#### Developing and Revising the Student Survey of Motivational Attitudes Toward Statistics: Results from a Pilot Study

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# Why motivational attitudes?

"People forget what they do not use. But attitudes 'stick'" (Ramirez et al., 2012, p. 57)

- Long history of measuring attitudes toward statistics
- Proliferation of instruments (Nolan et al., 2012; Ramirez et al., 2012)
- Survey of Attitudes Toward Statistics (SATS) instrument (Schau, 1992, 2003b) is widely used
  - Consistent with Expectancy-Value Theory (Schau, 2003a)
    - ... but "developed without a theoretical basis" (Xu & Schau, 2019, p. 42)
  - Growing challenges to the use of the SATS (e.g., Whitaker et al., 2019b, in press)

#### S-SOMAS: Overview

- Student Survey of Motivational Attitudes toward Statistics (S-SOMAS)
  - For more information see Unfried et al. (2018) and Whitaker et al. (2019a)
  - Based on Expectancy-Value Theory (Eccles (Parsons) et al., 1983; Eccles & Wigfield, 2020)



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	Student Instrument	Instructor Instrument	Environment Inventory
<b>Statistics</b>	S-SOMAS	I-SOMA <mark>S</mark>	E-SOMAS
Data Science	S-SOMADS	I-SOMADS	E-SOMADS



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	Student	Instructor	Environment	
	Instrument	Instrument	Inventory	
<b>Statistics</b>	S-SOMAS	I-SOMA <mark>S</mark>	E-SOMAS	
	(Pilot 1)	(in development)	(in development)	
Data Science	S-SOMADS	I-SOMADS	E-SOMADS	
	(in development)	(pre-development)	(pre-development)	



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## MASDER Team

The *Motivational Attitudes in Statistics and Data Science Education Research* (MASDER) team:

- Leyla Batakci Elizabethtown College
- Wendi Bolon Monmouth College
- Marjorie Bond *Monmouth College*
- April Kerby Winona State University
- Michael Posner Villanova University
- Alana Unfried California State University, Monterey Bay
- Douglas Whitaker *Mount Saint Vincent University*

Also: numerous undergraduate and graduate student assistants (including Matt Dunham); Research On Statistics Attitudes (ROSA) Working Group; USCOTS 2015 and 2017 Workshop participants; *many more*!



- Originally developed to explain motivation for learning mathematics among students in grades 5-12 (Eccles (Parsons) et al., 1983) and is actively developed (Eccles & Wigfield, 2020)
- Widely used across disciplines and age (Eccles & Wigfield, 2002)
- Has been applied with university students (Eccles & Wigfield, 2020)

# Challenges to using EVT for S-SOMAS

- Want the S-SOMAS to be useful longitudinally... and not require enrolment in a statistics course
- Some EVT constructs have been researched less than others
  - Especially Costs & Benefits (e.g., Flake et al., 2015; Wigfield et al., 2017)
- How should the EVT constructs be operationalized as scales?

#### EVT model for the S-SOMAS instrument

Planned to be Assessed by the S-SOMAS/SOMADS instruments

Not planned to be assessed by the S-SOMAS/SOMADS instruments

Survey of Motivational Attitudes toward Statistics (SOMAS) Survey of Motivational Attitudes toward Data Science (SOMADS)

Student Expectancy-Value Theory Model

Based on Eccles' Expectancy-Value Theory (EVT) (e.g. Eccles, 1983, 2014; Eccles & Wigfield, 2002, 2020)



## S-SOMAS: Pilot 0



- 92 items measuring 11 constructs
- Split into two forms (one construct on both)
  - Form 1: 49 items and 6 constructs, n = 1155 introductory statistics students
  - Form 2: 50 items and 6 constructs, n = 1159 introductory statistics students
- Main questions:
  - Which constructs are we able to measure?
  - Which scales need to be revised?
  - Which items need to be revised?

- Confirmatory Factor Analysis (CFA)
  - Work presented for Pilot 0 Form 2
- Item Response Theory (IRT)
  - Focus on the *Perception of Difficulty* (*Difficult*) scale from Pilot 0 Form 2

## Confirmatory Factor Analysis

• Testing factor structure against hypothesized EVT framework

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	Description	CFI	RMSEA	RMSEA 90% Cl Upper	SRMR	Note
Model 2.1	All items to hypothesized constructs	0.943	0.108	0.109	0.090	Covariance matrix not positive definite
Model 2.2	Some items from PCA analysis dropped	0.946	0.103	0.104	0.088	Covariance matrix not positive definite
Model 2.3	Model 2.2, but hierarchical	0.943	0.106	0.107	0.090	Covariance matrix not positive definite
Model 2.4	Model 2.2, but Academic SC and Statistics SC combined	0.935	0.112	0.114	0.095	Covariance matrix not positive definite
Model 2.5	Model 2.2, but Attainment Value and Costs combined	0.945	0.103	0.105	0.088	
Model 2.6	Model 2.2, but Difficulty and Expectancy combined	0.936	0.111	0.113	0.094	Covariance matrix not positive definite
	Recommended value (Hu & Bentler, 1999)	≥ 0.95	≤ 0.05	<i>≤ 0.10</i>	≤ 0.08	None of the above values satisfy the criteria

## Confirmatory Factor Analysis

- Testing factor structure against hypothesized EVT framework
- Evidence of misfit; model modification driven by EVT theory
  - ... still substantial model misfit
- Will revisit this after the next pilot!

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## Item Response Theory

- Goal: identify items that are performing poorly/not fitting well
- We will compare two models:
  - Generalized Partial Credit Model (GPCM; Muraki, 1992)

$$P_{ijc} = \frac{\exp\sum_{k=0}^{c} a_i (\theta_j - \delta_{ik})}{\sum_{h=0}^{m_i} \exp\sum_{k=0}^{h} a_i (\theta_j - \delta_{ik})}$$

- $P_{ijc}$  is the probability of person *j* scoring *c* on item *i*
- $\theta_j$  is the ability of person j
- $\delta_{ik}$  is the (threshold) parameter for item *i* for responding to category *k* rather than k-1
- $m_i$  is the number of response categories for item i
- $a_i$  is the discrimination parameter for item i
- Partial Credit Model (PCM; Masters, 1982)
  - Special case of the GPCM with  $a_i = 1$
- Note: Graded Response Model (GRM; Samejima, 1969) also considered but not presented here results are very similar to GPCM results

- PCA used to assess unidimensionality assumption for IRT
  - Gifi package in R (Mair & De Leeuw, 2019)
- Roughly homogenous loadings on the first two components suggests items are measuring the same construct (Mair, 2018)

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Component 1

Loadings Plot: Difficult

This construct is an individual's perceived difficulty of statistics. Task difficulty is relative: tasks that require greater information processing power or require higher levels of skill, knowledge, or effort than other tasks are termed *difficult tasks* (Huber, 1985; Mangos & Steele-Johnson, 2001). Statistics is viewed as a "task" to be performed.

Items in the *Difficult* scale on Pilot 0 Form 2:

- 1. You must work hard to understand statistics.
- 2. Interpreting statistical results is straightforward.
- 3. Statistics is easy.
- 4. Only smart people can do statistics.
- 5. Anybody can do statistics.
- 6. It is challenging to solve a problem that requires using statistics.
- 7. Learning statistics for the first time is hard.



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Component 1

## Partial Credit Model

- eRm package (Mair et al., 2021)
- Disordered category thresholds
  - Problematic (Andrich, 2013)

				Outfit	Infit				Difficult_
	Chisq	df	p-value	MSQ	MSQ	Outfit t	Infit t	Discrim	Difficult
Difficult_1	1044.168	1153	0.990	0.905	0.912	-2.204	-2.056	0.554	Difficult
Difficult_2	1142.479	1153	0.582	0.990	0.978	-0.238	-0.557	0.532	Difficult
Difficult_3	725.729	1153	1.000	0.629	0.623	-10.376	-11.339	0.778	Dimout_
Difficult_4	1278.371	1153	0.006	1.108	1.136	2.330	3.069	0.428	Difficult
Difficult_5	1324.238	1153	0.000	1.148	1.086	3.318	2.098	0.472	_
Difficult_6	858.580	1153	1.000	0.744	0.745	-7.035	-7.224	0.689	Difficult
Difficult_7	850.043	1153	1.000	0.737	0.712	-6.596	-7.668	0.705	_



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#### Generalized Partial Credit Model

#### • mirt package (Chalmers, 2012)

item	outfit	z.outfit	infit	z.infit	S_X2	df.S_X2	RMSEA.S_X2	p.S_X2
Difficult_1	0.900	-1.777	0.911	-1.737	129.928	91	0.019	0.005
Difficult_2	0.939	-1.514	0.937	-1.616	120.814	105	0.011	0.139
Difficult_3	0.694	-5.389	0.723	-6.649	106.358	77	0.018	0.015
Difficult_4	0.914	-1.809	0.945	-1.208	117.100	108	0.009	0.259
Difficult_5	0.938	-1.555	0.945	-1.458	139.181	125	0.010	0.182
Difficult_6	0.833	-3.916	0.850	-3.699	111.294	91	0.014	0.073
Difficult_7	0.790	-3.566	0.812	-4.022	93.465	82	0.011	0.182

	a1	<b>d1</b>	d2	d3	d4	d5	<b>d</b> 6
Difficult_1	1.518	1.880	-0.188	-2.054	-3.152	-4.413	-6.799
Difficult_2	1.285	3.661	1.960	0.411	-0.468	-2.251	-4.644
Difficult_3	2.728	3.265	1.107	-0.600	-2.064	-4.611	-7.641
Difficult_4	0.864	4.352	3.384	2.076	1.067	0.103	-1.753
Difficult_5	0.947	3.468	2.103	1.103	0.346	-0.854	-2.763
Difficult_6	1.903	4.556	2.273	0.166	-0.969	-2.470	-5.137
Difficult_7	2.379	2.772	0.346	-1.748	-2.713	-4.240	-6.590

Trace lines for item 2



Trace lines for item 4



#### Generalized Partial Credit Model

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Trace lines for item 4



# IRT Summary

- PCM fits poorly, GPCM fits better
- With GPCM there are still many items that exhibit misfit (either infit or outfit)
- Response scale too many points?
- Most scales have at least a few items that seem fine
  - (Build out new scales using these items?)

	# Items #	PCA #	# Misfit	Total
<b>Beliefs &amp; Stereotypes</b>	10	4	4	8
Intrinsic GO	7	0	7	7
Extrinsic GO	8	2	3	5
Utility Value	8	0	4	4
Interest value	9	0	3	3
Attainment Value (1)	7	4	3	4
Attainment Value (2)	7	2	4	5
Academic SC	9	0	1	1
Statistics SC	9	0	6	6
Difficulty	7	2	3	5
Expectancy	11	3	1	4
Costs & Benefits	7	2	2	4

Note: Misfit (infit or outfit) is from a GRM IRT analysis. Some items may have been identified as problematic in both the PCA and IRT analysis, so Total is not the sum of the two columns.

Difficulty	AIC	BIC	log.Lik	LRT	df	p.value
PCM	24660.64	24872.82	-12288.3		42	
GPCM	24599.38	24846.92	-12250.7	75.26	49	< 0.001

## Conclusions, Limitations, and Next Steps

- Lots of information for the MASDER team to review when revising the S-SOMAS instrument
  - CFA, PCA, IRT
  - Improved definitions
  - EFA results from colleagues (e.g., Unfried et al., 2018)
- Decision to split constructs into two forms limits interpretations
  - Pilot 1 includes all constructs on one form
- Next steps:
  - Revise items, remove items, write new items
  - Change number of response points (e.g., go from 7 to 5)
  - (Change response options? Rewrite items? [Drop Agree/Disagree?])
  - Use lessons when developing I-SOMAS, S-SOMADS



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