Why Do We Need Yet ANOTHER Instrument Measuring **Student Attitudes?**

JSM 2021

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DUE-2013392

Attitudes

- **Attitudes Matter in Education!**
  (Pearl et al., 2012)
- We want students to **thrive in the data deluge**
- **Instructor attitudes** and course environment impact **student attitudes**
- Understanding attitudes can help us identify **evidence-based best practices for teaching data science and statistics**

Outline

- Why New Instruments?
- Overview of MASDER grant
- The S-SOMAS Survey
- S-SOMAS Pilot Psychometrics
- S-SOMAS Pilot Attitude Results
- How to Get Involved

Why New Instruments?

Existing Instruments (Examples)

Student Instruments

- Survey of Attitudes toward Statistics (SATS; Schau, 1992)
  - Most widely used
- Issues (Whitaker, Unfried, & Bond, in press):
  - Lack of validity evidence
  - Incomplete alignment to theoretical framework
  - Ceiling effects on some scales
  - Rigid pre-post structure
  - Requires stats course enrollment
  - Use restricted - fees/permission

Instructor/Environment Instruments

- Statistics Teaching Inventory (STI; Zieffler et al., 2012)
  - Snapshot of instructor practices in Introductory Statistics
- Issues
  - Does not measure attitudes or learning environment characteristics
  - Not linked to student measures

No Validated Data Science Attitudes Instruments

What are we doing differently?

- Start with a strong theoretical framework
- Follow a rigorous survey development process
- Create a family of instruments

MASDER Overview

MASDER:

Motivational **A**ttitudes in **S**tatistics and **D**ata Science **E**ducation **R**esearch

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- 3-year NSF IUSE grant (Oct ‘20 - Sept ‘23)
- Develop **6 instruments** evaluating student and instructor attitudes toward statistics and data science, and the learning environment
- Conduct **nationally-representative sample** of students and instructors
- Promote **Stat/DS Ed Research** - improve instruction by understanding the relationships between components

Surveys Of Motivational Attitudes toward...

	Student Instrument	Instructor Instrument	Environment Inventory
Statistics	S-SOMAS	I-SOMAS	E-SOMAS
Data Science	S-SOMADS	I-SOMADS	E-SOMADS

Distinction between S, I, and E Surveys

Student Instruments

- Measures attitudes toward Stat or DS
- Pre and post semester
- Can be used longitudinally

Instructor Instruments

- Measures instructor attitudes toward teaching Stat or DS
- Perhaps administered annually

Environment Inventories

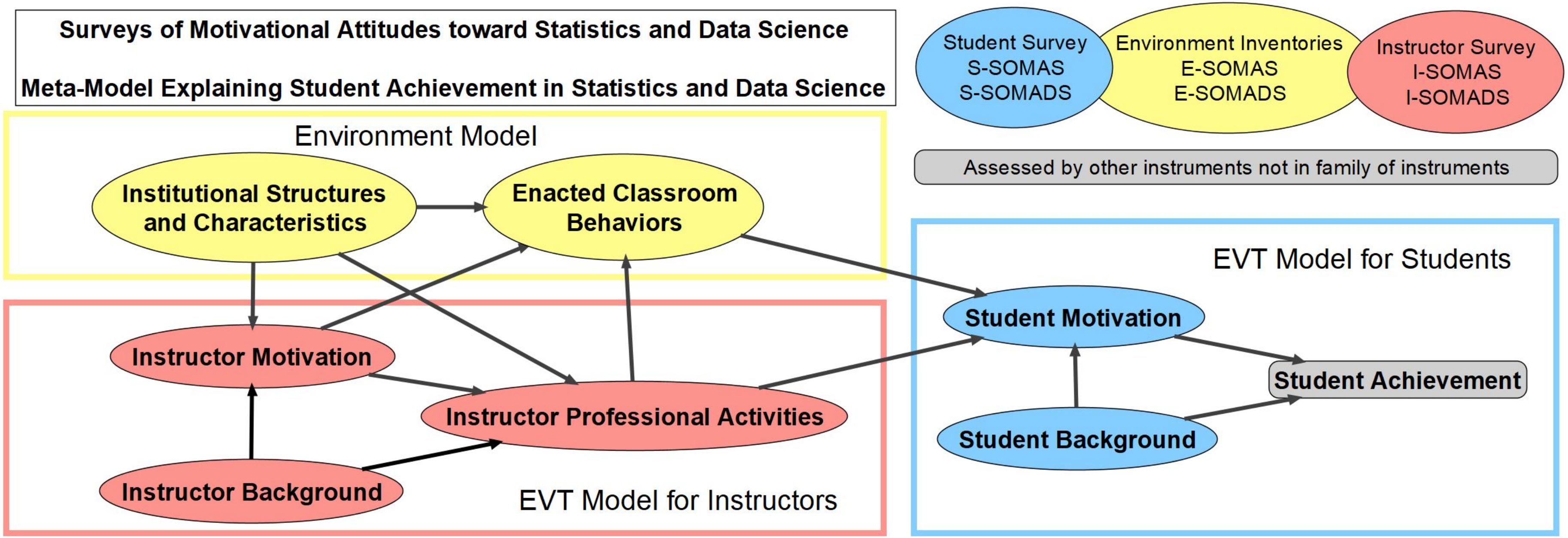
- Measures institutional and course characteristics, learning environment, and enacted classroom behaviors
- Instructor completes for each course

Survey Development for S-SOMAS

- Formulate the need for a new student instrument
  - Research on Statistics Attitudes (ROSA) working groups (beginning in 2009)
  - ASA Membership Initiative grant funded 3 workshops
- Develop theoretical models
  - Workshop at USCOTS (2017) focused on model development
  - Model refinement continues
- Create Pilot-0 S-SOMAS Instrument (2017-20)
  - Construct definitions, item writing
  - Student focus groups, Subject Matter Expert Review
- Administer, Analyze and Revise Pilot-0
  - Pilot data collected from ~2,400 students (2018-20)
- **Administer and Analyze Pilot-1 (2021)**

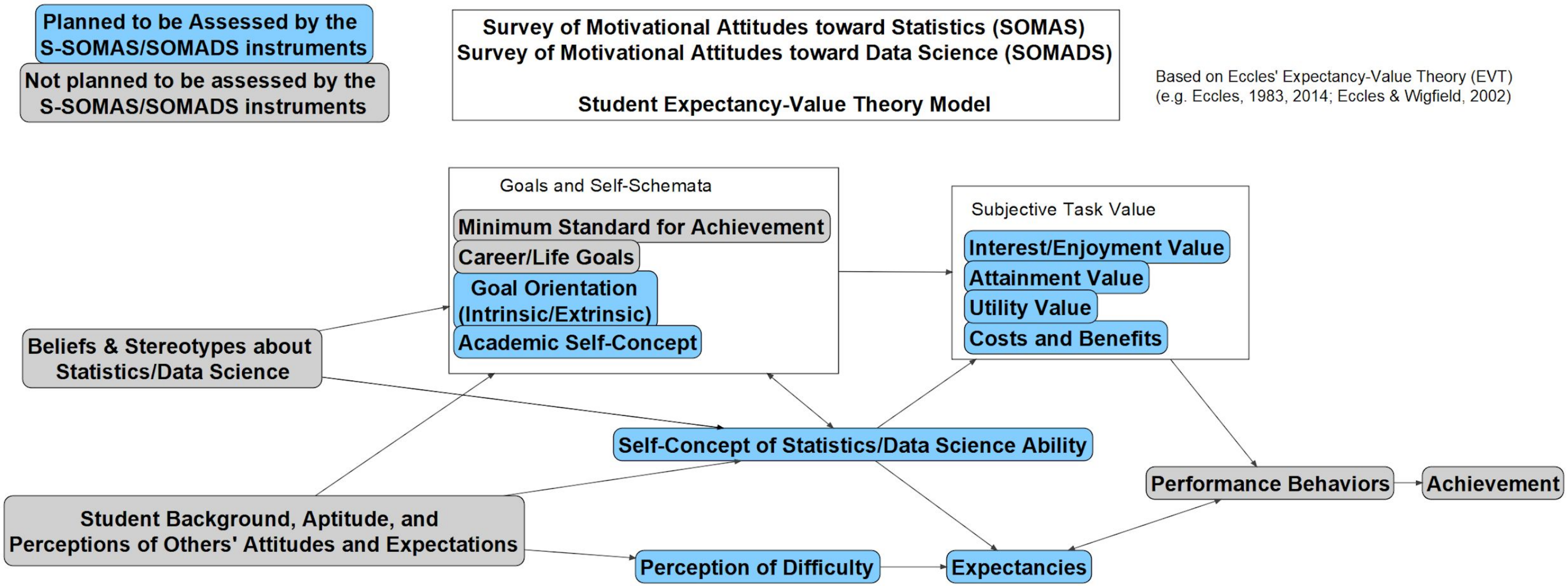
The S-SOMAS Survey

Meta-Model



Surveys of Motivational Attitudes toward Statistics and Data Science
Meta-Model Explaining Student Achievement in Statistics and Data Science
Student Survey
S-SOMAS
S-SOMADS
Environment Inventories
E-SOMAS
E-SOMADS
Instructor Survey
I-SOMAS
I-SOMADS
Assessed by other instruments not in family of instruments
Environment Model
Institutional Structures and Characteristics
Enacted Classroom Behaviors
EVT Model for Students
Student Motivation
Student Achievement
Student Background
Instructor Motivation
Instructor Professional Activities
Instructor Background
EVT Model for Instructors

Student Model



Construct	Definition
Expectancy	How the student thinks they will perform in the field of statistics
Perception of Difficulty	How difficult the student perceives statistics to be
Beliefs and Stereotypes	Student concepts and conceptions about statistics
Utility Value	**How much the student values statistics for serving or achieving their goals.**
Interest/Enjoyment Value	The interest a student has in statistics, or their enjoyment from it
Attainment Value	How important success in statistics is to the student
Costs and Benefits	Factors that deter from learning stats, or benefits of learning stats
Academic Self-Concept	Student perceptions about the academic achievement (general and stats-specific)
Goal Orientation	What drives the students to learn statistics

Utility Value Items

	Strongly Disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly Agree
I need to know statistics to satisfy employers.	○	○	○	○	○	○	○
I will rarely use statistics in the future.	○	○	○	○	○	○	○
No one in my career field uses statistics.	○	○	○	○	○	○	○
I value statistics because it makes me an informed citizen.	○	○	○	○	○	○	○
Studying statistics is pointless.	○	○	○	○	○	○	○

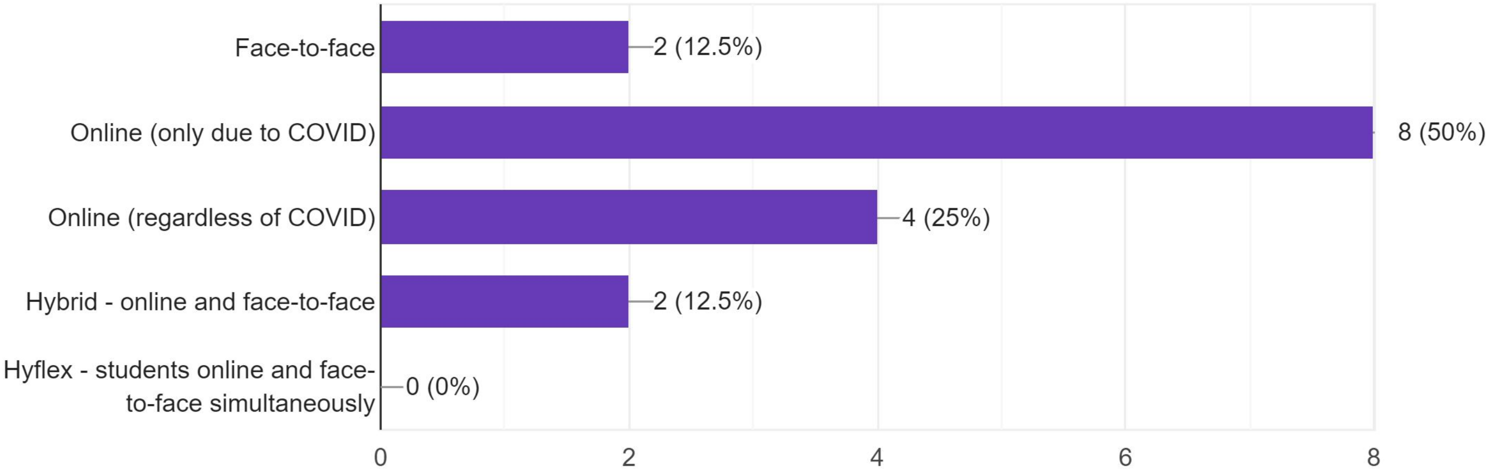
S-SOMAS Pilot 1 Results

Instructors, Institutions, Courses

15 Institutions, 16 Instructors, 20 Sections

How is the course (or these courses) being offered? Check all that apply.

16 responses

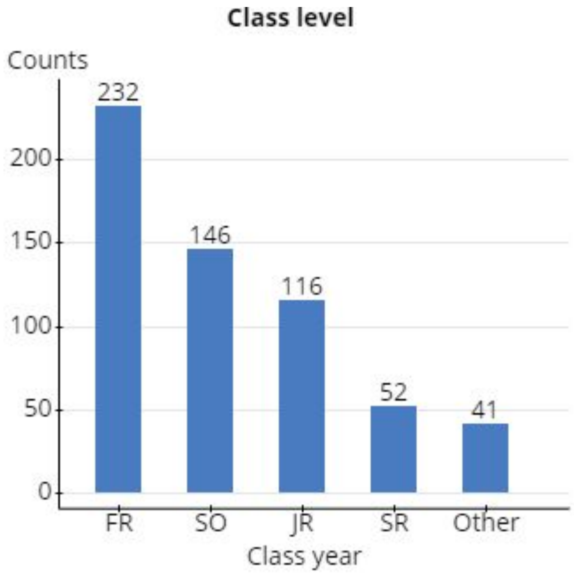


Students

- 50% Response Rate

- n = 588 Students
  - Focus on 7-point Likert (n = 452)
  - Also did 5-point Likert (n = 136)

- 65% Females
- Age: 20 / 21 (Median / Mean)



Analysis Overview

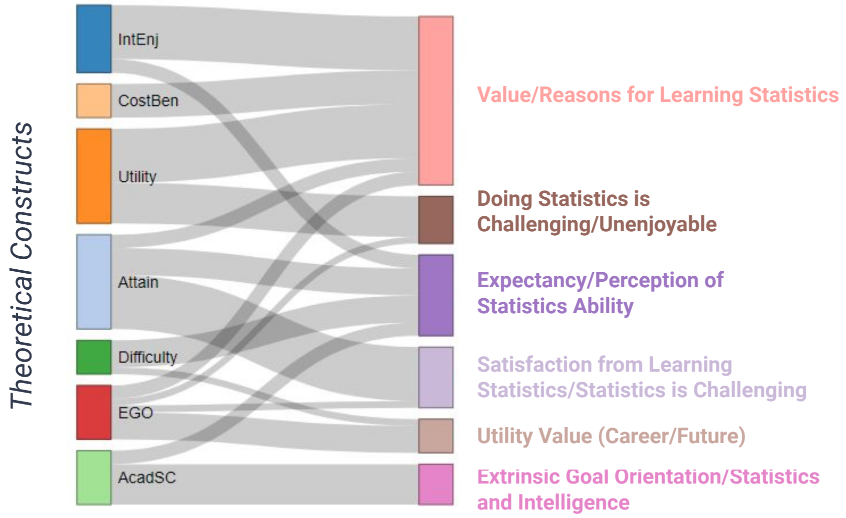
- Exploratory Factor Analysis
- Principal Components Analysis
- Item Response Theory (Graded Response Model)
- Confirmatory Factor Analysis (comparing models)

A brief summary of attitudes using the items from one preliminary model will be shown (using classical test theory).

Exploratory Factor Analysis

- Exploratory Factor Analysis (EFA)
  - Promax rotation
  - MLE
  - Polychoric correlations
- Empirical relationships similar to theory
- Misalignments inform survey revisions.

7-point data, 6-factor EFA, cutoff = 0.40



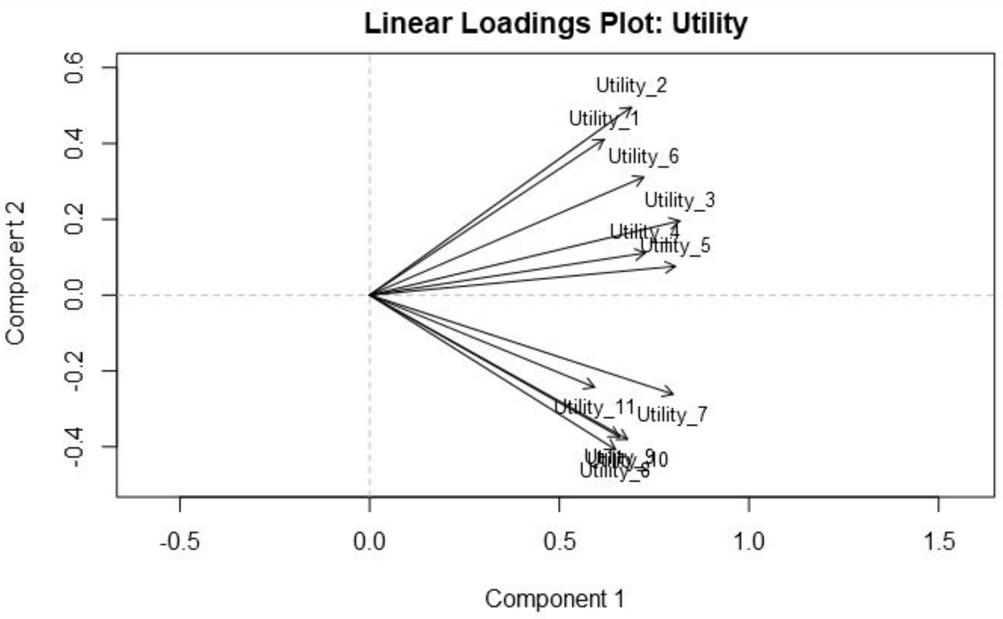
Hover over links to see which items loaded onto each factor.

Note: items may load onto more than one factor.

Empirical Factors

Dimensionality: Utility Value

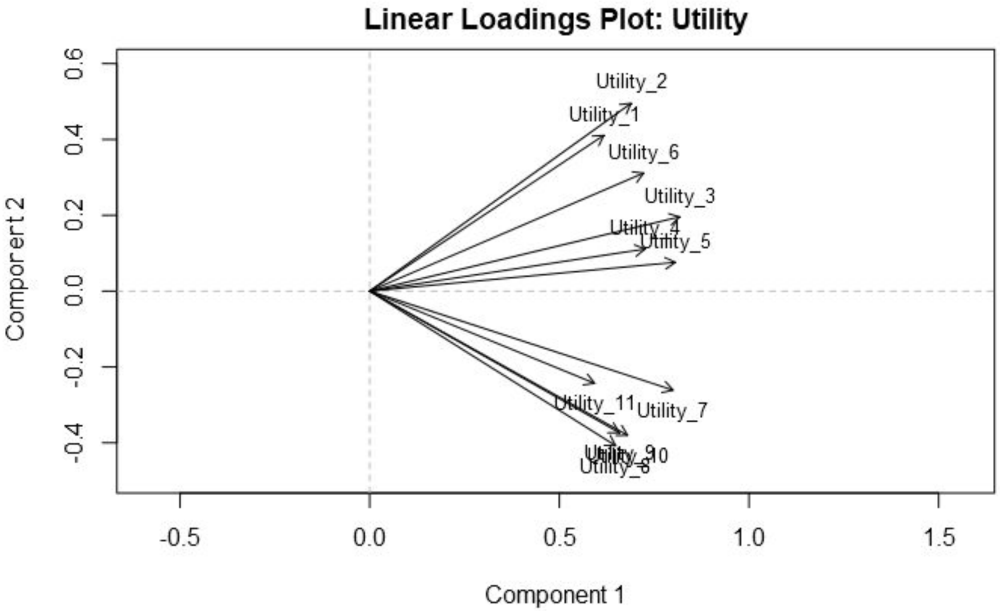
- PCA used to assess unidimensionality assumption for IRT
- Roughly homogenous loadings on the first two components suggests items are measuring the same construct (Mair, 2018)



Dimensionality: Utility Value

Utility Value Items

1. I need to know statistics to satisfy employers.
2. I need to know statistics because it will be expected of me in the future.
3. I will use statistics in my career.
4. Knowing statistics will help me look more appealing to employers.
5. I will rarely use statistics in the future.
6. No one in my career field uses statistics.
7. I want to know statistics to make informed choices for myself (e.g., health, politics, etc.).
8. Statistics is helpful for understanding the world around me.
9. Statistics will help me understand news reports.
10. I value statistics because it makes me an informed citizen.
11. Studying statistics is pointless.



Dimensionality: Utility Value

Utility Value Items

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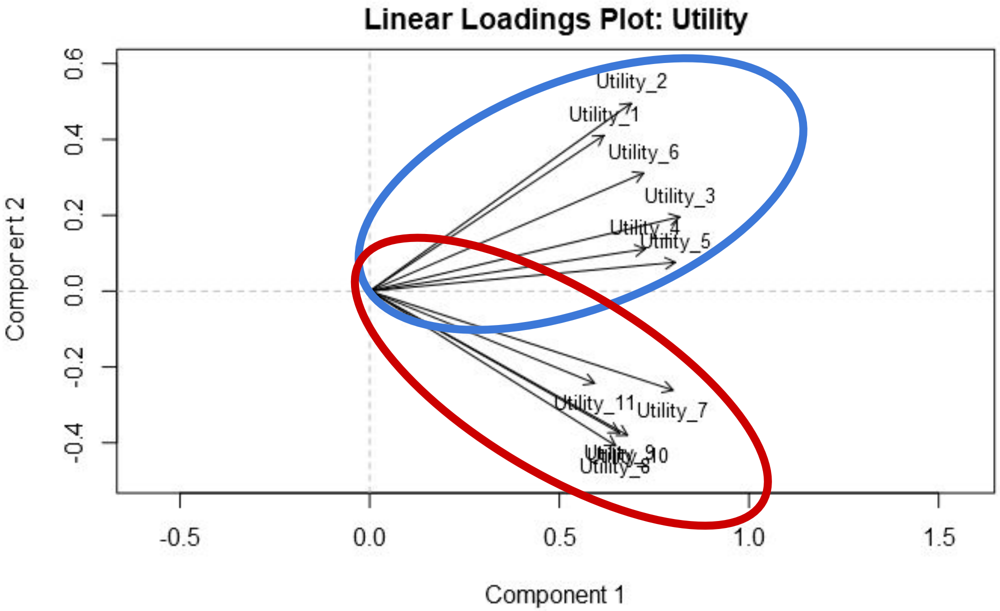
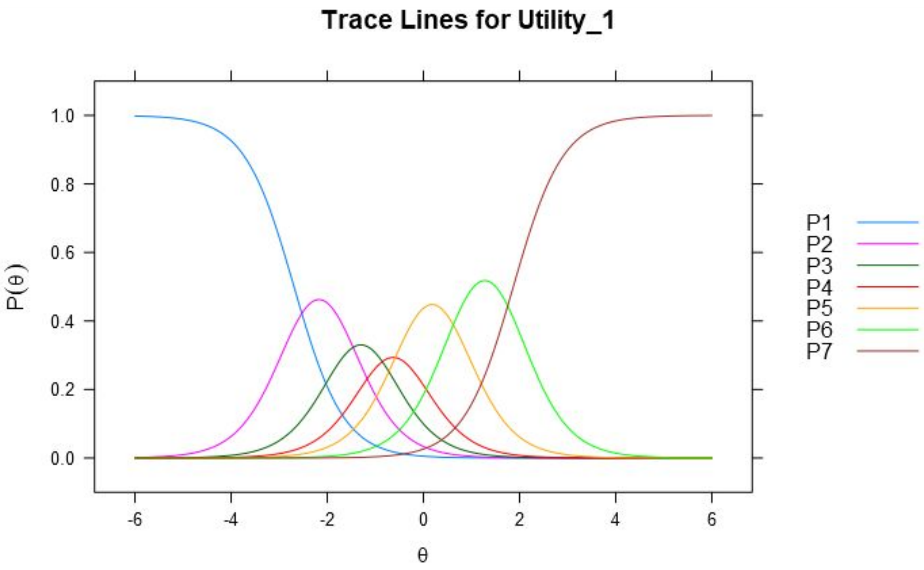
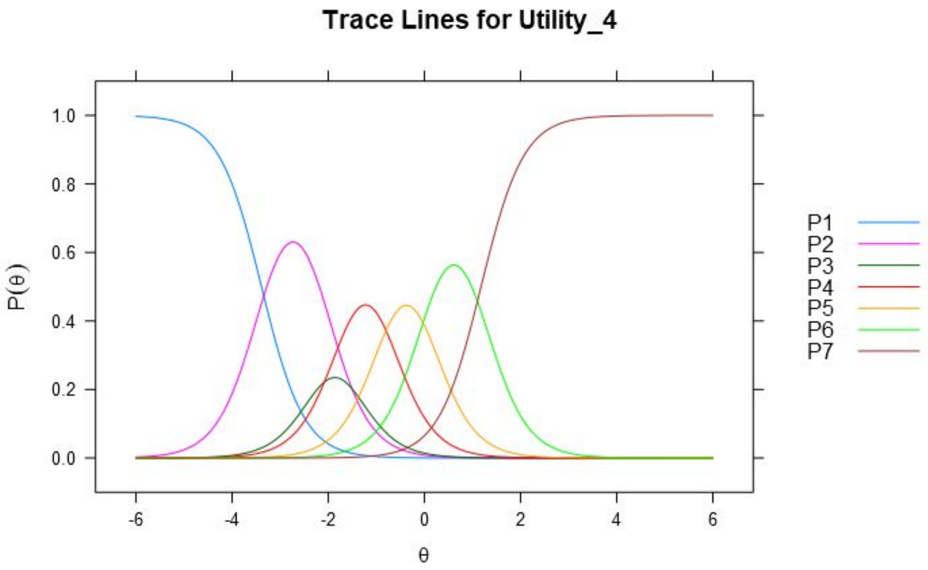


Item Response Theory: Utility Value

Utility_1: *I need to know statistics to satisfy employers.*



Utility_4: *Knowing statistics will help me look more appealing to employers.*



The Graded Response Model (GRM; Samejima, 1969) was used for each scale because the fit was preferable to other models. Few items in each scale exhibited any misfit.

Confirmatory Factor Analysis: Model Overview

Brief description of each model:

- **Model A** contains all items from Pilot-1 (66 items) loading on their hypothesized constructs
- **Model B** is Model A but with a higher-order factor for Subjective Task Values (STV) comprised of Interest, Attainment, and Utility
- **Model C** contains a subset of 38 items loading on their hypothesized constructs [see figure]
- **Model D** is Model C but with the STV higher-order factor
- **Model E** contains a subset of 35 items loading on their hypothesized constructs
    - Model E is *not* a proper subset of Model C

Model C	***Item Code within Each S-SOMAS Pilot 1 Scale***												
STV Higher-Order Factor?	No												
Interest	1	2	3	4	5	6	7	8	9				
Attainment	1	2	3	4	5	6	7	8	9	10	11	12	13
Utility	1	2	3	4	5	6	7	8	9	10	11		
Expectancy	1	2	3	4	5	6							
Cost	1	2	3	4	5	6							
Difficulty	1	2	3	4	5								
Academic Self-Concept	1	2	3	4	5	6	7	8	9				
Extrinsic Goal Orientation	1	2	3	4	5	6	7						

Highlighting indicates that the item was included in the model.

Confirmatory Factor Analysis

	Chi-Square	df	CFI	TLI	RMSEA	SRMR	Warnings
Model A	14527.43	2051	0.958	0.956	0.116	0.097	Estimated parameter covariance matrix not positive definite, Heywood case
Model B	15138.93	2061	0.956	0.954	0.119	0.098	Estimated parameter covariance matrix not positive definite, latent variable covariance matrix not positive definite, Heywood case
Model C	1952.86	637	0.986	0.984	0.068	0.062	Heywood case
Model D	2268.08	647	0.983	0.981	0.075	0.067	Latent variable covariance matrix not positive definite, Heywood case
Model E	1464.18	532	0.988	0.986	0.062	0.061	(None)

Interpretation (Hooper et al., 2008)
Good fit
Acceptable fit
Poor fit

- We compare Models C and D using a Chi-Squared Difference Test with the null hypothesis that Models C and D fit equally well and alternative that Model D fits worse than Model C.
- We reject the null (Chi-Square = 148.56, p-value < 0.0001) and conclude that Model C fits better than Model D.

Reliability Coefficients

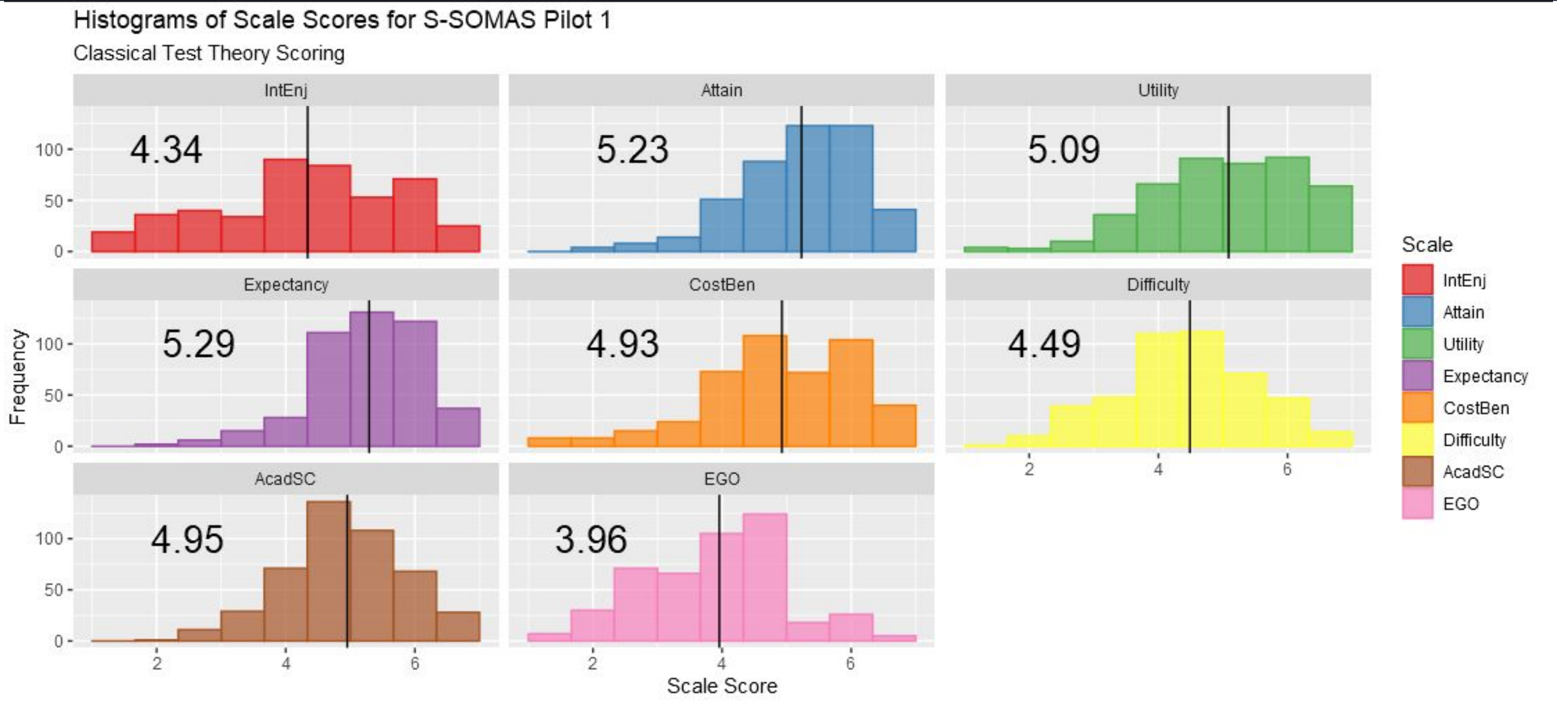
The reliability of a scale is the ratio of the variance of the true scores to the variance of the observed scores. This is a signal-to-noise ratio with larger values indicating a greater proportion of the total variability that is not attributable to random error. Many reliability estimates exist, but coefficient alpha and coefficient omega are quite common.

Using the items from Model C, internal consistency reliability coefficients are calculated for each scale:

Model C	**Interest**	**Attainment**	**Utility**	**Expectancy**	**Cost**	**Difficulty**	**AcadSC**	**EGO**
alpha	0.92	0.86	0.86	0.87	0.90	0.72	0.74	0.76
omega	0.91	0.66	0.78	0.84	0.88	0.74	0.64	0.77
Model E	**Interest**	**Attainment**	**Utility**	**Expectancy**	**Cost**	**Difficulty**	**AcadSC**	**EGO**
alpha	0.92	0.85	0.86	0.86	0.90	0.55	0.74	0.71
omega	0.91	0.83	0.78	0.83	0.88	0.56	0.64	0.67

S-SOMAS Pilot 1 Attitude Results

Attitude Overview



Computed using the items for each scale in Model C

Future Work

Please Join Us for our Next Steps

Serve as a Subject Matter Expert (SME)

Use the instruments in your own education research

Pilot the surveys in your classrooms and as an instructor

Help spread the word about the instruments and our website! http://SDSAttitudes.com

Click here to fill out the interest form

Thank You!

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Appendix

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Analysis Overview

All analyses were performed in Microsoft Open R version 4.0.2 (Microsoft, 2020; R Core Team, 2020) with Intel MKL. The following packages were used:

- ***IRT packages***: `ltm` (Rizopoulos, 2006), `mirt` (Chalmers, 2012), `Gifi` (Mair & De Leeuw, 2019), `WrightMap` (Torres Irribarra & Freund, 2014)
- ***EFA packages***: `nFactors` (Raiche, 2010), `networkD3` (Allaire et al., 2017)
- ***CFA packages***: `lavaan` (Rosseel, 2012), `semPlot` (Epskamp, 2019), `semTools` (semTools Contributors, 2016)
- ***Other packages***: `psych` (Revelle, 2021), `ggplot2` (Wickham, 2009), `RColorBrewer` (Neuwirth, 2014)

Analysis Overview

The development focus for the S-SOMAS is moving toward finalizing the instrument. Ultimately, we will use **Confirmatory Factor Analysis** (CFA) to provide validity evidence about the internal structure of the instrument. This process will begin with all 66 items administered during Pilot 1; items will be chosen for exclusion/inclusion based on evidence from other analyses and alignment to the EVT construct definitions.

Other analyses that will inform the revisions to the CFA models include:

- Exploratory Factor Analysis
- Principal Components Analysis
- Item Response Theory (Graded Response Model)

A brief summary of attitudes using the items from one preliminary model will be shown (using classical test theory).

Item Response Theory: Utility Value

- We evaluated the Partial Credit Model (PCM; Masters, 1982), Generalized Partial Credit Model (GPCM; Muraki, 1992), and Graded Response Model (GRM; Samejima, 1969) for each scale.
  - A likelihood ratio test was used to compare the PCM and GPCM.
  - AIC was recorded for each.
- For Utility Value:
  - GPCM was preferred to PCM based on the likelihood ratio test.
  - GRM was preferred overall because of lowest AIC.
    - GRM: AIC = 13970.64
    - GPCM: AIC = 14083.93
    - PCM: AIC = 14159.65
- For every scale, GRM was preferred.

Item Response Theory: Utility Value

item	outfit	z.outfit	infit	z.infit
Utility_1	0.9883	-0.1222	0.9650	-0.4574
Utility_2	0.8740	-1.4648	0.8836	-1.4766
Utility_3	0.7982	-1.6404	0.8588	-1.7097
Utility_4	0.9646	-0.3617	0.9537	-0.5387
Utility_5	0.9654	-0.2745	0.9984	0.0069
Utility_6	0.9335	-0.4445	0.8910	-1.3632
Utility_7	1.0161	0.2181	0.9486	-0.6302
Utility_8	0.8832	-1.2432	0.8746	-1.4353
Utility_9	0.9963	-0.0113	0.9355	-0.7597
Utility_10	1.0113	0.1683	0.9705	-0.3629
Utility_11	0.9284	-0.5745	0.9179	-0.9077

For Utility Value, no items seem to be problematic based on either outfit or infit.

Confirmatory Factor Analysis

	Chi-Square	df	CFI	TLI	RMSEA	SRMR	Warnings
Model A	14527.43	2051	0.958	0.956	0.116	0.097	Estimated parameter covariance matrix not positive definite, Heywood case
Model B	15138.93	2061	0.956	0.954	0.119	0.098	Estimated parameter covariance matrix not positive definite, latent variable covariance matrix not positive definite, Heywood case
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Model E	1464.18	532	0.988	0.986	0.062	0.061	(None)

Index	**Interpretation (Hooper et al., 2008)**
CFI	Greater than 0.95 generally indicates good fit.
TLI	Greater than 0.95 generally indicates good fit.
RMSEA	Less than 0.06 generally indicates good fit; cutoff values for acceptable fit of 0.07 to 0.10 have been proposed.
SRMR	Less than 0.05 generally indicates good fit; values above 0.05 but below 0.08 may be acceptable.

- We compare Models C and D using a Chi-Squared Difference Test with the null hypothesis that Models C and D fit equally well and alternative that Model D fits worse than Model C.
- We reject the null (Chi-Square = 148.56, p-value < 0.0001) and conclude that Model C fits better than Model D.

Confirmatory Factor Analysis: Model C

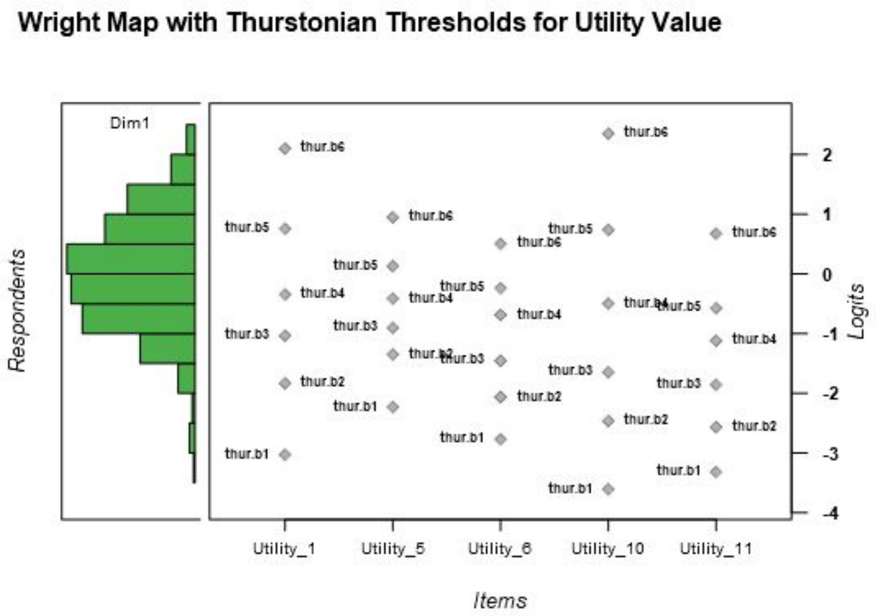
Model C	***Item Code within Each S-SOMAS Pilot 1 Scale***												
STV Higher-Order Factor?	No												
Interest	1	2	3	4	5	6	7	8	9				
Attainment	1	2	3	4	5	6	7	8	9	10	11	12	13
Utility	1	2	3	4	5	6	7	8	9	10	11		
Expectancy	1	2	3	4	5	6							
Cost	1	2	3	4	5	6							
Difficulty	1	2	3	4	5								
Academic Self-Concept	1	2	3	4	5	6	7	8	9				
Extrinsic Goal Orientation	1	2	3	4	5	6	7						

Confirmatory Factor Analysis

A table indicating which items are included in each of the models.

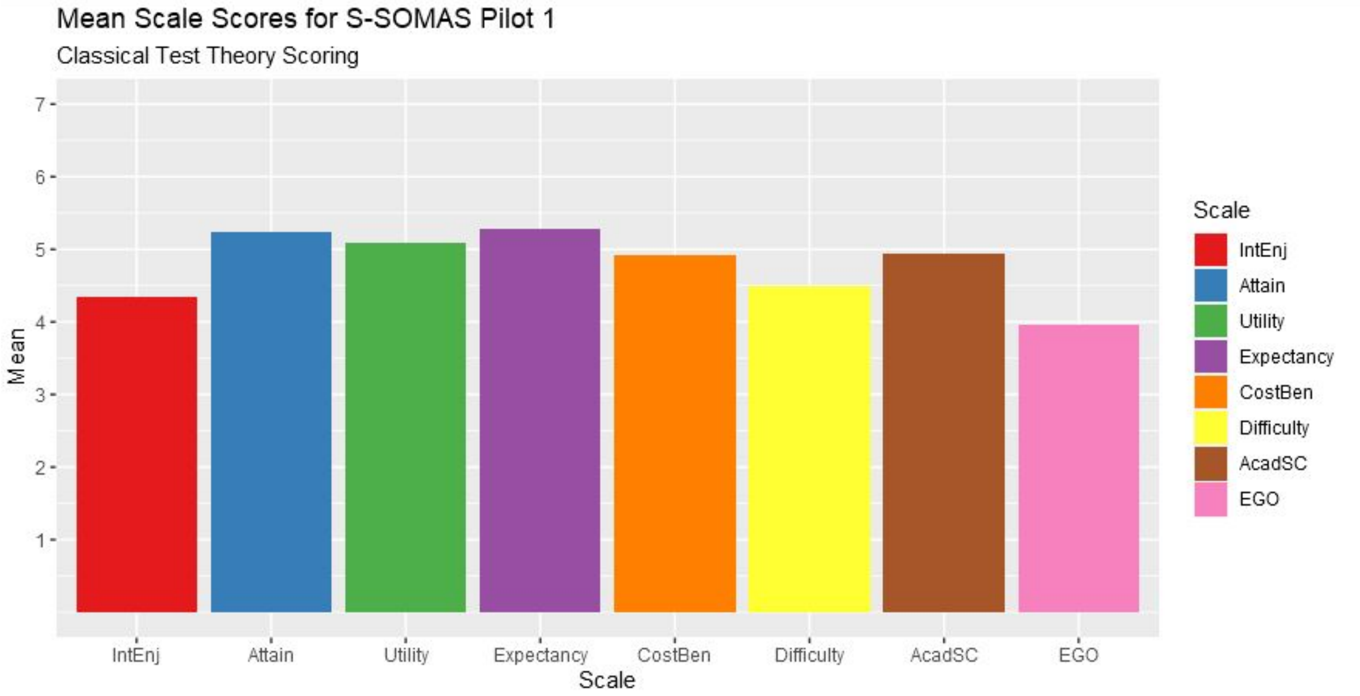
	Model A	**Model B**	**Model C**	**Model D**	**Model E**
STV Higher-Order	No	Yes	No	Yes	No
Interest	1,2,3,4,5,6,7,8,9	1,2,3,4,5,6,7,8,9	2,3,5,9	2,3,5,9	2,3,5,9
Attainment	1,2,3,4,5,6,7,8,9,10,11,12,13	1,2,3,4,5,6,7,8,9,10,11,12,13	1,2,5,7,11,12,13	1,2,5,7,11,12,13	2,5,7,12,13
Utility	1,2,3,4,5,6,7,8,9,10,11	1,2,3,4,5,6,7,8,9,10,11	1,5,6,10,11	1,5,6,10,11	1,5,6,10,11
Expectancy	1,2,3,4,5,6	1,2,3,4,5,6	1,2,3,4,6	1,2,3,4,6	1,2,3,5,6
Cost	1,2,3,4,5,6	1,2,3,4,5,6	1,2,5,6	1,2,5,6	1,2,5,6
Difficulty	1,2,3,4,5	1,2,3,4,5	2,3,4,5	2,3,4,5	2,3,5
Academic Self-Concept	1,2,3,4,5,6,7,8,9	1,2,3,4,5,6,7,8,9	1,2,3,7,8	1,2,3,7,8	1,2,3,7,8
Extrinsic Goal Orientation	1,2,3,4,5,6,7	1,2,3,4,5,6,7	1,5,6,7	1,5,6,7	1,2,3,6

Person-Item Map: Utility Value



Computed using the items for each scale in Model C

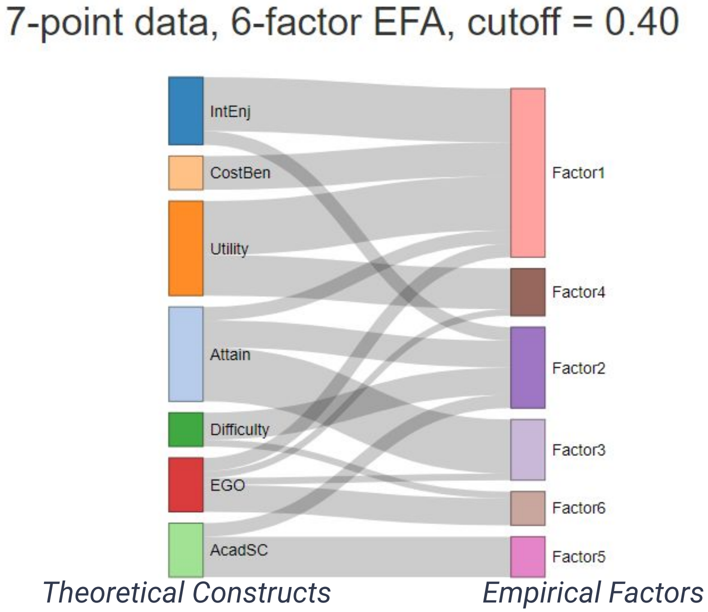
Attitude Overview



Computed using the items for each scale in Model C

Exploratory Factor Analysis

- Exploratory Factor Analysis (EFA) conducted using promax rotation, maximum likelihood estimation, and polychoric correlations.
- Parallel analysis suggests 6-factor solution appropriate, and there is a hypothesized 8-factor solution (from theory).
- Empirical relationships are similar to what is hypothesized by theory; misalignments will inform survey revisions.



Hover over links to see which items loaded onto each factor.

Note: items may load onto more than one factor.

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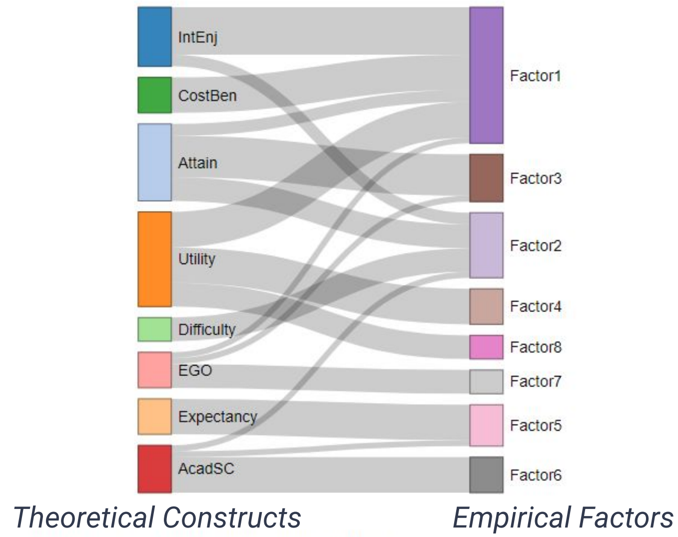
7-point data, 8-factor EFA, cutoff = 0.40



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Note: items may load onto more than one factor.

Without Model E

Confirmatory Factor Analysis: Model Overview

Brief description of each model:

- **Model A** contains all items from Pilot-1 (66 items) loading on their hypothesized constructs
- **Model B** is Model A but with a higher-order factor for Subjective Task Values (STV) comprised of Interest, Attainment, and Utility
- **Model C** contains a subset of 38 items loading on their hypothesized constructs [see figure]
- **Model D** is Model C but with the STV higher-order factor

Model C	***Item Code within Each S-SOMAS Pilot 1 Scale***												
STV Higher-Order Factor?	No												
Interest	1	**2**	**3**	4	**5**	6	7	8	**9**				
Attainment	**1**	**2**	3	4	**5**	6	**7**	8	9	10	**11**	**12**	**13**
Utility	**1**	2	3	4	**5**	**6**	7	8	9	**10**	**11**		
Expectancy	**1**	**2**	**3**	**4**	5	**6**							
Cost	**1**	**2**	3	4	**5**	**6**							
Difficulty	1	**2**	**3**	**4**	**5**								
Academic Self-Concept	**1**	**2**	**3**	4	5	6	**7**	**8**	9				
Extrinsic Goal Orientation	**1**	2	3	4	**5**	**6**	**7**						

Highlighting indicates that the item was included in the model.

Confirmatory Factor Analysis

	Chi-Square	df	CFI	TLI	RMSEA	SRMR	Warnings
Model A	14527.43	2051	0.958	0.956	0.116	0.097	Estimated parameter covariance matrix not positive definite, Heywood case
Model B	15138.93	2061	0.956	0.954	0.119	0.098	Estimated parameter covariance matrix not positive definite, latent variable covariance matrix not positive definite, Heywood case
Model C	1952.86	637	0.986	0.984	0.068	0.062	Heywood case
Model D	2268.08	647	0.983	0.981	0.075	0.067	Latent variable covariance matrix not positive definite, Heywood case

Interpretation (Hooper et al., 2008)
Good fit
Acceptable fit
Poor fit

- We compare Models C and D using a Chi-Squared Difference Test with the null hypothesis that Models C and D fit equally well and alternative that Model D fits worse than Model C.
- We reject the null (Chi-Square = 148.56, p-value < 0.0001) and conclude that Model C fits better than Model D.

Reliability Coefficients

The reliability of a scale is the ratio of the variance of the true scores to the variance of the observed scores. This is a signal-to-noise ratio with larger values indicating a greater proportion of the total variability that is not attributable to random error. Many reliability estimates exist, but coefficient alpha and coefficient omega are quite common.

Using the items from Model C, internal consistency reliability coefficients are calculated for each scale:

Model C	**Interest**	**Attainment**	**Utility**	**Expectancy**	**Cost**	**Difficulty**	**AcadSC**	**EGO**
alpha	0.92	0.86	0.86	0.87	0.90	0.72	0.74	0.76
omega	0.91	0.66	0.78	0.84	0.88	0.74	0.64	0.77