Exploratory Factor Analysis of the Student Survey of Motivational Attitudes Toward Statistics

Abstract

The workforce is collecting and analyzing more data every day, causing a great need to ensure a future workforce has proper data analysis skills. With research showing students' attitudes toward statistics are generally negative while simultaneously being important predictors of student success in statistics, there is a danger of future generations not having necessary data analysis skills. Measuring students' attitudes toward statistics is crucial, but current instruments are lacking. This is an analysis of the pilot S-SOMAS survey developed to measure students' attitudes toward statistics. The survey was administered in two halves and Factor Analysis was conducted to determine adequate factor extractions and item loadings. In total, ten factors were extracted from Factor Analysis. Original constructs created in the pilot survey did not entirely hold up, but new defined factors are now seen. This work will help lead to a validated instrument able to be used in statistics classrooms.

1 Introduction

Our society is becoming more and more data-driven every day. Data is being collected at an increasing rate with many fields using data to make progress. With this immense amount of data in the world, a need for proper analytical skills is vital in the workforce. A future generation lacking the proper data analysis skills and knowledge could hinder many fields that are relying more on data every day. In addition, an increase in data while lacking individuals to analyze this data could lead down a dangerous hole of inaccurate inferences and unethical analyses. Current research shows that students' attitudes and beliefs may have a significant influence on both their future success and career choices (Pearl et al., 2012; Schunk, 1991; Simon, Aulls, Dedic, Hubbard, & Hall, 2015). Motivating students in statistics and invoking positive attitudes towards statistics plays a large part in ensuring the future generation is equipped with the adequate knowledge and skills to enter the workforce with appropriate analytical training. Unfortunately, students' attitudes toward statistics have been shown to become more negative over the course of a semester (Bond, Perkins, & Ramirez, 2012; Schau & Emmioğlu, 2012). With Introductory Statistics courses being one of the only opportunities to teach and motivate many students in statistics, emphasis should be placed on these students' attitudes while enrolled in the course.

Although attitudes are seen as a real motivator and drive behind students' future success and career choices, accurately measuring those attitudes is challenging. Accurate measurements of students' attitudes can allow educators to confidently determine if various factors are influencing students' attitudes or not. Appropriate changes to the classroom environment, curriculum or various other aspects of education can be made if attitudes are seen to be negative toward statistics - but this is only true if our measurement of attitudes is accurate. Researchers have discussed existing instruments used for measuring students' attitudes towards statistics and have determined a critical need for a valid instrument with effective constructs (Gal & Ginsburg, 1994). A construct consists of various items (questions) that together capture an overall idea, commonly referred to as latent variable. These latent variables are not easy to measure and tend to require a clever combination of questions to accurately measure them. Since the initial call for an instrument, the Survey of Attitudes Toward Statistics (SATS) has been widely used since the mid-90's to measure various aspects of undergraduate students' attitudes towards statistics (Posner, 2014; Gundlach, Richards, Nelson, & Levesque-Bristol, 2015; Posner, 2011; Swanson, VanderStoep, & Tintle, 2014; Kerby & Wroughton, 2017). Although widely used in research, the SATS exhibits some flaws (such as a rigid pre-post structure) and has one main issue - a lack of theoretical framework. The SATS was not originally developed under any type of theoretical framework, although it was expanded on in 2012 to include various aspects of psychological theories (Ramirez et al. 2012). In addition, the SATS has an issue with one particular construct (Effort) showing heavy skew, causing potential inferential issues (Millar & Schau, 2010)

In 2012, the American Statistical Association (ASA) gathered a group of statistics education researchers to determine aspects of statistics education that need prioritizing. The group created the Connecting Research to Practice in a Culture of Assessment for Introductory College-level Statistics (CR2P) report which outlined a need for researchers to focus on affective construct development in measurement instruments. An instrument developed under a theoretical framework may allow for more defined constructs as the underlying variables being measured and items included are driven by psychological research. In 2016, the ASA funded a one-year initiative grant for the Research On Statistics Attitudes (ROSA) group that allowed researchers to determine the best route to measure students' attitudes toward statistics. Researchers determined that a new instrument, the Student Survey of Motivational Attitudes Toward Statistics (S-SOMAS), should be developed and that the Expectancy Value Theory (EVT) framework would be most appropriate for development of effective constructs.

The S-SOMAS is a pilot survey instrument that is designed to measure the various constructs that contribute to student motivational attitudes toward statistics. Researchers from the ROSA group worked individually to develop survey items that were then pooled together and underwent several revision processes. In addition, items were reviewed by 47 subject matter experts to determine how essential each survey item was, after which poor items were removed or edited. For the initial pilot S-SOMAS, questions were narrowed down to 92. (The pilot instrument was intentionally lengthy knowing that in the validation process, items will be culled.) The survey items are responded to on a 1-7 Likert scale (1 = Strongly disagree, 7 = Strongly agree) and assess each of the constructs mentioned above in the S-SOMAS EVT model. The constructs consist of: (1) students' beliefs and stereotypes about statistics, (2) intrinsic and (3) extrinsic goals, (4) academic and (5) statistical self-concept, (6) perception of difficulty, (7) expectancies, (8) perceived cost, (9) interest/enjoyment, (10) attainment value and (11) utility value. A combination of both negatively and positively worded items were used throughout the constructs to ensure responses were not driven by item wording but rather item content.

An initial study was conducted on the S-SOMAS to determine if items were grouping together as expected in the survey, but results were messy and suffered from a small sample size (Unfried, Kerby & Coffin, 2018). In this study, additional data is analyzed to better understand how students are breaking down their attitudes toward statistics into different types of attitudes, and if this follows the theorized model. In addition, Factor Analysis is conducted to determine how many constructs exist in the data and which items belong to which construct. Gaining insight on how items are grouping together may bring light to issues with certain items or their wording – allowing for well-defined and separate constructs. This will strengthen the overall constructs of the survey and bring the instrument closer to becoming a psychometrically validated measurement tool.

2 Theoretical Framework

The EVT framework looks at an individual's beliefs about the value of a task (values), as well as their beliefs about the success of a task (expectancies), and attempts to relate those beliefs to the individual's achievement-related outcomes (Eccles & Wigfield, 2002). The choice of task, performance on the task and persistence on the task are all affected by the values and expectancies one has, potentially causing both values and expectancies constructs to be great mediators in measuring effects on achievement (Eccles, 1983; Eccles & Wigfield, 2002; Eccles (Parsons), Adler, & Meece, 1984; Wigfield & Cambria, 2010). In this paper, the expectations and values of students will be referred to as their "motivational attitudes" as this is consistent with much of the statistical education research.

EVT has been used extensively in educational research. In its originality, EVT was used to attempt to explain differences in mathematics achievement due to gender (Eccles et al., 1983; Wigfield, Tonks, & Klauda, 2009). EVT would later be used even more in educational research, where one study applied the

EVT framework to longitudinal studies of mathematics values and beliefs of students in grades 5-12 (Eccles & Wigfield, 1995; Meece, Wigfield, & Eccles, 1990; Wigfield & Eccles, 2000). The framework was also used to model attitudes and beliefs in post-secondary education students (e.g., Bong, 2001; Simpkins, Davis-Kean, & Eccles, 2006). A combination of EVT's extensive background research involving expectancies and values on achievement, as well as its wide use in mathematics and statistics education literature (e.g., Unfried, Faber, Stanhope, & Wiebe, 2015), drove the decision to use the EVT framework for the S-SOMAS.

The EVT model used for the S-SOMAS consists of 17 different constructs (refer to Figure 1). As 17 constructs would result in a very lengthy survey, as well as a few constructs being simply too difficult to measure through a traditional survey, only 10 constructs were chosen to be used in the actual survey (Whitaker et al., 2018). Looking at the right side of Figure 1, both Performance Behaviors and Achievement are the two end outcomes from this model while, with the S-SOMAS survey, students' motivational attitudes are assessed. On the left side and middle of the figure, although Perception of Others' Attitudes and Expectations, Aptitude for Learning Statistics, Interpretation of Past Events and Career/Life Goals are all constructs deemed influential in the model, they would be too difficult to measure and are not included in the S-SOMAS survey. Finally, the Minimum Standard for Achievement may be assessed with supplementary questions, so this was also not included. The final S-SOMAS survey consists of 10 major constructs from the EVT model shown in Figure 1. The constructs used are highlighted in blue on Figure 1 with the specific items written for each construct shown in Tables 1 and 2.

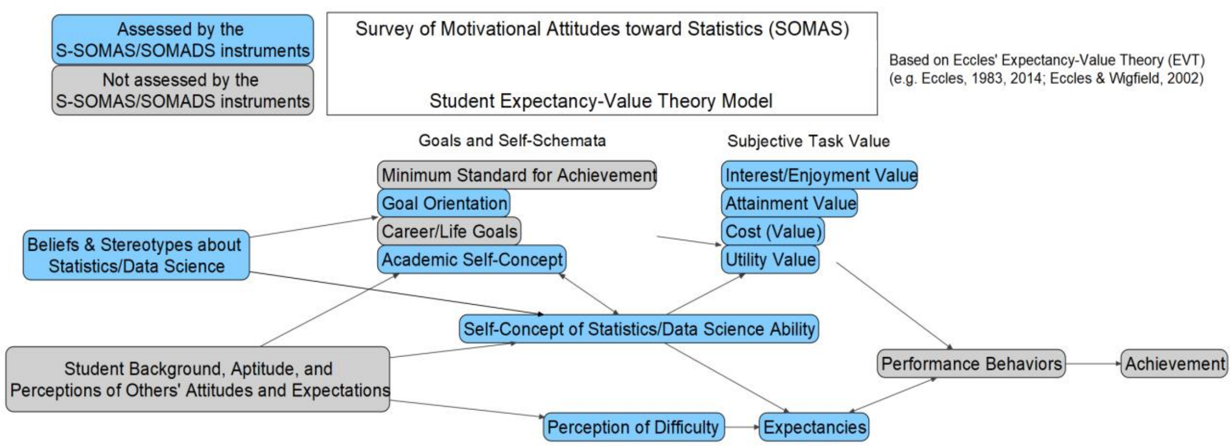

Figure 1: Representation of the theoretical model used for the S-SOMAS survey.

Referring to the left side of Figure 1, Beliefs & Stereotypes about Statistics contains items regarding the conceptions students have about statistics. Moving to the right, Goal Orientation contains items regarding what is driving students' performance in statistics. This drive can be broken down into an intrinsic and extrinsic drive (Eccles & Wigfield, 2002). An intrinsic drive is a drive for your own personal improvement and your desire to learn the material, while an extrinsic drive refers to your performance or ability on the subject in relation to other people. Due to this distinct separation in our goals construct, two sub-constructs were created, one for intrinsic motivation and another for extrinsic motivation - creating a total of 11 separate constructs to measure in the survey.

Self-Concept is measured in two separate ways in this survey: one in the academic sense and the other in the statistical ability sense. For Academic Self-Concept, students' overall academic fortitude, perseverance, and grit are being measured - capturing the students' knowledge and perception about themselves personally in academic achievement related situations. For Self-Concept of Statistics Ability, students instead answer items measuring their perceptions of who they are and where they fit in the area of statistics.

The Difficulty in this model is referring to how difficult statistics is perceived to be. The Expectancies construct concerns how students think they will perform on a task (Eccles & Wigfield, 2002), and more specifically in our case, a statistics-related task.

There are four different types of values assessed by the S-SOMAS survey: Interest/Enjoyment, Attainment Value, Cost Value and Utility Value. The Interest/Enjoyment construct contains items regarding if students value statistics because it is interesting or enjoyable. The Attainment Value construct contains items regarding if students' value statistics because success in statistics is important to their sense of self (Eccles et al., 1983). For example, if a student has high attainment value for a statistical task, performing well on that task is important for their own personal sense of self. The Cost Value construct refers to the cost, or sacrifice, necessary to understand statistics concepts and topics. This construct contains items attempting to capture the negative aspects of engaging in statistical tasks (fear of failing or being judged), the effort needed to succeed and other potential losses (e.g. in terms of opportunities) as a result of prioritizing a statistical task over other tasks (Eccles & Wigfield, 2002; Flake, Barron, Hulleman, McCoach, & Welsh, 2015). Finally, the Utility Value construct contains items referring to the value of statistics because it helps meet or progress towards a future goal. (Eccles & Wigfield, 2002). In total, the 11 constructs/sub-constructs that make up our theorized model are believed to capture students' motivational attitudes towards statistics.

3 Methodology

3.1 Data Collection

For this analysis, data was collected from undergraduate students enrolled in an Introductory Statistics course overt six universities and colleges across the United States where the research team members were employed. The survey was administered via Qualtrics between Fall 2017 and Spring 2020 and used a 1 - 7 Likert scale (1 = Strongly disagree; 7 = Strongly Agree). Among the 92 items and 11 constructs, the survey was split into two halves due to its length and correlation considerations. The research team carefully considered which constructs might be most related and intentionally included those constructs together on the same survey. One half (Group 1) contains 6 constructs with a total and 49 items and the other (Group 2) contains 6 constructs with a total of 50 items. The Attainment Value construct was implemented in both halves of the survey due to uncertainty of which group of items would most correlate with attainment value. Among the Group 1 survey, the Beliefs and Stereotypes, Intrinsic Motivation, Extrinsic Motivation, Utility Value, Attainment Value and Interest/Enjoyment constructs are included, and in Group 2, the Academic Self Concept, Attainment Value, Statistics Self Concept, Difficulty, Expectancy Value and Cost constructs are included. There are between 7 - 11 items within each construct. Students were randomly assigned to a group and were given extra credit upon completion of the survey. Questions in the survey were randomly ordered within each group to avoid potential bias in responses based on the order of the questions. All data collection was approved by the IRB.

3.2 Data Analysis

To determine the underlying empirical factor structure of the S-SOMAS items, Factor Analysis was conducted separately on each group in RStudio version 4.0.1. Parallel Analysis was performed to determine the number of factors that exist in our data, followed by Exploratory Factor Analysis (EFA) to determine what items define each factor. In our case, a factor refers to an empirical representation of how students are grouping items and is obtained through analysis, while a construct refers to the theoretically grouped items believed to be measuring some latent variable. Throughout the paper, factors obtained through Parallel Analysis will be referred to as "empirical factors", while constructs from our theoretical model will be referred to as "theoretical constructs." In Parallel Analysis, Likert responses are transformed into a polychoric correlation matrix in order to calculate eigenvalues. We calculate the same number of eigenvalues as the number of items in each respective group, with values increasing if a group of items correlates strongly with each other and not with other items. A correlation matrix of variables that are strongly related to each other will have some larger eigenvalues than a matrix of independent variables. If eigenvalues are large enough, this may indicate those combined items are be measuring some latent variable (construct). In Parallel Analysis, the number of factors are determined by comparing the eigenvalues from the observed data to eigenvalues from a random-data simulation of independent variables of the same sample size. Eigenvalues in each group are ordered by magnitude. The number of eigenvalues in the observed data that are larger than the corresponding eigenvalue from the simulated data is determined to be the number of factors in the observed data (Osborn, 2014). As a part of Parallel Analysis, there are various conditions and choices that must be made throughout the analysis that influence results and interpretations. The analysis was run with 100 repetitions of the simulated data and a centile of 0.95. This means that instead of averaging the eigenvalues across the 100 repetitions to find the eigenvalues used for comparison, the 95^{th} percentile of the 100 repetitions is used instead. Glorfeld (1995) and Hayton (2004) suggest using a centile of 0.95, which is a more conservative approach meaning this method tends to retain fewer factors.

For EFA, the number of factors to extract is determined from Parallel Analysis. EFA is a combination of extraction and rotation techniques used to maximize item loadings and produce distinguishable factors. The loading of an item can be viewed as the correlation between an item and the factor it is loading onto. For this reason, an item can have loadings between -1 and 1, with the question wording (positive or negative) dictating the direction of the correlation. The number of factors to extract is determined by Parallel Analysis. To maximize loadings and produce the most distinguishable factors possible, factor rotation is used; the factor solution is not unique, so factors are "rotated" to maximize the variance between factors and minimize variance within factors. Distinguishing factors is an important aspect of producing strong factors with confident definitions. A factor may become more distinct by ensuring the items loading on it have high loadings, while also ensuring those items load minimally on other factors. When considering if an item is significantly influential in a new empirical factor, a cutoff at $|0.4|$ for any item loading is used (if an item loads < |0.4|, their item was not considered significantly influential in the factor) (Field, Field & Miles, 2012).

For the rotation, promax rotation was chosen to allow for correlated factors. Principal factor solution was used because the data cannot be assumed to be normal. Finally, EFA requires a correlation matrix similar to Parallel Analysis. Since the data is ordinal, it is recommended to use a polychoric correlation when running EFA as well as applying a correction of zero, both of which was done (Savalei, 2011). Finally, EFA was conducted using the "psych" package, as the function in this package does not require the assumption that the data is normally distributed.

4 Results

The S-SOMAS was given out to classes of undergraduate students, with a total of 3902 students enrolled in the classes in which the survey was administered. From these students, 2381 completed the survey. Thirty-five students were removed as they did not consent to the survey, and 67 students were removed due to inaccurate responses. To determine if a student did not respond accurately to the survey, variation in responses were investigated across all students prior to reverse-coding any survey items. A small variation was an indicator of unreliable responses; negatively and positively worded items should produce a mix of low and high numbers, regardless of students' attitudes. This data cleaning resulted in 2381 students in the final data set and a 61.02% response rate. From these responses, 1194 students were randomized to Group 1, while 1187 students were randomized to Group 2. Factor analysis was conducted separately for Groups 1 and 2, and results are presented in separate tables and figures throughout this section. EFA also calculated cumulative proportion of variance explained by each factor. This is a measure of how well the factor model produced by EFA is capturing the variability in the data. The more variability that is captured, generally the better the model is.

4.1 Group One

Parallel Analysis in Group 1 resulted in a recommended 5 factors to be extracted. This result did not change regardless of a centile choice of 0.95 or 0.5. The eigenvalues obtained for Group 1 and threshold for number of factors chosen can be seen in Figure 2. Item loadings and cumulative variances can be found in Table 1, as well as a representation of how the theoretical constructs map onto the empirical factors in Figure 3. In addition, one item cross-loaded (loaded onto more than one factor) and four items did not have strong enough loadings to load onto any factors.

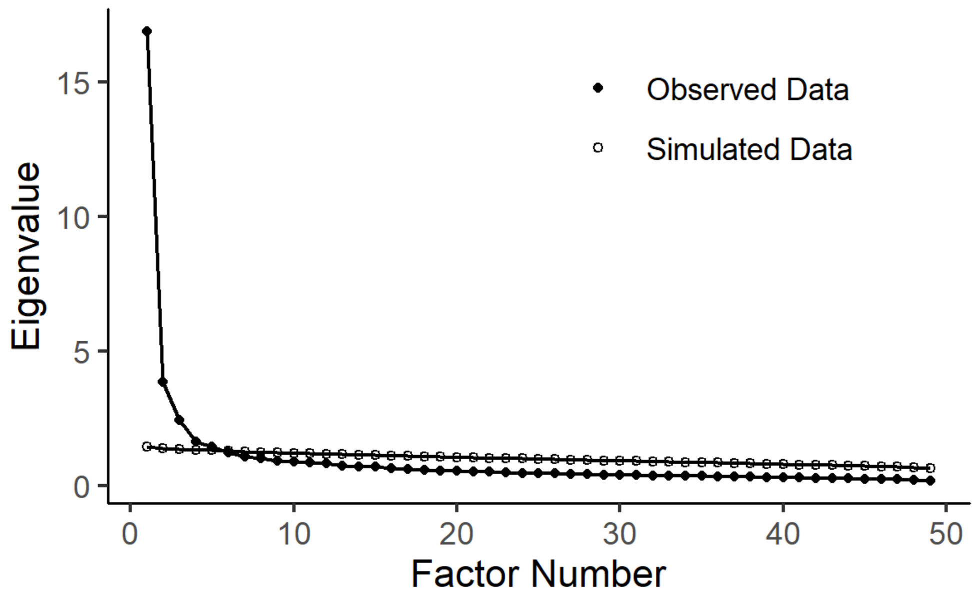

Figure 2: Scree plot of eigenvalues and simulated eigenvalues for Group 1.

Table 1: Factor loadings for each item in Group 1 and their corresponding factor. Loadings >|0.4| were suppressed.

Item	**Code**	**Interest/ Enjoyment**	**Utility Value (personal/ societal)**	**Utility Value (career/ future)**	**Extrinsic Motivation**	**Attainment Value**
I find statistics frustrating.	Interest_1	0.890				
I find statistics boring.	Interest_3	0.857				
I dread statistics.	Interest_8	0.834				
Doing statistics is fun for me.	Interest_5	-0.833				
If I could choose, I would never do statistics in the future.	Attain_2	0.733				
Statistics is intimidating	Belief_10	0.746				0.441
I find little enjoyment in doing statistics.	Interest_7	0.733				
I am interested in learning more about statistics.	Interest_2	-0.602				
I want to learn statistics.	Intrinsic_1	-0.579				
Using statistics to solve real-world problems is personally enjoyable.	Interest_4	-0.558				
I think conversations about statistics are stimulating.	Interest_9	-0.553				
I want to learn statistics for my personal fulfillment.	Intrinsic_6	-0.535				
I am curious about statistics.	Interest_6	-0.519				

I would only learn statistics if it helped me achieve my goals.	Attain_1	0.513				
I do not care if I understand statistics.	Attain_3	0.416				
Understanding statistics empowers me.	Attain_4					
Strong math skills are required to succeed in statistics.	Belief_2					
Statistics will help me understand news reports.	Utility_6		0.784			
Statistics is helpful for understanding the world around me.	Utility_4		0.758			
I value statistics because it makes me an informed citizen.	Utility_7		0.748			
Statistics can be used to make people's lives better.	Belief_9		0.745			
I want to know statistics to make informed choices for myself (e.g. health, politics, etc.).	Intrinsic_7		0.74			
Statistics helps makes sense of the world.	Belief_1		0.726			
Statistics help us solve complex problems in society.	Belief_6		0.693			
I want to learn statistics to be a better consumer of information.	Intrinsic_3		0.684			
I want to learn statistics so that I can be a competent citizen.	Intrinsic_5		0.652			
Statistics is a tool for discovering patterns in data.	Beleif_8		0.624			
Statistics is broadly applicable in many fields.	Belief_7		0.616			
There is little use for statistics outside the classroom.	Belief_3		-0.607			
I want to understand how statistics are used in everyday life.	Intrinsic_4		0.432			
Statistics is irrelevant for my life.	Utility_5					
Statistics can be manipulated to say whatever you want.	Belief_5					
I need to know statistics because it will be expected of me in the future.	Extrinsic_5			0.732		
I need to know statistics to satisfy employers.	Extrinsic_4			0.661		
I will use statistics in my career.	Utility_1			0.634		
I need to know statistics because it is required of me.	Extrinsic_2			0.556		
No one in my career field uses statistics.	Utility_8			-0.553		
I need to know statistics to obtain a degree/certification.	Extrinsic_3			0.512		
I need to know statistics.	Extrinsic_1			0.509		
Knowing statistics will help me look more appealing to employers.	Utility_2			0.476		
I will never use statistics in the future.	Utility_3			-0.422		
I want to learn statistics for professional opportunity and/or growth.	Intrinsic_2			0.414		
I need to know statistics because my family wants me to	Extinsic_8				0.585	

I need to know statistics because someone important to me wants me to.	Extrinsic_7				0.500	
I need to know statistics so that I appear intelligent to my peers.	Extrinsic_6				0.487	
Statistics is all about plugging numbers into formulas.	Belief_4					
Doing well in statistics is important to my sense of self.	Attain_6					0.614
If I did poorly in a statistics course, I would be disappointed in myself.	Attain_5					0.467
If I am unable to interpret statistical results, I feel insecure.	Attain_7					0.458
Proportion of Variance	-	0.163	0.149	0.072	0.045	0.033
Cumulative Proportion of Variance	-	0.163	0.309	0.381	0.427	0.459

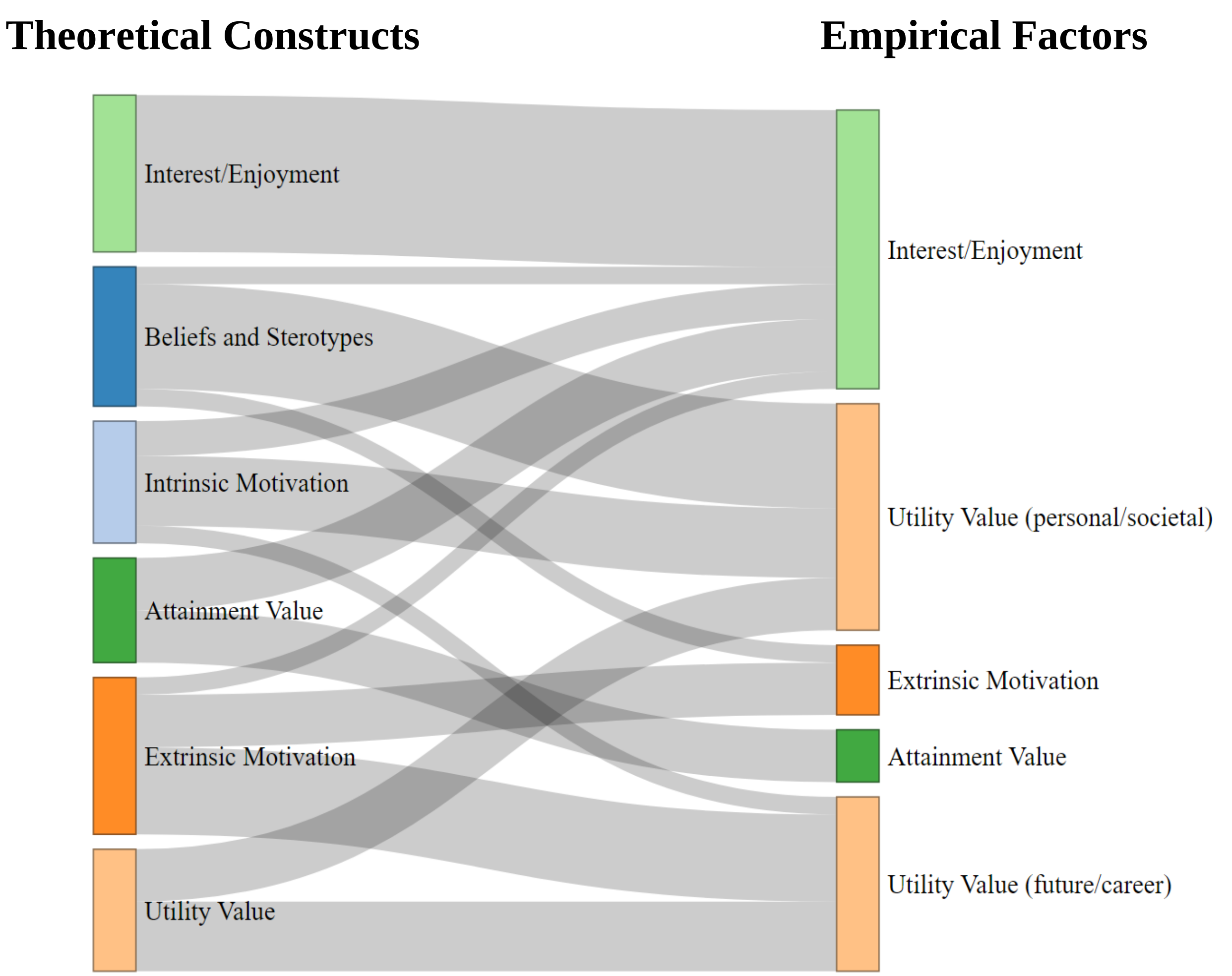

Figure 3: Theoretical constructs and their new empirical factors for Group 1

Originally, Group 1 consisted of six theoretical constructs but, after Parallel Analysis and EFA, only five empirical factors were extracted. From EFA, the first empirical factor contains all the items from the previous theorized Interest/Enjoyment construct, as well as a mix of items from the theorized Attainment Value, Intrinsic Motivation and Beliefs and Stereotypes constructs. This new empirical factor consists of 15 items regarding how much interest or enjoyment a student obtains from statistics. In addition, the seven highest loading items are all negatively worded. This new factor may be defined as students' interest and enjoyment in statistics **(Interest/Enjoyment)**.

The second empirical factor contains items from the theorized Utility Value, Intrinsic Motivation and Beliefs and Stereotypes constructs. This new empirical factor contains 13 predominately positively worded items regarding how students use or utilize statistics. This utilization is both on personal terms (i.e. "Statistics will help me understand news reports.") and societal terms (i.e. Statistics help us solve complex problems in society.") This new factor can be defined as the perceived utility (personal and societal) of statistics **(Utility Value (personal/societal))**.

The third empirical factor contains 10 items from the theorized Extrinsic Motivation, Intrinsic Motivation and Utility constructs, all of which are a mix of positive and negatively worded items. These items seem to all pertain again to a students' perceived usefulness of statistics, but now regarding their career (i.e. "I need to know statistics to satisfy employers.") and overall future (i.e. "I will never use statistics in the future.") This factor may be defined as the perceived utility (career and future) of statistics **(Utility Value (career/future))**.

The fourth empirical factor contains only three items, all from the theorized Extrinsic Motivation construct. These three items pertain to extrinsic motivators for doing well in statistics, but due to another individual's desire or pressure for you to do well. This empirical factor is defined as extrinsic motivation, or more specifically others wanting or pressuring you to do well in statistics **(Extrinsic Motivation)**.

The final empirical factor also contains only three items, all of which are from the theorized Attainment Value construct. The items in this factor discuss how well an individual wants to do in statistics. These items are generally to avoid feeling bad or disappointed by doing poorly in statistics, which distinguishes it from personal/social utility value. (i.e. "If I am unable to interpret statistical results, I feel insecure."). This new factor can be defined as the attainment value a student has for statistics **(Attainment Value)**.

4.2 Group Two

Similarly to group 1, five factors were determined to be extracted from Parallel Analysis. The scree plot of eigenvalues and simulated eigenvalues can be found in Figure 4. Our EFA also showed that many of our theorized constructs split off into several other factors, with no theorized constructs staying full intact. These loadings and cumulative variances can be found on Table 2, as well as a comparison of the theoretical constructs and how they now load onto the empirical factors can be found on Figure 5. In Group 2, two items cross-loaded with five items not having strong enough loadings to load onto any factors.

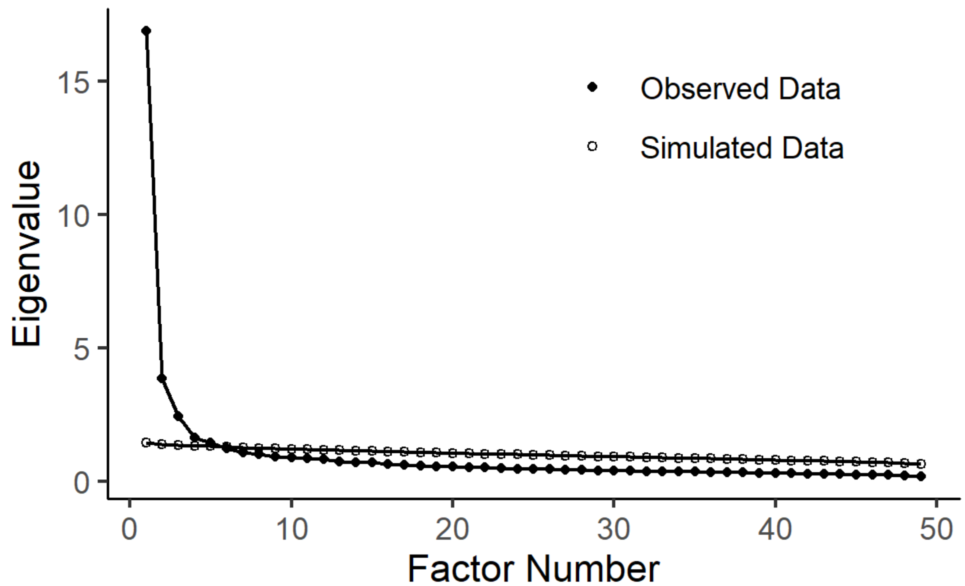

Figure 4: Scree plot of eigenvalues and simulated eigenvalues for group 2.

Table 2: Factor loadings for each item in Group 2 and their corresponding factor. Loadings >|0.4| were suppressed.

Item	Code	Difficulty	Expectancy/ Self-Efficacy	Personal Costs/ Benefits	Academic Perseverance	Attainment Value
Learning statistics for the first time is hard.	Difficult_7	0.876				
You must work hard to understand statistics.	Difficult_1	0.820				
Statistics is easy.	Difficult_3	-0.809				
I have trouble understanding statistics.	StatSC_4	0.784				
It is challenging to solve a problem that requires using statistics.	Difficult_6	0.759				
I often need guidance to understand statistics.	StatSC_8	0.737				
When I see a statistics question, I am unsure of how to begin.	StatSC_7	0.660				
I find it challenging to decide which statistical method to use in given context.	Expectancy_6	0.638				
I struggle to interpret statistical results.	Expectancy_1	0.586				
I am good at statistics.	StatSC_2	-0.584				
Taking statistics will limit my future prospects (for example, lower my GPA).	Cost_5	0.542				
Interpreting statistical results is straightforward.	Difficult_2	-0.466				
I avoid working on statistics because it makes me feel bad.	Cost_7	0.459				

I lack the skills to do well in statistics.	StatSC_5	0.431			
When I struggle with new material, I feel that I am not learning.	AcadSC_8				
Only smart people can do statistics.	Difficult_4				
I can interpret graphs when I see them.	Expectancy_4		0.708		
I am able to make decisions that require statistical thinking.	Expectancy_2		0.691		
I can identify when statistics is misused.	Expectancy_5		0.654		
I can complete tasks that require basic statistical skills.	Expectancy_3		0.617		
I can determine if a study is an experiment or observational.	Expectancy_10		0.606		
I am able to determine if data support a given hypothesis.	Expectancy_8		0.595		
I am able to explain statistical results to others.	StatSC_1		0.576		
I am confident that I can master learning difficult concepts.	AcadSC_2		0.552		
I can use statistics to make informed decisions about my life.	Expectancy_7		0.527	0.469	
I have the academic background to do well in statistics.	StatSC_6		0.468		
If I keep working at it, I know I can solve most statistics problems.	StatSC_3		0.454		
I am able to describe the variability for a given data set.	Expectancy_9		0.452		
I struggle to identify biases that exist in a sample.	Expectancy_11		-0.416		
I enjoy intellectual challenges.	AcadSC_4				
I like learning.	AcadSC_6				
Anybody can do statistics.	Difficult_5				
Learning statistics is a good use of my time.	Cost_1			0.784	
I have more important things to do than spending time learning statistics.	Cost_4			-0.753	
Learning statistics is worth spending money on.	Cost_6			0.732	
If I could choose, I would never do statistics in the future.	Attain_2			-0.692	
Acquiring statistical skills is worth the effort.	Cost_2			0.686	
I prioritize other tasks over statistics.	Cost_3			-0.637	
I do not care if I understand statistics.	Attain_3			-0.624	
Understanding statistics empowers me.	Attain_4			0.592	
I would only learn statistics if it helped me achieve my goals.	Attain_1			-0.445	
When I fail at something, I immediately give up.	AcadSC_9				0.832

When learning becomes difficult, I usually give up.	AcadSC_7				0.827	
I avoid working on things that are intimidating to me.	AcadSC_5				0.658	
When statistics becomes challenging, I stop trying.	StatSC_9				0.620	
If I can't solve a problem right away, I will try again.	AcadSC_3				-0.448	
If I did poorly in a statistics course, I would be disappointed in myself.	Attain_5					0.705
Doing well in school is important to me.	AcadSC_1					0.630
Doing well in statistics is important to my sense of self.	Attain_6			0.453		0.504
If I am unable to interpret statistical results, I feel insecure.	Attain_7					0.440
Proportion of Variance	-	0.142	0.112	0.094	0.073	0.037
Cumulative Proportion of Variance	-	0.142	0.255	0.349	0.422	0.459

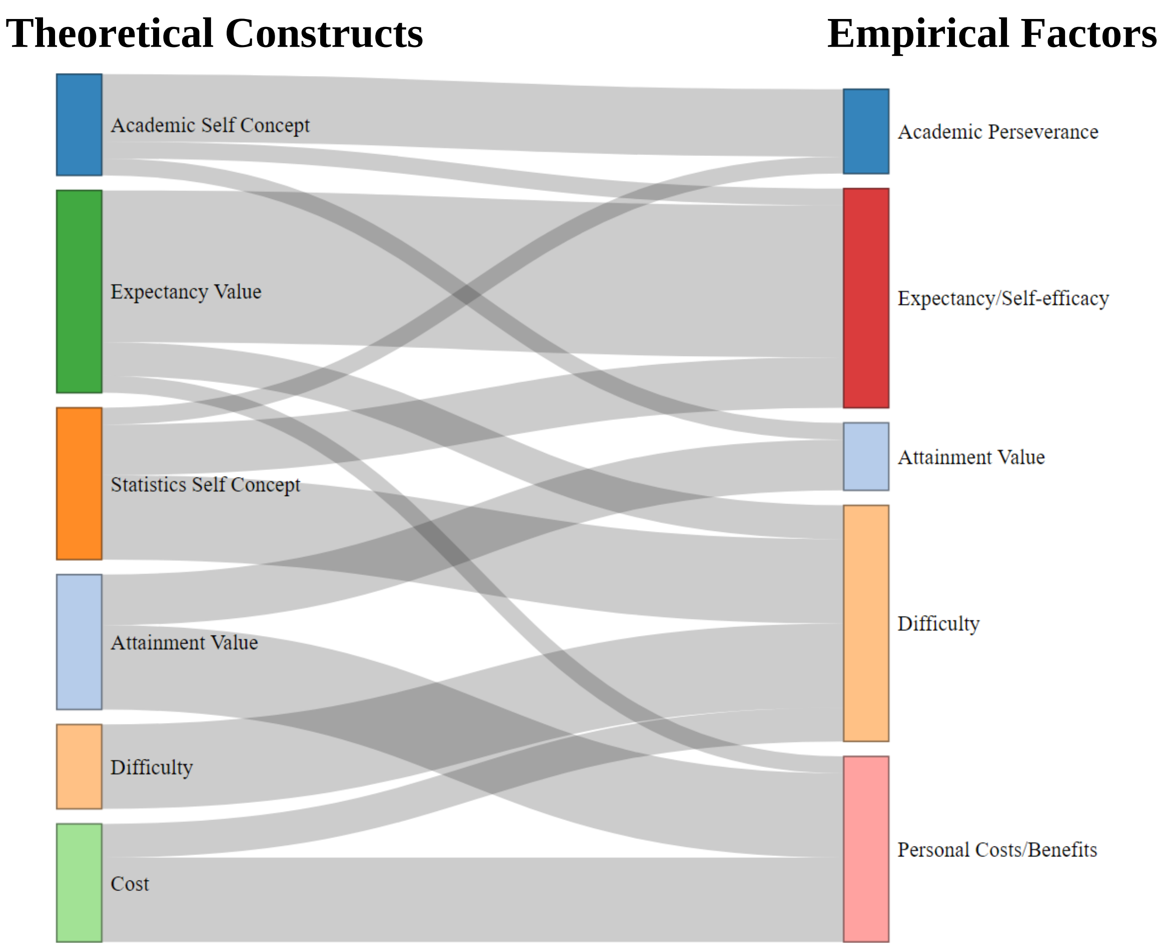

Figure 5: Theoretical constructs and their new empirical factors for group 2.

The first empirical factor extracted from Group 2 consisted of 14 items from the theorized Difficulty, Statistical Self-Concept, Expectancy and Cost Value constructs. These items were predominantly negatively worded. The items in this factor cover aspects regarding students' perceived difficulty of statistics and can be defined as such **(Perceived Difficulty)**.

The second empirical factor contains 13 items from the theorized Expectancy, Statistics Self-Concept and Academic Self-Concept constructs with all items being positively worded. The items in this factor cover expectancy or self-efficacy that students have regarding statistics. Many items are regarding if the student believes they can perform/choose correct statistical analysis/decisions (i.e. "I am able to make decisions that require statistical thinking."), as well as share that information (i.e. "I am able to describe the variability for a given data set."). This empirical factor can be defined as students' expectancies and self-efficacy regarding statistics and statistical abilities **(Expectancy/Self-efficacy)**.

The third empirical factor contains 9 items from the theorized Cost Value and Attainment Value constructs. These items are a mix of positively and negatively worded items, with many pertaining to the personal costs/benefits of statistics (and could be defined as such). The questions are more specific to the potential personal benefits of learning statistics (i.e. "Understanding statistics empowers me."), as well as the personal costs (i.e. "I have more important things to do than spending time learning statistics."). This factor can be defined as the personal costs and personal benefits students perceive statistics to have **(Personal Costs/Benefits)**.

The fourth empirical factor in group 2 contains five items from both the theorized Academic and Statistical Self-Concept constructs. However, these items differ somewhat from those found in the Expectancy/Self-efficacy factor previously defined. The items in this factor heavily pertain to students' general academic grit, with one item specifically assessing statistical grit. This factor can be defined as the persistence that students have in academia, with some emphasis on statistical persistence **(Academic Perseverance)**.

For our final empirical factor, there are four items from both the theorized Attainment Value and Academic Self-Concept constructs. These items are related to students wanting to do well in both statistics and school for themselves (i.e. "If I did poorly in a statistics course, I would be disappointed in myself."). This new construct can be defined as the attainment value students' have regarding statistics **(Attainment Value)**. Note that an attainment value factor was identified in both the Group 1 and Group 2 results; attainment value was the only theoretical construct administered with each of the survey groups. Future analyses will condense these factors when all items are administered in one survey instrument.

4.3 Empirical Factor Histograms and Summaries

Histograms of responses were generated for each empirical factor across both groups and can be found Figures 6 and 7. Empirical factors tended to be fairly symmetric, with some factors exhibiting some skew. A mean of 4 is considered neither agree nor disagree, with means represented on Tables 3 and 4. Means for the empirical factors in Group 1 range between 2.81 and 4.98. Means for the empirical factors in Group 2 range between 3.88 and 5.41. Generally, it looks like the empirical factors in both Group 1 have similar overall skewness as Group 2. Empirical factor skewness may be considered when making future edits to the survey if the skew is seen to be too extreme, as extreme skew can make inference from survey constructs challenging.

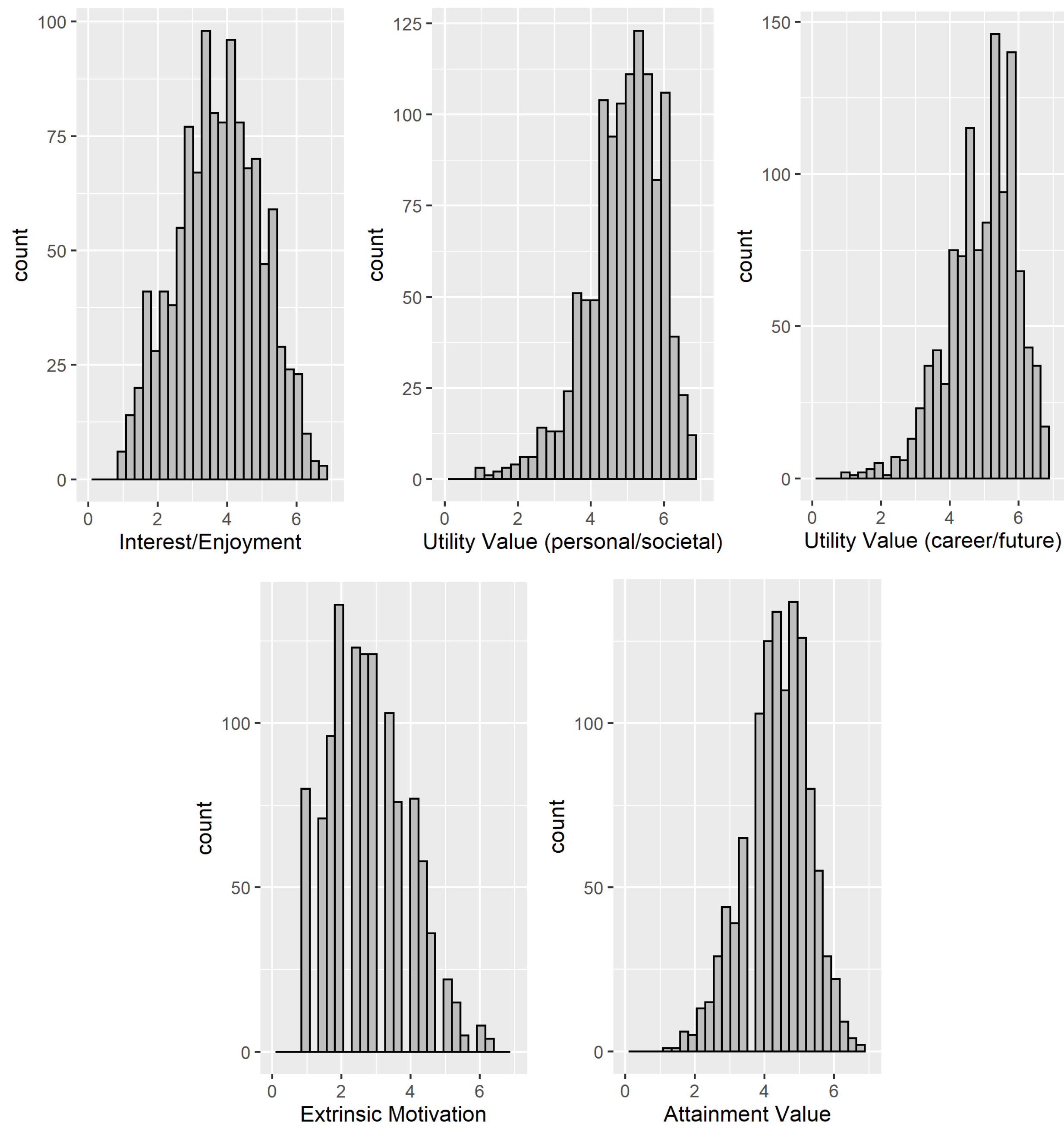

Figure 6: Histograms of each of the new empirical factors for Group 1.

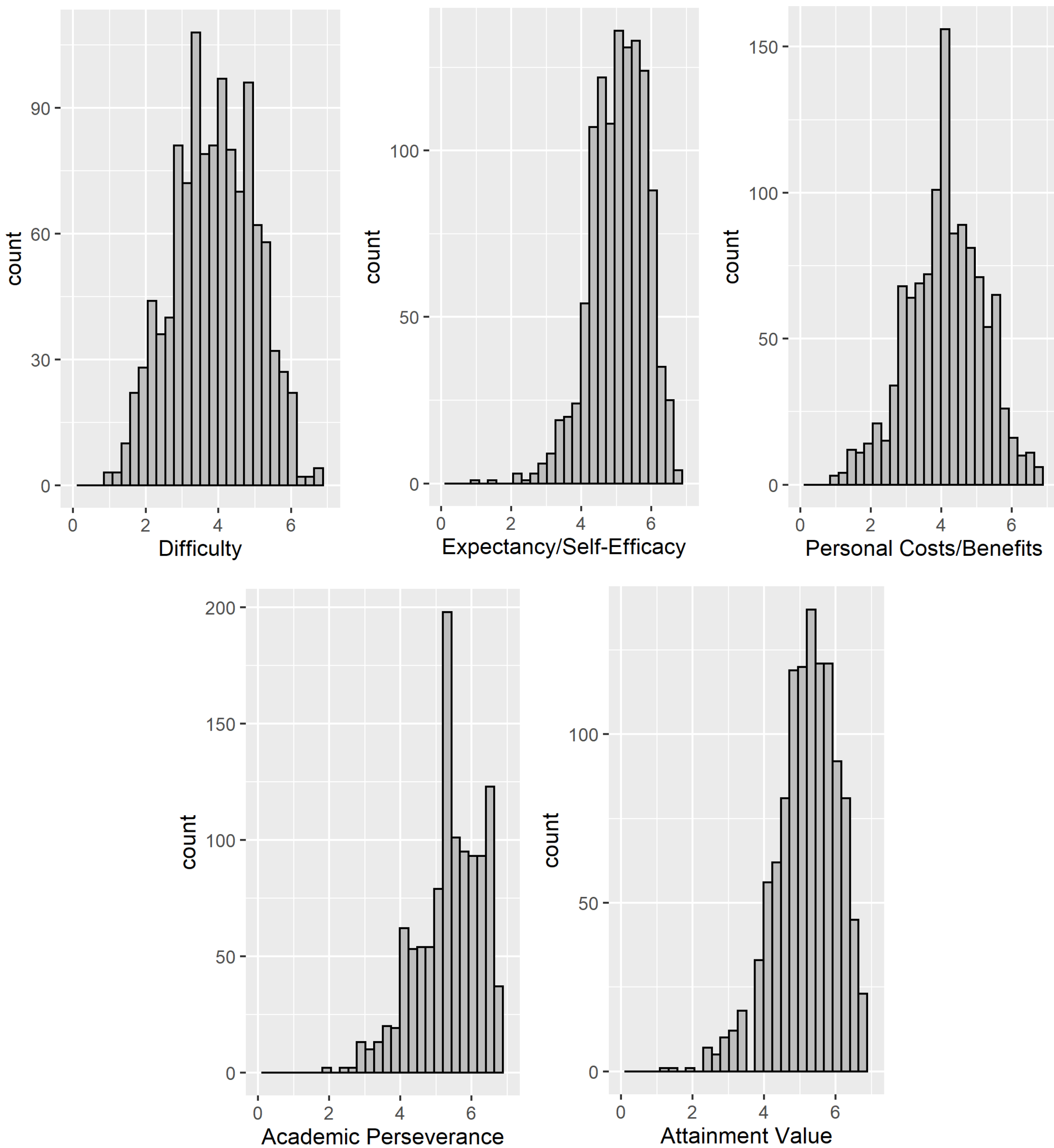

Figure 7: Histograms of each of the new empirical factors for group 2.

Table 3: Means and Standard Deviations of Empirical Factors found in Group 1.

Empirical Factor	Mean	Standard Deviation
Interest/Enjoyment	3.766	1.205
Utility Value (personal/societal)	4.925	0.991
Utility Value (career/future)	4.980	1.004
Extrinsic Motivation	2.806	1.157
Attainment Value	4.339	0.882

Table 4: Means and Standard Deviations of Empirical Factors found in Group 2.

Empirical Factor	Mean	Standard Deviation
Difficulty	3.883	1.112
Expectancy/Self-Efficacy	5.074	0.792
Personal Costs/Benefits	4.114	1.066
Academic Perseverance	5.406	0.935
Attainment Value	5.165	0.886

5 Discussion

From Factor Analysis, it is clear that the way the ROSA working group conceptualized the theoretical constructs and converted the construct ideas into items did not perfectly align with the students' interpretations of the survey items. However, the empirical factors still generally align with constructs expected from Expectancy Value Theory. This demonstrates the importance of conducting an exploratory analysis before proceeding into confirmatory models; most items performed well in the factor model, but did not always appear in the theorized construct. While the theoretical model is crucial for developing the survey framework, the empirical analysis is equally crucial for determining how actual survey items align with what the model expresses. In Figures 6 and 7, our theoretical constructs generally split up into at least two different empirical factors (except for the Interest/Enjoyment construct). Along with this, various new empirical factors contain either predominantly negatively or positively worded items, which is something important to consider moving forward with item edits and removals. Although many of the new empirical factors contain items from at least two different theorized constructs (except for the constructs with few items, of which the loadings are not extremely strong), these items have strong loadings with very few items either not loading or loading onto multiple factors. Thus, although the mental mapping of items to the model may need slight refining, the items and factors themselves are looking promising.

Although data was collected across the country, only a small fraction of the total universities and colleges in the United States are represented in our sample. These universities may not truly represent the population we are interested in as schools were self-selected based on the researchers' location, but the future analysis will account for this potential limitation. Demographic information was also not collected in this pilot but will be collected in the next phase of the study. In addition, the survey was split into two halves while it will eventually be condensed into one comprehensive survey. Information regarding potential relationships between items across our groups is unknown, but if our new factors and further changes hold strong, this should not be an issue.

5.1 Group One

In group 1, many of these theorized constructs, such as Utility Value and Attainment Value, split into two subcategories. In the Utility Value construct, we can see the construct split off into one related to students personal/societal use of statistics, and another on their future/career use of statistics. Our original model described overall utility as captured in one construct, but it appears that may not be the case. This can be seen throughout our results (e.g. Attainment - Interest/Enjoyment attainable through statistics versus personal desire to do well) and potential changes to the model will be considered in the future (although, results do not stray too far from our model).

While our theorized constructs split in most cases for group 1, a few of our empirical factors contained only items from the theorized construct. Our new empirical Extrinsic Motivation and Attainment Value factors contained only items from their respective theorized constructs (although, Attainment Value contains one cross-loading from the Beliefs & Stereotypes construct). These new empirical factors containing only items from their theorized constructs are promising in determining if said constructs have strong definitions and are effective, but changes to these items may take place due to the overall lack of items loading into these constructs. An aspect of this that is important to note is that new empirical Extrinsic Motivation and Attainment Value factors contain items that align well with the original theorized model, but items not loading on these factors have split off into another factor (an aspect discussed above).

In Group 1, the theorized model is generally holding up well with an added complexity potentially existing. The length of this survey alone (although, we did split up the survey to avoid this) could be adding to a lot of these constructs splitting up due to too many aspects being covered from the items. Due to how well items loaded onto our factors, reducing these items down to create more defined constructs should come with some ease. By removing certain questions that may not be truly adding to the survey, we may see our theorized constructs splitting up less and less as there is not as much room for relationships to occur between items. The new empirical factors in group 1 look strong and with future edits, constructs should become even more defined.

5.2 Group Two

Group 2 saw a similar pattern of theoretical constructs splitting off into two or three new empirical factors. These constructs are splitting about half-and-half into factors, where the second half is split amongst two other factor when the construct splits into three factors. The Attainment Value construct (also in Group 1), split up into two different factors that seem to capture subcategories of attainment values regarding statistics. These subcategories (general attainment value and attainment value related to personal costs/benefits) differ between groups, but this is most likely due to the two groups simply having different questions. The Attainment Value construct can give a small idea of how items may create different relationships with each other that we do not see when separating groups, although we expected this to some extent with Attainment Value (which is why is it is both groups). Similarly to Group 1, due to our strong item loadings obtained from EFA and the current length of the survey, removing and editing items will be crucial step that greatly improves the explicit definitions of our final constructs.

One construct, the Difficulty construct, stayed almost entirely intact. One item did not load significantly onto the Difficulty factor, although still loads onto this factor (although $>|0.4|$). Most all the other constructs in this group had some factor where most of their items loaded onto a single factor, with what seems like potentially suspect items loading onto other factors. A closer look will be taken at these items to determine the appropriate changes needed to ensure our construct hold true.

Group 1 and Group 2 produced similar patterns across their results, but we should still take into consideration the potential relationships that may occur when all items are condensed onto one final survey. The research team will use the results of the EFA to make the appropriate decisions for each item in the survey, ultimately condensing the survey down into one comprehensive instrument with various constructs attributing to students' attitudes towards statistics.

5.3 Future Directions

Now that the first phase of the S-SOMAS has concluded (EFA, Parallel Analysis, connecting results to the theoretical model), items will now be looked at to determine necessary changes to produce more defined constructs. This is a necessary and important step in furthering the survey to move it closer to becoming a psychometrically validated instrument. The S-SOMAS is longer than desired, so items were planned on being removed after this initial phase regardless of results (and this is the case in most all survey development). With item loadings and constructs in our survey looking so promising, determining the most impactful items in our new factors will be much more concrete. Wording changes will be made at the discretion of the researchers who originally designed the survey. Aspects such as grouping of negatively/positively worded items must also be reviewed to ensure we are truly capturing what we intend to capture.

While we performed EFA to determine how students are breaking down their motivational attitudes towards statistics, further analysis will be conducted with a revised instrument (new constructs considering our EFA results) to ensure our new constructs are valid. Future analysis will include Confirmatory Factor Analysis, as well as other more advanced analysis from a more representative national sample. The S-SOMAS will eventually be used in colleges and universities to measure students' motivational attitudes toward statistics and contribute in part to educational changes and help to motivate and inspire students in statistics and data analysis. Additionally, instructor surveys are also being developed so that the statistics education community can gain a broader understanding of how student attitudes relate to instructor teaching and attitudes.

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