#### Scale Validation Analyses The Suicidality Scale Development Studies

**Open & Sustainable Research – Psychometrics** 

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### This Presentation

- This presentation is intended for anyone interested in latent trait scale development
  - Scale development, research use, selecting scales, interpreting results
- Suicidality Scale development paper readers
  - Those interested in viewing an Open Methods discussion of more details on how we developed the SS
- Mental health professionals and students
  - Using scales to help form clinical decisions, diagnoses, etc.

Intro > Background > Demonstrations > Interpretations > Applications

#### Overall Aims

- Provide info on conducting similar studies and using scales
- Provide open methods info for Suicidality Scale projects
- Contribute to education on scale development practices
- Encourage localization of scales by language/culture
- Encourage sustainable psychological science
- Exchange among professionals, students and community
  - Steps toward open and sustainable practices

### Supporting Institutions & People

- Chinese & English teams: Keith M. Harris<sup>1,2\*,</sup> Lu Wang<sup>3</sup>, Guanglun M. Mu<sup>4,5</sup>, Yanxia Lu<sup>6</sup>, Cheryl So<sup>7</sup>, Wei Zhang<sup>8</sup>, Jing Ma<sup>9</sup>, Kefei Liu<sup>10</sup>, Wei Wang<sup>11</sup>, Melvyn W. Zhang<sup>12</sup>, Roger C. Ho<sup>13</sup>
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- Colombian Spanish team: Castaño, M, Arenas, A, Pastrana, K, Van den Enden, P, Castro, J,

Fandiño. O., Harris, KM

• Universidad de Caldas, Charles Sturt University











Universidad de Caldas

#### Presenter

#### Keith M. Harris

- PhD Psychology, The University of Queensland, Australia, 2009
  - Examinations of how suicidal people use the internet for suicide-related purposes
- MA Social Psychology, Claremont Graduate University, USA
- BS Psychology/Political Science, Michigan State University, USA
- Currently teaching psychopathology, postgraduate research methods
- Conducting research on mental health and information technologies, climate, scale development, and suicidality
- NOT a psychometrician!
  - For expert guidance in psychometrics, go to the real experts, see References for some
- Apply psychometrics to answer research questions, improve methods



#### UN Sustainable Development Goals https://sdgs.un.org/goals

· Good Health and Wellbeing improving health and mental health

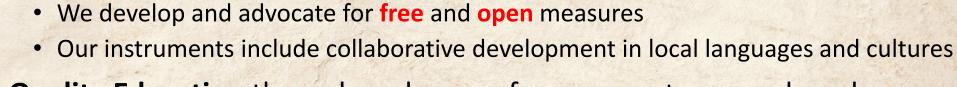
assessments requires good science

3 GOOD HEALTH AND WELL-BEING





17 PARTNERSHIPS FOR THE GOALS



This project is driven to provide quality outputs that are free culture and localized.

We aim to support the UN SDGs in the following ways

- Quality Education through exchange of assessment, research and psychometric knowledge and skills, and by encouraging cultural diversity
- Gender Equality through collaborating and promoting women, girls and nonbinary<sup>+</sup> leadership in research and clinical practice
- Global Partnerships by enhancing regional and international cooperation and access to science, innovation and knowledge sharing

## Starting with the Classics

### Classical Test Theory (CTT) & Scores



1 = latent trait, the construct of interest; a, b, c.. are attributes, unique aspects of the same trait

Sum score = 1a + 1b + 1c..; Assumes tau-equivalency – all items are equal

See References for several papers on measurement models and the limitations of CTT

#### Terms (see References for further info)

- Validity does the scale/instrument measure what it is supposed to measure?
- Factor latent trait construct, items correlate 'load' on factors
  - E.g., suicidality, depression, extroverted personality, emotional intelligence
    - DASS-21 (Depression, Anxiety, Stress Scales) has three factors: depressive symptoms, anxiety symptoms, etc.
    - Suicidality scales (e.g., SABCS, SS) generally aim for one factor suicidality/risk
  - Exploratory Factor Analysis (EFA) most common scale development analysis
- Unidimensional only one factor, no subfactors
- Loading individual item's association with factor (range -1.0 1.0)
  - Absolute higher value ≈ better, e.g., -.75 is a stronger loading that .68
- Communalities  $(h^2)$  degree other items explain one item (0 1.0), higher  $\approx$  better
- Fit degree scale fits the factor structure/model (range 0 1.0; near 1.0 is good)
  - Example: Tucker-Lewis Index (TLI), cluster fit
- Error error fitting the factor structure/model (0 1.0, near 0 ≈ good)

#### More Terms

- Theta the quantification of the latent trait, x-axis in IRT graphs
  - Typical range -4.0 4.0, mid-point near 0, end-points ≈ extreme levels of trait
- Cutoff, cut points distinct scale scores differentiating low/med/high
  - The Hamilton Anxiety Scale (HAM-A): < 17 = mild, 18-24 moderate, > 24 severe
  - Area under the curve (AUC) used to form cutoff scores
- Tau-equivalent basis of CTT, all items have equal weighting etc.
  - Test requirement for Cronbach's alpha, AUC, CFA
- Congeneric model contrasts with tau-equivalent, items vary in weighting etc.
- Common variance degree scale explains changes in construct scores
- Reliability consistency between items, between assessments over time
- DIF Differential item functioning, do scale items assess trait equivalently across groups (e.g., sex, age bands, first-language)

#### Measurement Models (see References for further info)

- Hierarchical Cluster Modeling similar to EFA, how many clusters, loadings, includes fit and error (cluster model graph)
- Factor analysis many types, do NOT use PCA; use ML, PAF, min-res (minimum residual, robust to skew)
  - psych package provides loadings, h<sup>2</sup>, fit (TLI), error, common variance
- Bifactor analysis (EBFA, BA) includes general factor loadings, h<sup>2</sup>, ECV, error; general & group factor loadings, (bifactor graphic)
- Item Response Theory (IRT) many models, test data first for which model
  - Graded response model (GRM) used for SS and many others
  - GRM includes item discrimination, information functions, cut points on theta, item details, scale coverage of theta
- Scale internal consistency McDonald's omega
  - Suitable for congeneric models (items vary in weight etc.)
  - Close results to alpha, but Cronbach's alpha requires all items equal (tau-equivalent)

### Aims & Subjectivity

- Caveat: while we may make suggestions, there will be many alternative approaches to achieving similar goals and different views on interpreting results
- Seminar aims: Introduce newer, valuable measurement models
  - EFA; EBFA; HCA; IRT (GRM; [DIF, scores]) Brief Demonstrations
  - Our psychometric aim: What set of items best measures 'suicidality'?

## Suicidality Scale Studies

English 1, N = 5,115, English 2, N = 814, English 3, N = 626; All online surveys Chinese Simplified, N = 1,595, Chinese Traditional, N = 1,393; All online surveys Colombian Spanish, N = 313; Clinical and online survey, also clinician ratings

#### The Suicidality Scale 1.0

See the
manual, link
below, for
more details

Code	Item/prompt	Responses		
Ideation	How often have you thought about killing yourself in the past year?	1 = Never, 5 = Very often		
Debate	In the past year, have you had an internal debate/argument (in your head) about whether to live or die?	1 = Never, 5 = Very often		
Dead	Recently, have you been bothered by thoughts that you would be better off dead?	1 = Never, 5 = Very often		
Meaning	Recently, have you felt your life is meaningless?	1 = Never, 5 = Very often		
WTD	Recently, how much do you wish to die?	1 = Not at all, 5 = Very much		
Predict	How likely is it that you will attempt suicide someday?	1 = Not at all, 5 = Very likely		
RFD		1 = My reasons for living are greater than my reasons for dying, 5 = My reasons for dying are greater than my reasons for living = 5		
DKS	and the is the	I have no desire to kill myself = 1, I have a strong desire to kill myself		
	Supplementary items (not included in calculations)			
WTL*	Recently, how much do you wish to live?	5 = Not at all, 1 = Very much		
Attempt	Have you ever attempted to kill yourself?	1 = Never; 2 = Yes, but never really wanted to die, 3 = Yes, but was uncertain about dying, 4 = Yes, and at least once really wanted to die		
Plan	Have you ever made a plan to kill yourself?	1 = Never, 2 = Yes, but never really wanted to die, 3 = Yes, but was uncertain about dying, 4 = Yes, and at least once really wanted to die		

## Publications & Open Resources

#### • You can find further details in manuscripts related to this talk

- English Suicidality Scale development: Harris, K. M., Wang, L., Mu, G. M., Lu, Y., So, C., Zhang, W., Ma, J., Liu, K., Wang, W., Zhang, M. W., & Ho, R. C. (2022). Measuring the suicidal mind: The 'open source' Suicidality Scale, for adolescents and adults. *Preprint*. <u>https://doi.org/10.31219/osf.io/b4qut</u>
- Colombian Spanish Suicidality Scale: In preparation.
- Chinese Suicidality Scale development: Wang, L., Harris, K. M., et al. (2022). Improving Chinese suicide risk assessment: Development of the Chinese Suicidality Scale. *In preparation*.

#### Open data and resources

- English study data: <u>https://osf.io/vjxnq/</u>
- English SS manual: <u>https://osf.io/6tknd/</u>

# Developing a Scale

#### Main Steps in Scale Development/Validation

See more detailed guidelines in the **References** and elsewhere

- This is just a very brief presentation of our steps
- Start with a quality item set, include an item pool when possible
  - Example: Colombia study used 8 validated SS items, plus 2 items
- Community testing test the language/meanings with small community samples
- Open Discussion project team discuss wording, community responses, other scales, items
- Collect good data consider the population (community, clinical)
  - You want to cover the spectrum of your variables (suicidality, low to high)
  - Collect enough data, as many participants as possible

#### Scale Development – First Steps

#### Choose quality items

- Previously published scales, examine EFA and other statistics to choose best
- Expert recommendations
- Personal experience (critically examine your own data)
- Item Pool bigger is better, sort of. Too many items will fatigue participants, remove poor and redundant items
- Conduct sound survey methods (see References)
- Cleanse data and replace missing values (sources in References)

### **Community** Sampling

- After determining near-final versions of our scale, item pool
  - We sent brief questionnaires to community locations
  - We included, one by one, the Scale instructions, and each item
  - We asked community members to rate each item: Low, Medium, High
    - Clarity is this easy to understand? Is anything unclear?
    - Validity could you answer this questions accurately, as worded here?
    - Suggestions we asked people to provide suggestions on improving the wording
  - Next, the team evaluated community responses and finalized the items

 Next slide, examples from the Colombian-Spanish and Chinese (simplified and traditional scripts) projects

#### **Community** Sample Results

#### **Colombian-Spanish**

T1P = De 1 a 6 que tantas razones tiene para vivir?, siendo 1 que sus razones para vivir superan las razones para morir; y 6 que sus razones para morir superan sus razones para vivir.

T1R1 = (1)Mis razones para VIVIR son mayores que mis razones para morir.

- 1. "Este énfasis con mayúsculas me parece importante".
- 2. "Consideraria modificar esta opción de la siguiente manera "Tengo más razones para vivir que para morir" de esa manera me parece mas claro".

T1R6 = (6) Mis razones para MORIR son mayores que mis razones para vivir.

#### Chinese

Simplified	Clarity	Validity	Comments
以下问题是关于自杀的私人问题。 请选择最适合您的选项。	Μ	Μ	"个人问题" 比 "私人问题"更好
Traditional	Clarity	Validity	Comments
我們需要問你一些有關自殺的個 人問題。請標出與你本人情況最	М	н	1."我們需要問你一些有關自殺

### Community Sampling Outcomes

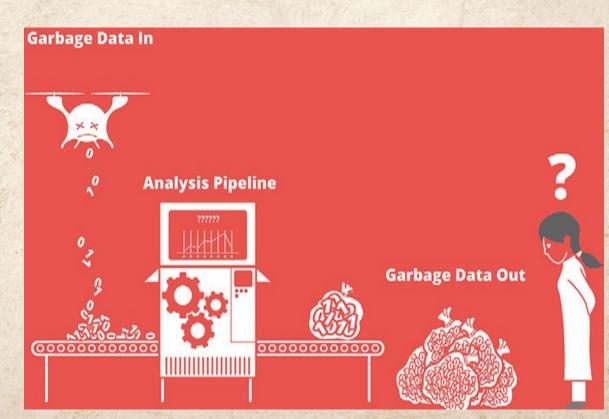
#### Why do community sampling?

- We found some items, could be made clearer, including in English
  - E.g., For reasons for dying (RFD), the original item stated "my reasons for dying outweigh my reasons for living." For younger people and non-native speakers, we thought "are greater than" worked better than "outweigh"
  - Usually, we want to make scales and items as concise as possible, but validity outweighs nearly all else
- For other languages (e.g., Colombian-Spanish, Chinese traditional script), there were quite different ways of expressing a specific cognition or affect. Many items underwent several revisions and further testing
- This also fits with our SDG goals for localizing these instruments and giving more voice to community members

### In Sum

To measure traits accurately and produce valid findings... Avoid Garbage In – Garbage Out GIGO

- Cleanse dataset, replace missing values, etc. (other seminars)
- Validate Factors/Dimensions
- Validate Items
- Finalize Best-possible Scales
- Report Scale Diagnostics



## We Have Good Data, What Next?

#### Data

- Checking the Data how can we use our data?
  - Check frequencies for all variables
  - Are any variable response options missing?
  - Example: Item scored 1 7, but no responses for '6'
  - Any odd patterns?
  - Example: Only a few responses at low end, many high
  - See your data Rest-score plots, Histograms

### SS Examples - Frequencies

These are basic
descriptive statistics
of two pool items. Our
main concern here is
that each response
option is endorsed.

		AttemptB	AttemptIntent
Ν	Valid	5115	5115
	Missing	0	0
Mean		.29	2.15
Std. Deviation		.454	1.556
Skewness		.919	.953
Std. Error o	fSkewness	.034	.034
Kurtosis		-1.156	749
Std. Error o	f Kurtosis	.068	.068

AttemptB = binary item, have you attempted suicide? No = 0, Yes = 1 Attemptintent Have you attempted suicide?

1 = never, 2 = yes, but didn't really want to die, 5 = yes and really wanted to die

#### AttemptB

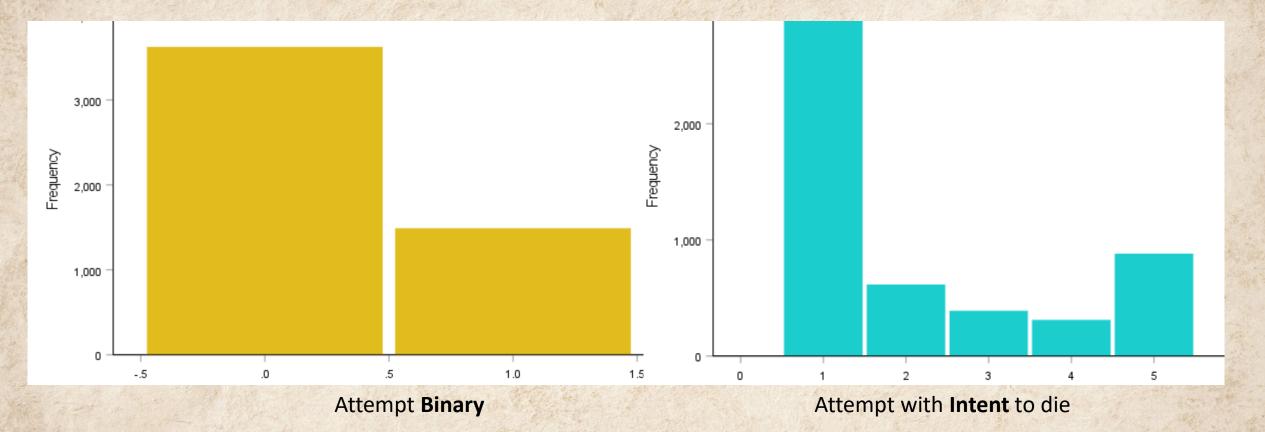
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	3625	70.9	70.9	70.9
	1	1490	29.1	29.1	100.0
	Total	5115	100.0	100.0	

**Notice** that many more reported 'no suicide attempt' with the binary version than the continuous version. **Why?** 

#### Attemptintent

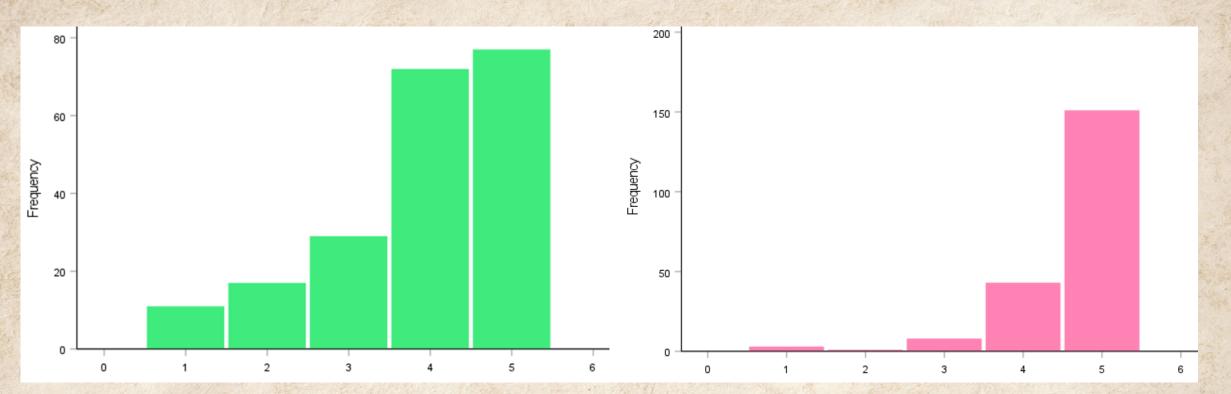
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2915	57.0	57.0	57.0
	2	616	12.0	12.0	69.0
	3	390	7.6	7.6	76.7
	4	312	6.1	6.1	82.8
	5	882	17.2	17.2	100.0
	Total	5115	100.0	100.0	

#### Item Response Frequencies



These histograms show the frequencies of the items from the previous slide. We are looking for any responses that are under-endorsed. We are not really concerned by skew here. Which item do you think would provide more information on suicidality/risk?

#### Other Examples: Item or Sample?

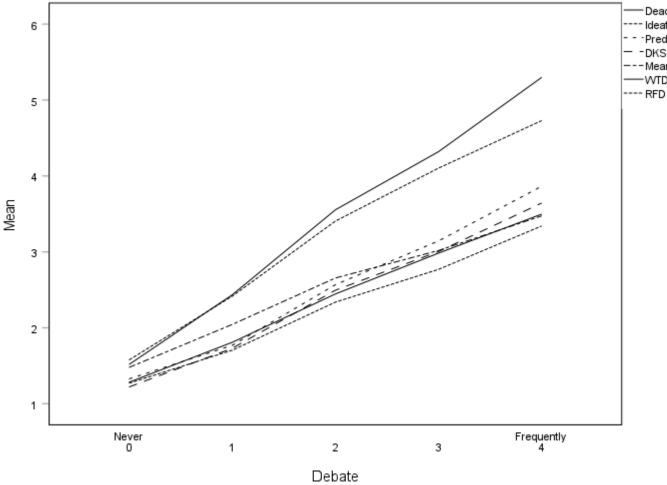


The item on the left appears fine, skew is not usually a problem at the item level

The item on the right has serious problems. What would you do with this? Rescore, delete, something else?

**Next**, is the problem the **item** (poorly formed?), or the **sample** (not diverse?)?

#### SS – Rest-Score Plot: Debate



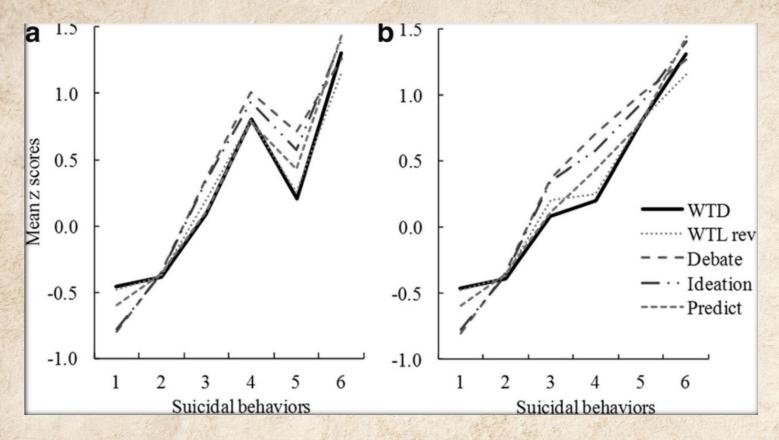
— Dead ---- IdeationYear - - Predict - - DKS ---- Meaningless — WTD ---- RFD

This is a rest-score plot. We put one item on the x-axis, then examine how it correlates with other items.

This works best when we have some good/solid items to compare the reference item to.

*Note* that there is a (reasonably) consistent linear relationship between all variables

#### **Rescore**?



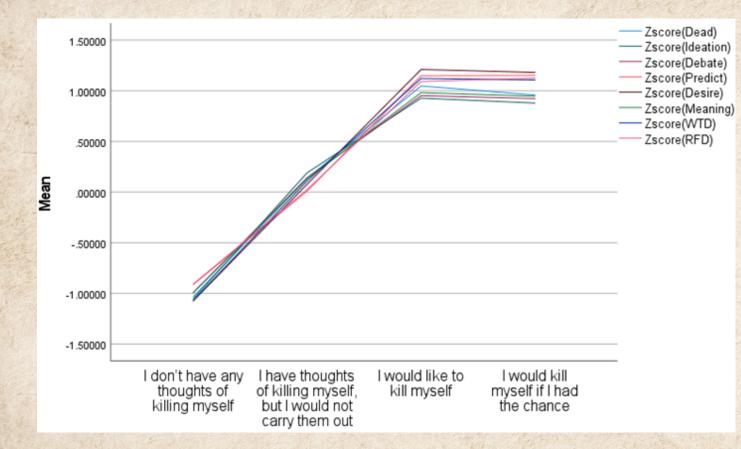
**Source**: Harris, K. M., Lello, O. D., & Willcox, C. H. (2017). Reevaluating suicidal behaviors: Comparing assessment methods to improve risk evaluations. *Journal of Psychopathology* and Behavioral Assessment, 39(1), 128-139.

Guttman item – ordered categories. Google for examples.

Monotonicity – consistent order, item responses demonstrate consistent increasing or decreasing levels of the latent trait

The graph on the left shows the original scoring of a Guttman-type item on suicidal behaviors as it correlates with 5 items from the Suicidal Affect-Behaviors-Cognition Scale. Due to clear violations of monotonicity (in multiple studies and subsamples), it was rescored: 5 as 4, and 4 as 5, resulting in the figure on the right. Would you use the original item scoring shown on the left?

#### Item Detective Work

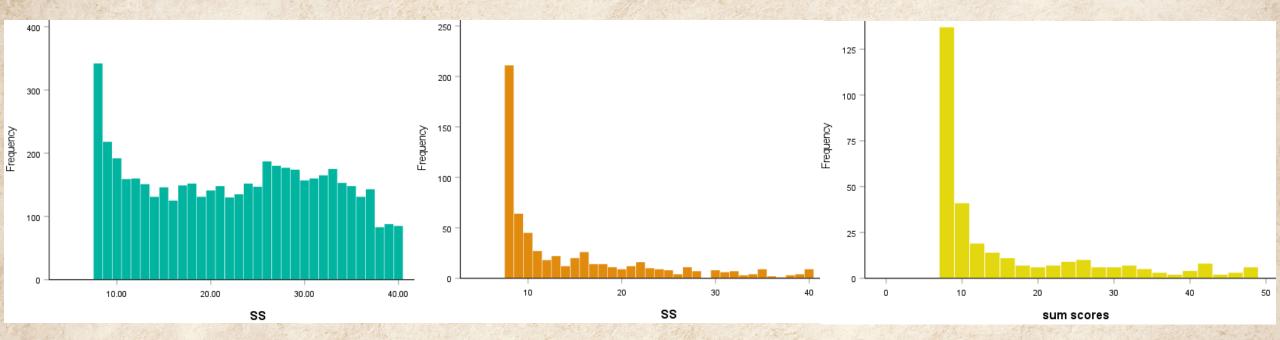


This rest-score plat shows a strong linear relationship over the first three of these **Guttman-type** responses. However, there is no difference between responses 3 and 4. Thus, **violating monotonicity**.

*But*, which is better, the 3<sup>rd</sup> or 4<sup>th</sup> option? Further research is needed to understand which, if either, might work best.

How might you design a study to test this?

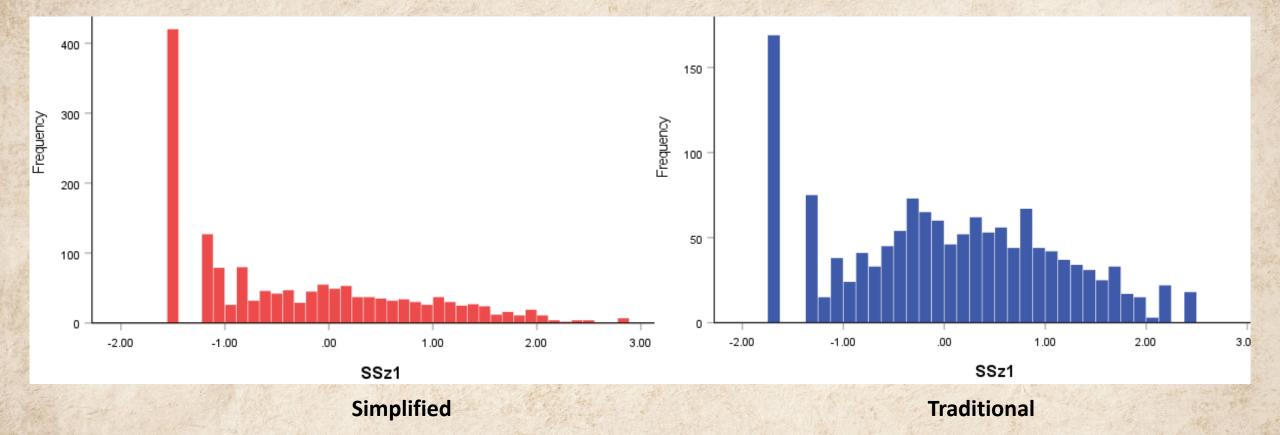
#### Sample Construct Coverage



Here, we see three histograms of SS sum scores, from independent studies (English S1, S2, Colombia). Note that the left graph shows very good coverage of the full assessed range of suicidality. However, the other two graphs show small numbers of participants at high ranges. While common, to provide more definitive findings on scale properties, larger more diverse samples are needed.

How would you obtain a sample with large numbers of suicidal participants?

#### **Coverage** – Chinese (ability scores)



Similar to the previous slide, these graphs show the sample range on suicidality, but through **IRT-derived ability scores**, which better approximate true suicidality levels (compared with sum scores).

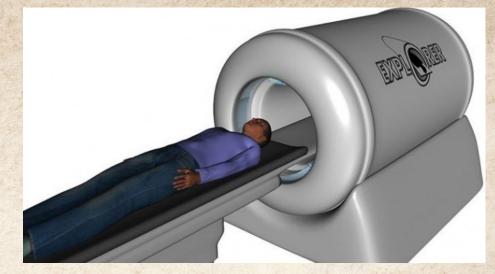
## Choosing a Measurement Model

### The Model & Your Aims

- Project aims: Best possible measure of suicidality
  - Strong item properties (linear relationships, monotonic, high discrimination, high loadings)
  - Strong scale properties (high unidimensional fit, low error, high internal consistency, high test-retest)
  - Consistency across demographic groups age, gender, first-language, etc.
- Next, match your data with your measurement model
  - All known suicide risk assessment studies have shown suicide-related items fit a congeneric model (items have different weighting, etc.). No known study has validated the use of tau-equivalent models for this construct
- There are several measurement models to choose from (check References)
- Would you choose a toaster to make coffee? Would you choose a vintage X-ray machine to do a brain scan?

### Measurement Models







### **CTT** Model Statistics

- These are the most common scale development analyses
- Green indicates flexibility in data/model
- Red stats require tau-equivalency (all items equal)
- Standards (e.g., > .70) are common reference points
- **EFA** to identify factors, determine *appropriate* items (loadings ≥ .32?)
- Cronbach's **alpha** for reliability, scale quality? ( $\alpha \ge .70$ ?)
- CFA to validate *factors* in new samples (fit ≥ .90?, RMSEA < .08?)
- Pearson's r for test-retest reliability ( $r \ge .70$ ?)

## Single or Multimodel?

#### Are All Items Equal?



Factor analysis statistics (loadings, communalities, inter-item correlations), indicate varying associations between items/attributes. No known study has shown that all items of a latent trait scale are equal across psychometric tests. Sum score = ?

An alternative scoring method uses *response patterns*, resulting in '**ability**' (aka factor/person/individual) scores. – see **IRT** 

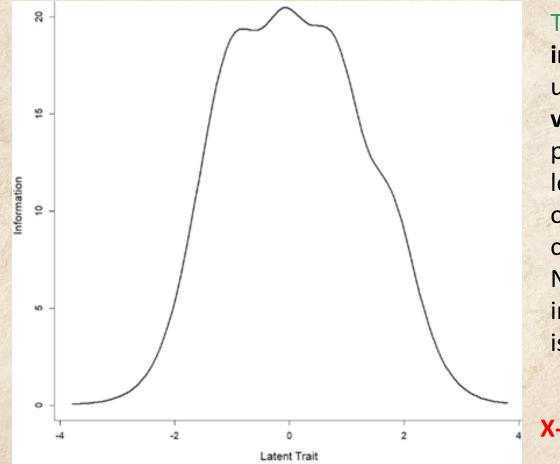
### Multimodel Scale Testing

- Next, we use four measurement models to examine strengths and weaknesses in candidate items for a suicidality scale
- For the first three, HCA, EFA, BFA, we are looking for:
  - High item loadings (roughly .70 .99)
  - High item communalities/h2 (roughly .60 .99)
  - High model fit and unidimensionality (varies; .70 .99)
  - High explained variance of the latent trait (roughly .70+)
  - Low model error (roughly .00 .20)
  - Item and scale values can be compared with other included scales

### Adding IRT to Multimodel Testing

- For IRT, we need to choose from various models
- We chose the graded response model (GRM)
  - GRM is flexible, allowing items to vary on various parameters
  - Within GRM, we need to determine if a constrained or unconstrained model fits best
  - Unconstrained items can vary in discrimination (a)
- For IRT results, we look for
  - High item discrimination levels (a, roughly > 1.80)
  - Item response monotonicity/validity
  - Scales that cover a broad range of theta (the latent trait)

#### Suicidality Scale Test Information (IRT)



This line shows the SS test information curve. The area under the line indicates the volume of information the test provides on the latent trait. The location of the line shows where on theta the information is captured. Note that, for all scales, less information – and less certainty, is found at extreme levels.

X-axis = Theta (latent trait)

### Additional Item/Scale Tests

- Through GRM, we can test whether items or scales show evidence of differential functioning, or fail invariance, across groups
  - DIF/DTF can test whether items/tests measure the latent trait differently for females/males/nonbinary+; urban/rural residence; first-language, etc.
  - If items/scales fail these tests, scale scores can have qualitatively different meanings across groups
- We used McDonald's ω for testing scale internal consistency
  - Omega is suitable for congeneric models, while alpha requires tau-equivalency
  - Bootstrapping helps address subjectivity and sample-specific findings
- Please see References and other sources for more info

# R



#### For most advanced stats we use the open-source R statistical environment

 R Core Team. (2022). R: A language and environment for statistical computing. In (Version 4.2.0) R Foundation for Statistical Computing. <u>https://www.R-project.org/</u>

#### We used these R packages

- **psych** Revelle, W. (2021). *psych: Procedures for psychological, psychometric, and personality research* [R package version 3.6.2]. Northwestern University. <u>https://personality-project.org/r/psych/psych-manual.pdf</u>
- coefficientalpha Zhang, Z., & Yuan, K.-H. (2016). Robust coefficients alpha and omega and confidence intervals with outlying observations and missing data: Methods and software. *Educational and Psychological Measurement*, 76(3), 387-411. <u>https://doi.org/10.1177/0013164415594658</u>
- **Itm** Rizopoulos, D. (2006). Itm: An R package for latent variable modelling and item response theory analyses. *Journal of Statistical Software*, *17*(5), 1-25. <u>http://www.jstatsoft.org/v17/i05/</u>
- **lordif** Choi, S. W., Gibbons, L. E., & Crane, P. K. (2011). lordif: An R package for detecting differential item functioning using iterative hybrid ordinal logistic regression/item response theory and Monte Carlo simulations. *Journal of Statistical Software*, 39(8), 1-30. <u>http://www.jstatsoft.org/v39/i08/</u>

### **R** Basics

- Download latest version of R for Windows/Mac/Linux: <u>https://cran.r-project.org/bin/windows/base/</u>
- Download RStudio <u>https://www.rstudio.com/products/rstudio/download/</u>
- Get help: <u>https://rstudio-education.github.io/hopr/starting.html</u>
- Get latest manuals for packages
  - R basics: https://cran.r-project.org/manuals.html
  - Some recommended packages: <u>https://support.rstudio.com/hc/en-us/articles/201057987-Quick-list-of-useful-R-packages</u>
  - Google package name, e.g., "r package psych" to get link
    - <u>https://cran.r-project.org/web/packages/psych/index.html</u>

#### Getting Started in R

- Define a scale/item set (matrix)
- In R/Rstudio, define item set/scale, example: "scaleA"
  - Text within "quote marks" can be copied and pasted into R
  - "scaleA <- study1[, 3:10]"</li>
    - This assigns a name 'scaleA' to a matrix
    - study1 = name of dataset; 3:10 = columns for scaleA variables in dataset
  - "scaleB <- study1[c(2,5,7,9,10)]" Use this method for noncontinuous columns</li>

### **HCA** Demonstration

psych package (download and activate)

- Extra help for psych: <u>https://personality-project.org/r/psych/</u>
- Type "iclust" to do HCA, and identify the item set/matrix (e.g., 'scaleA')
- "iclust(scaleA)"
- Copy and interpret results, see next slide

#### HCA Output (English S1 Item Pool)

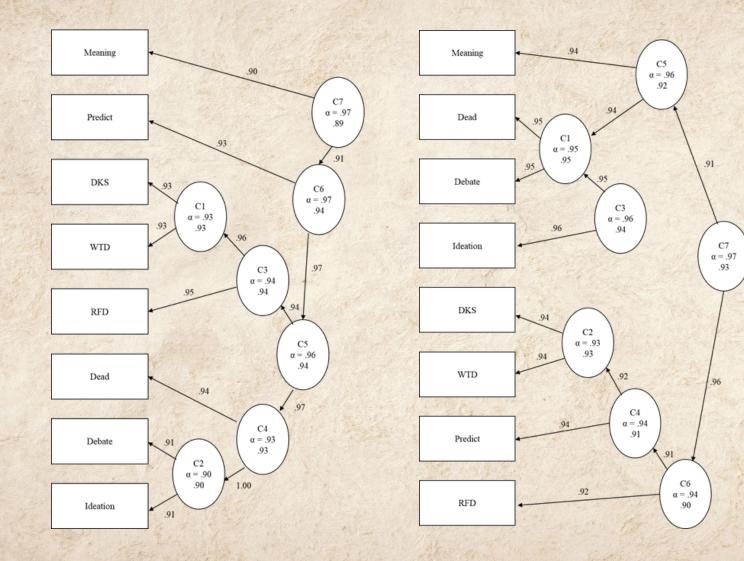
#### **Example R output**

ICLUST (Item Cluster Analysis)							
Call: iclust(r.mat = pool)							
Purified Alpha: [1] 0.97							
G6* reliability: [1] 1							
Original Beta: [1] 0.68							
Cluster size: [1] 30							
Item by Cluster Structure matrix: [,1]							
Dead	0.80	Sec. 1					
Ideation	0.83	A.					
StopThoughts	0.74						
Deterrents	0.55						
Reasons	0.65						
Wish-HAMD	0.65						
Cluster fit = $0.96$	Pattern fit = 0.98 RMSR =	0.07					

This is a selection of Item Pool output Of note, in blue, you can see cluster 'loadings.' In yellow, we see the cluster fit and error. You can also see that only 1 cluster was identified [1], if there were 2, there would be loadings etc. for the second.

Main points to note are: Number of clusters, strength of loadings, fit, error.

#### Suicidality Scale Hierarchical Cluster Analyses English S1 (left) S3 (right)



These are graphs from HCA results. They provide item cluster loadings, and info on how items relate to each other, and possible hierarchies of trait attributes.

KMHarris 2022

#### **EFA** Demonstration

- psych package
- Define item set/scale, example: "scaleA"

- Choose FA type, ML, PAF, minres we chose minres
- "mr <- fa(scaleA, fm = "minres", alpha = TRUE, values = TRUE)"</li>
- "mr"
- Copy and interpret results

### EFA Output

mr <- fa(pool, fm = "minres", cor = "mixed", alpha = TRUE, values = TRUE) [command, type this, use
"cor = "mixed"" if you have both dichotomous and polytomous items, otherwise use default for
polytomous]</pre>

> mr [type this]

Factor Analysis using method = minres

Call: fa(r = pool, fm = "minres", alpha = TRUE, cor = "mixed")

Standardized loadings (pattern matrix) based upon correlation matrix

	MR1	h2	u2	com
Dead	0.84	0.71	0.29	1
Ideation	0.87	0.76	0.24	1
Debate	0.89	0.79	0.21	1
SelfHarm	0.65	0.43	0.57	1
Stop	0.73	0.53	0.47	1

MR1 = factor 1, h2 = communalityNote loading, h2, other info useful too

#### Proportion Var 0.66

Mean item complexity = 1 Test of the hypothesis that 1 factor is sufficient. Tucker Lewis Index of factoring reliability = 0.469RMSEA index = 0.271 Note common variance indicates 1 factor is sufficient (unidimensional)

Note TLI (model fit) Note RMSEA (error)

#### **BFA** Demonstration

- psych package
- Define item set/scale, example: "scaleA"
- "omega(scaleA)"
- Copy and interpret results

#### **BFA** Output

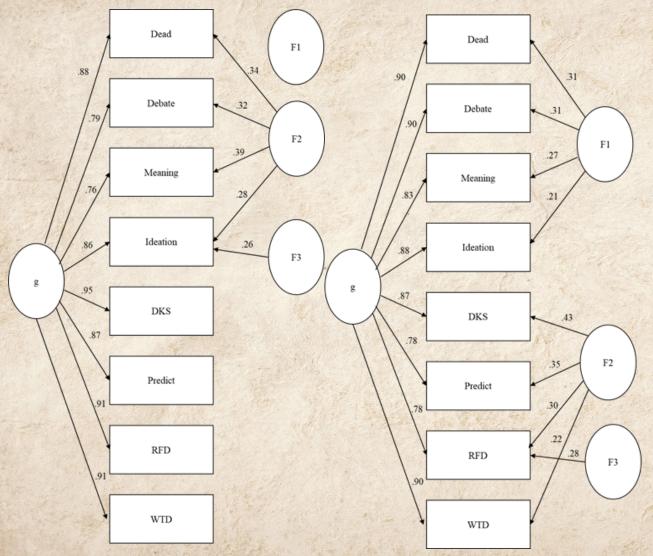
> omega(pool)						
Omega						
Alpha:	0.97					
G.6:	0.98					
Omega Hierarchical:	0.83					
Omega H asymptotic:	0.85					
Omega Total	<mark>0.98</mark>					

Schmid Leiman Factor loadings greater than 0.2								
	g	F1*	F2* F3*	h2				
Dead	0.76	0.37		0.71				
Ideation	0.78	0.27	0.23	0.73				
Debate	0.79	0.26		0.73	145 Des			

Explained Common Variance of the general factor = 0.72RMSEA index = 0.055 There are many statistics from BFA. Note the Omega-H; the g loadings, the h2 Also, examine the F1-F3 loadings

Note the ECV and RMSEA (error)

#### Suicidality Scale Bifactor Analyses English S2 (left) S3 (right)



Similar to the HCA diagram, the bifactor diagram shows how some items relate to others, and the overall construct.

g = general factor – the latent trait
F = group factor, item subgroups
Numbers = loadings, higher ≈ stronger

These relationships can help us understand how the latent trait works. Possibly opening the door to more sophisticated assessment of trait characteristics.

Here we see preliminary evidence that there may be two sets of four items, that show assessment strengths at low or high levels of the trait. How would you investigate that?

### IRT – GRM Demonstration

- Itm package
- Decide/test appropriate model, GPCM, GRM, etc. We selected GRM
  - 1. Run constrained GRM model (all items have equal difficulty/value) = Fit1
  - 2. Run unconstrained GRM model (items are allowed to vary in difficulty/value) = Fit2
  - 3. Run ANOVA to test for information loss levels between Fit 1 and 2, lower AIC (information loss) is better, a significant p value means the AIC/BIC significantly differ, meaning the model/fit with lower AIC and BIC is better
  - 4. Run analyses with the better GRM fit
  - "fit1 <- grm(data = scaleA, constrained = TRUE)"</pre>
  - "fit2 <- grm(scaleA, , IRT.param = TRUE, constrained = FALSE)"</pre>
  - "anova(fit1, fit2)"

### IRT – GRM – item statistics (b, a)

Itm package

- "fit2 <- grm(scaleA, , IRT.param = TRUE, constrained = FALSE)"
- "fit2"
- "summary(fit2)"
- Copy and interpret results

#### **GRM** Output

grm(data = pool, constrained = FALSE, IRT.param = TRUE)
Coefficients:
\$Dead

Extrmt1 Extrmt2 Extrmt3 Dscrmn -0.821 0.270 0.922 2.400

**\$Ideation** 

Extrmt1Extrmt2Extrmt3Extrmt4Dscrmn-1.504-0.5370.1520.6922.727

Note the discrimination values = a, the Extrmt values =  $b_1$ ,  $b_2$ , ...

See the next slide for an example

### IRT – GRM (test & item information functions)

#### Itm package

- Test/Item Information
- "information(fit2, c(-4,4))"
- "information(fit2, c(-4,4), items = c(1))"
- "information(fit2, c(-4,4), items = c(2))"
  - Repeat for all items

full test (scale) information item 1 (first) info item 2 (second) info

#### Item Information Functions

information(fit2, c(-4,4), items = c(1)) Call: grm(data = ss, constrained = FALSE, IRT.param = TRUE) Ideation Total Information = 11.55 Information in (-4, 4) = 11.55 (99.96%) Based on items 1

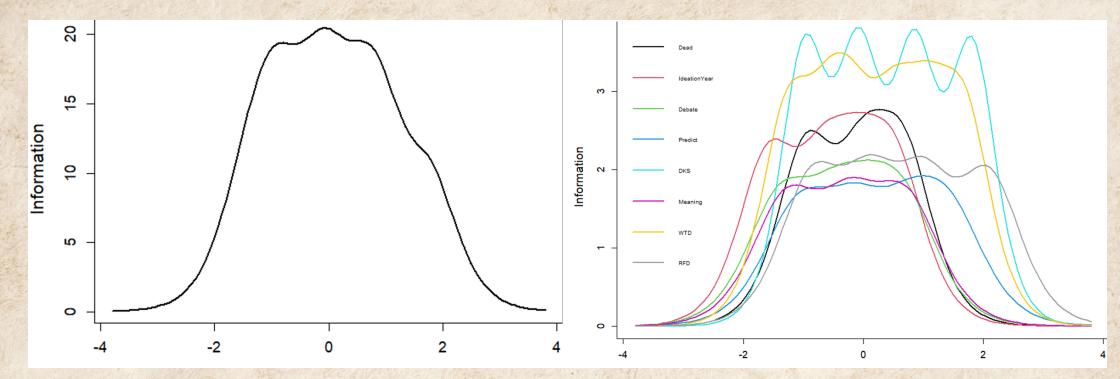
```
> information(fit2, c(-4,4), items = c(2))
Call:
grm(data = ss, constrained = FALSE, IRT.param = TRUE)
Debate
Total Information = 9.95
Information in (-4, 4) = 9.9 (99.47%)
Based on items 2
```

Here are two SS items. You need to type in the item name, in yellow, as this is not provided in R output. The only number we use here is the **Total Information (IF)** which we can put in our table. This tells us how much info on theta each item captures. We can compare this to the **Test Information** value to see proportion per item.

### IRT – GRM - IICs

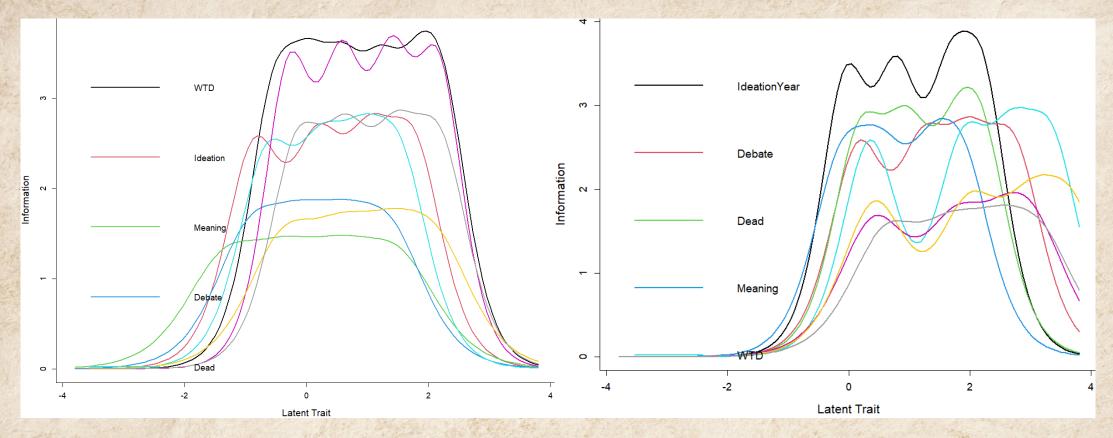
- Itm package
- Test/Item Information Curves
- "plot(fit2, legend = TRUE, type = "IIC", cex = 1.0, lwd = 2, cx = "topleft", xlab = "Latent Trait", cex.main = 1.5, cex.lab = 1.3, cex.axis = 1.1)"
- = all test items plotted together, compare info levels, range
- Item Response Category Characteristic Curves
- plot(fit2, lwd = 2, cex = 1.0, legend = TRUE, cx = "left", xlab = "Latent Trait", cex.main = 1.5, cex.lab = 1.3, cex.axis = 1.1)
  - = each item, one by one, check response patterns

#### SS Test & Item Information Curves (English S1)



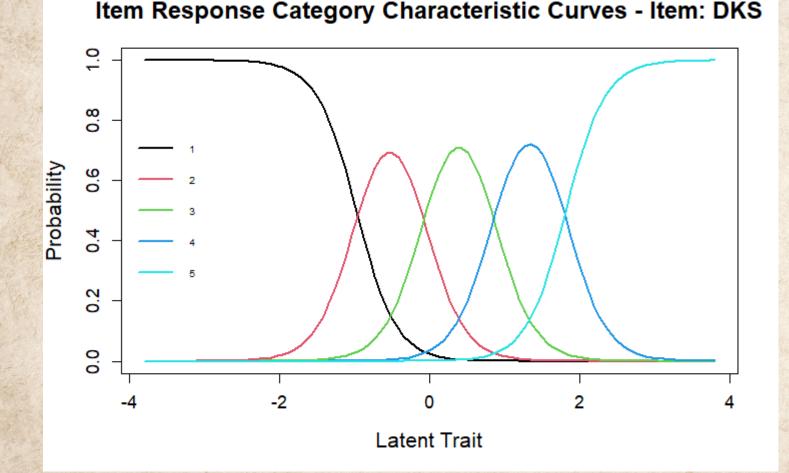
The **Test IC**, left, shows the total information captured on theta, for the full test (Suicidality Scale). Most information, under the line, comes from low-moderate to moderate-high levels of theta, with less information and more error at tails. The Item ICs, right, show information captured on theta by each item. Some items show strength at low or high tails, no two are the same. Even if two items overlapped, they may provide unique information at theta levels.

#### Item Characteristic Curves (English S2, S3)



These ICCs are from smaller samples but still provide good information on how items capture unique information on theta. These graphs can also be used to help identify weak items in item pools.

#### Item Response Category Characteristic Curve – Desire to Kill Self

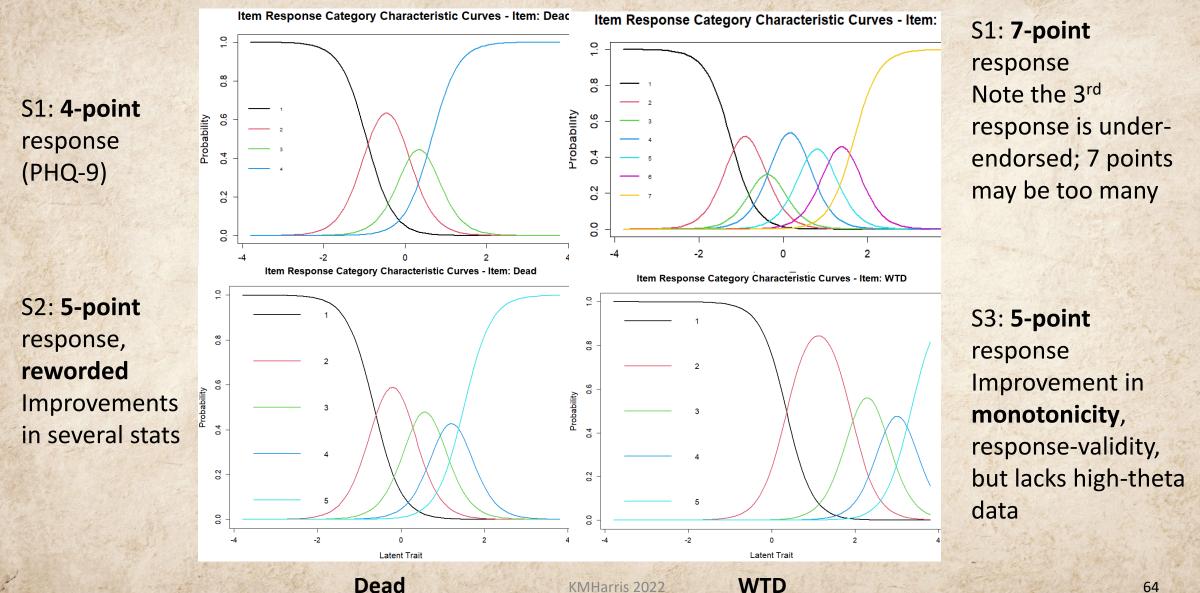


This graphic illustrates **b** coefficients (item response cutpoints), indicating the *theta location* of response boundaries. E.g., the intersection between response 2 and response 3 (where the red and green lines intersect) b<sub>2</sub> = -0.09. We see the information, area under each line, each response captures.

Compare b coefficients across items. They do not necessarily match, indicating item responses are not equivalent.

Can test monotonicity – responses consistently increase/decrease along theta. This item shows a near-textbooklevel perfection. Nice orderly curves, lines nearly the same height and width.

#### Item Response Category Characteristic Curves (English S1: S2/S3)



### Putting it together – SS Item Stats

	Item	Graded response model				Clus	k	'A	B	FA
1 1 1 1		b <sub>l</sub>	b <sub>u</sub>	а	IF	L	L	$h^2$	g	$h^2$
A State of the sta	DKS	-0.88	1.84	3.79	13.19	.92	.93	.86	.93	.89
14. 1 1	WTD	-1.20	1.61	3.29	12.33	.91	.91	.83	.92	.85
	RFD	-0.89	1.98	2.64	8.15	.83	.83	.68	.85	.73
	Ideation-year	-1.55	0.44	2.81	7.46	.84	.84	.70	.79	.83
	Dead	-0.96	0.61	3.01	6.93	.85	.85	.72	.83	.75
	Predict	-0.99	1.33	2.40	6.39	.83	.83	.69	.83	.72
	Debate	-1.26	0.60	2.57	6.34	.85	.85	.72	.81	.80
	Meaning	-1.19	0.66	2.36	5.33	.82	.82	.67	.83	.73

Here are detailed statistics of final SS items. All items showed strengths across all analyses.

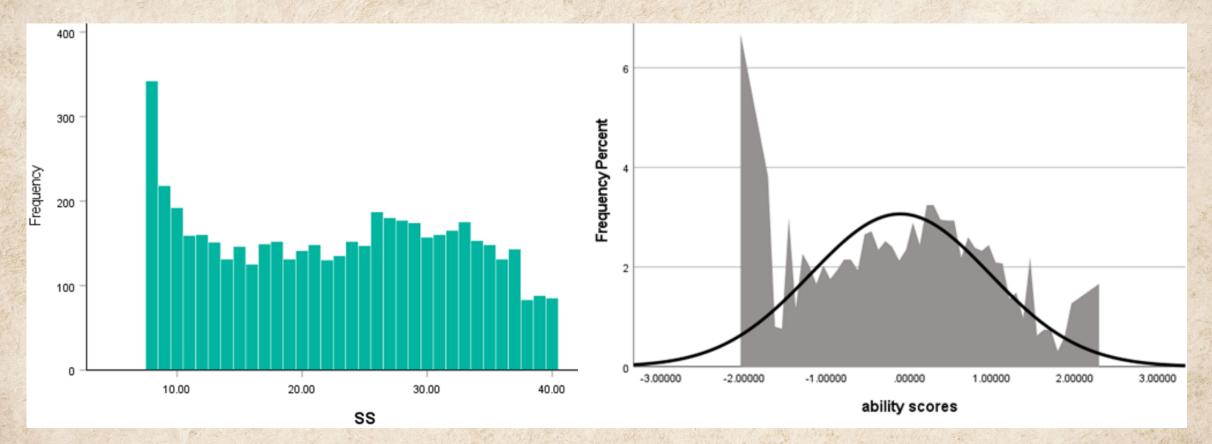
In green, we see two items that appear equal through some analyses. However, considering GRM and BFA, they have different strengths.

### IRT – GRM – Ability Scores - Demonstration

- Itm package Factor/ability scores PROMIS© 'response pattern scoring'
- (ensure data is sorted by ID first!)
- "options(max.print = 99999)"
  - > "fit2 <- grm(scaleA, , IRT.param = TRUE, constrained = FALSE)"</p>
  - > "fs <- factor.scores(fit2, resp.patterns = data)"</li>
  - > "sink('data.csv')" data = your name for the new file, as you like
  - > "fs"
  - > "sink()"

• Locate 'data.csv' file, copy ability scores (scaleAz1) and se (scaleAse.z1) paste into dataset

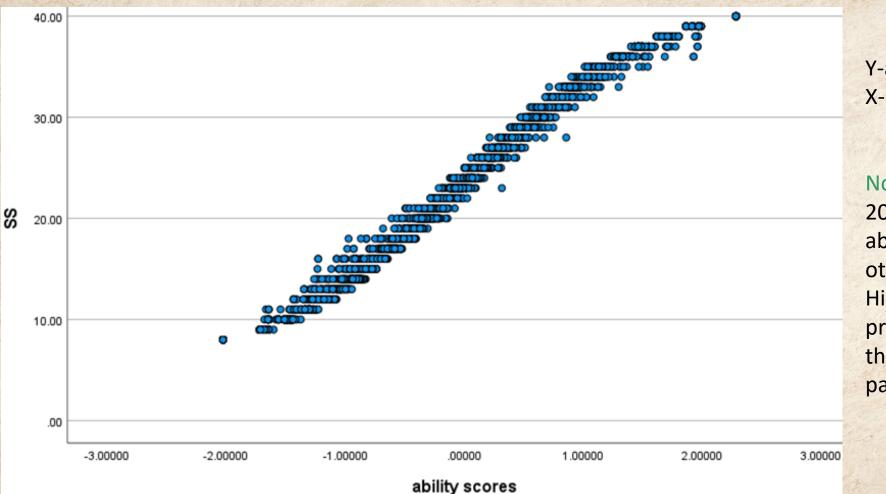
#### SS Sum & Ability Scores (English S1)



This histogram of SS **sum scores** shows good coverage of the trait.

This graph of SS **ability scores**, from the same dataset, shows many more score points and a more normal distribution.

#### Scatterplot SS Sum Scores & Ability Scores (English S1)



Y-axis = **sum** scores X-axis = **ability** scores

Note that a sum score of 20 shows a range of ability scores, as do other sum scores. Highlighting better precision of ability scores through response pattern scoring.

### IRT – GRM – DIF – Demonstration

#### lordif package – DIF

- Differential item functioning: do items assess the latent trait equivalently, or not (DIF), across groups (e.g., genders, age groups, ethnicity)
- Currently, categories are limited to 2 or 3. There need to be sufficient cases across levels of theta to determine DIF
- > "gender <- study1[, 36]"</li>
  - Gender = new variable name (DIF variable); 36 = column in dataset for gender
- > "difgender <- lordif(scaleA, gender, criterion = "R2")"</li>
  - Difgender = new variable name (DIF test of gender variable)

### DIF Output

```
lordif(resp.data = data, group = diagnosis, criterion = "R2")
 Number of DIF groups: 2
 Number of items flagged for DIF: 0 of 8
 Items flagged:
 Number of iterations for purification: 1 of 10
 Detection criterion: R2
 Threshold: R-square change \geq 0.02
DFIT Analysis
Group: 0
Iteration: 85, Log-Lik: -28885.141, Max-Change: 0.00010
(mirt)
Group: 1
Iteration: 99, Log-Lik: -14918.401, Max-Change: 0.00008
(mirt)
DTF(1) = 0.017
```

For DIF, we set the criterion for a meaningful difference in assessment at R2 < .02. These results show that self-reported diagnosis for a mental disorder status (yes/no) showed no evidence of DIF (0 of 8 items) or DTF.

#### Internal Consistency – Omega – $\omega$

coefficientalpha package

- Disconnect psych package!
- Obtain bootstrapped robust omegas
  - Internal consistency (similar to Cronbach's alpha)
  - This will yield coefficient  $\omega$ , and bootstrapped 95% CI intervals
  - You can just report the 95% CI, they are most important

> "omega <-bootstrap(scaleA, type='omega', nboot=10, plot=TRUE)"</li>

#### McDonald's w Output

omega <-bootstrap(ss, type='omega', nboot=10, plot=TRUE)

The estimated omega is 0.9668936

Its bootstrap se is 0.002

Its bootstrap confidence interval is [0.964, 0.968]

Here, we calculate the robust omega coefficient, and even more important – the bootstrapped 95% Cl. You can just report the Cl if you like.

## Putting the Results Together

#### Basic Interpretation of Statistics

- Model fit and common trait variance = TLI, Fit, V (variance), ECV (explained common variance),  $\omega_h$  Closer to 1.0 is best
  - Each of these gives some indication of how well the scale fits the model
  - If the measure is unidimensional, these results should help confirm that
- Model error = RMSEA, RMSR (should be near 0, depending on metric)
- Loadings closer to 1.0 is strong; < .60 may be concerning</li>
- Communalities (h<sup>2</sup>) closer to 1.0 is good; < .50 may be concerning</li>
- Internal **consistency** =  $\omega$ , close to 1.0 is good; < .85 may be concerning
- These statistics may be best understood by comparing metrics across scales and studies. Please see References for expert guidance!

#### Scale EFA Results

We conducted psychometric analyses on all scales used in our studies, including bifactor analysis, GRM, HCA. Here, we present EFA and omega statistics.

These can be compared across studies, and with the Suicidality Scale.

More details in the SS English manuscript.

		ω				
Study/scale	TLI	RMSEA	V	Loading	$h^2$	95% CI
Study 1 ( <i>N</i> = 5115)		11.12			Martin .	
SWLS	.98	.09	.65	.6890	.4681	[.88, .89]
PHQ-9	.89	.12	.56	.6586	.4275	[.89, .90]
PHQ-8	.91	.12	.55	.6683	.4469	[.87, .88]
DASS-Anxiety	.96	.09	.63	.6388	.4077	[.89, .90]
DASS-Depression	.94	.14	.74	.8188	.6578	[.93, .93]
C-SSRS-10	.82	.21	.70	.6496	.4192	[.87, .88]
C-SSRS-5	.98	.06	.54	.5683	.3169	[.85, .86]
SABCS-m	.87	.20	.65	.5487	.2976	[.91, .92]

### SS – Scale Statistics (English)

These results show multimodel scale statistics. We see high fit, *mostly* low error, high variance explained, high internal consistency – across models and studies.

More details in the manuscript.

	Cluster		Factor Analysis			Bifa	ctor A	ω	
Study	Fit	RMSR	TU	RMSEA	v	ω <sub>h</sub>	ECV	RMSEA	95% CI
S1	.98	.03	.94	.12	.74	.94	.92	.05	[.96, .96]
S2	.99	.03	.95	.14	.84	.93	.91	.06	[.96, .97]
S3	.99	.04	.89	.24	.87	.93	.87	.02	[.96, .97]

#### **GRM** Table

Graded Response Model Analyses of Suicidality Scale Items

					The second			
Item	<i>b</i> <sub>l</sub>	<i>b</i> <sub>2</sub>	<i>b</i> 3	<i>b</i> 4	<i>b</i> 5	<i>b</i> <sub>6</sub>	а	IF
DKS	-0.28	0.58	1.39	2.15	-	2	3.67	12.22
WTD	-0.52	0.03	0.60	1.23	1.84	2.22	3.52	9.41
RFD	-0.14	0.65	1.47	2.17		3 <u></u>	3.17	11.11
Ideation	-0.97	-0.18	0.63	1.27		-	3.60	11.97
Dead	-0.66	0.11	0.61	1.12	The second	-	3.53	10.66
Predict	-0.24	0.51	1.19	1.89		-	2.42	6.43
Debate	-1.32	-0.43	0.36	1.08		<u> </u>	2.79	7.81
Meaning	-1.53	-0.43	0.49	1.29		—	2.34	6.92

This is a more complete GRM table. We see the individual item response threshold levels for each item, the b coefficients. b1 shows where responses 1 and 2 cross. The b statistic relates to the level of theta, where those responses cross. Lower values indicate lower levels of the latent trait. We can see that some capture information on theta at lower levels than others (e.g., Meaning), some at higher levels (e.g., DKS). We also see that items can differ in many ways on thresholds. *a* = discrimination, how well the item discriminates test-takers on theta IF = information function, the amount of information captured on theta

#### **Problems** with Scores

- Sum scores not precise, not individualized, excess error
- Cutoffs/cut points rely on all items being equal
  - Not valid, excess error
- Ability scores complicated, time consuming, often unavailable
- How can we improve latent trait scores for usability & interpretation?

#### **T**-Scores

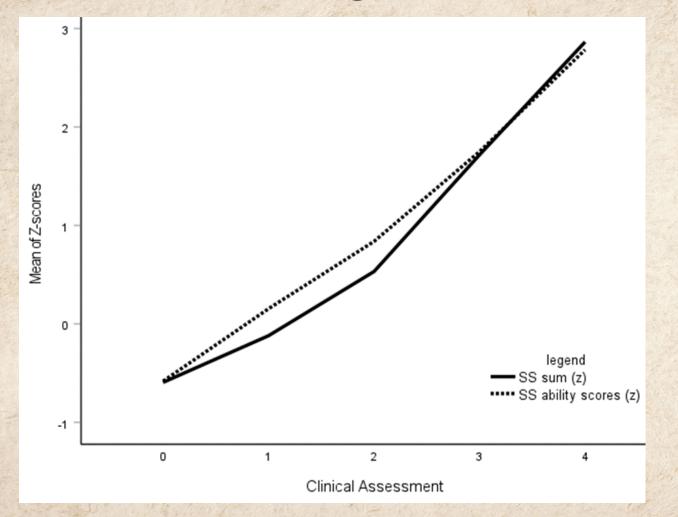
- T-scores are popular and easy to interpret (M = 50, SD = 10)
  - A T-score of 70 on a suicide risk assessment = two standard deviations worse than the average person assessed
- Can create T-scores from ability scores by including ranges
- Steps
  - Calculate z-scores (sum scores and ability scores)
  - T = 50 + (10 \* z-score)
  - T-scores: SD = 10.0; M = 50.0
  - SE = SD/ $\sqrt{n}$
  - N = sample size (should be large, diverse, representative for *official* T-scores)
  - 95% CI = 1.96 \* SE
- Colombia study: SE = 10/ √313 = 0.57
  - (1.96 \* SE) = 1.12
  - Best estimate = T-score +/- 1.12
- Interpretations T-score = 49 51, about average suicidality (of community)
  - T-score = 59 61, one standard deviation above *average*, significantly higher symptoms
  - T-score = 79-81, three SDs above *average*, extreme symptoms

### **Approximate Ability T**-Scores

- Not possible to match single sum score with a specific ability score
- When comparing with sum scores, these will have a range
- In addition, there will be 95% CI, increasing the range
- We can present tables with sum scores = approximate ability T-score ranges
  - See PROMIS manuals for additional examples
- Example: sum score = 40 ≈ *ability* T-scores 68 71
  - +/- 1.12, Approximate Ability T-score = 67 72
  - Sum scores will show overlapping ability T-scores
  - These are approximate ability scores. A true ability score might fall out of this range

	Sum Scores	Sum T-Scores	<b>GRM T-Scores</b>	2.5		Risk	Possible facets	Clinical response
Clinical	48 47 45	80 79 77	79 76-77 73-74	2.0		Very high ⇔	Strong with to die; strong desire to kill self; more reasons for dying than living	Urgent care
Guide	40	72	68-71	1.5				
The left table shows Colombian	35	68	65	1.0 (1.0			Combinations of low and very high- risk facets, and	
sample sum scores can translate to T- scores, and how	29	62	61-63	Ability estimate (theta) c c c		Equivocal ⇔	feelings of being better off dead; acknowledging possible future	Moderate to urgent care
these compare to GRM T-scores.	21 15	55 50	56-59 51-56	Ability 50-			suicide attempts	uigent care
On the right, we have English S1	11	46	47-51	-1.0			Infrequent thoughts of suicide; some internal debate between choosing	
ability (GRM) scores related to suicidal facets and	10 9	45 44	<b>47-50</b> 46-48	-1.5		Low ⇒ Very low	life or death; sometimes feeling one's life is	None currently needed, but
clinical directions.	8	43	41	-2.0			meaningless	scores > minimum suggest follow-up evaluations
	95% CI =	+/- 1.12	+ <b>/- 1.12</b> KMHar	-2.5 ris 2022	Case cou	nt		81

#### Clinician Ratings – Colombian sample



This plot shows Clinical decisions, xaxis, ordered from 0 = no treatment to 4 = immediate hospitalization The lines represent z-scores of SS sum scores and SS ability scores.

*Note* that the clinical decisions are more closely correlated with the ability scores at 1 and 2. This may indicate that clinical decisions are based on information beyond the sum scores, making them more valid, and closer to the more precise ability scores.

# Applying Knowledge

### **Choosing** Latent-trait Measures

#### Consider

- IRT-tested > concise, highly informative
- DIF-tested > works equivalently in different demographic groups
  - E.g.: PROMIS <a href="https://www.healthmeasures.net/explore-measurement-systems/promis">https://www.healthmeasures.net/explore-measurement-systems/promis</a>
  - PROMIS has several validated scales, free to use but not modifiable
- CAT (computer adaptive testing), important direction, but beware of GIGO
  - CAT requires highly valid instruments to be effective

#### Requirements

- Assesses individual traits, not group factors
  - E.g., SADPERSONS includes items on sex, age which may indicate group risk, not personal
- Scale should include critically tested items, evidence-based
- Does not emphasize cutoff scores (low, medium, high-risk)
  - E.g., DASS-21, emphasizes ranges, subjective interpretation of sum scores
- Does not rely on: Cronbach's alpha > .70; Factor loadings > .32+; CFA fit/error
  - Provides more item/scale statistics and emphasizes strengths/weaknesses

#### **Proactive** Directions

- Support/Promote Open Science
  - e.g., set up accounts, contribute 1 thing
- Support/Promote SDGs: How can your work contribute?
  - e.g., women & minority leadership; global connections; sharing knowledge
- Support/Promote Free & Valid Instruments
  - Choose scales/measures/instruments carefully
  - Mention/cite free culture licensed resources
- All Science is needs to be Local
  - Support/Promote localization of skills, instruments, etc.



#### **Contact** – Keith Harris <u>keithharris@csu.edu.au</u> <u>kmh.psyc@gmail.com</u>

Original talk:

https://charlessturt.zoom.us/rec/share/VI78EZPEvEheOTul\_YCmgBNDsaIb24oxgLCyuHrTQWWUMoiKxKx 2hp1JfqHK\_ggi.eWwiLPW6odsn8LcR?startTime=1658440991000



## Extra Resources

Do **1** thing! Open science sites Research ethics/guidelines References

#### Get started: Do 1 Thing!

- Contact someone through OSF or other
- Preregister, post preprint of, your research @ OSF or similar
- Post some good work you have done, but perhaps won't be a published paper
- An example of 1 thing
  - A revised poster presentation, published through figshare, including a doi, and publicly available
  - <a href="https://figshare.com/account/projects/4566/articles/20237100">https://figshare.com/account/projects/4566/articles/20237100</a> Reasons for Dying (RFD)



#### License your paper/data/poster/etc. as Free Cultural

• We copyrighted the Suicidality Scale as CC BY 4.0 (free cultural)









For open data, preprints, preregistration, etc.: <u>https://osf.io/</u>



Similar to OSF: <a href="https://figshare.com/">https://figshare.com/</a>

#### More Open Science Links

- Start by getting an ORCID, setting up accounts at OSF, Scholar, etc.
- Researcher ID: <u>https://orcid.org/</u>
- Google Scholar: <u>https://scholar.google.com</u>
- ResearchGate: <u>https://www.researchgate.net/</u>
  - Example project: <u>https://www.researchgate.net/project/Assessing-Suicidality-Development-of-State-of-the-Science-Measures-of-Suicide-Risk-Across-Languages-and-Cultures</u>
- More free & open source statistics packages: Jamovi: <u>https://www.jamovi.org/</u>
  - JASP: <u>https://jasp-stats.org/download/</u>
- There are many more open science sites!

### Research Ethics/Guides

- The Helsinki Declaration: Ethics in medical research (see World Medical Association)
  - <u>https://www.wma.net/policies-post/wma-declaration-of-helsinki-ethical-principles-for-medical-research-involving-human-subjects/</u>
- Data management: FAIR Wilkinson et al. (2016)
  - https://www.nature.com/articles/sdata201618#citeas
- Author roles: <u>https://credit.niso.org/</u>
- **TOP** open research:
  - Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., . . . Yarkoni, T. (2015). Promoting an open research culture. Science, 348(6242), 1422-1425. doi:10.1126/science.aab2374
- Nature's Scientific Data offers guidance, with links, on data repositories:
  - <u>https://www.nature.com/sdata/policies/repositories#general</u>
  - Nature's data policy page: <a href="https://www.nature.com/sdata/policies/data-policies">https://www.nature.com/sdata/policies/data-policies</a>
- PLOS also offers data info and links: <u>https://journals.plos.org/plosone/s/recommended-repositories</u>

#### Select References for Surveys, Psychometrics, etc.

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