimating and Evaluating Convergent Validity

#### Validity coefficients

- Correlation (Pearson *r*) with the other measure is the *validity coefficient*
- Squaring correlation  $(r^2)$  gives the proportion shared variance (*coefficient of determination*)
- No conventional cutoff for acceptable validity coefficient
- Equivalent correlation coefficients (point-biserial, if criterion is binary, or phi, if both are binary) or regression coefficients (slopes) may also be reported by authors



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# I. Estimating and Evaluating Convergent Validity

#### Factors Affecting Validity Coefficients

True relationships

Measurement error attenuates correlations

Restricted range (including floor or ceiling type effects)

Outliers

Method variance (different methods, such as self-report and observation will tend to be more weakly related)

Time

Single events



# II. Validity Generalization

#### Validity Generalization

Establishment of validity takes place across large set of studies

Sample size

Representativeness (and diversity) of samples

Variation in procedures and settings

Cultural or group comparisons

Meta-analysis (quantitative summary of many studies) may be used to assess state of evidence of measures validity after much research

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# II. Discriminant Validity

Discriminant validity – new measure should not be related to measures of unrelated constructs Also recommended to include measures of other constructs not expected to be related to the new measure's construct Correlations should be close to zero and/or nonsignificant Also, no real conventional cutoff for acceptable values Convergent and discriminant evidence usually gathered at the same time



### IV. Multitrait Multimethod Matrices

Multitrait Multimethod Matrices (MTMMM; Campbell & Fiske, 1959)

- Method variance the method used in the measure will account for some of the variance
- *Monomethod* correlations should be higher than *heteromethod* correlations (e.g., self-reported anger vs. observations of anger)
- Monotrait correlations should be higher than heterotrait correlations
- So, expect monotrait-monomethod correlations to be the highest and heterotraitmethod-heteromethod correlatios to be the lowest
- Provides information about how much method affects measure and what real convergent validity might be

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# IV. Multitrait Multimethod Matrices

	1	Self-Report				Acquaintance Report			Interviewer Report				
Methods	Traits	Social Skill	Impulsivity	Conscien- tiousness	Emotional Stability	Social Skill	Impulsivity	Conscien- tiousness	Emotional Stability	Social Skili	Impulsivity	Conscien- tiousness	
Self-report	Social skill Impulsivity Conscientiousness Emotional stability	(.85) .14 .20 .35	(.81) .22 .24	(.75)	. (87)								
Acquaintance	Social skill Impulsivity Conscientiousness Emotional stability	40 .13 .09 .20	.14 .32 .17 .23	.10 .13 .36 .11	.12 .19 .14 .41	(.76) .18 .14 .30	(.80) .26 .28	(.68)	(.78)				
Interviewer report	Social skill Impulsivity Conscientiousness Emotional stability	.34 .03 .09 .14	.11 .25 .09 .16	.19 .12 .30 .08	.20 .19 .14 .33	.23 .06 .09 .13	.01 .24 .08 .12	.11 10 20 .66	.19 .14 .06 .19	(.81) .22 .24 .44	(.77) .30 .38	(.86)	(.76)

#### Table 9.3 Example of MTMMM Correlations

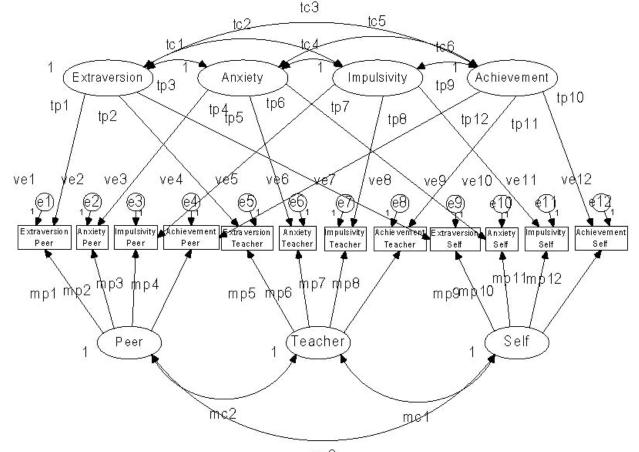


# IV. Multitrait Multimethod Matrices

Estimates of associations can be attenuated because of measurement error May lead to incorrect conclusions of relative size of correlations (Reichardt & Coleman, 1995) Structural equation modeling (confirmatory factor analysis) approach has advantages, because measurement error can be estimated and removed

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### IV. Multitrait Multimethod Matrices



Bentler, P. M., & Lee, S. Y. (1979). A statistical development of three-mode factor analysis. British Journal of Mathematical and Statistical Psychology, 32(1), 87-104.



Predictive and criterion validity closely related

Predictive validity usually used when predicting future state, whereas criterion usually used for association with concurrent state

Either can be assessed in study of convergent validity



Validity of a measure can be assessed by predicting classification, often in comparison with a "gold standard"

Examples

- Self-reported depression scale and diagnosis by clinician
- Educational test and admission to college
- Personnel test and job success



Cutoff of measure established theoretically or empirically to compare to classification

Correct classification rate provides information about predictive validity of the measure



Four ways of predicting category membership in the text: Binomial effect size display (BESD: Rosenthal & Rubin, 1982) Taylor-Russell tables (Taylor & Russell, 1939) Utility analysis (Brogden & Taylor, 1950) Sensitivity and specificity



#### Binomial effect size display (BESD)

2 × 2 table constructed for below average vs. above average on test and below average vs. above average performance (e.g., SAT and college GPA)
Trable 9.6 Example of the Binomial Effect Size Display

	College GPA	
(a) For a correlation of $r = .00$		
Test Score	Below Average	Above Average
Below average	50	50
Above average	50	50

#### (b) For a correlation of *r* = .48

Test Score	Below Average	Above Average
Below average	А	В
	74	26
Above average	С	D
	26	74

**NOTE:** GPA = grade point average.



Taylor-Russell tables (Taylor & Russell, 1939)

Used to evaluate personnel tests for hiring decisions – test vs. later success in position

Similar to BESD except other criteria than average can be used (e.g., hiring only 4% of applicants



Utility analysis (Brogden & Taylor, 1950)

Cost vs. benefit (utility) of testing procedure – does the test predict sufficiently beyond not using a test to be worth the monetary cost?



Sensitivity and specificity

Widely used in medical and clinical settings to evaluate the predictive accuracy of a particular test



Sensitivity represents the probability that a test indicates a client has a condition (e.g., depression) when the client truly does have the condition

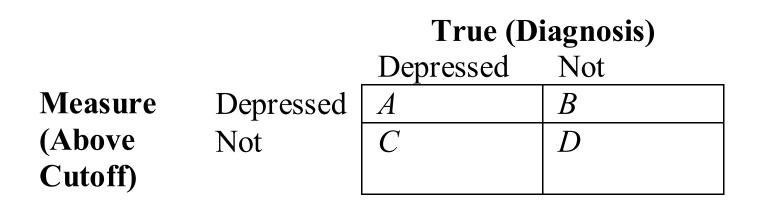
*Specificity* then is when the test indicates the client does not have the condition when the client truly does not have it.



Positive predictive value (PPV) represents the proportion of those classified as depressed who really are depressed
Negative predictive value (NPV) represents the proportion of

those who are classified as not depressed who really are not depressed

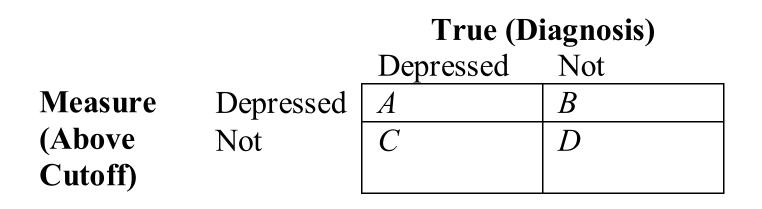




$$Sensitivity = \frac{A}{\left(A+C\right)}$$

$$Specificity = \frac{D}{(B+D)}$$





$$PPV = \frac{A}{\left(A+B\right)}$$

$$NPV = \frac{D}{\left(D+C\right)}$$



Furr and Bacharach discuss *alerting* ( $r_{alerting-CV}$ ) and *contrast* ( $r_{contrast-CV}$ ) correlations (Rosenthal, Rosnow, & Rubin, 2000) Special computations of construct validity (the "CV" here) coefficients that compare predicted correlations to obtained correlations



- Higher  $r_{alerting-CV}$  values if close match between convergent and divergent correlations obtained and predicted by a set of expert judges
- Higher ( $r_{contrast-CV}$ ) also reflect good match between obtained and predicted correlations but adjusts for absolute magnitude of the correlations



Relies on judges' accurate predictions about convergent and discriminant validity coefficients, which may be difficult

May result in concluding high estimates of validity even if judges do not agree on prediction values



*Statistical significance* is used to infer whether or not the validity is different from 0 in the population

Statistical test of Pearson r correlation

Null hypothesis that  $\rho$  = 0 more likely to be rejected if

Sample value (*effect size*) is large

Sample size is large

Sampling variability is small



Need to distinguish between

- Statistical significance
- Large effect size



### Cohen's (1988) effect size standards for correlation

Small 
$$r \le .10 (r^2 = .01)$$

Medium 
$$r > .1$$
 and  $\leq .30$  ( $r^2 = .09$ )

Researchers commonly refer to these effect size standards, but they are arbitrary descriptors



- The term *face validity* refers to whether the measure or item seems to be a good reflection of the hypothetical construct on its surface
- There are no tests for face validity—just a judgement of whether it makes sense
- Could use of multiple raters, expert judges, cognitive testing, focus groups could all be used to support face validity
- In some instances face validity might be undesirable, because overly obvious questions could lead to social desirable responses, lying, or concealment/faking



Some scales that are "empirically derived" may lack face validity, but may predict well

- In such measures, items are selected based on their criterion validity without regard to face validity
- Subtle items as opposed to obvious items are thought to be less subject to faking, but evidence is not always in support of this assertion (e.g., Thornton & Giersach, 1980)



Minnesota Multiphasic Personality Inventory (MMPI) is an example of a test with many items that are not obvious

"I prefer a shower to a bath" is predictive of higher empathy (Hogan Empathy Scale; Hogan, 1969)



Revision of a scale to improve reliability or validity should be confirmed in another sample

- Example: in one sample, a particular item may have a lower correlation with the total scale just by random chance
- Example: a cutoff for clinical anxiety which works well for one sample may not be optimal for another sample