DFI?

Demystifying Dynamic Fit Indices

Jay Jeffries

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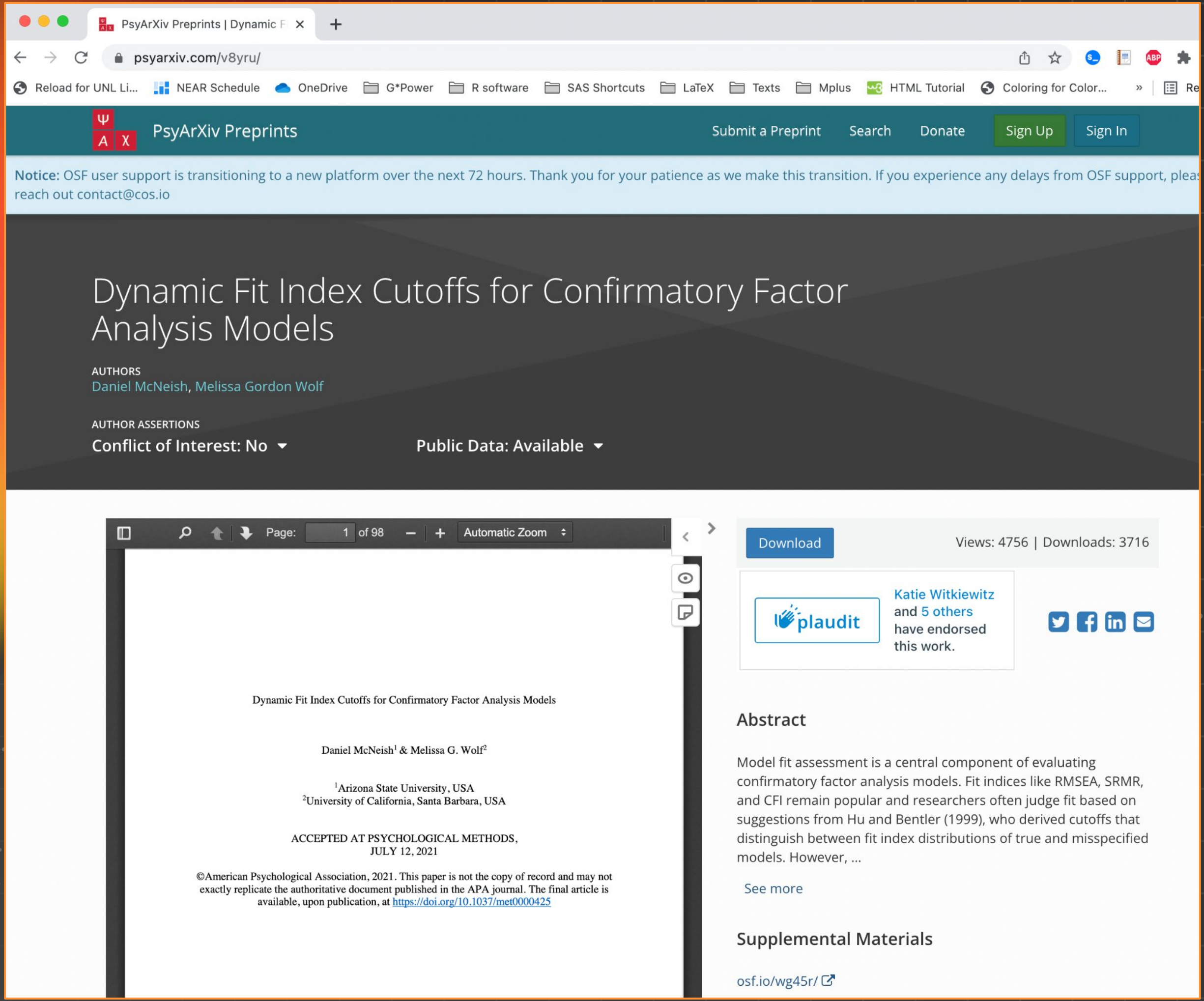
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Dynamic Fit Index Cutoffs for Confirmatory Factor Analysis Models
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AUTHOR ASSERTIONS
Conflict of Interest: No
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Dynamic Fit Index Cutoffs for Confirmatory Factor Analysis Models
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ACCEPTED AT PSYCHOLOGICAL METHODS,
JULY 12, 2021
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Katie Witkiewitz and 5 others have endorsed this work.
Abstract
Model fit assessment is a central component of evaluating confirmatory factor analysis models. Fit indices like RMSEA, SRMR, and CFI remain popular and researchers often judge fit based on suggestions from Hu and Bentler (1999), who derived cutoffs that distinguish between fit index distributions of true and misspecified models. However, ...
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Supplemental Materials
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GOALS AND CURIOSITIES

EXPLORATION

Practice and implement DFI simulation with real data.

MODEL IDENTIFICATION

How do DFIs change depending on method of model identification?

- Specifically, do effects-coding scaled factors change the cutoff for a hypothesized model?
  - ➢ Test the 3 common model identification methods

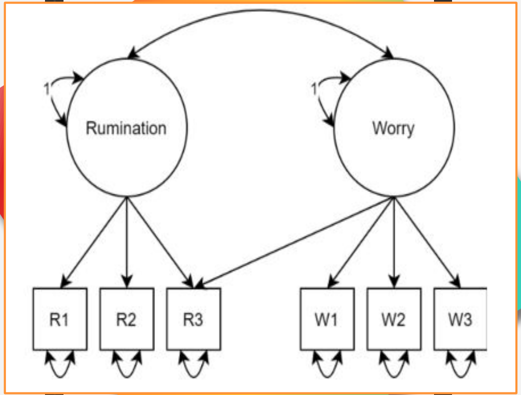
How do DFIs change depending on factor reliability?

- ➢ Compare factor models of differing reliability

MODEL SPECIFICATION

Important step in the process of model building that includes:

- Rationalizing the inclusion or omission of causal pathways
- Operationalizing constructs
- Specifying direction of paths
- Indicating correlated residuals & variances



TRADITIONAL MODEL FIT INDICES

NAME	DEFINITION
χ^2	Exact fit test that identifies if hypothesized model and observed data are equal; sensitive to *N*, as an increasing *N* and constant *df* results in increased χ^2.
CFI	Incremental fit index that examines discrepancy between obtained covariance matrix to independence covariance matrix and mostly unaffected by *N*
RMSEA	Absolute fit index that assesses how far the observed model is from a perfect (saturated) model; parsimony-adjusted index that is unaffected by *N*
SRMR	Absolute fit index comparing the average of standardized residuals between the observed and hypothesized covariance matrices; relatively unaffected by *N*

FLAWS IN FIXED CUTOFFS

Hu & Bentler (1999)

- Unless models match, these cutoffs may not generalize
- Fit can be compared between full/reduced models but not across models with different characteristics

Model Conditions

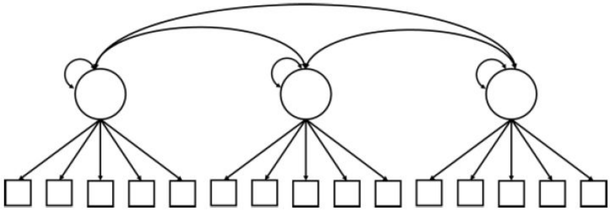
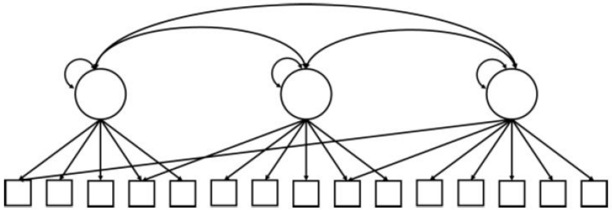
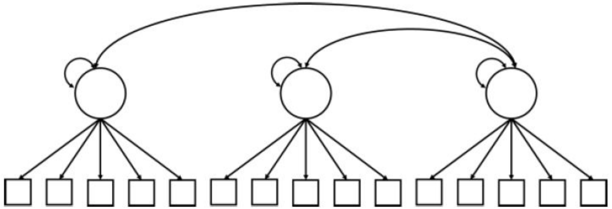
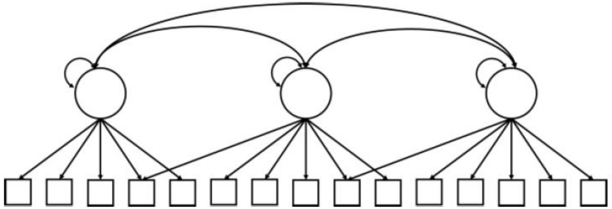
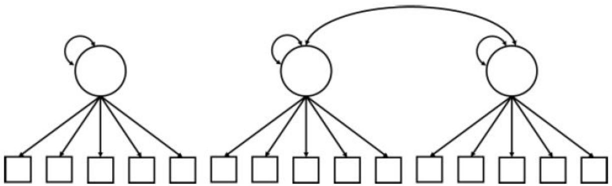
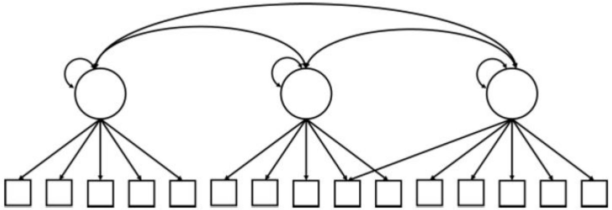
- Narrow and discordant model subspace
- Cutoff values change depending on number of items & factors, df, size of loadings, factor reliability, model type

Misspecifications

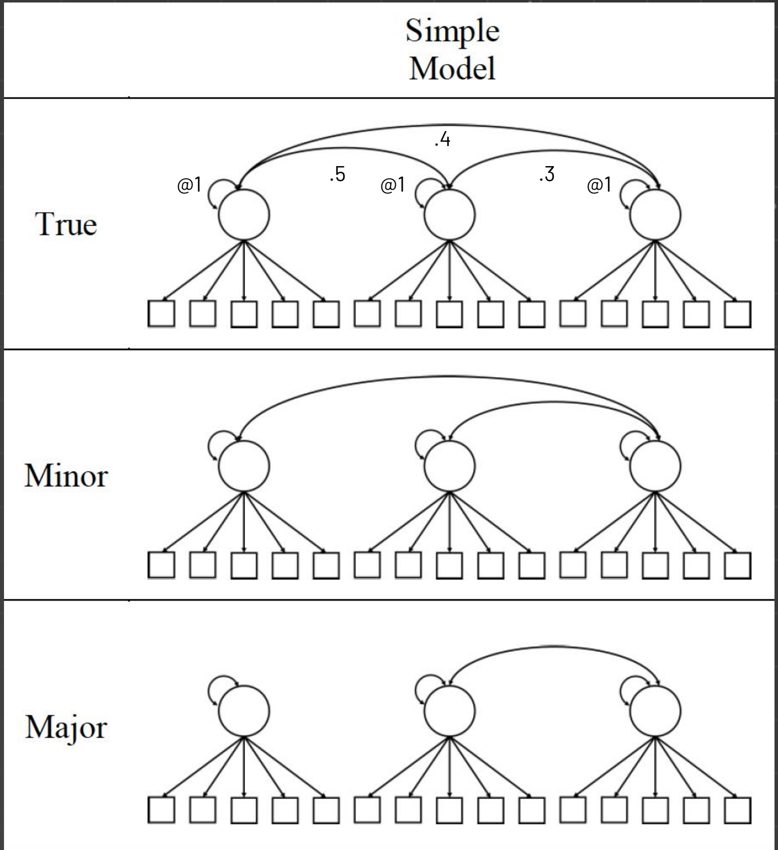
- Biased parameters lead to inaccurate conclusions
- “All models are wrong” but we should aspire for better

Table 1

Path diagrams of different model and misspecification conditions in Hu and Bentler (1999)

	Simple Model	Complex Model
True		
Minor		
Major		

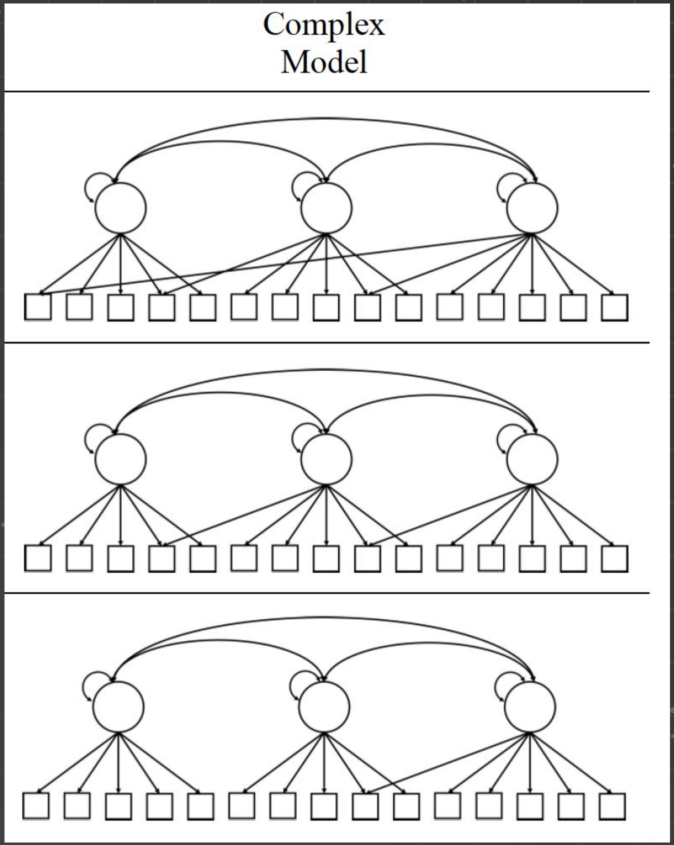
Note: Error variances for the observed variables are present but not shown in the path diagrams.



“Simple” model strips away covariances.

$$\begin{bmatrix} .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 \\ .00 & .00 & .00 & .00 & .00 & .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 \\ .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .70 & .70 & .75 & .80 & .80 \end{bmatrix}$$

Loadings not manipulated across models.



“Complex” model adds away cross-loadings.

$$\begin{bmatrix} .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 \\ .00 & .00 & .00 & .70 & .00 & .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 \\ .70 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .70 & .00 & .70 & .70 & .75 & .80 & .80 \end{bmatrix}$$

Loadings not manipulated across models.
Orange indicates cross-loadings.

WHAT DO I DO?

DYNAMIC FIT INDICES

- Use the web-hosted or software-based custom sims (approachable tool – little manual code required)
- Algorithm generalizes misspecifications derived from Hu & Bentler (1999)

SYSTEM-LEVEL CHANGE

- Consider cost-benefit of reporting simulated cutoffs for your model
- Difficult if reviewers are content with traditional, fixed cutoffs

TRADITIONAL CUTOFFS

- Hu & Bentler (1999) used 200 replications (samples) drawn from a known population to simulate and model conditions
  - Iteratively compare true model vs. different levels of misspecified models (i.e., simple/complex, minor/major, different sample sizes)
  - Tendency to commit Type I error evaluated based on over-rejection rates obtained from difference in rates from both models
    - Track fit index values that discriminate between the distributions of misspecified and true fit indices
  - Thresholds: 95% rejection of misspecified and 5% of true models

MECHANISMS OF DFI

- DFI utilizes the same algorithm as Hu & Bentler (1999) but allows user to alter their model conditions
    - Similar to a power analysis
        - Rather than sample size needed to detect an effect, the goal is to uncover fit indices that detect misspecification
    - If 95%/5% thresholds cannot be met, 90%/10% are computed
    - If neither of above can be computed, then a dynamic fit index cutoff between true and misspecified models cannot be determined with the available tools

STEPS OF DFI

01

Fit empirical model and obtain standardized parameter estimates

- Preference for Lavaan object, but not required

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02 Standardized estimates are used to create a data generation model for simulation (empirical model is not used as data generation model)

- Path is purposefully added to data generation model to elicit misspecification (i.e., the extra path is not in the empirical model)

Need a degree of freedom!

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Model created in step 2.) used to generate 500 datasets to which the empirical model is fit to. Distribution of fit index values are created.

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04

The 5th percentile (for lower-is-better) and 95th percentile (for higher is better) of fit indices values from these distributions are found.

STEPS OF DFI

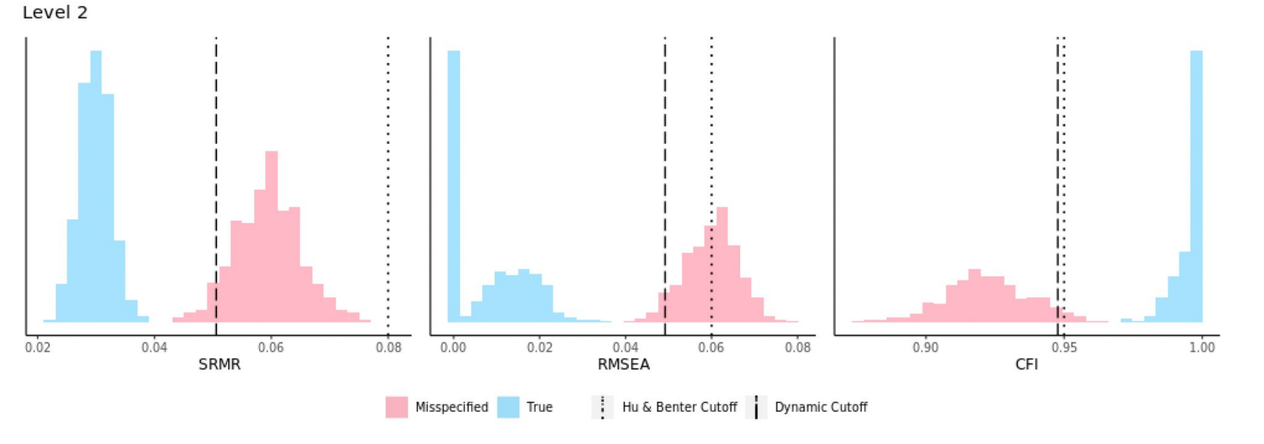
05 Repeat step 2 through 5 but use the empirical model in place of the data generation model.

- Empirical model treated as “True” model
- Essentially reverse-engineer a plausible misspecified model to which you compare the empirical model

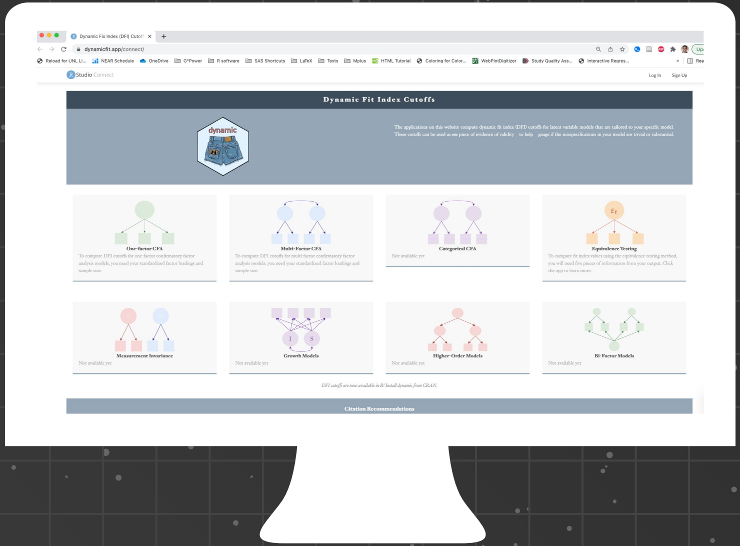
	SRMR	RMSEA	CFI
Level 1: 95/5	.035	NONE	NONE
Level 1: 90/10	--	.026	.983
Level 2: 95/5	.051	.049	.948
Level 2: 90/10	--	--	--

OUTPUT OF DFI

	SRMR	RMSEA	CFI
Level 1: 95/5	.035	NONE	NONE
Level 1: 90/10	--	.026	.983
Level 2: 95/5	.051	.049	.948
Level 2: 90/10	--	--	--



R AND SHINY APP DEMONSTRATION



LIMITATIONS

(OF CURRENT VERSION)

COMPUTATION

CODING

Need light manual coding or .txt file for app

SETTLING

Using traditional cutoffs requires no additional effort; reviewers may be content

DATA TYPES

ASSUMED NORMALITY

Robust variance estimators not available

CONTINUOUS DATA

Categorical items and WLS a high-priority for extension of package

MODEL TYPES

CFA

Path or mixed models not considered

BASIC DESIGNS

Measurement Invariance, Growth Models, Multi-Level, and Bi-Factor Models not yet available

QUESTIONS OR CONCERNS?

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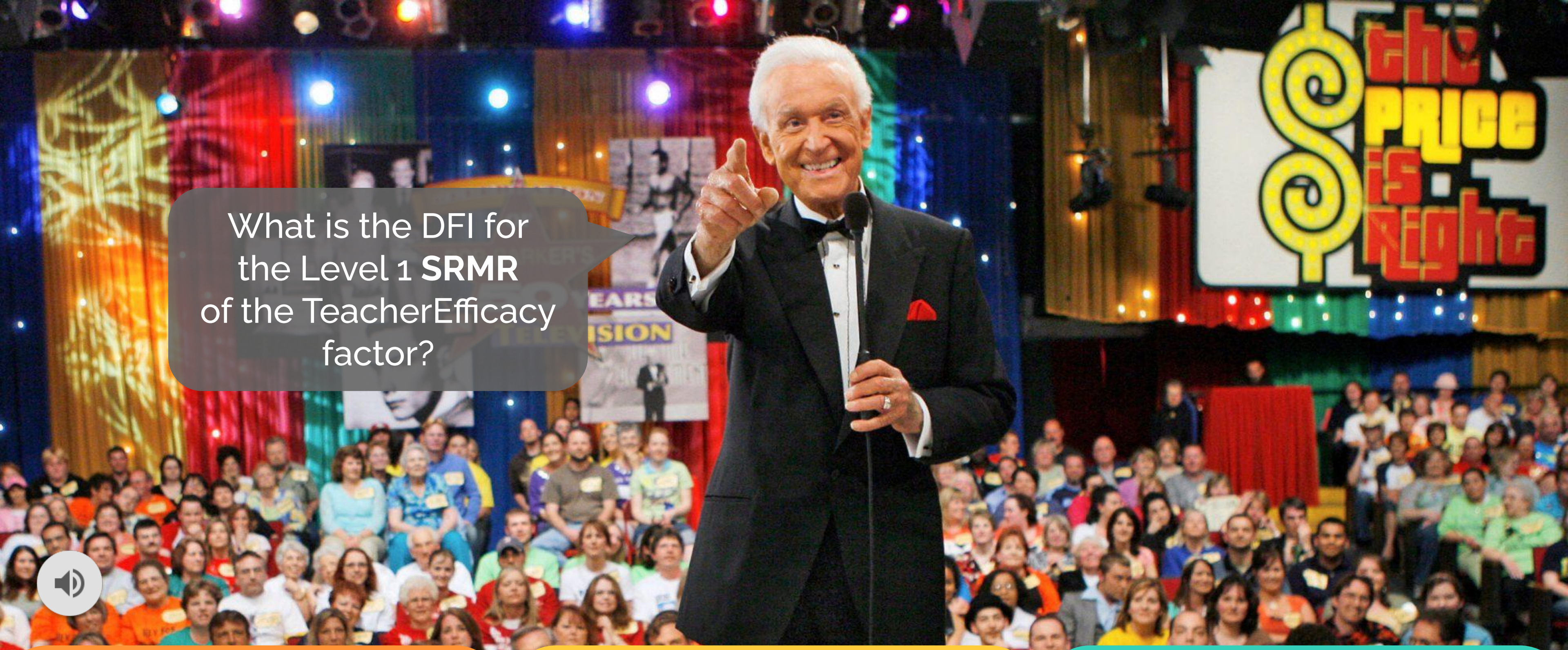

What is the DFI for the Level 1 **SRMR** of the TeacherEfficacy factor?

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What is the DFI for the Level 1 **RMSEA** of the TeacherEfficacy factor?

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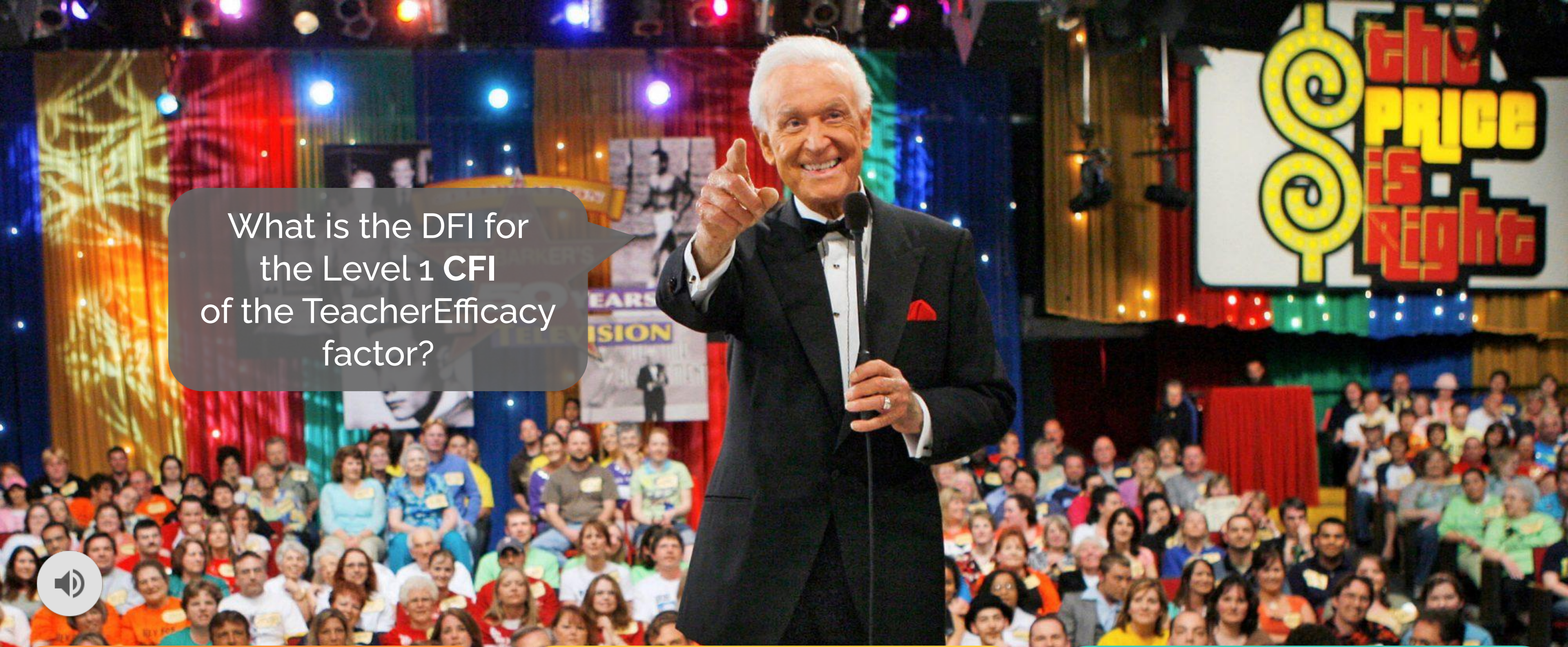

What is the DFI for the Level 1 **CFI** of the TeacherEfficacy factor?

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