FACTORIAL STRUCTURE OF ATTITUDES AND SOCIAL NORMS SCALES IN MATH

TESTING MEASUREMENT INVARIANCE ACROSS CULTURAL GROUPS

M3

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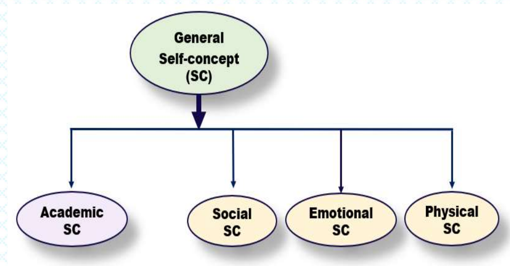
Background of the Study

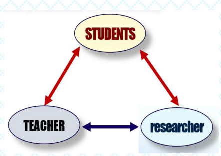
multidimensional/multifaceted SELF-CONCEPT



Self-Concept model from Shavelson, Hubner, & Stanton (1976)

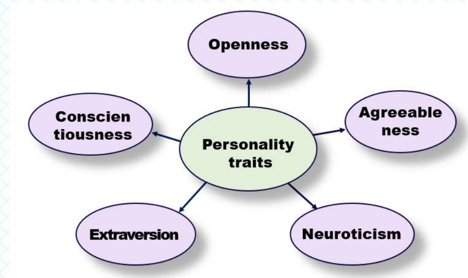
OUTLINE ►►►►►

- **BACKGROND OF THE STUDY**
  - Psychometrics examination of various constructs
- **DATA SOURCE:** (2012 PISA student questionnaires)
- **Analyses:** CFA & MGCFA within the Structural equation modeling framework
- **RESULTS**
- **IMPLICATIONS & WHAT'S NEXT?**



Background of the Study

multiple traits in PERSONALITY CONSTURCT



Alport, 1936; Cattell, 1941; Goldberg , 1980; Costa, & McCrae, 1992 + more

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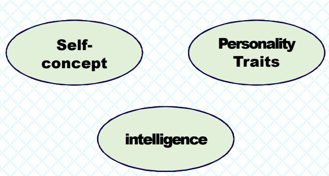
Background of the Study

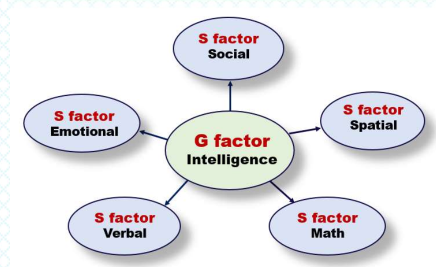
Psychological traits, hypothetical constructs, or social concepts are frequently examined as...

multidimensional/multifaceted



Background of the Study

multiple factors in HUMAN ABILITY



Intelligence: G factor (general intelligence) → S factor (specific intelligence)
(Cattell, 1941; Spearman, 1904; see also Horn, 1991 for CG & FG)

Background of the Study

How about

other constructs like

attitude & subjective norm?

Gaps in the literature

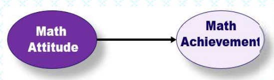
No studies have examined the construct validity of multidimensional math attitudes and perceived math social norms, together, in empirical investigation using internationally representative large-scale samples

Purpose of the Present Study

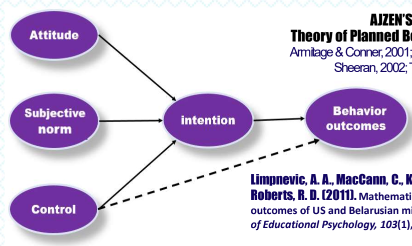
1. to evaluate the construct validity of multidimensional math attitudes (Affective, Behavioral, & Cognitive factors) and perceived math social norms (Peer, Parent, & Teacher factors) using 2012 PISA data

2. to test if measurement of the six factors would be invariant across national groups (USA, Hong Kong, & Singapore)

Background of the Study



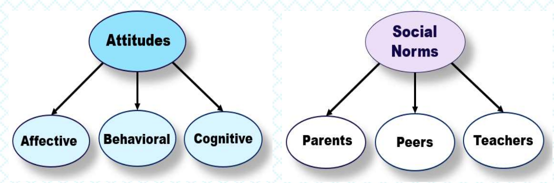
RELATIONS BETWEEN MATH ATTITUDE & MATH ACHIEVEMENT
107 independent studies from 1966 to 1993, Ma and Kishor's (1997) meta-analysis



AJZEN'S (1991) Theory of Planned Behavior (TPB) model
Armitage & Conner, 2001; Lee, Cerreto, & Lee, 2010; Sheeran, 2002; Teo & Tan, 2012)

Limpnevic, A. A., MacCann, C., Krumm, S., Burrus, J., & Roberts, R. D. (2011). Mathematics attitudes and mathematics outcomes of US and Belarusian middle school students. *Journal of Educational Psychology, 103*(1), 105-118.

HYPOTHESED 3-FACTOR MODELS

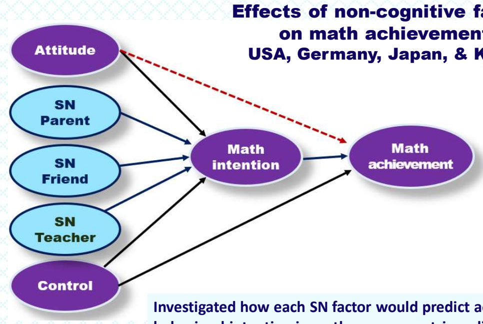


Affective - emotional responses to math
Behavioral - academic behavioral tendencies related to math
Cognitive - one's belief about his/her capabilities in math

Lim & Chapman, 2013; McLeod, 1992; Majeed, Darmawan, & Lynch, 2013; Neale, 1969; Walker, 2017; Wentzel; 1998; Zan, & Di Martino, 2007, 2014

My Dissertation

Effects of non-cognitive factors on math achievement: USA, Germany, Japan, & Korea



Investigated how each SN factor would predict academic behavioral intention in math across countries…direct effect of attitude on math achievement

HYPOTHESES OF THE CURRENT STUDY

1. Math attitudes and perceived math social norms are multidimensional constructs that are consisted with three distinctively independent factors.

math attitudes	perceived math social norms
▪ Affective factor	▪ Peer factor
▪ Behavioral factor	▪ Parent factor
▪ Cognitive factor	▪ Teacher factor

HYPOTHESES OF THE CURRENT STUDY

2. **Multidimensional attitudes and social norms scales in math are *conveyed the same meaning across the national groups* (USA, Hong Kong, and Singapore**

Measurement invariance

If measurement were not invariant across groups, conclusions of a study and/or interpretations of a research finding would be bias, weak, or misleading

(Horn & McArdle, 1992; Schmitt, & Kuljanin, 2008; Widaman & Reise, 1997; Yap et al., 2014)

DATA ANALYSES

- **Conducted CFA** within the Structural Equation Modeling (SEM) framework because…
  - SEM is a *confirmatory* framework for testing a-priori hypotheses about the structures in the data
  - Factor loadings (0 – 1.0) show the strength of the relations between the observed variables (i.e., items) and the latent factors – the higher the better
- **Conducted Correlation Analyses** (all 20 observed variables & 6 factors) for…
  - Alpha coefficients
  - Composite Reliability & Average Variance Extracted
  - Convergent & discriminant validity

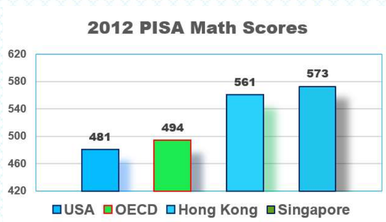
Data Source

Student Background Questionnaires from PISA 2012 database

(Programme of International student assessment)

Total sample (*N* = 15,194, age = 15 yrs)

from USA, Hong Kong, & Singapore



DATA ANALYSES

- **Conducted MGCFA** within SEM framework for…
  - Measurement invariance across national groups
  - Goal for SEM is to match the theory with model and data *as closely as possible* ex] testing model fit between observed data & hypothesized model

    Observed data = 2012 PISA sample data
    Hypothesized model = multidimensional 3- factor models of attitude & social norm
  - Evaluating tools….

Chi-square	Non significant → desirable
TLI/CFI	Good fit > .95; Acceptable > .90
RMSEA	Good fit < .06; Unacceptable > .10

(Hu & Bentler 1999; Kline, 2011; Raykov & Marcoulides, 2006)

Construct Validity

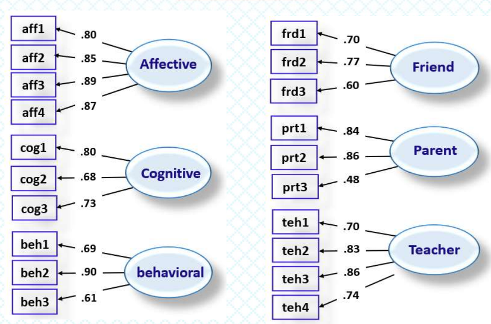
- Explicitly examine how well the instruments measure the constructs that were designed to measure
- *No single method, rather several different analyses/approaches were* conducted to establish the overall CV of the proposed theoretical constructs
  - Confirmatory factor analysis;
  - correlation analyses; convergent & discriminant validity

(Fornell & Larcker, 1981)

Construct Reliability

- Refers to the internal consistency of the observed test items (indicators)
  - Cronbach Alpha coefficients (Cronbach, 1951)
  - Composite Reliability & Average Variance Extracted (Fornell & Larcker, 1981)

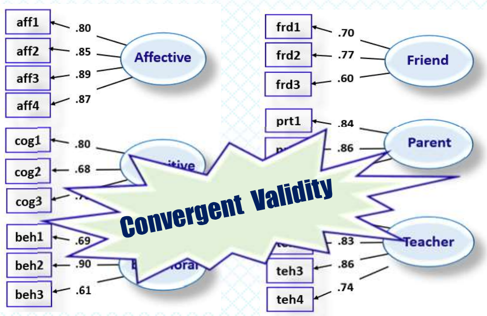
RESULTS OF CFA



"A factor loading is "less than .30 indicates that the items had weak validity"

(Abu-Hilal, Abdelfattah, Alshumrani, Abduljabbar, & Marsh, 2013; see also Marsh, 1986)

RESULTS OF CFA



"A factor loading is "<u>less than .30 indicates</u> that the items had weak validity"
(Abu-Hilal, Abdelfattah, Alshumrani, Abduljabbar, & Marsh, 2013; see also Marsh, 1986)

RESULTS OF FACTOR CORRELATION

	1	2	3	4	5	6
1. Affective	1					
2. Cognitive	.51	1				
3. Behavioral	.49	.36	1			
4. Friend	.39	.25	.31	1		
5. Parent	.34	.41	.27	.34	1	
6. Teacher	.33	.28	.32	.27	.21	1

All correlation coefficients are statistically significant but not alarmingly high

discriminant validity
Also used Fornell & Larker's method

CORRELATION MATRIX FOR THE OBSERVED VARIABLES

	1	2	3	4	5	6	7	8	9	10
1. aff1	--									
2. aff2	.67									
3. aff3	.72	.75	--							
4. aff4	.71	.74	.77	--						
5. cog1	.33	.37	.36	.38	--					
6. cog2	.25	.28	.28	.29	.54	--				
7. cog3	.30	.30	.32	.33	.58	.51	--			
8. beh1	.21	.27	.25	.25	.23	.16	.16	--		
9. beh2	.32	.41	.38	.38	.29	.19	.20	.63	--	
10. beh3	.32	.36	.34	.34	.22	.15	.14	.40	.54	--
11. frd1	.17	.20	.16	.18	.16	.13	.13	.12	.16	.14
12. frd2	.22	.26	.23	.24	.19	.13	.14	.14	.24	.22
13. frd3	.32	.35	.35	.32	.11	.11	.10	.09	.18	.23
14. prt1	.18	.23	.18	.24	.30	.22	.24	.14	.20	.16
15. prt2	.22	.26	.21	.29	.28	.22	.23	.13	.20	.18
16. prt3	.31	.31	.30	.33	.21	.17	.17	.14	.19	.21
17. teh1	.19	.28	.21	.24	.18	.14	.13	.20	.23	.19
18. teh2	.18	.26	.20	.22	.20	.14	.14	.19	.23	.16
19. teh3	.17	.26	.20	.21	.20	.14	.13	.18	.22	.16
20. teh4	.23	.31	.24	.26	.20	.16	.15	.17	.21	.18
	11	12	13	14	15	16	17	18	19	20
11. frd1	--									
12. frd2	.55	--								
13. frd3	.42	.44	--							
14. prt1	.20	.23	.12	--						
15. prt2	.20	.21	.16	.72	--					
16. prt3	.20	.20	.27	.38	.40	--				
17. teh1	.15	.18	.15	.13	.12	.15	--			
18. teh2	.15	.17	.11	.15	.13	.12	.57	--		
19. teh3	.14	.17	.10	.16	.14	.13	.58	.72	--	
20. teh4	.15	.18	.14	.12	.13	.14	.54	.59	.64	--

DISCRIMINANT VALIDITY

<u>DISCRIMINANT VALIDITY is being established</u>
if the square root of the average variance extracted (AVE) for each latent variable is higher than any of the bivariate correlations involving the latent variables in the proposed theories (Fornell & Larcker, 1981)

	1	2	3	4	5	6
1. Affective	(.88)					
2. Cognitive	.51	(.74)				
3. Behavioral	.49	.36	(.74)			
4. Friend	.39	.25	.31	(.69)		
5. Parent	.34	.41	.27	.34	(.72)	
6. Teacher	.33	.28	.32	.27	.21	(.79)

Yellow parentheses in diagonal are square root of AVE

CORRELATION MATRIX FOR THE OBSERVED VARIABLES

	1	2	3	4	5	6	7	8	9	10
1. aff1	--									
2. aff2	.67	--								
3. aff3	.72	.75	--							
4. aff4	.71	.74	.77	--						
5. cog1	.33	.37	.36	.38	--					
6. cog2	.25	.28	.28	.29	.54	--				
7. cog3	.30	.30	.32	.33	.58	.51	--			
8. beh1	.21	.27	.25	.25	.23	.16	.16	--		
9. beh2	.32	.41	.38	.38	.29	.19	.20	.63	--	
10. beh3	.32	.36	.34	.34	.22	.15	.14	.40	.54	--

Affective factor
Cognitive factor
Behavioral factor

Convergent validity & Discriminant validity
Ex] Aff1 x aff2 (r = .67) > aff1 x cog1 (r = .33)
Items within the same constructs have higher correlations than items with the difference constructs

RESULTS OF RELIABILITY TESTS

Factors	Cronbach's α	AVE	CR
1. Affective (4 items)	.91	.73	.91
2. Cognitive (3 items)	.78	.55	.78
3. Behavior (3 items)	.76	.55	.78
4. Peer (3 items)	.73	.48	.73
5. Parent (3 items)	.75	.52	.78
6. Teacher (4 items)	.86	.62	.86

Cronbach Alpha (Cronbach, 1951); AVE = Average Variance Extracted; CR = Composite Reliability (Fornell & Larcker, 1981)

$$\alpha = \frac{k\bar{r}}{(1+(k-1)\bar{r})} \qquad \frac{\sum \lambda^2}{n} \qquad \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + (\sum \varepsilon)}$$

Measurement Invariance Testing

H#2: Multidimensional attitudes and social norms scales in math are conveyed the same meaning across the national groups (USA, Hong Kong, and Singapore)

- **In order to avoid getting the results by chance…**

  Sample data was divided into 2 sets of data from each country

- **First half (derivation) sample (*N*= 7,506) was used for initial MI investigation**

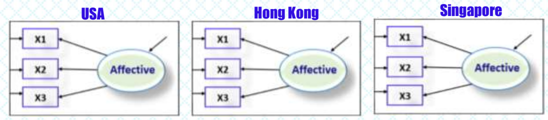
- **Second half (cross-validation) sample (*N*= 7513) was employed to replicate results**

TESTING MEASUREMENT INVARIANCE
MULTIGROUP CONFIRMATORY FACTOR ANALYSIS APPROACH

	Types of invariance	description
Step 1:	Configural	Same pattern of fixed and free loadings
Step 2:	Weak (Metric)	Factor loadings are constrained
Step 3:	Strong (Scalar)	Item intercepts are constrained + Step 2

(Schmitt & Kuljanin, 2008;Widaman & Reise, 1997)

USA Hong Kong Singapore



Step 1: Configural Invariance = serves as a baseline

Why Measurement Invariance Testing?

2. **Multidimensional attitudes and social norms scales in math are conveyed the same meaning across the national groups (USA, Hong Kong, and Singapore)**

If measurement were not invariant across groups, conclusions of a study and/or interpretations of a research finding would be bias, weak, or misleading

(Horn & McArdle, 1992; Schmitt, & Kuljanin, 2008; Widaman & Reise, 1997; Yap et al., 2014)

RESULTS OF SEQUENTIAL FACTORIAL MEASUREMENT INVARIANCE TESTING

Model	χ^2	df	RMSEA (90% CI)	CFI	TLI
First Half Samples (Derivation)					
Model 1	1119.24	462	.036 (.034 - .037)	.967	.959

RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis index (also called the non-normed fit index)

Step 1: Configural invariance model (baseline model)

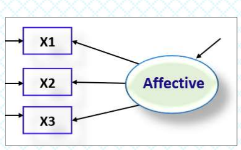
- **Considerably good fit to data**
  → (***RMSEA*: less than .06; *CFI*: close to or greater than .95**)
- **Facture structure of the all constructs (latent factors) had been measured the same way across groups**
  → **(i.e., patterns of indicator-latent factor relations were equivalent)**

SEQUENTIAL FACTORIAL MEASUREMENT INVARIANCE TESTING

	Types of invariance	description
Step 1:	Configural	Same pattern of fixed and free loadings
Step 2:	Weak (Metric)	Factor loadings are constrained
Step 3:	Strong (Scalar)	Item intercepts are constrained + Step 2
Step 4:	Strict	Unique variances are constrained + Step 3

Step 4 → This occurs hardly ever in empirical research

(Schmitt & Kuljanin, 2008;Widaman & Reise, 1997)



Ex] common factor model

TESTING MEASUREMENT INVARIANCE
MULTIGROUP CONFIRMATORY FACTOR ANALYSIS APPROACH

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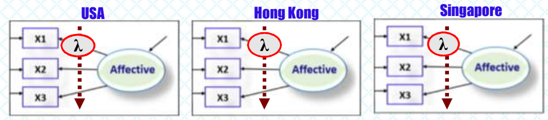
USA Hong Kong Singapore



Step 2: Weak (Metric) invariance = same factor loadings across groups

Ex] $\lambda^A_{11} = \lambda^B_{11} = \lambda^C_{11}$

RESULTS OF SEQUENTIAL FACTORIAL MEASUREMENT INVARIANCE TESTING

Model	χ^2	df	RMSEA (90% CI)	CFI	TLI
First Half Samples (Derivation)					
Model 1	1119.24	462	.036 (.034 - .037)	.967	.959
Model 2	2114.87	490	.036 (.035 - .038)	.963	.957

Step 2: Weak (metric) invariance model (factor loadings are constrained)

- Results of Model 2 did not differ much from the baseline model
  → Still good fit to data (*RMSEA*: less than .06; *CFI*: greater than .95)
- 6 latent factors being measured by the same items across groups (USA, Hong Kong, & Singapore)

OVERALL RESULTS OF SEQUENTIAL FACTORIAL MGCFA

Model	χ^2	df	RMSEA (90% CI)	CFI	TLI
First Half Samples (Derivation)					
Model 1	1119.24	462	.036 (.034 - .037)	.967	.959
Model 2	2114.87	490	.036 (.035 - .038)	.963	.957
Model 3	2778.36	517	.042 (.040 - .043)	.948	.943
Second Half Samples (Cross-Validation)					
Model 1	1849.21	462	.035 (.033 - .036)	.966	.959
Model 2	2010.74	490	.035 (.034 - .037)	.963	.957
Model 3	2701.81	517	.041 (.040 - .043)	.947	.942

Significant findings of MGCFA for testing measurement invariance

Replication samples (cross-validation) yielded the similar results from the initial MGCFA analyses, which suggest that the findings are not by chance

TESTING MEASUREMENT INVARIANCE
MULTIGROUP CONFIRMATORY FACTOR ANALYSIS APPROACH

	Types of invariance	description
Step 1:	Configural	Same pattern of fixed and free loadings
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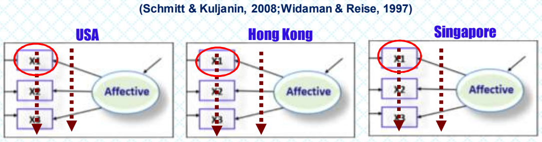

Step 3: Strong (Scalar) invariance = same intercepts (+ step2) across groups

Ex) $\tau^{A}_{aff1} = \tau^{B}_{aff1} = \tau^{C}_{aff1}$

DISCUSSIONS & IMPLICATIONS

- Results confirmed that the measurements hold equivalence across national groups (USA, Hong Kong, and Singapore) at the level of strong/scalar factorial invariance
- The factorial structures of attitude and social norm scales reflected well as hypothesized as multidimensional constructs
- Thus, the current study findings contributed to the theory and measurement development of multidimensional attitude and social Norm constructs

RESULTS OF SEQUENTIAL FACTORIAL MEASUREMENT INVARIANCE TESTING

Model	χ^2	df	RMSEA (90% CI)	CFI	TLI
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Model 2	2114.87	490	.036 (.035 - .038)	.963	.957
Model 3	2778.36	517	.042 (.040 - .043)	.948	.943

Strong (Scalar) invariance model (item intercepts are constrained)

- results of Model 3 did not differ much from Model 2
  → Still reasonably good fit to data (*RMSEA* = less than .06 , *CFI* = close to .95)
- Same constructs implied across countries (USA, Hong Kong, and Singapore)
  → since intercepts are equivalent, meaningful cultural comparisons can be made using latent mean differences across countries

LIMITATIONS & FUTURE RESEARCH

- 15 years old students from USA, Hong Kong, & Singapore

  - Gender comparisons ?
  - Other PISA participating countries?

- The 3 factor- model of attitudes and social norms in math may serve as valuable instruments in the future research to study which components of math attitude/social norm would be associated with math achievement
- The 3 factor-model of attitude and social norm may applied to different disciplines instead of math

THANK YOU FOR COMING

Any questions or concerns??

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Lecturer

M3

Affective Factor	Enjoy reading about math
	Look forward to my math lessons
	Do math because I enjoy it
	Interested in the things I learn in math
Cognitive Factor	If putting in enough effort, I can succeed in math
	Doing well in math is completely up to me
	If I wanted to, I could do well in math
Behavioral Factor	Finish my math homework in time
	Work hard on my math homework
	Study hard for math quizzes

Friend Factor	Most of my friends do well in math
	Most of my friends work hard at math
	My friends enjoy taking math tests
Parent Factor	My parents believe math is important to study
	My parents believe math is important for career
	My parents like math
Teacher Factor	Shows an interest in student's math learning
	Gives extra math help when students need it
	Helps students with their learning in math
	Continues teaching until the students understand