Do Women Treat Math and Science the Same? A Q Factor Analysis of Female Undergraduate Students' Self-Perceived Abilities and Attitudes toward Math and Science

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Although women overall receive university degrees and are entering the work force in greater numbers than ever, they remain significantly underrepresented in most STEM (Science, Technology, Engineering, Mathematics) majors or careers (National Science Foundation, 2009). Because there are labor supply shortages in these fields, there have been calls from the US government to increase efforts to encourage women and other underrepresented groups to enter into these fields (U.S. Department of Commerce, 2011). Often ignored in research on gender disparities in STEM is the fact that not all STEM disciplines experience the same degree of gender imbalance. The most recent data on bachelor degrees in STEM reveals that women are on parity with men for degrees in the biosciences, approaching parity in mathematics, but are still grossly underrepresented in computer science and engineering degrees (National Science Foundation, 2013). This variability might be explained by women having different patterns of experience across different STEM fields. Understanding differences in these experiences might lead to more refined explanations for the shortage of women in STEM and further aid in the recruitment of women to these fields. In this research we examined a new approach to understanding these experiences, Q-Factor Analysis.

Q-Factor Analysis (QFA) seeks to identify typologies of people with similar subjective experiences and perceptions, and consequently could be useful for understanding if women in different STEM fields have distinct backgrounds. This approach differs from the more common social cognitive research paradigms that focus on career decisions (e.g., Lent, Brown, & Hackett,

2000) and academic outcomes (e.g., Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Eccles et al., 1983) which have identified common processes that are employed in making these choices. Perhaps because the theoretical complexity of the social cognitive models requires sophisticated statistical analyses to evaluate them, research in this area often focuses on a single STEM field (e.g., Fredericks & Eccles, 2002; Lent et al., 2008; Wilkins & Ma, 2003) or collapses all STEM fields into one category (Ferry et al., 2000; Fouad & Smith, 1996). QFA in contrast, can readily deal with multiple disciplines. It is concerned with identifying similar groups of people based on their interests, attitudes and experiences. Thus, as a complementary approach to more traditional research in this area, QFA can help us understand more about women's perceptions of different STEM fields. Q Factor Analysis was employed in this study to examine whether different interest groups can be identified based on college students' attitudes toward and experiences with math, science, and computer science subjects. We first review key constructs from the social cognitive models and then describe how these constructs can be incorporated into the QFA to identify typologies of women.

Social Cognitive Theories of Learning and Career Choices

Social Cognitive Theory was first proposed by Bandura (1977). Self-efficacy, learners' beliefs concerning their capabilities to accomplish academic-related tasks and activities, lies at the center of the Social Cognitive Theory as it affects what we do and how we perceive the environment (Schraw, Crippen, & Hartley, 2006). Recent Social Cognitive models of academic outcomes and career choice (e.g., Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Fredericks & Eccles, 2002; Lent et al., 2000) propose that motivational constructs such as attitudes, interest, and value beliefs are key factors that affect students' self-efficacy and pursuit of STEM courses and careers. Although there are differences in terminology in how some constructs are defined, Social Cognitive Theory (e.g., Bandura et al., 2001), Social Cognitive Career Theory (Lent, Brown, & Hackett, 2000; 1994), and the Expectancy Value Model (Eccles et al., 1983) propose similar models for academic and career outcomes: demographic characteristics, gender, and age influence learning and achievement in school, which in turn affect a number of social cognitive factors such as self-efficacy, perceived ability, and outcome expectations. These factors are proposed to be causally related to later academic behaviors in achievement models or to interest in and intention to pursue specific careers in occupation choice models. Generally, academic pursuits and occupation interest are better predicted by self-perceptions of abilities than previous achievement (Bandura, et al., 2001; Ferry et al., 2000; Frome & Eccles, 1998; Lent, Brown, & Hackett, 2000; Zimmerman, 2000). Furthermore, research has shown that self-efficacy beliefs largely influence individuals' attitudes and interest and various behaviors such as goal setting, strategy execution, and persistence in academic or career pursuits (Pajares, 2008; Pintrich & Zusho, 2007; Schraw et al., 2006; Schunk & Zimmerman, 2006).

Although there is a good deal of social cognitive research on students' attitudes and perceptions of their abilities in STEM areas, very few have examined math, science and computer science subjects separately. Furthermore, among those studies that have investigated these subjects within the same study, the results have been mixed as to how similar students' treatment of the subjects are (Bandura et al., 2001; Barth et al., 2011). For example, Barth et al., (2011) found that girls' perceived-efficacy beliefs and attitudes toward math and science showed different trajectories over adolescence. Yet different patterns in students' experiences were not found in other studies (Bandura et al., 2001; Simpkins et al., 2006). Additional considerations, however, suggest that it is worthwhile pulling apart science, math and computer sciences as distinct interest fields. First, as described earlier, not all STEM fields experience a shortage of women suggesting that women's efficacy, interest and motivation vary among them. Second, STEM disciplines differ in the degree to which they require mathematics, advanced science and computer science courses. For example, although engineering and computer science majors require several advanced courses in mathematics, a math major might not be required to take any courses in either of these fields. Similarly, a computer science major might need to take very few science courses in other disciplines. Due to these differences, it is expected that distinct profiles of women could be developed that align with different beliefs and attitudes toward math, science, and computer science. We investigate this possibility using QFA. In addition, to provide some validity for the profiles, we examined if they were related to other constructs in social cognitive models in meaningful ways, specifically, social support.

Social cognitive models suggest that support from parent, peers, and teachers affects academic performance and career choices by influencing students' self-perceptions and interests (Lent et al., 2000). Previous research has primarily focused on parent support (e.g., Frome & Eccles, 1998), but some research suggests that teachers and friends also have an impact on students' attitudes toward academic subjects (Bokhorst, Sumter, & Westenberg, 2010; Wilkins & Ma, 2003) and career aspirations (Wang & Staver, 2001). For example, Barth et al., (2011) found that students' perceptions of positive instructional approaches including teacher support and use of engaging instruction were associated with better attitudes and higher self-efficacy for math and science during the transition to middle school or high school. More recently, Rice et al. (2013) found that social support from parents, teachers and friends was positively related to math and science efficacy and interest. In this study we examined if support for interest and academic performance in science, math, and computers is aligned in meaningful ways with different QFA profiles.

Overview of Q Factor Analysis

Q Factor Analysis is a method that reveals a person's responses or opinions on a given topic and the extent to which that person's responses are shared by other individuals (McKeown & Thomas, 1988). Individuals with a similar pattern of behaviors or responses on an issue can be categorized into a typical group, also known as a typology of subjects (McKeown & Thomas, 1988; Newman & Ramlo, 2010). Equipped with Q analysis, researchers are able to further compare various typologies of individuals in order to find out the similarities and differences among behavior patterns held by distinct groups of people.

It is called Q in order to contrast it with R factor analysis, which refers to a generalization of Pearson's *r*, mostly used in the behavioral study of relationships among distinct traits, such as academic ability (Addams & Proops, 2000). In traditional research using R analysis, researchers seek to determine the relationship among variables represented by instrument items (McKeown & Thomas, 1988). In other words, it generates patterns across particular variables. By contrast, QFA establishes patterns across individuals; that is, the patterns are generated from people's similar responses on a given issue (Galayda, 2006). Simply put, Q factor analysis groups people rather than items (Newman & Ramlo, 2010).

Its capacity to systematically understand human subjectivity through rigorous statistical analyses has made Q method useful in various disciplines, such as medicine, agriculture, public policy, marketing, political science, and education (e.g., Kerr, 2011; Mally, 2011; Sylvester, 2010; Ward, 2011; Zenor & Kinsey, 2011). In education, Q studies have examined individuals' views on various general educational topics, such as academic readiness (Coggins, 2011), teaching methods (Carpenter, 2012), academic misconduct (Wink, Henderson, Coe, & Read, 2012), policy changes (Zhang, Satlykgylyjova, Almuhajiri, & Brown, 2012), and college choices

(Thorman & Howard, 2011).

In this study we examine many of the factors that have been identified in social cognitive models as important for career and academic decisions, but instead of looking at them sequentially as a decision making process, we look for patterns of responses across different fields that might potentially identify different academic interests. A few studies have previously used Q method to investigate topics in STEM-related disciplines. For example, Ramlo (2008) has used Q technique to determine physics students' epistemologies and their learning in a first semester college physics course. Similarly, Sparks (2011) explored student conceptions of learning in an undergraduate physical geography course through Q method. Arter (2012) used the Q method to examine the beliefs, opinions and attitudes that typically affect engineering technology students' willingness to learn. Finally, Q methodology was also used as part of a program evaluation plan to determine students' views about a newly developed bioinformatics course (Ramlo, McConnell, Duan, &Moore, 2008). To our knowledge, no research has used the Q technique to explore students' views on multiple STEM subjects, in this case, math, science, and computer science simultaneously. Furthermore, no research has focused on female students exclusively to understand their experiences and attitudes toward math, science, and computer science subjects.

Purpose of the Study

The Q factors analysis allows us to examine whether women's perceived abilities, attitudes, outcome expectations and gender-based beliefs are similar across science, math and computer science, or if women systematically vary in their perceptions of different subject areas. If the former is true, then the Q factor analysis will yield only one typology and support the approach taken by a number of previous studies (Ferry et al., 2000; Wilkins & Ma, 2003); but if the latter is true, two or more types should emerge. Female college students enrolled in entry level STEM courses were targeted for this study because they were more likely to have the math and science background to enter into any number of STEM fields compared to a general female college student population. Thus, the women who have low perceived abilities, background or interest in STEM were not the focus of this study.

Our hypothesis is that more than one typology will emerge because women's participation and interest in different STEM majors varies. Consequently, we compared the major choices of women in the different typologies that emerge from the analyses. Furthermore, to link this study back to the social cognitive models of career decision making, we examined the relations between the typologies and social support provided by different agents, including teachers, parents, and peers. Support is chosen because it has been repeatedly identified as an important factor affecting choice of a STEM academic interest and career pursuits (e.g., Ahmed et al., 2010; Barth et al., 2011; Rice et al., 2013) and is present in different theoretical models of academic and career decisions (Frederick & Eccles, 2002; Lent et al., 2000). Importantly, because we had measures of social support for each of the academic areas separately, we can further evaluate the importance of making distinctions among different STEM fields.

Method

Participants

The sample in the current study was a subsample from a NSF-funded longitudinal research project awarded to the second author, which examined factors related to students perceptions of and interest in STEM academic topics and careers. All participants were undergraduate students at a large public University and were enrolled in an entry level engineering, calculus, physics, chemistry, or geology courses. Potential male and female participants were approached on the first day of classes in the Fall term and asked to complete a questionnaire on their math, science, and computer interest, abilities, classroom experiences and career interest. Approximately 60% of students attending class agreed to participate (N=994; 294 female). From that larger group of participants, a sample of 114 female undergraduate students (Mean age = 19.7 years, SD = 1.06) were selected (39% of the original sample). Table 1 presented the descriptive characteristics of the sample used in the analyses for this report.

Procedure

A member of the research team went to each class and explained the purpose of the study and read a consent statement. Students wishing to participate stayed after class to complete a survey. This questionnaire included 338 items designed to assess several factors related to STEM classes and careers. The measures used in this study are described below. Participants generally were able to complete the survey in about 15 minutes.

Measures

QFA questions. Questions were drawn from the Michigan *Study of Adolescent and Adult Transitions* (MSALT, 2006). Items related to computers were developed for this study by substituting in "computers" for science or math in the questions. In contrast to math and science courses, computer science courses are not universally common to college students, although attitudes and interest toward computers could still be measured. As a result, questions related to performance in a course were not included for computers.

A total of 24 self-report items (see Appendix A) were included in the QFA. Each item was rated on a five-point scale (1= Strongly disagree to 5= Strongly agree). Items on perceived ability items included two questions for each subject on students' evaluation of their abilities (e.g., I could learn to do any kind of science/math/computer skills if I wanted to). Attitudinal items included two questions for each field on their liking and feelings (e.g., I like math/ science/working on computers). Four additional attitudinal questions asked about how much participants liked to engage in different STEM activities (e.g., I like visiting science museums). Outcome expectations items included two items for each subject related to how studying a field is related to educational or career goals (e.g., If I learn math/ science/computer then I will be able to do lots of different types of careers). Because of our focus on women, a question related to the usefulness of science, math and computer skills for boys and girls was included (Learning about science/math/computers is more useful for boys than girls).

Social support. The measure of social support was adapted from the *Longitudinal Study of American Youth* (see Wilkins & Ma, 2003). Social support was measured through three sets of questions that related to teacher, parent and peer support for math, science, and computer science. For Teacher support, there were six items devoted to math, seven items focused on science, and one item on computer science respectively. Example items include: “My science teacher cares how we feel”, “My math teacher expects me to do well in math”, and “My teacher cares if I like doing work on the computer.” Parent support was assessed similarly with seven items focused on math, eight items on science, and two items focused on computer science. Example items include: “My parents have always encouraged me to work hard on math”, “My parents care if I like science”, and “My parents care if I like working on computers.” Lastly, peer support consisted of five items for math, five items for science, and two items on computers. Example items include: “My friends encourage me to take all the math I can get in school”. Included in the peer support items were measures that assessed the norms in the peer group for performance in math, science and computers “Most of my friends are good at science”, and “Most of my friends have good computer skills.” Scale scores were calculated as averages over the items and thus had a possible range of one to five.

Majors. Participants were also asked to specify their majors or the majors they would have chosen on that day if they did not have a major yet during the survey. This was an open-ended question and responses were categorized into five broad areas: science, computer science, engineering, mathematics, and other subjects (e.g., business, nursing, psychology, art, anthropology, etc.).

Data Analysis

The PQMethod program (Schmolck, 2011) was utilized to perform the statistical analyses. Following general procedures of the PQMethod program (Schmolck, 2012), we included only the cases with complete survey data (no missing responses across the 24 items). Out of a total sample 114 female undergraduate participants, 98 answered the 24 QFA items completely. Then PQMethod program performed a sequence of statistical procedures: correlation between students' scores, Q factor analysis, and computation of Q factor scores (Newman & Ramlo, 2010).

Correlation. The completed individual survey responses are first correlated with one another to calculate the degree to which these responses are similar or different. A good way to understand Q analysis is to envision it as inverted R (correlation) matrix. That is, the R data matrix will be rotated 90 degrees to have a Q data matrix with columns being persons and rows being statement items. Therefore, given N persons in a Q data set, an N x N correlation matrix with all possible pair-wise correlation coefficients between participants will be calculated. A high positive correlation means the two participants rated the items in a similar way and thus shared a similar pattern on the issue. For the current study, since there were 98 participants, the correlation matrix consisted of 9,604 (98 × 98) correlation coefficients. Determining correlations between participants was not the principal purpose of the data analysis, but it served to prepare the data for factor analysis.

Q factor analysis. We then conducted principal components factor analyses with varimax rotation in the PQMethod. It should be noted that often times, Q methodologists prefer centroid extraction with hand rotation over the frequently used principal components extraction with varimax rotation (S. R. Brown, 1980; Stephenson, 1975). But several Q methodologists have suggested that there is little statistical difference between using principal components, centroid, or any other available method (e.g., S. R. Brown, 1971; McKeown & Thomas, 1988). In the current study, varimax rotation was used in order to maximize the loadings of as many items as possible on one or more of the factors (McKeown & Thomas, 1988).

Computation of Q factor scores. In the PQMethod program, each participant will be assigned a factor loading value on each factor ranging from -1 to 1, which indicates the magnitude of association between a person's response and the underlying factor. Based upon the participant factor loadings, "defining respondents" can be identified, who are respondents that load strongly on a factor and thus characterize that factor. These defining subjects are the key to understanding the factors because their shared attitudes and perceptions are the primary representation of the underlying patterns of the group. The defining participants' responses scores across different items in the measurement instrument are averaged to create a factor score for each item.

PQMethod automatically normalizes factor scores, which are essentially weighted z-scores for each item on the instrument. A z-score represents the average score of an item based on the responses from all definers of a factor type. The z-scores are mainly used to understand and compare the characteristics of different profile types. Graphing the z-scores across the items for each profile reveals different shapes of responses which represent different types of participants. An exemplary shape from the results of the current study is shown in Figure 1 and will be discussed in the results sections.

Results

The Q factor analysis yielded a two factor structure representing two distinctive female student types regarding their self-perceived abilities and attitudes in math and science (Table 2). Two factors combined explained 62% of the variance in the sample, with Factor 1 explaining 34%. Among 98 participants, 55 were grouped in Factor 1 and 38 were grouped in Factor 2. In order to understand and interpret each factor type, we examined the factor scores of each instrument item for each factor type. A table of the all the items and factor scores for each item on each factor can be found in Appendices A and B. Here we focus on the items with high absolute values on z-scores in each factor as they represent the significant patterns embodied in that factor type.

Table 3 listed the statement items with high and low z-scores for Factor 1. This first group of women (Type 1) expressed preferences in working on computer science subject and math subject (agreement with items 7, 8, 9) as well as strong beliefs of their own abilities in learning both (agreement with items 1, 2, 4). Also based on the z-scores, Type 1 women strongly disagreed that learning math and computer science made them nervous (disagreement with items 24, 20), which supported their high-level of perceived abilities in learning math and computer science. However, this group was not fond of doing any extracurricular activities related to science (disagreement with item 18); although they were not nervous working on science subject (disagreement with item 19). That being said, these women did strongly believe that learning math, science, and computer science are equally usefulness for both genders (disagreement with items 23, 22, 21).

Regarding the second group of female students (Type 2), some of the extreme z-scores, as illustrated in Table 4, suggested this group held strong beliefs in their abilities to learn science (agreement with items 6, 13) as well as liking science (agreement with items 12, 17). When it comes to computer science, Type 2 women strongly disliked working on computer (disagreement with items 7, 8) and they were uncertain about their own abilities of learning computer science subject either. Additionally, the self-perceived abilities and attitudes toward math in this group were neutral as indicated by *z*-scores on related items near *zero* (items 9, 20). Similar to Type 1 group, the Type 2 group strongly believed learning math, science, and computer science are equally usefulness for both genders (disagreement with Item 23, 22, 21).

So far, the statements with extreme ranked z-scores for each student type has shown both groups of women are characterized by some perceptions and attitudes toward math, science, and computer science that are unique to their own group; whereas they also shared similar views on certain topics. We further looked at the statements with large z-score differences provided by the PQMethod output. PQMethod program labels these statements "distinguishing statements" as the two groups have great difference/distance of the z-scores on these statements. Table 5 shows the distinguishing statements based on the z-score differences between two factors. Figure 1 represents exemplary shapes for the two types of participants, based on four items with the greatest z-score differences in the results (i.e., Item 7, 8, 17, 20). From Figure 1, we could identify two different shapes, thus two distinct typologies (of people) that exist in the study. Clearly, distinguishing statements reinforced the interpretation of extreme ranked statements. Specifically, women of the first typology showed great interests as well as strong beliefs of their abilities in working with computer whereas those from Type 2 group had very negative feelings and lack of perceived abilities on this very subject. The first type of women indicated similar interests and perceived abilities in the math subject whereas Type 2 group expressed neutral feelings toward it. On the other hand, women of the second typology expressed great enthusiasm and confidence in dealing with science subjects while Type 1 women as a group showed some negativity and less interests toward it.

In summary, two contrasting types of female STEM undergraduates emerged from Q factor analysis regarding their perceptions and attitudes toward math, science, and computer science subjects. Type 1 women had both strong positive attitudes toward and high-level self-perceived abilities in learning computer science as well as math; whereas Type 2 women held similarly favorable attitudes and perceptions toward learning science. In addition, Type 1 women not only liked math to a greater degree than Type 2 group, they also indicated much more confidence of their own abilities in learning math than Type 2 women. Meanwhile, both Type 1 and Type 2 women held strong beliefs in the equal usefulness of math and science for both sexes. We named Type 1 Math and Computer Science (MCS) group and Type 2 Science (SC) group.

Relationship between Types and Major Choice

We compared the major choices between two groups of women. Women in the MCS group were more likely to choose Engineering major than those in SC group. Out of 21 women who chose Engineering major, 15 (71.4%) were from MCS group and 5 (23.8%) from SC group. By contrast, women in the SC group selected a science major such as biology more often than those in MCS group. Among 30 women in a science major, 21 (70%) were from SC group and 8 (26.7%) from MCS group. Few women in either group indicated their major as mathematics, (3 and 2 respectively in MCS and SC types) and as computer science (1 in MCS type, none in SC type). Yet more interestingly, MCS group are much more likely to have chosen a major unrelated to STEM fields (e.g., Business, Finance, and Psychology.) than SC type. A total of 38 women indicated to have selected a non-STEM major, among which 27 (71.1%) and 9 (23.7%) were from MCS group and SC types respectively. A Chi-Square analysis was conducted examining the relationship between three major groups (Engineering, Science, and non-STEM) and the two typologies (MCS and SC) and was significant χ^2 (2) = 17.73, $p < .001$.

Relationship between Types and Social Support

We tested whether there were differences in perceived support from teachers, parents, and peers for math, science, and computer science subjects by the two typologies. A 2 (Typology) X 3 (Source of support: teachers, parents, peers) X 3 (Subject: math, science, computers) MANOVA was conducted. For the purposes of this research, the most relevant effects are those that interact with the Q-Type. We found that the Typology X Subject interaction was significant, $F(2, 178) = 17.89$, $p < .001$, partial $\eta^2 = .191$. MCS students had greater support for math and computer science compared to SC students who had relatively greater support for science, Means for MCS and SC, are respectively for math 3.68, 3.47; computers 3.77, 3.00; and science 3.56, 3.80.

Discussion

Prior research has often treated STEM as a single discipline, without consideration of whether women could be interested in some STEM fields, but not necessarily all. QFA allowed us to examine if unique profiles of women could be extracted based on responses to questions about perceived abilities, attitudes, outcome expectations, and gender-based beliefs about science, math, and computers. Two unique typologies of college women emerged with distinct patterns of perceptions and attitudes toward math, science, and computer science subjects, which supported our hypothesis. Women from the MCS group (Type 1) held positive views of math and computer science subjects as they not only indicated strong perceived abilities in the subjects, they also enjoyed working in them. However, they were not especially positive about science subjects. Unlike the MCS typology, women in the SC typology (Type 2) clearly favored science subjects over math and computer science. They not only preferred science over math, but also expressed much more confidence of their own abilities in learning science than math.

The meaningfulness of these typologies is bolstered by the analyses that indicated that women associated with the MCS typology were most likely to select a non-STEM related major (54%) or Engineering (30%). In contrast, the women associated with the SC typology were predominantly science majors (60%). Furthermore, consistent with predictions from Social Cognitive Career Theory (Lent et al, 2000) and other social cognitive models (e.g., Bandura et al., 2001), perceptions of support from parents, teachers and friends for math and computer science were higher for the MCS group compared to the SC group; however, support for science was higher for the SC group compared to the MCS group. Thus, women in the different typologies appear to behave in ways that are consistent with the characteristics of their profile (major choice), and their perceptions of support also appeared to be aligned with the profile characteristics.

It is interesting that women in the MCS group were much more likely to choose a major unrelated to STEM fields. One possible explanation is that math (and increasingly computer skills) is widely used in many non-STEM fields such as finance, economics, business, and many behavioral sciences. Women who are good at math and enjoy it can readily apply their skills to a variety of fields rather than only STEM. Meanwhile, although the SC women were not strongly oriented toward math per se, they did not express strong negative beliefs about their own competence or attitudes toward math either. Rather, their science experiences were what made them distinct from the MCS group. Together this suggests that narrowly focusing on math academic skills might not be sufficient to promote interest in many STEM disciplines among women. In future studies, it would be very informative to examine what career paths the two types of women eventually pursue. We expect that women in the MCS group may very well choose a career outside of traditional STEM fields.

A goal of this study was to introduce and demonstrate the utility of Q Factor Analysis as a tool for understanding the experiences that contribute to women's pursuit of STEM fields. Developing typologies of women based on their own subjective experiences provides a powerful device for understanding the factors that underlie academic and career choices. QFA led to the discovery that math was viewed as important for STEM and non-STEM majors alike, and to our knowledge this has not been recognized as an issue in the gender and STEM literature. By basing the typologies on measures of several social cognitive attributes, our findings also inform research based on social cognitive models of academic and career decisions. Specifically, these findings suggest that it is useful to treat the STEM fields as distinct entities in these models.

It is important to recognize that the typologies in this study were developed on a sample of women who, by virtue of being enrolled in introductory STEM courses (ones that were required for a STEM major), must have already had considerable math and science background. This sample seemed appropriate to us because college students with little or no STEM aptitude or experiences had likely ruled out STEM careers at an earlier point in time. It would be valuable to utilize QFA on a sample of female high school or middle school students because course selection during these years often sets a pathway toward or away from the possibility of a STEM major. Understanding profiles of girls at these ages might lead to better interventions to encourage STEM careers.

Another limitation of the study is that there were relatively few women who had chosen computer science as a major, despite targeting computer science classes in our sampling. Unfortunately, this reflects a national demographic of very few women being in computer science fields. In addition, the women in this sample were largely first and second year college students, and different typologies might have emerged if we had sampled women in their final year of college with a firmly dedicated major and a clearer career path. The younger sample seemed more appropriate to us because of our interest in understanding factors that affect early academic decisions in college.

In conclusion, Q factor analysis provided some new evidence that STEM research should examine math, science, and computer science independently, especially for female students. We believe that the QFA approach would be useful for understanding academic and career decisions for girls and women at different stage of the lifespan.

References

Addams, H., & Proops, J. (Eds.). (2000). *Social discourse and environmental policy: An application of Q methodology.* Cheltenham, UK: Edward Elgar.

Ahmed, W., Minnaert, A., Van der Werf, G., & Kuyper, H (2010). Perceived social support and early adolescents' achievement: The mediational roles of motivational beliefs and emotions. *Journal of Youth and Adolescence, 39*, 36-46.

Arter, R. (2012, September). *The assent to learn of engineering technology students.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Pittsburgh, PA.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*, 191-215.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: Freeman.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52,* 1-26.

Bandura, A., Barbaranelli, C., Caprara, G.V., & Pastorelli, C. (2001). Self-efficacy beliefs as shapers of children's aspirations and career trajectories. *Child Development, 72*, 187-206.

Barth, J. M., Todd, B., McCallum, D. M., Goldston, M., Guadagno, R. E., Roskos, B., & Burkhalter, C. (2011). Effects of Engaging Classroom Strategies and Teacher support on Student Outcomes Over School Transitions. *Proceedings of the American Society for Engineering Education, 2011.*

Behn, D. (2011, September). *On the shared subjectivity of value claims in legal decision and discourse.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Bokhorst, C. L., Sumter, S. R. & Westenberg, P. M. (2010). Social support from parents, friends, classmates, and teachers in children and adolescents aged 9 to 18 years: Who is perceived as most supportive? *Social Development, 19,* 417-426. doi: 10.1111/j.1467-9507.2009.00540.x.

Brown, L. D. (1986). Q technique and method: Principles and procedures. In W. D. Berry & M. S. Lewis-Beck (Eds.), *New tools for social scientists* (pp. 57-76). Beverly Hills, CA: Sage.

Brown, L. D. (1991). Bridging organizations and sustainable development. *Human Resources, 44,* 807-831.

Brown, S. R. (1971). The forced-free distinction in Q-technique. *Journal of Educational Measurement, 8*, 283-287.

Brown, S. R. (1980). *Political subjectivity: Applications of Q methodology in political science.* New Haven: Yale University Press.

Brown, S. R. (1991/1992). *A Q Methodological tutorial.* Eight postings to QUALRS-L@UGA. Available at http://facstaff.uww.edu/cottlec/QArchive/Primer1.html.

Brown, S. R. (1997). *The history and principles of Q methodology in psychology and the social sciences.* Available at http://facstaff.uww.edu/cottlec/Qarchive/Bps.htm.

Carpenter, W. (2012, September). *Investigating student preferences of faculty teaching methods in relation to their own learning styles.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Pittsburgh, PA.

Cattell, R. B. (1978). *The scientific use of factor analysis in behavioral and life sciences.* New York, NY: Plenum.

Ceci, S. J., Williams, W. M., & Burnett, S. M. (2009). Women's underrepresentation in science: Sociocultural and biological considerations. *Psychological Bulletin, 135*, 218-261.

Coggins., L. A. (2011, September). Ready *or not: Remedial education for college students.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Correll, S. J. (2001). Gender and career choice process: The role of biased self-assessments. *American Journal of Sociology, 106*, 1691-1730.

Duncan, M., Sherry, K., Watson, R., Booi, M., Gcaza, S., Mckenzie, J., Coomber, K., Crankshaw; J; Marais, C-L., & Lungana, M. (2011). *Lost in translation: Using Q methodology in isiXHOSA speaking rural communities in South Africa.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Eccles, J. S., Midgley, C., & Adler, T. (1984). Grade-related changes in the school environment: Effects on achievement motivation. In J. G. Nicholls (Ed.) *The development of achievement motivation* (pp. 283-331)*,* Greenwich, XT: JAI.

Ferry, T. R., Fouad, N., & Smith, P. L., (2000). The roles of family contest in a social cognitive model for career-related choice behavior: A math and science perspective. *Journal of Vocational Behavior, 57,* 348-364.

Fouad, N., & Smith, P. L. (1996). A test of a social cognitive model for middle school students: Math and science. *Journal of Counseling Psychology, 43,* 338-366.

Fredricks, J. A. & Eccles, J. S. (2002). Children’s competence and value beliefs from childhood through adolescence: Growth trajectories in two male-sex-typed domains. *Developmental Psychology, 38,* 519-533.

Frome, P. M., & Eccles, J. S. (1998). Parents’ influence on children’s achievement-related perceptions. *Journal of Personality and Social Psychology, 74,* 435-452.

Galayda, J. (2006). *Community supported agriculture, economic preference theory and subjective well-being.* (Doctoral dissertation, Rensselaer Polytechnic Institute, 2006) Proquest Dissertations & Theses. (AAT 3232608).

Garner, I. (2011). *A Q-methodological study of male attitudes towards testicular cancer and testicular self-examination.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Greener, J. (2011). *In search of the food citizen: Using Q-methodology to explore consumer choice.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Hay, I., Ashman, A. F. & Van Kraayenoord, C. E. (1998). The influence of gender, academic achievement and non-school factors upon preadolescent self-concept. *Educational Psychology, 18*, 461-470.

Jedeloo, S., & van der Knaap, L. (2011). *Sexual behavior profiles: Dutch HIV positive youths preferences about sexuality.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Kerr, G. (2011). *Can Q enhance the acceptance of market-based instruments for environmental objectives?* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Lent, R. W., Brown, S. D. & Hackett, G. (2000). Contextual support and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology, 47*, 36-49.

Lent, R. W., Sheu, H. B., Singley, D., Schmidt, J. A., Schmidt, L. C. & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior, 73*, 328-335.

Lindberg, S. M., Hyde, J., Petersen, J. L., & Linn, M. C. (2010). New trends in gender and mathematics performance: A meta-analysis. *Psychological Bulletin*, *136*, 1123-1135. doi:10.1037/a0021276

Mally, M. (2011). *International regional political organizations as lobbyists in the multilevel governance system of the Baltic Sea area - a Q methodological study.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Mckenzie, J. A. (2011). *Exploring subjectivity in intellectual disability.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

McKeown, B., & Thomas, D. B. (1988). *Q methodology.* (Quantitative Applications in the Social Sciences, Vol. 66). Newbury Park, CA: Sage.

Michigan Study of Adolescent and Adult Life Transitions (2006). University of Michigan Gender and Achievement Research Program, http://www.rcgd.isr.umich.edu/msalt.

Morf, M. E., Miller, C. M., & Syrotuik, J. M. (1976). A comparison of cluster analysis and Q-factor analysis. *Journal of Clinical Psychology, 32*, 59-64.

National Science Foundation. (2009). Women, minorities, and persons with disabilities in science and engineering: 2009. Washington, DC: NSF. Retrieved August 3, 2012, from http://www.nsf.gov/statistics/wmpd/.

Newman, I., Howley, A., & Ramlo, S. (2011). *Research on mixed methods approaches to addressing generalization and transferability in evaluations in rural contexts: The use of Q factor analysis as potential tool for evaluating rural education programs.* Roundtable paper presented at the American Educational Research Association Conference, New

Orleans, LA.

Newman, I., & Ramlo, S. E. (2010). The use of two multivariate techniques, Q methodology and Q factor analysis, to facilitate interpretation of mixed methods research. In C. Teddlie & A. Tashakkori (Eds.), *Handbook of mixed methods in social and behavioral research* (pp.505-530). Thousand Oaks, CA: Sage.

Pajares, F. (2008). Motivational role of self-efficacy beliefs in self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research and applications* (pp. 111–139). New York: Lawrence Erlbaum Associates.

Pintrich, P., & Zusho, A. (2007). Student motivation and self-regulated learning in the college classroom. In R. Perry & J. C. Smart (Eds.), *The scholarship of teaching and learning in higher education: An evidence-based perspective* (pp. 731–810). New York, NY: Springer.

Pullen, H. (2010). *Community engagement in health care: Developing a framework to facilitate involvement of community members in hospital system planning.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Arkon, OH.

Ramlo, S. (2008). Student perspectives on learning physics and their relationship with learning force and motion concepts: A study using Q methodology. *Human Subjectivity, 2*, 73-90.

Ramlo, S., McConnell, D., Duan, Z., & Moore, F. (2008). Evaluating an inquiry-based bioinformatics course using Q methodology. *Journal of Science Education and Technology, 17*, 219-225.

Rice, L., Barth, J. M., Guadagno, R. E., Smith, G. P. A., McCallum, D. M. & ASERT (2012). The role of social support in students' perceived abilities and attitudes toward math and science. *Journal of Youth and Adolescence, 42,* 1028-1040.

Schmolck, P. (May 13, 2011). *PQMethod Page.* Retrieved from http://www.lrz.de/~schmolck/qmethod/#PQMethod.

Schmolck, P. (2012). PQMethod 2.33 Manual. [online]. Available at http://schmolck.userweb.mwn.de/qmethod/downpqwin.htm.

Schraw, G., Crippen, K. J., & Hartley, K. (2006). Promoting self-regulation in science education: Metacognition as part of a broader perspective on learning. *Research in Science Education, 36*, 111-139.

Schunk, D. H., & Zimmerman, B. J. (2006). Competence and control beliefs: Distinguishing the means and ends. In P. A. Alexander & P. H. Winne (Eds.), *Handbook of educational psychology* (2nd ed., pp. 349–367). Mahwah, NJ: Lawrence Erlbaum Associates.

Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology, 42,* 70-83.

Smith, N. W. (2001). *Current systems in psychology: History, theory, research, and applications.* Belmont, CA: Wadsworth/Thompson Learning.

Sparks, K. (2011). *Students' conceptions of learning and approaches to learning in an undergraduate physical geography course.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Stephenson, W. (1975). *The study of behavior: Q-technique and its methodology.* Chicago: University of Chicago Press.

Sylvester, J. (2010). *Public attitudes toward health care reform and the media that drive them.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Arkon, OH.

Thorman, J., & Howard, M. (2011). *College choice: Student perceptions regarding the influence of past, present and future.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

U.S. Department of Commerce, Economics & Statistics Administration. (2011). Women in STEM: A gender gap to innovation. Retrieved from http://www.esa.doc.gov/sites/default /files/reports/documents/womeninstemagaptoinnovation8311.pdf.

Ward, T. (2011). *Exploring Chinese medicine's diversity.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Webler, T., Danielson, S., & Tuler, S. (2009). Using Q method to reveal social perspectives in environmental research. Greenfield MA: Social and Environmental Research Institute. Available from: http://seri-us.org/sites/default/files/Qprimer.pdf

Wilkins, J. L. M., & Ma, X. (2003). Modeling change in student attitude toward and beliefs about mathematics. *Journal of Educational Research, 97,* 52-63.

Wink, B., Henderson, S., Coe, D., & Read, A. (2012). *It's a shame: Student perspectives on academic misconduct.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Pittsburgh, PA.

Woodfall, A. (2011). *Exploring children's 'needs' in cross-platform media environments: A mixed method approach.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Woods, C. (2012). Exploring emotion in the higher education workplace: Capturing contrasting perspectives using Q methodology. *Higher Education, 6*, 891-909.

Zenor, J., & Kinsey, D. (2011). *Cool as a carrot? A Q-study on the marketing of carrots as junk food.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Birmingham, England.

Zhang, H., Satlykgylyjova, M. S., Almuhajiri, M., & Brown, S. R. (2012). *Harvesting suggestions: A strategy for promoting policies designed to improve academic life for international students.* Paper presented at the annual meeting of the International Society for the Scientific Study of Subjectivity, Pittsburgh, PA.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology, 25,* 82-91.

Table 1
Participant Characteristics

Characteristic	Frequency	Percentage
Years in School		
1st year	32	28.1%
2nd year	45	39.5%
3rd year	25	21.9%
4th year	12	10.5%
Ethnicity		
White non-Hispanic	99	86.8%
Black/ African American	6	5.3%
Asian	3	2.6%
Hispanic	2	1.8%
All Others	4	3.5%

Table 2

Two-Factor Solution With Number of Defining Respondents (n = 98)

Characteristic	Factor 1	Factor 2	Total
Number of Definers	55	38	93
Percent of Variation Explained	34%	28%	62%

Table 3

Factor 1 Statements With High and Low z-scores

No.	Statement	z-score
1	When taking a math test I have studied for, I do very well.	1.040
2	I could learn any kind of computer skills if I wanted to.	1.000
3	If I learn about computers, then I will be able to do lots of different types of careers.	0.983
4	I could learn to do any type of math problem if I wanted to.	0.912
5	If I do learn a lot about computers, then I will be better prepared to go to college.	0.889
6	When taking a science test I've studied for, I do very well.	0.864
7	I like working on computers.	0.810
8	I like figuring out how to do different things on the computer.	0.762
9	I like math.	0.694
18	I would like to do science experiments outside of school.	-0.614
19	Doing science makes me nervous.	-1.068
20	Doing math makes me nervous.	-1.301
21	Learning math is more useful for boys than girls.	-1.629
22	Learning about science is more useful for boys than girls.	-1.672
23	Learning about computers is more useful for boys than girls.	-1.712
24	Working on computers makes me nervous.	-1.755

Table 4

Factor 2 Statements With High and Low z-scores

No.	Statement	z-score
6	When taking a science test I've studied for, I do very well.	1.045
1	When taking a math test I have studied for, I do very well.	1.002
15	If I do well in science, then I will be better prepared to go to college.	0.981
12	I like science.	0.930
11	If I learn science, then I will be able to do lots of different types of careers.	0.886
10	If I do well in math, then I will be better prepared to go to college.	0.768
14	If I learn math, then I will be able to do lots of different types of careers.	0.714
17	I like watching science and technology programs on television.	0.710
13	I could learn to do any type of science problem if I wanted to.	0.677
9	I like math.	-0.148
8	I like figuring out how to do different things on the computer.	-0.571
24	Working on computers makes me nervous.	-0.803
19	Doing science makes me nervous.	-0.991
7	I like working on computers.	-1.052
23	Learning about computers is more useful for boys than girls.	-1.986
22	Learning about science is more useful for boys than girls.	-1.997
21	Learning math is more useful for boys than girls.	-2.006

Note: For Comparative purposes, statement numbers represent the descending orders for Factor 1 statements.

Table 5

Distinguishing Statements for Factor 1 and Factor 2

No.	Statement	F1 z-score	F2 z-score	Difference
7	I like working on computers.	0.810	-1.052	1.862
8	I like figuring out how to do different things on the computer.	0.762	-0.571	1.333
2	I could learn any kind of computer skills if I wanted to.	1.000	0.029	0.971
9	I like math.	0.694	-0.148	0.842
12	I like science.	0.413	0.930	-0.517
18	I would like to do science experiments outside of school.	-0.614	-0.004	-0.610
15	If I do well in science, then I will be better prepared to go to college.	0.334	0.981	-0.647
16	I like visiting science museums.	-0.303	0.387	-0.690
24	Working on computers makes me nervous.	-1.755	-0.803	-0.952
17	I like watching science and technology programs on television.	-0.326	0.710	-1.036
20	Doing math makes me nervous.	-1.301	-0.258	-1.043

Note: For comparative purposes, statement numbers represent the descending orders for Factor 1 statements.

Figure 1. Profiles of the Two Typologies

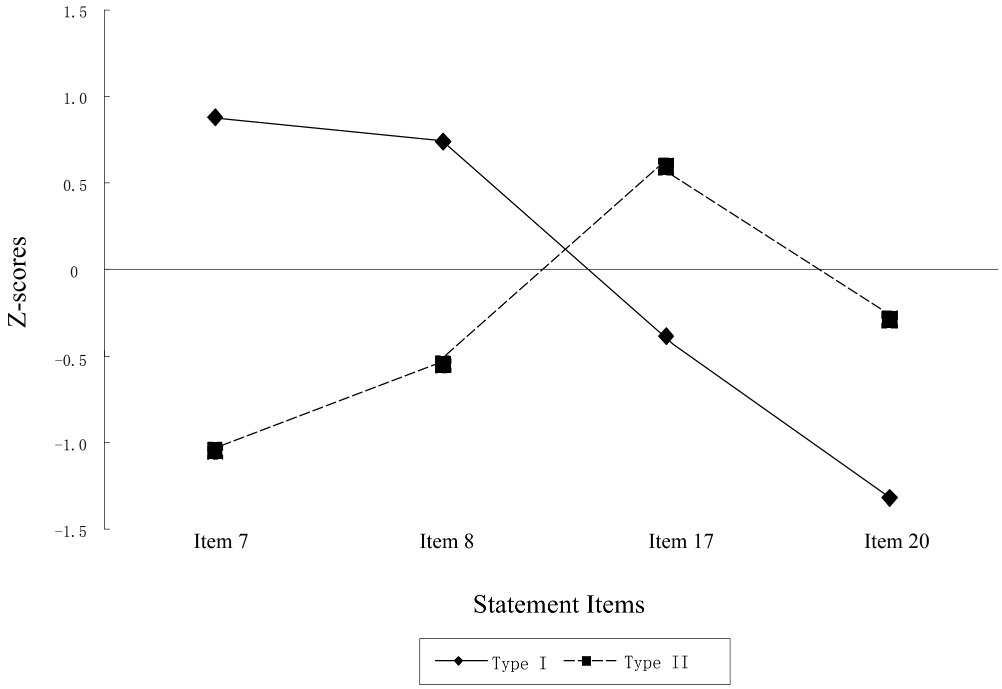

Figure 1. Profiles of two participant typologies based on their z-scores of four exemplary statement items. Item 7 reads "I like working on computers." Item 8 reads "I like figuring out how to do different things on the computer." Item 17 reads "I like watching science and technology programs on television." Item 20 reads "Doing math makes me nervous."

APPENDIX A

Factor Array for Factor/Type 1 with Descending z-scores on Each Statement

No.	Statement	z-score
1	When taking a math test I have studied for, I do very well.	1.040
2	I could learn any kind of computer skills if I wanted to.	1.000
3	If I learn about computers, then I will be able to do lots of different types of careers.	0.983
4	I could learn to do any type of math problem if I wanted to.	0.912
5	If I do learn a lot about computers, then I will be better prepared to go to college.	0.889
6	When taking a science test I've studied for, I do very well.	0.864
7	I like working on computers.	0.810
8	I like figuring out how to do different things on the computer.	0.762
9	I like math.	0.694
10	If I do well in math, then I will be better prepared to go to college.	0.486
11	If I learn science, then I will be able to do lots of different types of careers.	0.440
12	I like science.	0.413
13	I could learn to do any type of science problem if I wanted to.	0.407
14	If I learn math, then I will be able to do lots of different types of careers.	0.346
15	If I do well in science, then I will be better prepared to go to college.	0.334
16	I like visiting science museums.	-0.303
17	I like watching science and technology programs on television.	-0.326
18	I would like to do science experiments outside of school.	-0.614

19	Doing science makes me nervous.	-1.068
20	Doing math makes me nervous.	-1.301
21	Learning math is more useful for boys than girls.	-1.629
22	Learning about science is more useful for boys than girls.	-1.672
23	Learning about computers is more useful for boys than girls.	-1.712
24	Working on computers makes me nervous.	-1.755

APPENDIX B

Factor Array for Factor/Type 2 with Descending Z-scores on each Statement

No.	Statement	z-score
6	When taking a science test I've studied for, I do very well.	1.045
1	When taking a math test I have studied for, I do very well.	1.002
15	If I do well in science, then I will be better prepared to go to college.	0.981
12	I like science.	0.930
11	If I learn science, then I will be able to do lots of different types of careers.	0.886
10	If I do well in math, then I will be better prepared to go to college.	0.768
14	If I learn math, then I will be able to do lots of different types of careers.	0.714
17	I like watching science and technology programs on television.	0.710
3	If I learn about computers, then I will be able to do lots of different types of careers.	0.689
13	I could learn to do any type of science problem if I wanted to.	0.677
4	I could learn to do any type of math problem if I wanted to.	0.520
5	If I do learn a lot about computers, then I will be better prepared to go to college.	0.477
16	I like visiting science museums.	0.387
2	I could learn any kind of computer skills if I wanted to.	0.029
18	I would like to do science experiments outside of school.	-0.004
9	I like math.	-0.148
20	Doing math makes me nervous.	-0.258

8	I like figuring out how to do different things on the computer.	-0.571
24	Working on computers makes me nervous.	-0.803
19	Doing science makes me nervous.	-0.991
7	I like working on computers.	-1.052
23	Learning about computers is more useful for boys than girls.	-1.986
22	Learning about science is more useful for boys than girls.	-1.997
21	Learning math is more useful for boys than girls.	-2.006

* *Note*: Statement numbers represent the descending orders for Factor 1 statements.

APPENDIX C

Distinguishing Statements for Factor 1 and Factor 2 with Descending z-scores

No.	Statement	F1 z-score	F2 z-score	Difference
7	I like working on computers.	0.810	-1.052	1.862
8	I like figuring out how to do different things on the computer.	0.762	-0.571	1.333
2	I could learn any kind of computer skills if I wanted to.	1.000	0.029	0.971
9	I like math.	0.694	-0.148	0.842
5	If I do learn a lot about computers, then I will be better prepared to go to college.	0.889	0.477	0.412
4	I could learn to do any type of math problem if I wanted to.	0.912	0.520	0.391
21	Learning math is more useful for boys than girls.	-1.629	-2.006	0.377
22	Learning about science is more useful for boys than girls.	-1.672	-1.997	0.325
3	If I learn about computers, then I will be able to do lots of different types of careers.	0.983	0.689	0.294
23	Learning about computers is more useful for boys than girls.	-1.712	-1.986	0.274
1	When taking a math test I have studied for, I do	1.040	1.002	0.038

	very well.			
19	Doing science makes me nervous.	-1.068	-0.991	-0.077
6	When taking a science test I've studied for, I do very well.	0.864	1.045	-0.181
13	I could learn to do any type of science problem if I wanted to.	0.407	0.677	-0.270
10	If I do well in math, then I will be better prepared to go to college.	0.486	0.768	-0.281
14	If I learn math, then I will be able to do lots of different types of careers.	0.346	0.714	-0.368
11	If I learn science, then I will be able to do lots of different types of careers.	0.440	0.886	-0.446
12	I like science.	0.413	0.930	-0.517
18	I would like to do science experiments outside of school.	-0.614	-0.004	-0.610
15	If I do well in science, then I will be better prepared to go to college.	0.334	0.981	-0.647
16	I like visiting science museums.	-0.303	0.387	-0.690
24	Working on computers makes me nervous.	-1.755	-0.803	-0.952
17	I like watching science and technology programs on television.	-0.326	0.710	-1.036
20	Doing math makes me nervous.	-1.301	-0.258	-1.043