Developing a Student Survey of Motivational Attitudes Toward Statistics

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Abstract
Attitudes toward statistics play an important role in a student's statistics achievement and retention (Kerby & Wroughton, 2017; Ramirez, Schau, & Emmioglu, 2012). In an ASA-approved report, *Connecting Research to Practice in a Culture of Assessment for Introductory College-level Statistics*, authors cite the need for improved metrics by which to measure such attitudes (Pearl et al., 2012). In response, in 2016 the Research on Statistics Attitudes workgroup began development of new instruments to measure attitudes toward statistics. This paper discusses the resulting pilot Student Survey of Motivational Attitudes toward Statistics (S-SOMAS). This includes the theoretical framework for the surveys, based on Expectancy-Value Theory (Eccles et al., 1983; Eccles & Wigfield, 2002), as well as the item development, subject-matter-expert review, pilot data collection, and exploratory factor analysis results. Initial result indicate that students take a more simplified view of the structure of motivational attitudes toward statistics, in comparison to the theoretical model.

Key Words: statistics education, attitudes, undergraduate students, survey, psychometrics, expectancy-value theory

1. Introduction

As the world becomes progressively more data-driven, increasing student interest and performance in statistics is essential. Beliefs and attitudes have been found to influence student success in addition to future career choices, which has caused educators to take a new approach to learning (Pearl et al., 2012; Schunk, 1991; Simon, Aulls, Dedic, Hubbard, & Hall, 2015). Research has shown that student attitudes in undergraduate introductory statistics courses tend to become more negative over the course of the semester (Bond, Perkins, & Ramirez, 2012; Schau & Emmioğlu, 2012). This is echoed by Evans (2007) and Budé et al. (2007), who looked into relationships between students' attitudes and conceptions, along with achievement in the course. A significant correlation was found between negative attitudes and poor achievement in undergraduate introductory statistics courses (both at the beginning and end of the course). Ramirez, Schau, and Emmioğlu (2012) advocate that the introductory statistics course may be the only chance statistics educators have to motivate students to learn the statistical skills they will need; thus, their attitudes are an important piece to a successful experience.

Through a discussion of existing instruments for measuring student' attitudes toward statistics, Gal and Ginsburg's call to action brought to light the importance of affective constructs and the critical need for valid assessment instruments (Gal & Ginsburg, 1994).

In the following years, the Survey of Attitudes Toward Statistics (SATS) became the most commonly used instrument to assess students' attitudes in the introductory statistics course. This instrument exists in two forms: a 28-item instrument (Schau, 1992) and a 36-item instrument (Schau, 2003). Many statistics educators have used the 36-item instrument to study how students' attitudes change over the course of a semester (Kerby & Wroughton, 2017), how curriculum changes impact the learning of statistics (Gundlach, Richards, Nelson, & Levesque-Bristol, 2015; Posner, 2011; Swanson, VanderStoep, & Tintle, 2014), and how the timing of administration of the instrument affects students' attitudes (Posner, 2014).

Although the SATS is widely used and accepted, it was not created using educational or psychological theories. Ramirez et al. (2012) attempted to fill this void by developing the Model of Students' Attitudes Toward Statistics (SATS-M) which contains 3 main constructs: (1) student characteristics, (2) previous achievement-related experiences, and (3) statistics attitudes. The third construct includes the items from the SATS-36. The authors based the SATS-M on Eccles' Expectancy-Value Theory (EVT; Eccles et al., 1983), in addition to the Self-determination Theory, Self-efficacy Theory, and Achievement Goal Theory. However, this model was developed post-hoc.

In 2012 the American Statistical Association (ASA) formed a group of statistics education researchers to identify research priorities in the statistics education field. The Connecting Research to Practice in a Culture of Assessment for Introductory College-level Statistics (CR2P) report (Pearl et al., 2012) was created and approved by the executive board of the ASA. Four research priorities for affective constructs were spelled out in this document: (1) How can affective constructs be accurately measured? (2) How do affective constructs contribute to the success in learning statistics, in either the short or long term? (3) How do affective constructs contribute to long-term engagement with statistics (e.g. statistically literate citizenship)? and (4) What are the important affective constructs to measure about teachers, and how do these influence teaching practices and ultimately impact student outcomes?

In 2016, the ASA recognized the need for supported research in the areas outlined in the CR2P report, and it funded a one-year membership initiative grant for Research On Statistics Attitudes (ROSA). The grant allowed researchers from across the United States (including two authors of this paper) to come together for three different workshops to determine what would be the best approach to creating an assessment for students' attitudes toward statistics. Though pre-existing measures of statistics attitudes such as the SATS have already been created, the post-hoc alignment with EVT as well as psychometric limitations led to the decision that a new instrument should be created rather than attempting to revise the SATS-36 (Whitaker, Unfried, & Batakci, 2018). In alignment with the CR2P report, the ROSA team determined that EVT is the most appropriate framework for the development of the new instrument.

In order to address issues with past attitudes instruments and to adhere to the EVT framework, the current study focuses on the creation of the Student Survey of Motivational Attitudes toward Statistics (S-SOMAS). This paper discusses 1) the theoretical model developed for the S-SOMAS based on EVT, 2) the development of the pilot S-SOMAS instrument based on the theoretical model, 3) pilot data collection and factor analysis for assessing item relationships, and 4) the difference between how students view the relationships between constructs compared to the relationships outlined in the theoretical model.

2. Theoretical Model

Expectancy-Value Theory (EVT) is a model of motivational attitudes that describes how attitudes lead to certain behaviors and achievements (Eccles et al., 1983; Eccles & Wigfield, 2002). This framework was originally used to explain differences in mathematics achievement due to gender (Eccles et al., 1983; Wigfield, Tonks, & Klauda, 2009), but has also been applied to longitudinal studies of mathematics values and beliefs with students in grades 5-12 (Eccles & Wigfield, 1995; Meece, Wigfield, & Eccles, 1990; Wigfield & Eccles, 2000). Not only has the EVT model been used with students in grades 5-12, but it has also been used to model attitudes and beliefs of post-secondary students (e.g., Bong, 2001; Simpkins, Davis-Kean, & Eccles, 2006). The decision to use this theoretical framework to create the S-SOMAS was two-fold: (1) studies have shown that expectancies and values are predictive of achievement and (2) the EVT model is widely-used in the mathematics and statistics education literature (e.g., Unfried, Faber, Stanhope, & Wiebe, 2015).

The S-SOMAS EVT model consists of seventeen constructs in total (given in Figure 1 below), ten of which are being used to assess students' motivational attitudes toward statistics (Whitaker et al., 2018). The decision about which constructs to assess was a balance of wanting to assess as many germane constructs as possible and identifying which constructs are too difficult to measure in a standardized way. Performance behaviors and achievement are the final outcomes in the model, such as course grades or statistical understanding, rather than motivational attitudes that should be assessed by the S-SOMAS. Perceptions of others' attitudes and expectations, Aptitude for Learning Statistics, Interpretation of Past Events, and Career/Life Goals were determined to be too difficult to measure in a standardized way and are not assessed by the S-SOMAS. Additionally, Minimum Standard for Achievement may be assessed by supplementary questions that do not inform instrument development.

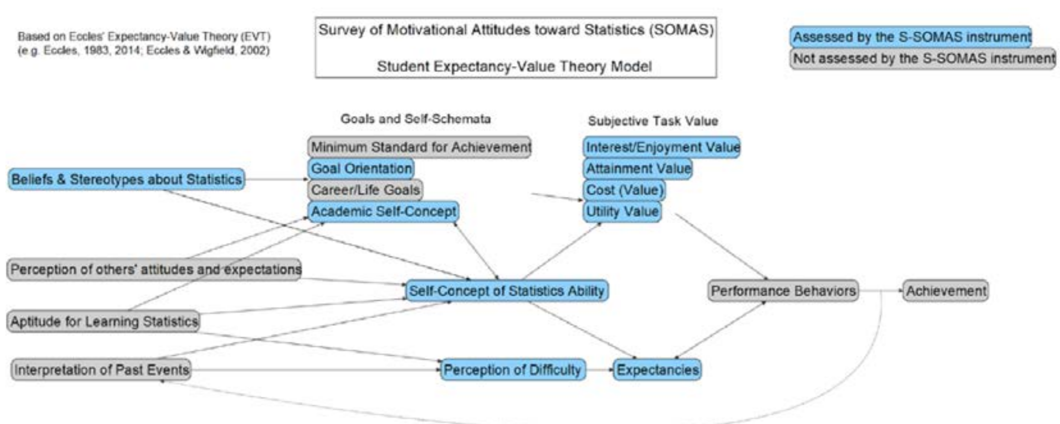

Figure 1: Theoretical model for the Student Survey of Motivational Attitudes toward Statistics

The ten major constructs of the S-SOMAS are described as follows. Statements that are theorized to assess each of these constructs can be seen in Tables 1 and 2. Beginning on the left-hand side of Figure 1, Beliefs and Stereotypes about Statistics refers to statements concerning student concepts and conceptions about statistics. Goal Orientation (Intrinsic and Extrinsic) refers to statements concerning what drives the students (Eccles & Wigfield, 2002). A learning/mastery goal is one that is for personal improvement and learning of the material, while a performance/ability goal is for demonstrating ability in relation to other people. Goal orientation questions were explicitly written for both intrinsic and extrinsic motivation, leading to two Goal Orientation sub-constructs and a total of eleven separate constructs measured by the S-SOMAS.

Self-concept is measured both in the general academic sense, and in particular for statistics ability. Academic Self-Concept refers to statements concerning a student's overall academic grit, perseverance, intellectual challenges, or fortitude; this refers to an individual's knowledge and perceptions about themselves in achievement situations. Alternatively, Self-Concept of Statistics Ability refers to statements concerning a student's concept of who they are in the domain of statistics, more specifically, students' perceptions of who they are in the domain of statistics.

Perception of Difficulty refers to the perceived difficulty of a task. This construct will contain statements concerning how difficult the student perceives statistics to be. Expectancies (Personal Self-Efficacy) refers to statements concerning how the student thinks they will do or perform on upcoming tasks (Eccles & Wigfield, 2002); more specifically here, in the field of statistics.

There are four different types of values assessed by the S-SOMAS. Interest/Enjoyment Value refers to statements concerning whether the student values statistics because it is interesting, enjoyable, or fun. Attainment Value refers to statements concerning whether statistics is valued because attaining the task is important to one's sense of self (Eccles et al., 1983). That is, a task with higher attainment value is a task that an individual find central to their identity. Cost Value refers to statements concerning the sacrifice necessary to understand statistics. This includes both negative aspects of engaging in a task, such as fear of failure, as well as the amount of effort needed to succeed, and lost opportunities from choosing one task over another (Eccles & Wigfield, 2002; Flake, Barron, Hulleman, McCoach, & Welsh, 2015). Utility Value refers to statements concerning the value of statistics because it meets some future goal (Eccles & Wigfield, 2002).

3. Survey Development

3.1 Measure

The Student Survey of Motivational Attitudes Toward Statistics (S-SOMAS) is an instrument under development that measures student attitudes and motivations for learning statistics. Items are rated on a 7-point scale of agreement (1=Strongly disagree, 7=Strongly agree) and assess 1) student beliefs and stereotypes, 2) extrinsic and 3) intrinsic goal orientation, 4) academic self-concept, 5) self-concept of statistical ability, 6) perception of difficulty, 7) expectancies for success, 8) perceived cost, and 9) interest, 10) attainment, and 11) utility value of learning statistics. These proposed constructs are measured with a balance of both positively and negatively worded items. The following paragraphs will describe the creation of initial survey items to align with the constructs defined by EVT, and the results section will demonstrate the empirical findings. The final survey instrument will also include detailed demographic items, but at the time of the initial pilot phase, demographic information such as name and date of birth was gathered with the sole intention of granting participants extra credit incentive points in their statistics courses.

3.2 Procedure

3.2.1 Initial Item Development

During summer 2017, the core team of researchers first worked to develop the theoretical model as described previously. Then, the core team created working definitions of each construct for distribution to a larger work group for item development. Each group member was given construct definitions, a list of citations for each construct, and a template for writing their own survey items to align with each construct. Group members were instructed to work individually without viewing the work of their peers, or other attitudes survey instruments, in order to generate a wide range of creative, unique items. This working group generated an item pool for each construct, then came to together in person to work through each construct and pare down the item pool to the top contenders. Ten to fifteen items for each construct for review by subject matter experts, for a total of 108 potential construct items, knowing that the final instrument would need to be much shorter. (Additionally, 23 non-construct items were reviewed by SME's, such as demographic questions, which are beyond the scope of this paper.)

3.2.2 Subject Matter Expert Review

The S-SOMAS measure was submitted to a subject matter expert review panel in September 2017. Forty-seven subject matter experts (SMEs) were identified by the research team for inclusion on the panel. These SMEs were identified based on their authorship records in statistics or STEM attitudes research, or their broader knowledge of statistics education. Twenty-five of the SMEs responded to the request and completed the survey. Each SME was asked to rate the necessity of including each of the original 131 items on a 3-point scale (1= Essential, 3= Not necessary). To ensure that we were measuring our desired constructs, Lawshe's Content Validity Ratio (CVR; Lawshe, 1975) was calculated for all 131 items.

Concerns voiced by the review board primarily surrounded student understanding of the definition of statistics, item overlap between constructs, and organization. Since S-SOMAS respondents are expected to primarily be students enrolled in introductory statistics classes, reviewers suggested enhancing clarity by including a definition of statistics prior to collecting the responses. Regarding construct overlap, items categorized under utility value and intrinsic and extrinsic goal orientation appeared similar to reviewers. Attainment value also contained items that may fall into intrinsic and extrinsic goal orientation, along with items measuring student interest in statistics. In addition, beliefs and stereotypes were thought to overlap frequently in wording and type. In terms of organization, reviewers posed questions regarding the effects of integrating both negatively and positively worded questions into construct measurement. Many of the reviewers suggested that negatively worded items be eliminated, as some studies have shown that negatively worded items introduce error in factor loadings.

The core research team considered both Lawshe's CVR and the qualitative feedback, and items with scores lower than 0.4 were removed from the S-SOMAS pilot instrument, or reworded to be included in pilot testing. Other items were edited based on SME suggestions. For the initial pilot survey, a definition of statistics was not added, and both positively and negatively worded items were retained. The resulting pilot measure consisted of 92 items.

3.2.3 Pilot Data Collection

During the 2017-18 academic year and summer 2018, the pilot S-SOMAS instrument was administered via Qualtrics in undergraduate introductory statistics courses at six colleges and universities in different parts of the country where the research team members were employed. The purpose of this pilot implementation was not to fully validate the instrument, but rather to assess if the items were aligning with the anticipated structure at all, and to identify the most problematic items and where further refinement is needed in a subsequent draft. Therefore, it was not important that each respondent see all 89 survey items. Due to the potential cognitive overload from responding to 92 items, S-SOMAS was divided into two pilot surveys with five unique constructs and one overlapping construct in each survey. Group one contained 49 of the original 92 items and measured constructs of Interest/Enjoyment Value, Beliefs and Stereotypes about Statistics, Intrinsic and Extrinsic Goal Orientation, Utility Value, and Attainment Value. Group Two contained 50 items that measured Academic Self Concept, Self-Concept of Statistics Ability, Perceived Difficulty, Expectancy, Cost Value, and Attainment Value. These divisions were made based on what constructs the researchers thought might have large areas of overlap in order to determine needed refinements of the constructs. Attainment value items were included on both survey versions because it was unclear how these items might correlate with other items.

After obtaining proper human subjects permissions, researchers assigned the S-SOMAS as an extra credit assignment in their undergraduate statistics courses. An alternative extra credit assignment was also made available to students so that they did not feel obligated to complete the survey. Within Qualtrics, survey participants were randomly assigned to one of the two survey versions.

3.2.4 Analysis

Parallel analysis with 100 repetitions was conducted in R to assess the number of factors needed to summarize the items for each survey version. The 95th percentile of each set of eigenvalues, rather than the average, was used for comparisons between simulated and observed data, as suggested by Glorfeld (1995).

After the number of expected factors was determined for each survey version, maximum likelihood factor analysis was conducted with varimax rotation to determine factor loadings. Items with no loadings greater than 0.4 in absolute value were classified as not loading on any factor. Items with two or more loadings greater than 0.4 in absolute value were classified as cross-loading. Items with only one loading greater than 0.4 in absolute value were considered well-performing.

4. Results

A total of 266 participants completed the S-SOMAS pilot instrument; 132 were randomized to Group One and 134 were randomized to Group Two. With a total of 654 students enrolled in the courses included in the study, the response rate was 40.7 percent. Parallel analysis determined that a three factor structure was appropriate for Group One, and a five factor structure was appropriate for Group Two. The corresponding factor loadings are shown in Tables 1 and 2, for Groups One and Two respectively.

Group One, which contained six theoretical constructs, can be summarized in three factors. The first factor might be defined broadly as the usefulness or worth of statistics, both to an individual and society. The second factor contains items related to personal interest and

Table 1: Group One Exploratory Factor Analysis Varimax-Rotated Loadings

Item	Code	Factor 1	Factor 2	Factor 3
I want to learn statistics for professional opportunity and/or growth.	Intrinsic.2	0.776	0.143	0.001
I need to know statistics because it will be expected of me in the future.	Extrinsic.5	0.754		
I will use statistics in my career.	Utility.1	0.729		
I need to know statistics.	Extrinsic.1	0.724		
No one in my career field uses statistics.	Utility.8	-0.706		
Statistics help us solve complex problems in society.	Belief.6	0.703		
Statistics is helpful for understanding the world around me.	Utility.4	0.701		
I want to learn statistics to be a better consumer of information.	Intrinsic.3	0.698		
I will never use statistics in the future.	Utility.3	-0.680		
I want to learn statistics.	Intrinsic.1	0.665	0.533	
Statistics can be used to make people's lives better.	Belief.9	0.656		
Statistics is broadly applicable in many fields.	Belief.7	0.633		
Statistics will help me understand news reports.	Utility.6	0.617		
I value statistics because it makes me an informed citizen.	Utility.7	0.615	0.418	
Knowing statistics will help me look more appealing to employers.	Utility.2	0.607		
I need to know statistics to satisfy employers.	Extrinsic.4	0.604		
I want to know statistics to make informed choices for myself (e.g. health, politics, etc.).	Intrinsic.7	0.603		
Statistics is a tool for discovering patterns in data.	Belief8	0.602		
Understanding statistics empowers me.	Attain.4	0.594		
I am curious about statistics.	Interest.6	0.585	0.473	
I do not care if I understand statistics.	Attain.3	-0.578		
I want to learn statistics so that I can be a competent citizen.	Intrinsic.5	0.541		

Item	Code	Factor 1	Factor 2	Factor 3
I want to understand how statistics are used in everyday life.	Intrinsic.4	0.524	0.454	
Statistics is irrelevant for my life.	Utility.5	-0.513		0.481
Statistics helps makes sense of the world.	Belief.1	0.509		
Using statistics to solve real-world problems is personally enjoyable.	Interest.4	0.477	0.461	
I want to learn statistics for my personal fulfillment.	Intrinsic.6	0.455	0.442	
If I could choose, I would never do statistics in the future.	Attain.2		-0.767	
I dread statistics.	Interest.8		-0.836	
Doing statistics is fun for me.	Interest.5	0.400	0.753	
I find statistics frustrating.	Interest.1		-0.704	
I find statistics boring.	Interest.3		-0.726	
I am interested in learning more about statistics.	Interest.2	0.542	0.57	
Statistics is intimidating	Belief.10		-0.551	
I think conversations about statistics are stimulating.	Interest.9	0.42	0.538	
I would only learn statistics if it helped me achieve my goals.	Attain.1		-0.537	
I find little enjoyment in doing statistics.	Interest.7		-0.516	
I need to know statistics because my family wants me to.	Extrinsic.8			0.484
Doing well in statistics is important to my sense of self.	Attain.6			0.43
There is little use for statistics outside the classroom.	Belief.3			0.425
If I did poorly in a statistics course, I would be disappointed in myself.	Attain.5			
I need to know statistics so that I appear intelligent to my peers.	Extrinsic.6			
Statistics can be manipulated to say whatever you want.	Belief.5			
I need to know statistics because someone important to me wants me to.	Extrinsic.7			
Strong math skills are required to succeed in statistics.	Belief.2			
I need to know statistics to obtain a degree/certification.	Extrinsic.3			
Statistics is all about plugging numbers into formulas.	Belief.4			

Item	Code	Factor 1	Factor 2	Factor 3
If I am unable to interpret statistical results, I feel insecure.	Attain.7			
I need to know statistics because it is required of me.	Extrinsic.2			

NOTES: Only loadings ≥ |0.4| are displayed. Items are ordered according to factor loading strength, and item codes indicate what construct the item was originally written for.
Intrinsic = Intrinsic Goal Orientation; Extrinsic = Extrinsic Goal Orientation; Belief = Beliefs and Stereotypes about Statistics; Attain = Attainment Value; Interest = Interest/Enjoyment Value; Utility = Utility Value.

Table 2: Group Two Exploratory Factor Analysis Varimax-Rotated Loadings

Item	Code	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
I have trouble understanding statistics.	StatSC.4	0.783				
It is challenging to solve a problem that requires using statistics.	Difficult.6	0.737				
I struggle to interpret statistical results.	Expectancy.1	0.722				
Learning statistics for the first time is hard.	Difficult.7	0.663				
I often need guidance to understand statistics.	StatSC.8	0.622				
Statistics is easy.	Difficult.3	-0.617				
Taking statistics will limit my future prospects (for example, lower my GPA).	Cost.5	0.601				
When I see a statistics question, I am unsure of how to begin.	StatSC.7	0.600				
You must work hard to understand statistics.	Difficult.1	0.589				
I am good at statistics.	StatSC.2	-0.575	0.536			
I find it challenging to decide which statistical method to use in a given context.	Expectancy.6	0.568				
I avoid working on statistics because it makes me feel bad.	Cost.7	0.536				
When I struggle with new material, I feel that I am not learning.	AcadSC.8	0.529				

Item	Code	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Only smart people can do statistics.	Difficult.4	0.513				
I lack the skills to do well in statistics.	StatSC.5	0.512				
If I am unable to interpret statistical results, I feel insecure.	Attain.7	0.447				
I am able to explain statistical results to others.	StatSC.1		0.643			
I can identify when statistics is misused.	Expectancy.5		0.631			
I am able to determine if data support a given hypothesis.	Expectancy.8		0.630			
I am able to make decisions that require statistical thinking.	Expectancy.2		0.601			
I am able to describe the variability for a given data set.	Expectancy.9		0.502			
If I keep working at it, I know I can solve most statistics problems.	StatSC.3		0.497			
I can determine if a study is an experiment or observational.	Expectancy.10		0.484			
I can interpret graphs when I see them.	Expectancy.4		0.457			
I can complete tasks that require basic statistical skills.	Expectancy.3		0.455			
I have the academic background to do well in statistics.	StatSC.6		0.446			
I can use statistics to make informed decisions about my life.	Expectancy.7		0.443			
I have more important things to do than spending time learning statistics.	Cost.4			-0.743		
Learning statistics is a good use of my time.	Cost.1			0.701		
Acquiring statistical skills is worth the effort.	Cost.2		0.458	0.675		
If I could choose, I would never do statistics in the future.	Attain.2			-0.614		
Learning statistics is worth spending money on.	Cost.6			0.589		
I do not care if I understand statistics.	Attain.3			-0.572		
I would only learn statistics if it helped me achieve my goals.	Attain.1			-0.556		
Understanding statistics empowers me.	Attain.4		0.418	0.483		
I prioritize other tasks over statistics.	Cost.3			-0.406		
When I fail at something, I immediately give up.	AcadSC.9				0.833	

Item	Code	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
When learning becomes difficult, I usually give up.	AcadSC.7				0.813	
When statistics becomes challenging, I stop trying.	StatSC.9				0.564	
I avoid working on things that are intimidating to me.	AcadSC.5				0.563	-0.013
If I can't solve a problem right away, I will try again.	AcadSC.3				-0.401	0.133
If I did poorly in a statistics course, I would be disappointed in myself.	Attain.5					0.621
Doing well in statistics is important to my sense of self.	Attain.6					0.551
Doing well in school is important to me.	AcadSC.1					0.418
Interpreting statistical results is straightforward.	Difficult.2					
I like learning.	AcadSC.6					
I am confident that I can master learning difficult concepts.	AcadSC.2					
I enjoy intellectual challenges.	AcadSC.4					
I struggle to identify biases that exist in a sample.	Expectancy.11					
Anybody can do statistics.	Difficult.5					

NOTES: Only loadings ≥ |0.4| are displayed. Items are ordered according to factor loading strength, and item codes indicate what construct the item was originally written for.
StatSC = Self-Concept of Statistics Ability; AcadSC = Academic Self-Concept; Difficult = Perceived Difficulty; Attain = Attainment Value; Cost = Cost Value; Expectancy = Expectancy.

enjoyment of statistics. The third factor is composed of only three items (that do not cross-load) that are difficult to summarize easily. It includes items about motivation for learning statistics, and relevance of statistics. Forty items loaded significantly on at least one factor, and 33 of these items had no cross-loading. Nine items did not load significantly on any factor. Figure 2 maps the original theoretical constructs onto the three empirical factors in order to display how each construct contributed to defining the factors.

Group Two also contained six theoretical constructs but can be summarized in five factors. These factors might be defined as difficulty, expectancy and statistical ability, the cost of learning statistics (or conversely, the importance relative to the cost), grit and perseverance in academics, and academic self-concept. Forty-four items loaded significantly on at least one factor, and 40 of these had no cross-loading. Six items did not load significantly on any factor. Figure 3 maps the original theoretical constructs onto the five empirical factors in order to display how each construct contributed to defining the factors.

5. Discussion

5.1 Insights

The factor analysis results clearly show the overlap in definitions of many of the theoretical constructs; it is difficult to fully separate ideas such as utility value and goal orientation, as these are related in students' minds. This validates the original concern that was raised by the Subject Matter Experts. The exploratory factor analysis results indicate that students think of attitudes toward statistics more simplistically than our original model. For instance, utility value, extrinsic and intrinsic motivation, and beliefs and stereotypes about statistics seem to be merged into one large factor about the overall usefulness of statistics, whether it be for individual usefulness or societal usefulness.

We also notice that the second factor, interest and enjoyment of statistics, is comprised mostly of items from the theoretical construct of interest, but some items from attainment value and beliefs and stereotypes also appear. Interestingly, this construct mostly contains negatively worded items that reflect a lack of interest in statistics; positively worded items from the theoretical construct of interest sometimes appear in the first factor, usefulness of statistics. Therefore moving forward it will be important to explore whether or not it is the positive versus negative wording of items that creates these constructs. The third factor in Group One is not easy to define, and the research team must determine if these three items cover an important idea such that more items should be developed around this factor, or if the factor is simply a result of noise in the data and should be discarded.

Attainment value items were included on both survey versions. In Group One, we see that the Attainment Value items appeared scattered throughout the three factors. However, in Group Two, most Attainment Value items are found on factor six, regarding the cost of learning statistics. Students do not seem to differentiate between some aspects of costs and attainment value; or perhaps, the item writing might need refinement.

In Group Two, we find that items from many constructs came together to create a broader difficulty scale (factor four), pulling in items intended for other constructs but which also discuss the struggle of doing statistics. Factor five, expectancy, seems to be one of the clearest factors, combining Expectancy and Statistical Self-Concept items to broadly define a student's ability to learn statistics. Referring back to the theoretical model in Figure 1, we see that Self-Concept of Statistics Ability feeds directly into Expectancies, so it makes sense that students might group these concepts together. Factor seven also appears

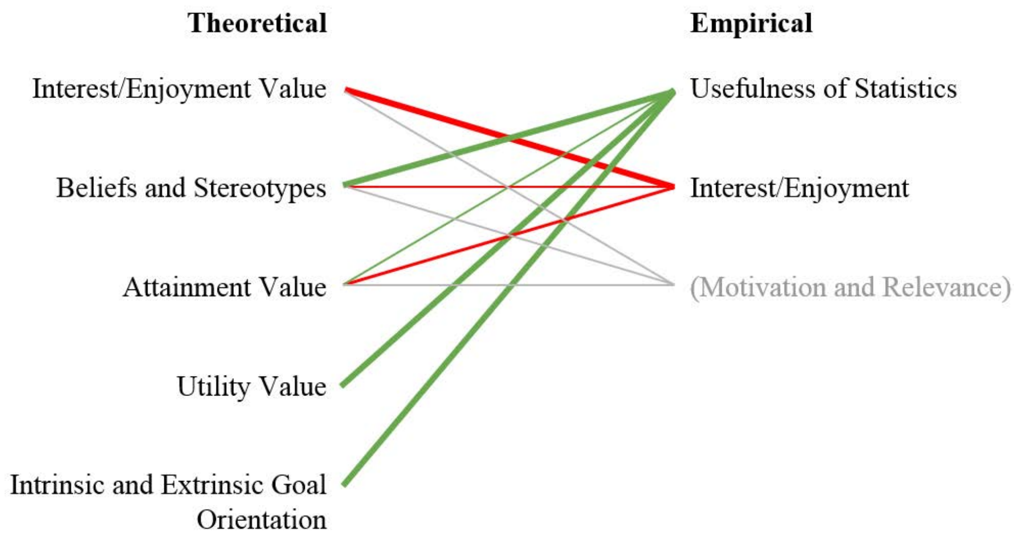

Figure 2: A comparison of Group One theoretical constructs and empirical factors 1 through 3. Lines are colored by empirical factor. Thicker lines indicate that the theoretical construct played a larger role in the composition of the empirical factor. The third empirical factor is greyed out because it is thought to be a remnant of the sample that is not suitable for interpretation.

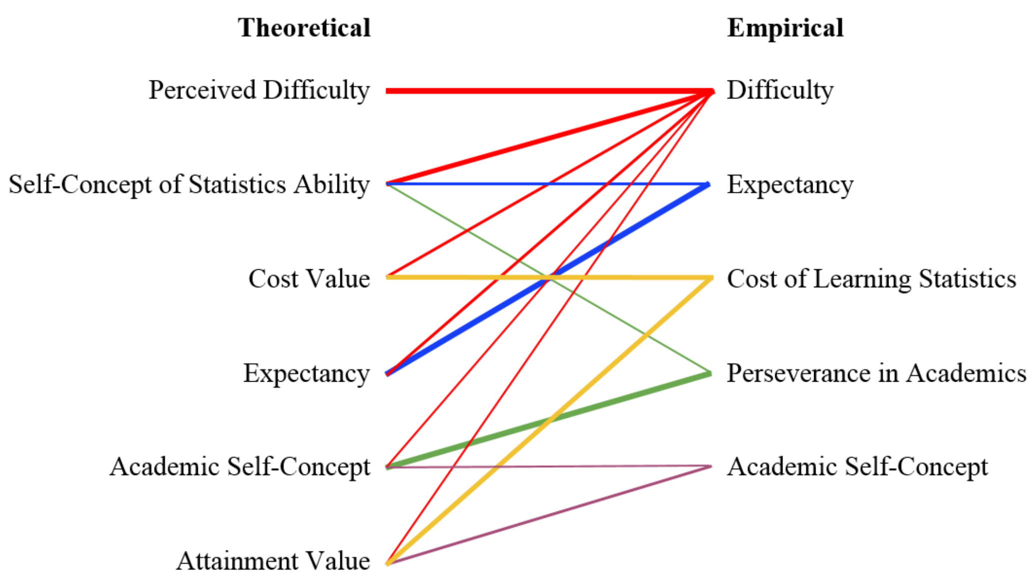

Figure 3: A comparison of Group Two theoretical constructs and empirical factors 4 through 8. Lines are colored by empirical factor. Thicker lines indicate that the theoretical construct played a larger role in the composition of the empirical factor.

relatively clear, interpreted as perseverance in academics, comprised of self-concept items specifically related to perseverance. Only one item in this factor is specifically worded about statistics. Lastly, factor eight is the remainder of Academic Self-Concept items focused on the importance of performing well to one's sense of self.

Although the factor analysis results do not reflect the original theoretical model perfectly, the groupings of items do make sense, other than perhaps factor three (believed to be an artifact of the sample). From starting with the theoretical model based on EVT, the research team was able to cover a much broader domain of constructs than is reflected in other attitudes surveys such as the SATS. However, the research team now must consider if the original model should be modified to reflect student understandings of attitudes, or if the original model remains valuable as the more detailed underpinning of these factors.

5.2 Next Steps

Regarding the groupings of items that were found in factor analysis, the research team will carefully consider how to build up the factors that were found to ensure the proper depth and breadth of the survey. Decisions to remove survey items will be made both in terms of empirical evidence (cross-loading or no loading) and based on aligning constructs with the theoretical model. Of course, the team must also consider if the theoretical model should remain in its current state, or if it should be altered to better align with the more simplistic model that students have reflected in this study. Further, since students grouped most negatively worded items together, the research team must further investigate whether having negatively worded items in constructs aside from Difficulty is worthwhile, or if it impedes the clarity of the survey structure.

It is also possible that item writing might need refinement across the constructs in order for students to differentiate constructs such as cost and attainment value. Alternatively, students might not see these as separate constructs, in which case they should remain as one factor (Factor 7). Perhaps focus groups could shed light on these differences.

Due to the number of items in the pilot S-SOMAS instrument, students were randomly assigned to only half of the survey items. In the future, it will be crucial to have students respond to a full suite of items so we can view all constructs in relation to one another. First, items will be removed, refined, left alone, or added to the instrument based on the factor analysis findings. Then the refined instrument will be administered starting in the 2018-19 academic year to a more nationally representative sample. Statistical analyses will include (but are not limited to) confirmatory factor analysis to determine how a theoretical model corresponds to empirical data.

Acknowledgements

The authors would like to acknowledge the contributions of the entire SOMAS research team in developing and administering these instruments, in particular Marjorie Bond, Douglas Whitaker, Wendine Bolon, Leyla Batakci, and Michael Posner. Additionally, the authors would like to thank the participants of the ROSA workshops for their efforts in moving this work forward, and the American Statistical Association for providing funding to begin this important work.

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