Validating a New Survey Instrument Measuring Factors Contributing to Transfer in STEM

Purpose of the Study

Despite community colleges' important role in expanding the nation's talent holding baccalaureate degrees in science, technology, engineering, and mathematics (STEM) fields (Author, 2013), many baccalaureate-aspiring community college students meet unexpected roadblocks once they make it to the point of transfer into a STEM major at four-year institutions (American Association of Colleges & Universities [AAC&U], 2012). Recognizing this challenge, a number of policy initiatives focus on current efforts at the national or local level to improve transfer pathways in STEM (e.g., AAC&U, 2012; Baber, 2011; Bensimon & Dowd, 2012; Bragg, 2011; Packard, 2011). While the identified issues and practices illuminate vital facets of the pathway, most existing initiatives adopted by institutions are not closely coupled with rigorous empirical research to document their efficacy. An even larger issue is the lack of a holistic measurement tool based on a sound theoretical framework to guide empirical research targeting STEM transfer and its many nuances. To fill this void, our study advances a new survey instrument measuring factors influencing transfer in STEM, and based on data collected using the instrument, we investigate its psychometric properties using confirmatory factor analysis (CFA) and Item Response Theory (IRT) as means to validate the instrument.

Theoretical and Empirical Background of the Survey Instrument

The survey was developed based on the STEM Transfer Model (Author, 2014), which is the first comprehensive theoretical framework depicting transfer in STEM as a distinctive outcome. According to this framework, STEM transfer is hypothesized to be influenced by person inputs, contextual factors, learning experiences in STEM, and motivational beliefs related to STEM learning and transfer. This model is largely informed by the social cognitive career theory (SCCT), which extends Bandura's (1986) social cognitive theory by illustrating the process by which individuals guide their career development and choices through cognitive-personal factors, which are linked to personal background and situated within environmental contexts (Lent, Brown, & Hackett,1994, 2000). SCCT has informed a growing body of research that deals with academic choices, intentions, and outcomes in STEM fields of study (e.g., Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Lent, Lopez, & Bieschke, 1993; Lent, Lopez, Lopez, & Sheu, 2008; Lent et al., 2013; Author, 2013), and is a particularly sound theory to inform research on factors associated with transfer in STEM.

The following six constructs constitute key domains of the STEM Transfer model and are measured by the new survey instrument: (a) initial attitudes toward math, (b) initial attitudes toward science, (c) self-efficacy in math, (d) self-efficacy in science, (e) active learning, and (f) transfer capital. The inclusion of each of these factors is supported by SCCT and relevant prior literature, discussed below.

Students bring a set of predispositions—attitudes and beliefs—that have a pronounced impact on the likelihood of transfer (Author, 2012; 2013). Particularly pertaining to our topic, research has also shown that positive attitudes toward math and science subjects may positively affect STEM intent and entrance (Hackett & Betz, 1989; Singh, Granville, & Dika, 2002). SCCT's social-cognitive mechanism also highlights self-efficacy as a central factor since it influences students' expectations of certain outcomes occurring (Bandura, 1986; Hackett & Betz, 1989; Sewell, Haller, & Portes, 1969). Thus, self-efficacy in math and science may well impact interest in STEM fields and intent to transfer (Betz & Hackett, 1983; Pike, 2006; Scott & Mallinckrodt, 2005). In addition to these motivational beliefs, what occurs within the classroom is also of great import. A substantial body of empirical research has drawn a convincing conclusion that engaging students in active learning—pedagogical approaches that "truly engage students intellectually and involve thinking, problem-solving, questioning, or analyzing information" (PCAST, 2012, p. 86)—can transform STEM education and improve student performance. Finally, as a highly contextualized process, STEM transfer is subject to contextual influences, particularly the environmental structure of opportunity for students to accumulate STEM transfer capital—a notion based on "transfer capital" (Laanan, Starobin, & Eggleston, 2010), which refers to a student's ability to acquire needed information or skills to navigate the process of transfer (Bahr, Toth, Thirolf, & Massé, 2013).

Both the STEM Transfer model and survey instrument include other information relevant to the topic, such as demographic backgrounds and STEM course taking. Those items are not subject to the types of validation study described here as they are measured by observable questions. Due to space constraints, these elements are not discussed here but will be elaborated in the full paper.

Methods

Survey Development

The survey was developed in summer 2014 (Author, 2014). It includes items measuring the previously described factors (listed in Table 1), along with other observable domains such as personal background and course taking. Its content validity was assessed by a panel of experts who specialize in research on SCCT, transfer, and STEM education. The survey was also piloted among roughly 100 students similar to but not included in the main study sample. Exploratory factor analysis was performed to identify the factor structure and indicated that the general theoretical structure of the survey holds. In addition, 20-30 minute cognitive interviews were conducted with 12 students to check the readability of survey items as well as response process validity—the extent to which survey participants' thought processes indicate that they interpret the items in the same way as the researcher. Based on information collected from these sources, the survey instrument was revised and implemented in Fall 2014.

Data

The survey data were collected from three 2-year institutions in a Midwestern state, including two comprehensive community colleges and the entire set of 2-year campuses as part of the state university system. At each research site, the study sample included approximately 1,000 first-time students beginning in Fall 2014 and enrolled in programs or courses within STEM disciplines. In order to achieve a sufficient number of students within specific racial groups and STEM fields, a stratified random sampling approach with two strata, race/ethnicity and STEM fields, was adopted. Weights were created and applied in the analysis to compensate for the unequal probabilities of sample member selection. The final sample size for this study was 1,668, for a response rate of 56.6%. Other details of the survey administration will be included in the full paper and the sample characteristics are presented in Table 2.

Analysis

CFA was first utilized to verify the 6-factor structure. CFA allows for the specification of relationships between items and underlying factors (i.e, latent traits) as well as the number of factors (Brown, 2006; Floyd & Widaman, 1995). The adequacy of the hypothesized structure was evaluated by the comparative fit index (CFI), Tucker-Lewis index (TLI), and root-mean-square error of approximation index (RMSEA). Following Hu and Bentler (1999), a TLI and CFI value greater than .95 and a RMSEA value smaller than .06 indicate a good model fit.

After confirming the factor structure, the performance of each item underlying each factor scale was evaluated by IRT, which describes the relationship between each item response and a latent trait by estimating the probability of an individual responding in a category of an item given the level of a latent trait (Clark & Watson, 1995; Edelen & Reeve, 2007; Embretson & Reise, 2000). In IRT, a latent trait is assumed to be a continuous variable with a mean of zero, and the latent trait for each individual is a value on the continuum. While CFA serves to validate factor structures, IRT delves deeper into the item characteristics and the relationship between each item and the level of the latent trait. Using IRT, we can investigate whether a specific item appropriately represents a characteristic that is commonly observed among individuals within a certain level of the trait. The Graded Response Model (GRM; Samejima, 1969) was applied as it is well suited to address ordinal response categories scored on Likert scales, as in our survey. Each item's performance was described by item discrimination and threshold parameters. The item discrimination parameter reflects the magnitude of the relationship between each item response and its latent trait, and the item threshold parameter is the point of the latent trait where the probability of selecting a particular category or higher is .50. Item category characteristic curves—visual representations of an item characteristic—were also generated to illustrate the performance of each item.

Both CFA and IRT analysis were conducted using Mplus 6.11 (Muthén & Muthén, 1998-2011), with weighted least squares means and variance adjusted estimation for CFA analysis and marginal maximum likelihood estimation for IRT analysis.

Results

For the hypothesized 6-factor model, the fit indices indicate that the model fit the data well (RMSEA=.064, CFI=.969, TLI=.967). In addition, standardized factor loadings in Table 3 ranged from .517 to .964, suggesting a strong relationship between an individual item and its underlying factor. These results show that the six distinct factors are well-represented by the items on the survey instrument and the items indeed measure their intended factors.

IRT analysis was conducted separately for each factor because IRT assumes unidimensionality, meaning that items in the scale for a factor measure a single latent trait. Item parameter estimates for each scale are presented in Table 4. Due to space constraints, we describe the IRT results pertaining to *initial attitudes toward math* as an example, and detailed interpretation for other factors will be included in the full paper. The item discrimination parameters for item 1 and 2 measuring initial attitudes toward math were reasonably high, meaning that they are strongly related to the attitudes and thereby good indicators of the attitudes. Item 3 and 4 showed an even stronger relationship. However, the discrimination parameters appeared to be possibly inflated by the relationship among items, in addition to the relationship between each item and its latent trait (Yen, 1993).

The item threshold parameters for item 1 and 2 were leaning toward the lower levels of the factor measuring initial attitudes toward math. As displayed in Figure 1, students were likely to respond in the highest category at slightly above the trait mean. On the other hand, those for item 3 and 4 were spread out around the mean within limited levels of the latent trait. These results suggest that item 1 and 2 describe the initial attitudes toward math generally observed for students who have low levels of the attitudes, whereas item 3 and 4 are more suitable to capture the attitudes observed for average students.

IRT results showed that each item contributes well to measuring its corresponding latent trait. However, other than items underlying the transfer capital factor, items tend to describe the characteristics of students observed at the lower level of each latent trait. It implies that students' responses to the highest category do not necessarily indicate that they are high on the latent trait. To overcome this weakness, we will consider elaborating items or adding more items to describe the characteristics of high-level traits to further refine the survey instrument.

Study Significance

Expanding the STEM transfer pathway is an issue of national importance that has major implications for STEM success and outcomes for the many underrepresented students beginning at community colleges. Yet, existing research dealing with STEM education often provides limited insight that illustrates only isolated aspects of the issue. Our study describes a new survey instrument addressing this important gap that will help generate new research-based knowledge to illuminate mechanisms underlying successful upward transfer in STEM, a policy concern of critical importance given the vital and diverse pool of potential STEM talent supplied by community colleges. Our study also makes methodological contributions to higher education research relying on survey methods. Other than a few notable exceptions (e.g, Carle, Jaffee, Vaughan, & Eder, 2009; Sharkness & DeAngelo, 2011), IRT has not been applied broadly in validating survey instruments in a higher education research context. In this study, we argue that, by performing both the conventionally adopted CFA and the more innovative IRT approach, we strengthen the rigor of our validation study while adding to the methodological richness of education research based on survey data.

References

Association of American Colleges and Universities. (2012). *Ramping up for STEM success: Pathways for student transfer*. Retrieved from http://www.aacu.org/pkal/rampingupstem/documents/rampingupnewsletter.pdf

Author. (2012)

Author. (2013)

Author. (2014)

Baber, A. (2011). Using Community Colleges to Build a STEM-Skilled Workforce. Washington, DC: NGA Center for Best Practices. Retrieved from www.nga.org/files/live/sites/NGA/files/.../1106STEMWORKFORCE.PDF

Bahr, P. R., Toth, C., Thirolf, K., & Massé, J. C. (2013). A review and critique of the literature on community college students' transition processes and outcomes in four-year institutions. *Higher Education: Handbook of Theory and Research, 28*, 459-511.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bensimon, E. M., & Dowd, A. C. (2012). *Developing the capacity of faculty to become institutional agents for Latinos in STEM*. Los Angeles, CA: University of Southern California. Retrieved from http://cue.usc.edu/assests/Bensimon_Developing%20IAs_NSF%20Report%20CUE_2012.pdf

Betz, N. E., & Hackett, G. (1983). The relationship of mathematics self-efficacy expectations to the selection of science-based college majors. *Journal of Vocational Behavior, 23*(3), 329–345.

Bragg, D. D. (2011). Two-year college mathematics and student progression in STEM programs of study. In S. Olson & J. B. Labov (Eds.), *Community colleges in the evolving STEM education landscape* (pp. 80-100). Washington, DC: The National Academies Press.

Brown, T. A.(2006). *Confirmatory factor analysis for applied research.* New York: Guilford.

Byars-Winston, A. M., Estrada, Y., Howard, C., Davis, D., & Zalapa, J. (2010). Influence of social cognitive and ethnic variables on academic goals of underrepresented students in science and engineering: A multiple-groups analysis. *Journal of Counseling Psychology, 57*(2), 205-218.

Carle, A. C., Jaffee, D., Vaughan, N. W., & Eder, D. (2009). Psychometric properties of three new national survey of student engagement based engagement scales: An item response theory analysis. *Research in Higher Education, 50*, 775-794.

Clark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment, 7*, 309-319.

Edelen, M. O., & Reeve, B.B. (2005). Applying item response theory (IRT) modeling to questionnaire development, evaluation, and refinement. *Quality of Life Research, 16* (Supp 1), 5-18.

Embretson, S. E., & Reise, S. P. (2000). *Item response theory for psychologists*. Mahwah, NJ: Lawrence Erlbaum Associates.

Floyd, F.J., & Widaman, K.F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. *Psychological Assessment*, 7, 286-299.

Hackett, G. & N. E. Betz. (1989). An exploration of the mathematics self-efficacy/mathematics performance correspondence. *Journal for Research in Mathematics Education, 20*(3), 261-273.

Hu, L-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6, 1-55.

Laanan, F. S., Starobin, S. S., & Eggleston, L. E. (2010). Adjustment of community college students at a four-year university: Role and relevance of transfer student capital for student retention. *Journal of College Student Retention: Research, Theory and Practice, 12*(2) 175-209.

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice and performance. *Journal of Vocational Behavior, 45*(1), 79-122.

Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology, 47*(1), 36-49.

Lent, R. W., Lopez, A. M., Lopez, F. G., & Sheu, H.-B. (2008). Social cognitive career theory and the prediction of interests and choice goals in the computing disciplines. *Journal of Vocational Behavior,* 73, 52-62. doi: 10.1016/j.jvb.2008.01.002

Lent, R. W., Lopez, F. G., & Bieschke, K. J. (1993). Predicting mathematics-related choice and success behaviors: Test of an expanded social cognitive model. *Journal of Vocational Behavior, 42*, 223-236.

Lent, R. W., Miller, J. M., Smith, P. E., Watford, B. A., Lim, R. H., & Hui, K., … Williams, K. (2013). Social cognitive predictors of adjustment to engineering majors across gender and race/ethnicity. *Journal of Vocational Behavior*, *83*, 22-30. doi:10.1016/j.jvb.2013.02.006

Muthén, L.K., & Muthén, B.O. (1998-2011). Mplus User's Guide. Sixth Edition. Los Angeles, CA: Muthén & Muthén.

Packard, B. W.-L. (2011, December). Effective outreach, recruitment, and mentoring into STEM pathways: Strengthening partnerships with community colleges. In S. Olson & J. B. Labov (Eds.), *Community colleges in the evolving STEM education landscape* (pp. 58-79). Washington, DC: The National Academies Press.

Pike, G. R. (2006). Students' personality types, intended majors, and college expectations: Further evidence concerning psychological and sociological interpretations of Holland's theory. *Research in Higher Education, 47*(7), 801–822.

President's Council of Advisors on Science and Technology. (2012). *Report to the president: Engage to excel: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics*. Retrieved from http://www.whitehouse.gov/sites/default/files/microsites/ostp/pcast-engage-to-excel-final_2-25-12.pdf

Samejina, F. (1969). Estimation of latent ability using a response pattern of graded scores. *Psychometrika Monograph Supplement, 34*(4, Pt. 2).

Scott, A. B., & Mallinckrodt, B. (2005). Parental emotional support, science self-efficacy, and choice of science major in undergraduate women. *The Career Development Quarterly, 53*(3), 263–273.

Sewell, W., & Haller, A., & Portes, A. (1969). The educational and early occupational attainment process. *American sociological review, 34*(1), 82-92.

Sharkness, J., & DeAngelo, L. (2011). Measuring student involvement: A comparison of classical test theory and item response theory in the construction of scales from student survey. *Research in Higher Education, 52*, 480-507.

Singh, K., Granville, M. & Dika, S. (2002). Mathematics and science achievement: Effects of motivation, interest, and academic engagements. *The Journal of Educational Research, 95*(6), 323-332.

Yen, W. M. (1993). Scaling performance assessments: Strategies for managing local item dependence. *Journal of Educational Measurement, 30,*187-213.

Table 1

Latent Factors and Underlying Survey Items

Factor	Item	Survey Question
Initial attitudes toward math	1	How important will it be for you to know mathematics to succeed at college
	2	How much will you need math for your future career
	3	How much do you enjoy solving math problems
	4	How much do you enjoy applying math in your daily life
Initial attitudes toward science	1	How important will it be for you to know science subjects to succeed at college
	2	How much will you need science for your future career
	3	How much do you enjoy solving science problems
	4	How much do you enjoy reading science articles, magazines, or news
Self-efficacy in math	1	How confident are you that you have the ability to master the material taught in math
	2	How confident are you that you can do well on math exams
	3	How confident are you that you can complete math assignments successfully
	4	How confident are you that you can receive a good grade in college math courses
	5	How confident are you that you can perform well in course activities in math classes
Self-efficacy in science	1	How confident are you that you have the ability to master the material taught in science
	2	How confident are you that you can do well on science exams
	3	How confident are you that you can complete science assignments successfully
	4	How confident are you that you can receive a good grade in college science courses
	5	How confident are you that you can perform well in course activities in science classes
Active learning	1	How often do courses require you to apply what you have learned to real life situations
	2	How often do courses require you to present what you have learned to instructor and peers
	3	How often do courses require you to explore key concepts, data, beliefs, or values within small groups
	4	How often do courses require you to think about instructor's question on your own first, and then discuss the question with peers before the instructor explains the answer to the class
	5	How often do courses require you to identify what you already know, what you need to know, and how and where to access new information in order to solve a given problem
	6	How often do courses require you to consider, compare, and generate multiple potential solutions to a given problem
	7	How often do courses require you to integrate skills and knowledge learned to

		solve problems
	8	How often do courses require you to work in groups to research necessary background material in order to solve complex, realistic problems
	9	How often do courses require you to draw diagrams to visually show the connection between a new concept and other concepts that you already learned
	10	How often do courses require you to gather information from a variety of sources
	11	How often do courses require you to draw conclusions and make decisions given a detailed description of a situation
	12	How often do courses require you to evaluate student peers' written work
	13	How often do courses require you to work on real-world problems
	14	How often do courses require you to work on your own projects or experiments
	15	How often do courses require you to choose your own topics or projects to investigate
Transfer capital	1	How often do you use the service provided by your college or campus: advising for future transfer to a four-year college, either walk-in or online
	2	How often do you use the service provided by your college or campus: published transfer information or guidelines
	3	How often do you use the service provided by your college or campus: transfer credit assistance, which helps you in determining how your course credits transfer to other colleges and universities
	4	How often do you contact the following individuals to discuss matters related to transfer to a four-year college or university : academic advisors or counselors
	5	How often do you contact the following individuals to discuss matters related to transfer to a four-year college or university : instructors
	6	How often do you contact the following individuals to discuss matters related to transfer to a four-year college or university : student peers
	7	How often do you contact the following individuals to discuss matters related to transfer to a four-year college or university : family members or friends

Note. Survey items rely on a 5-point Likert scale, with 1 indicating “not at all” and 5 indicating “extremely.”

Table 2

Sample Characteristics

	N	(%)
Gender		
Male	969	(58.09)
Female	693	(41.55)
Race/ethnicity		
White	1,088	(65.23)
Asian	125	(7.49)
Underrepresented minority	455	(27.28)
STEM fields		
Biological, agricultural, environmental life sciences	487	(29.20)
Computer or mathematical sciences	508	(30.46)
Engineering or engineering technologies	376	(22.54)
physical sciences	186	(11.15)
Total	1,668	(100.00)

Table 3

Standardized Factor Loadings for the Hypothesized 6-Factor Model

Factor	Item	Estimate	(se)
Initial attitudes toward math	1	0.749	(.018)
	2	0.721	(.017)
	3	0.904	(.011)
	4	0.861	(.011)
Initial attitudes toward science	1	0.829	(.012)
	2	0.807	(.012)
	3	0.927	(.009)
	4	0.731	(.015)
Self-efficacy in math	1	0.920	(.005)
	2	0.933	(.004)
	3	0.904	(.005)
	4	0.942	(.003)
	5	0.964	(.003)
Self-efficacy in science	1	0.938	(.004)
	2	0.930	(.003)
	3	0.932	(.004)
	4	0.949	(.003)
	5	0.946	(.003)
Active learning	1	0.632	(.016)
	2	0.641	(.016)
	3	0.718	(.013)
	4	0.701	(.014)
	5	0.668	(.015)
	6	0.733	(.013)
	7	0.717	(.014)
	8	0.708	(.013)
	9	0.569	(.019)
	10	0.640	(.015)
	11	0.718	(.014)
	12	0.517	(.020)
	13	0.620	(.016)
	14	0.602	(.017)
	15	0.576	(.018)
Transfer capital	1	0.848	(.008)
	2	0.843	(.009)
	3	0.878	(.008)
	4	0.794	(.011)
	5	0.755	(.014)
	6	0.718	(.014)
	7	0.648	(.017)

Table 4

Item Parameter Estimates for Each Factor

Factor	item	a (se)	b_1 (se)	b_2 (se)	b_3 (se)	b_4 (se)
Initial attitudes toward math	1	1.34 (.08)	-3.85 (.24)	-2.65 (.14)	-1.07 (.08)	0.53 (.07)
	2	1.51 (.08)	-3.16 (.19)	-1.76 (.11)	-0.35 (.07)	0.83 (.08)
	3	3.29 (.19)	-1.40 (.24)	-0.77 (.16)	0.10 (.12)	0.99 (.19)
	4	4.25 (.35)	-1.37 (.42)	-0.64 (.23)	0.28 (.16)	1.14 (.37)
Initial attitudes toward science	1	2.79 (.20)	-2.24 (.33)	-1.40 (.22)	-0.53 (.12)	0.37 (.11)
	2	3.35 (.29)	-1.62 (.37)	-0.90 (.23)	-0.19 (.12)	0.40 (.14)
	3	2.59 (.20)	-1.69 (.26)	-0.88 (.16)	0.05 (.10)	1.00 (.17)
	4	1.47 (.11)	-2.07 (.13)	-1.03 (.09)	-0.02 (.07)	1.03 (.09)
Self-efficacy in math	1	4.24 (.23)	-2.20 (.48)	-1.40 (.31)	-0.47 (.17)	0.68 (.19)
	2	4.82 (.26)	-1.96 (.48)	-1.24 (.32)	-0.28 (.17)	0.88 (.25)
	3	4.37 (.25)	-2.49 (.59)	-1.54 (.36)	-0.63 (.20)	0.59 (.19)
	4	6.38 (.46)	-2.14 (.96)	-1.37 (.60)	-0.47 (.29)	0.65 (.33)
	5	7.67 (.64)	-2.17 (1.32)	-1.39 (.87)	-0.49 (.38)	0.61 (.43)
Self-efficacy in science	1	4.64 (.25)	-2.23 (.57)	-1.40 (.34)	-0.32 (.17)	0.90 (.25)
	2	5.29 (.30)	-2.13 (.62)	-1.19 (.36)	-0.17 (.18)	0.99 (.32)
	3	4.86 (.31)	-2.34 (.72)	-1.46 (.43)	-0.50 (.21)	0.70 (.25)
	4	7.12 (.57)	-2.18 (1.24)	-1.34 (.75)	-0.33 (.29)	0.83 (.48)
	5	5.51 (.34)	-2.29 (.82)	-1.43 (.47)	-0.46 (.22)	0.70 (.27)
Active learning	1	1.40 (.08)	-3.78 (.24)	-1.88 (.10)	-.18 (.07)	1.49 (.09)
	2	1.59 (.09)	-2.60 (.16)	-1.27 (.09)	.04 (.07)	1.53 (.10)
	3	1.84 (.10)	-2.19 (.15)	-1.18 (.10)	.03 (.08)	1.48 (.11)
	4	1.83 (.10)	-2.05 (.14)	-1.06 (.09)	.10 (.08)	1.46 (.11)
	5	1.62 (.09)	-3.33 (.24)	-2.01 (.12)	-.51 (.08)	1.18 (.09)
	6	2.02 (.10)	-2.59 (.21)	-1.40 (.12)	-.09 (.08)	1.33 (.12)
	7	1.71 (.10)	-3.45 (.27)	-2.39 (.15)	-.94 (.09)	.84 (.09)
	8	1.99 (.10)	-1.71 (.13)	-.70 (.09)	.34 (.08)	1.61 (.13)
	9	1.17 (.07)	-2.26 (.10)	-.69 (.07)	.67 (.07)	2.18 (.10)
	10	1.51 (.09)	-2.59 (.14)	-1.36 (.09)	-.09 (.07)	1.46 (.10)
	11	1.81 (.10)	-2.54 (.17)	-1.52 (.11)	-.27 (.08)	1.39 (.11)
	12	1.00 (.07)	-1.49 (.07)	-.22 (.06)	1.26 (.07)	2.98 (.11)
	13	1.45 (.08)	-2.75 (.15)	-1.36 (.09)	.03 (.07)	1.43 (.09)
	14	1.52 (.09)	-2.11 (.12)	-1.04 (.08)	.06 (.07)	1.37 (.09)
	15	1.25 (.08)	-1.85 (.09)	-.71 (.07)	.63 (.07)	2.18 (.10)
Transfer capital	1	3.65 (.21)	-.37 (.14)	.29 (.14)	1.15 (.22)	1.88 (.33)
	2	2.70 (.17)	-.39 (.11)	.37 (.11)	1.18 (.17)	1.99 (.26)
	3	3.22 (.22)	-.37 (.13)	.32 (.13)	1.05 (.20)	1.75 (.31)
	4	2.53 (.14)	-.41 (.10)	.31 (.10)	1.12 (.14)	1.97 (.21)
	5	1.83 (.11)	.00 (.08)	.79 (.09)	1.65 (.13)	2.46 (.19)
	6	1.54 (.10)	-.35 (.07)	.44 (.08)	1.32 (.09)	2.50 (.15)
	7	1.34 (.08)	-.91 (.07)	-.12 (.07)	.86 (.07)	1.93 (.10)

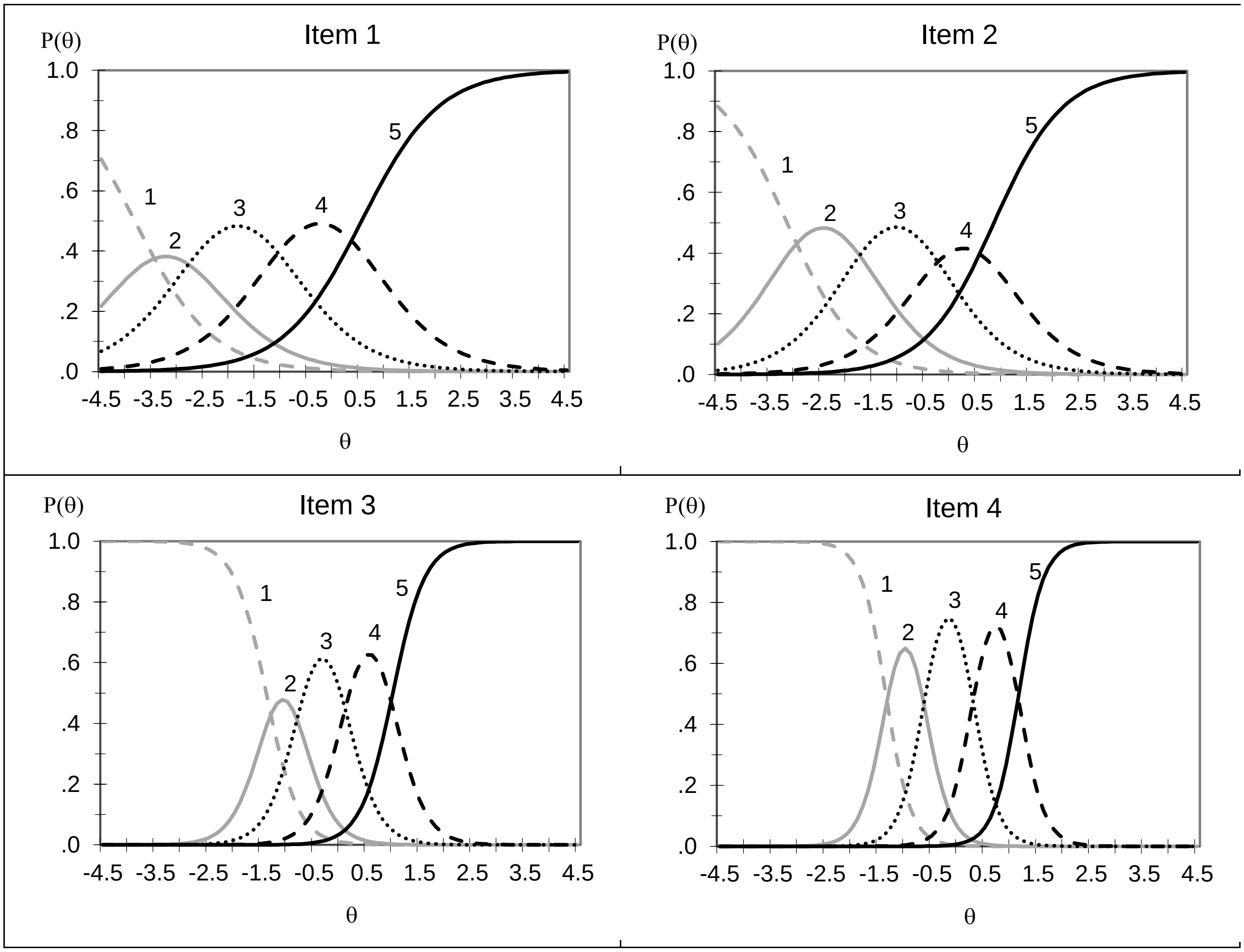

Figure 1. Item category characteristic curves: Initial attitudes toward math