Evaluating Confirmatory Factor Analysis with Dynamic Fit Indices: Integrating Statistical and Conceptual Approaches

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https://doi.org/10.20982/tqmp.22.1.p009

INTRODUCTION

- **Confirmatory factor analysis** (**CFA**) is a **statistical method** that quantifies how well the **factorial structure** of a **psychological measure** fits the **data** (e.g., Byrne et al., 2005; Brown, 2023; Jöreskog, 2007).
- **Fit indices** are **effect sizes** that quantify the degree of **model/data fit** or **misspecification** (e.g., Bentler, 1995; Bentler, 1990; Jöreskog, 1969; Steiger & Lind, 1980; Tucker & Lewis, 1973).
- To judge the **appropriateness** of their **factorial models**, **researchers** often use **fixed cutoffs** values (e.g., Hu & Bentler, 1999; **CFI** and **TLI** > .95; **RMSEA** < .06, **SRMR** < .08). However, these **values** cannot be **generalized** to all **models** with all **characteristics** (e.g., Marsh et al., 2004)
- The **Dynamic Fit Index approach** (**DFI**; McNeish & Wolf, 2023) generates **fit index cutoffs** that are tailored to the **characteristics** of the **model** being **tested** (i.e., **sample size, factor loadings, number of items, internal reliability of factors, degrees of freedom**, etc.).

OBJECTIVES

- In this tutorial, we show how to implement the **DFI approach** in ***R*** (*R* Core Team, 2025).
- By building upon **statistical** and **conceptual approaches**, we hope to help **researchers** make **informed decisions** when **implementing** the **DFI approach** to evaluate their **CFA models**.

METHODS

- 527 undergraduate university students.
- Mean age = 19.16 years old (S.D. = 3.29).
- 72.2% Female, 27.8% Male.
- 75.1% first-year students, 16.2% second-year students, 6.3% third-year students, and 2.5% fourth-year students.
- 97.9% full-time students, 2.1% part-time students.
- 60.3% are Caucasian,12.1% Asian, 6.8% Arabic, 6.3% African American, 0.9% Hispanic-Latino, 0.9% Aboriginal/Native, 12.5% other.

- Attainment of School Achievement Goals Scale (**A-SAGS**; adapted from Gaudreau & Blondin, 2004).
  - **3-factor hierarchical model** (i.e., mastery-goal attainment, self-referenced goal-attainment, normative goal-attainment grouped under a general goal attainment dimension).

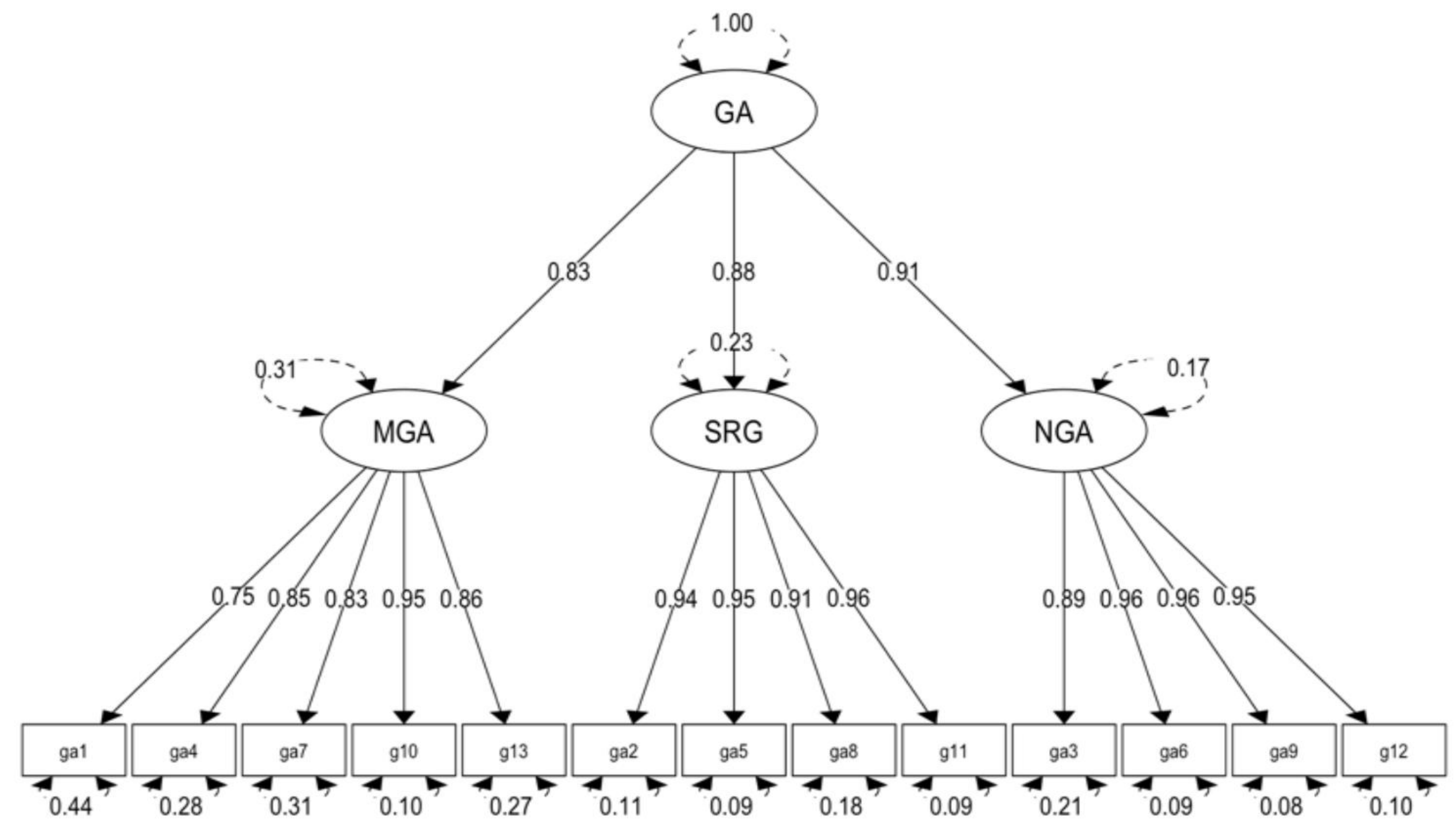
R packages:
- `lavaan` (Rosseel, 2012)
- `dynamic` (Wolf & McNeish, 2023)
- `semPlot` (Epskamp, 2013)

RESULTS

Model	χ^2	df	*p*	CFI	TLI	RMSEA	SRMR
3-factor model	461.359	62	*p* < .001	**.975**	**.968**	.171	**.049**
Alternative 2-factor model	1395.253	64	*p* < .001	**.953**	.943	.230	.093
$\Delta\chi^2$	260.46	2	*p* < .001	-	-	-	-

Note. **Bold** indicates **fit indices** that **meet** the **cutoffs derived** from **Hu & Bentler (1999)**

Figure 1 ■ Factorial structure of the A-SAGS illustrated using `semPlot`. MGA = Mastery goal attainment; SRG = Self-referenced goal attainment; NGA = Normative goal attainment; GA = Goal attainment



Fit Index Cutoffs	CFI	RMSEA	SRMR	95% of the largest allowable cross-loading(s)
3-factor model	.975	.171	.049	-
DFIs of Level 1	> .987	< .062	< .025	.290
DFIs of Level 2	> .983	< .075	< .026	.290 and .126

DISCUSSION AND CONCLUSION

- Using **fixed cutoffs**, we would have **concluded** that the **A-SAGS fits** the **data** well.
- We observe that the **A-SAGS** does not meet the **DFI cutoffs**. **Misfit** in the **model** is due to **more** than **95% of** the **two largest allowable cross-loadings** in the **model**. Therefore, we must investigate **sources** of **misspecification**.
- Looking at **modification indices**, the main **problem** in our **model** is that **item 10** wants to **cross-load** on the other two **factors**, especially **normative goal attainment**. This **cross-loading** (.342) is **substantial** enough to warrant **future attention**. If this **replicates** across multiple **samples**, **item 10** could be **revised**.
- What should you do if your **model** does not meet **DFIs**?
  - **Investigate sources** of **misspecification** with:
    - **Modification indices**. Should **not** be **used** to **modify** the **factorial model**. **Misspeficiation** may be due to **sampling variability** and **modifications** may not be **theoretically founded** (MacCallum et al., 1992).
    - **Bayesian CFA**. A **better alternative** than looking at **modification indices** (Muthén & Asparouhov, 2012).
  - Are **CFA**'s **assumptions** too **strict** for the **model** you are **testing**?
    - Consider **Exploratory Structural Equation Modeling** (**ESEM**; Asparouhov & Muthén, 2009; Marsh et al., 2014).