Examining the Factor Structure and Measurement Invariance of Science Attitude Items across Genders

Ji Yoon Jung & Anne Traynor, PhD
Purdue University

MODERN MODELING METHODS CONFERENCE
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Overview

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- Modeling Methods
  - Exploratory structural equation modeling (ESEM)
  - Independent-clusters model of confirmatory factor analysis (ICM-CFA)
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Introduction

- The power of favorable **attitudes toward science** (science attitudes) is that they reinforce higher performance.
- There continue to be **gender disparity** in science attitudes across many countries (Provasnik et al, 2012).
- Most research related to science attitudes have been based on the TIMSS Student Questionnaire.
- However, there remain two open questions about TIMSS science attitudes items: (1) **the latent factor structure**, and (2) the existence of **measurement invariance** across genders.

Data Source

- What is **TIMSS**?
  - The Trends in International Mathematics and Science Study
  - Conducted by the International Association for the Evaluation of Educational Achievement (IEA)
  - Measuring students' mathematics and science achievement
  - **TIMSS Student Questionnaire**: student attitudes, home background, and school experiences

- TIMSS 2015 Student Questionnaire
- USA sample - 10,221 students (50.1% girls, 49.9% boys)
- Eighth grade students

Modeling Methods

STEP 1: Identifying the Best Fitting Model

- **Bifactor structure**
  - A general factor and three secondary factors (Foy, 2017)
    - *Students Enjoy Learning Science (SES)*
    - *Students' Confidence in Science (SCS)*
    - *Students' Perceived Value of Learning Science (SVS)*
- Independent-clusters model of confirmatory factor analysis (**ICM-CFA**)
- Exploratory structural equation modeling (**ESEM**)
- Model comparison: approximate fit indices, general and local fits, and interpretability of each model

Modeling Methods

STEP 1: Identifying the Best Fitting Model

- Bifactor ICM-CFA Model

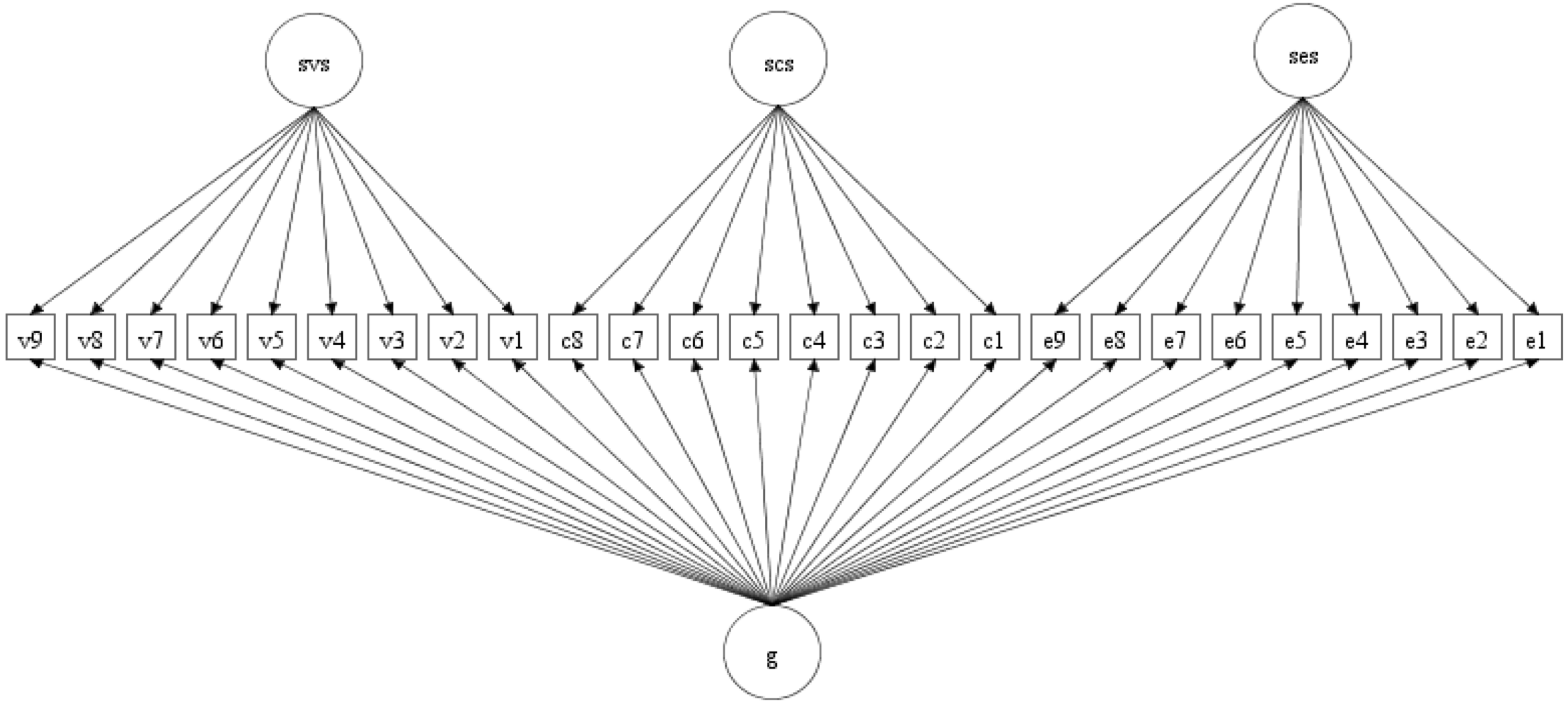

Figure 1. Path Diagram for Bifactor ICM-CFA Model

MODELING METHODS

STEP 1: Identifying the Best Fitting Model

- Bifactor ESEM Model

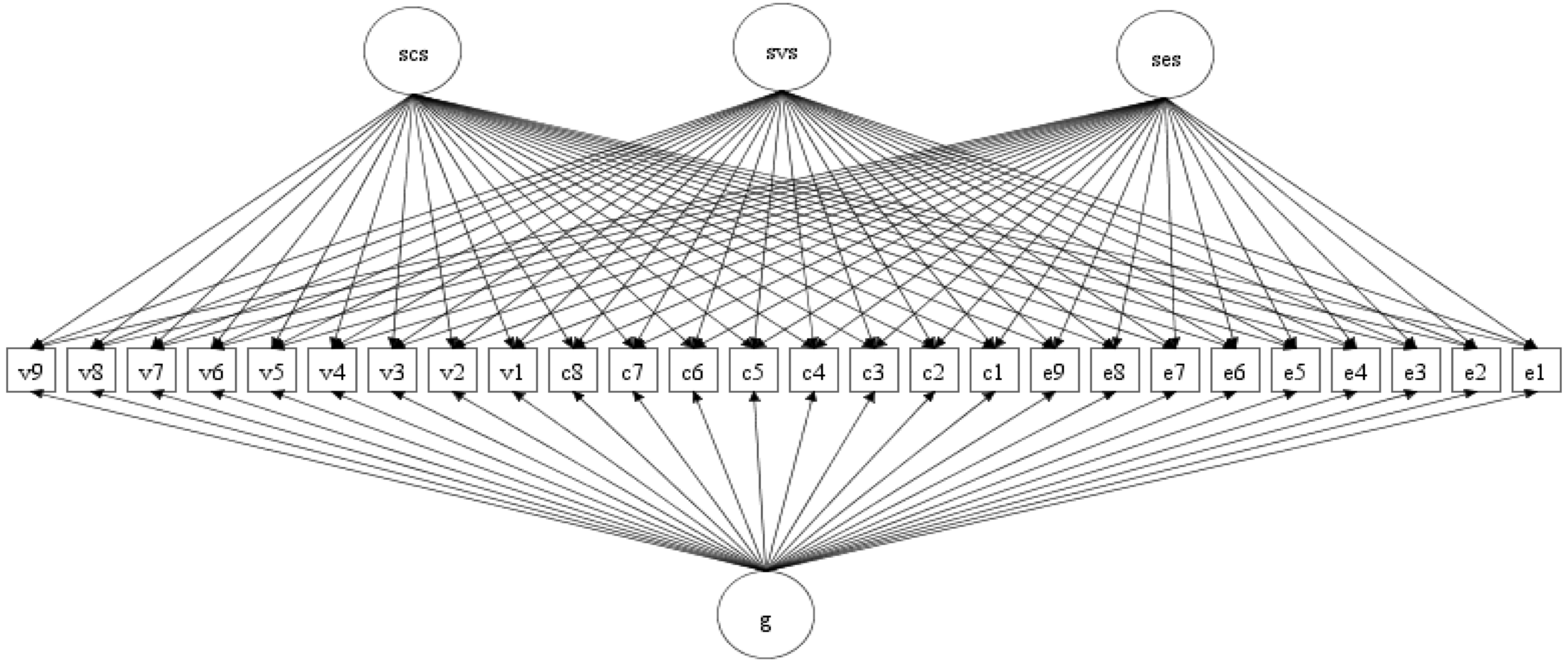

Figure 2. Path Diagram for Bifactor ESEM Model

Modeling Methods

STEP 2: Examining Measurement Invariance

- Nested models were tested progressively (Meredith, 1993)
- **Configural** invariance model
  - Same factor structure, and similar pattern of factor loadings
- **Metric** invariance model
  - Same factor structure, and equal factor loadings
- **Strict** invariance model
  - Same factor structure, equal factor loadings, and equal intercept values

Modeling Methods

STEP 2: Examining Measurement Invariance

- **Changes in goodness-of-fit indices** were examined to make comparison between nested models.
- A diminution of .010 and .015 for **CFI** and **RMSEA** are respectively indicative of a preferred model (Chen, 2007).
- Models with lower Baysian information criterion (**BIC**) values are considered superior in terms of fit and parsimony.

RESULTS

STEP 1: Identifying the Best Fitting Model

- Model fit comparison

	χ^2	*df*	SCF	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR	BIC
ICM-CFA Bifactor	11880	273	1.331	.065	.064 to .066	.910	.893	.067	539618
ESEM Bifactor	7821	227	1.343	.058	.057 to .059	.941	.915	.025	534258

Note. χ^2 = adjusted chi-square fit statistic with robust standard errors; *df* = degrees of freedom; SCF = Scale correction factor; RMSEA = root mean square error of approximation; CI = confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean residual; BIC = Bayesian information correction.

Table 1. Goodness-of-fit Indices for ICM-CFA and ESEM Models

Results

STEP 1: Identifying the Best Fitting Model

- Model fit comparison

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Results

STEP 1: Identifying the Best Fitting Model

- Factor loadings for bifactor ICM-CFA

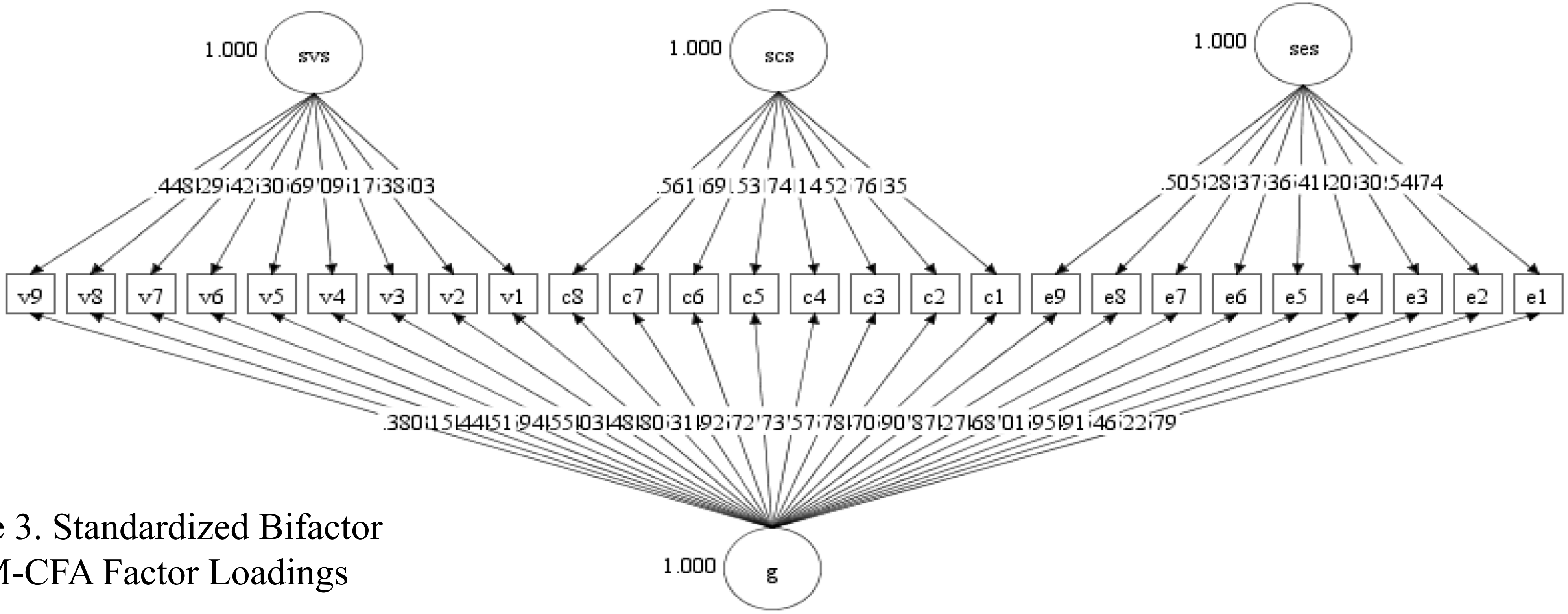

Figure 3. Standardized Bifactor ICM-CFA Factor Loadings

RESULTS

STEP 1: Identifying the Best Fitting Model

- Factor loadings for bifactor ESEM

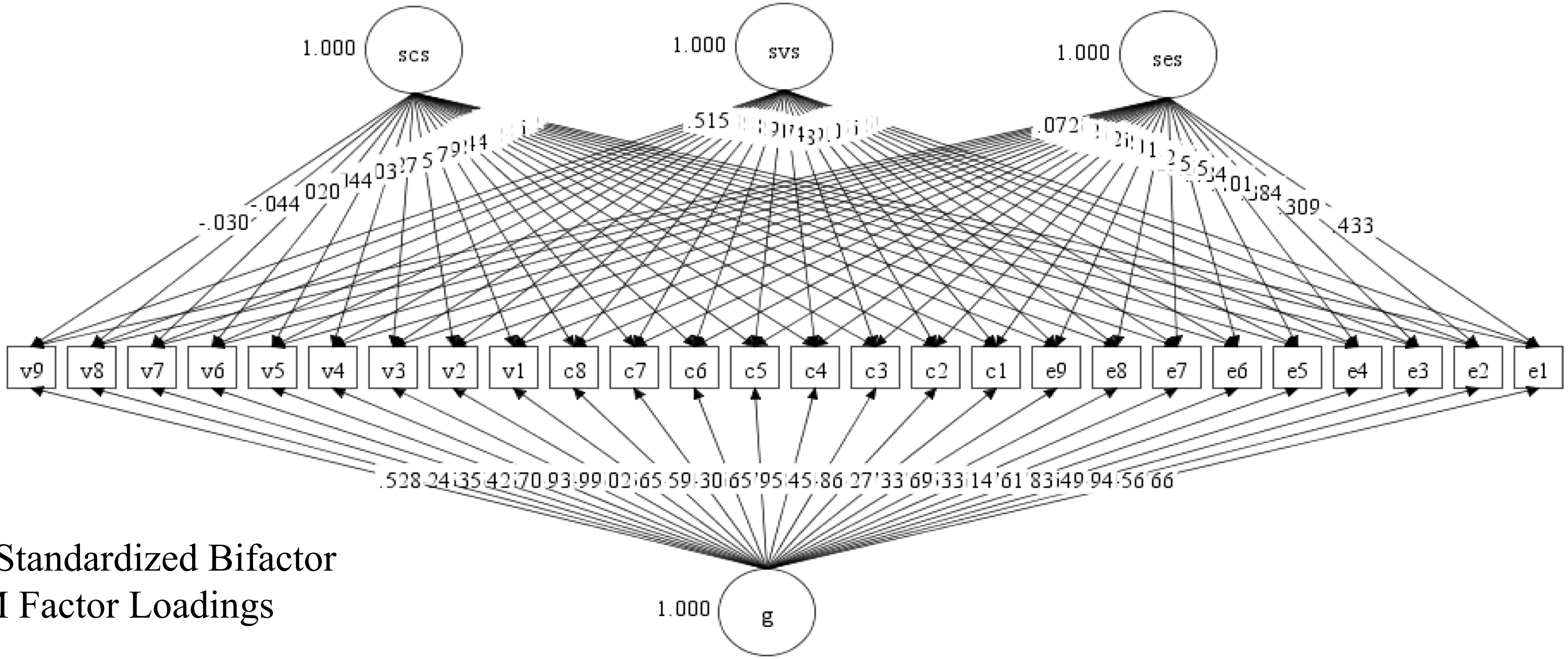

Figure 4. Standardized Bifactor ESEM Factor Loadings

Results

STEP 1: Identifying the Best Fitting Model

- All items in the bifactor ESEM had substantial loadings on the general factor (λ = .42 to .85.; M = .59) as well as most questions had specific factor loadings that exceeded .30.
- The **bifactor ESEM** yielded an improved level of fit in comparison to the corresponding ICM-CFA model.
- Interpretability of the model – **science attitudes** are general and enduring feelings about science, and predisposition to learn science (Lovelace & Brickman, 2013).

Results

STEP 2: Examining Measurement Invariance

- The model fit for each gender group

	χ^2	*df*	SCF	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR	BIC
Female	4304	227	1.280	.060	.058 to .061	.939	.912	.025	274166
Male	3669	227	1.399	.055	.054 to .057	.944	.921	.025	260061

Note. χ^2 = adjusted chi-square fit statistic with robust standard errors; *df* = degrees of freedom; SCF = Scale correction factor; RMSEA = root mean square error of approximation; CI = confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean residual; BIC = Bayesian information correction.

Table 2. Goodness-of-fit Indices for the Baseline Model across Genders

Results

STEP 2: Examining Measurement Invariance

	χ^2	*df*	SCF	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR	BIC	*p*	ΔCFI	ΔRMSEA
M1	7822	227	1.343	.058	.057 to .059	.941	.915	.025	534258			
M2	7944	454	1.339	.057	.056 to .058	.942	.916	.025	534436	0	**.001**	**–.001**
M3	8193	542	1.338	.053	.052 to .054	.940	.929	.028	533950	0	**–.002**	**–.004**
M4	8594	564	1.325	.053	.052 to .054	.937	.928	.030	534171	0	**–.003**	**0**

Note. χ^2 = adjusted chi-square fit statistic with robust standard errors; *df* = degrees of freedom; SCF = Scale correction factor; RMSEA = root mean square error of approximation; CI = confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean residual; BIC = Bayesian information correction; **M1 = baseline model (no invariance imposed); M2 = configural invariance; M3 = metric invariance; M4 = scalar invariance.**

Table 3. Goodness-of-fit Indices for Measurement Invariance across Genders

Results

STEP 2: Examining Measurement Invariance

- All the configural, metric, and scalar invariance models were tenable.
  - All the changes between nested models in CFIs and RMSEAs were less than .010 and .015 respectively.
- The results support the constraints of equal factor structure, factor loadings, and intercepts for the TIMSS science attitude items across genders.

Discussion

- The **bifactor ESEM** should be the model of choice.
  - An excellent level of good-of-fit indices
  - Considerable general factor loadings and reasonable local fits
  - Information about both a composite score and residualized subscores
  - The substantive interpretability of the model
- The model allows more in-depth analyses of the relationship between student attitudes and other external variables.
- The TIMSS science attitudes items can be safely used when inspecting the effect of genders on science attitudes-related issues.

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LIMITATIONS

- This study is focused only on science attitudes in USA eighth grade students.
- The direction of future research can be applied to other content areas such as mathematics, and to samples derived from other countries.
- More in-depth qualitative analyses of each construct – general factor, *SES*, *SCS*, and *SVS* – should be performed in future studies.

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Thank You

jung225@purdue.edu