Identifying Students' Expectancy-Value Beliefs: A Latent Class Analysis Approach to Analyzing Middle School Students' Science Self-Perceptions

Julia Phelan
University of California, Los Angeles

Marsha Ing
University of California, Riverside

Karen Nylund-Gibson
University of California, Santa Barbara

Richard S. Brown
National Math + Science Initiative

Abstract

This study extends current research by organizing information about students' expectancy-value achievement motivation, in a way that helps parents and teachers identify specific entry points to encourage and support students' science aspirations. This study uses latent class analysis to describe underlying differences in ability beliefs, task values and links these science-self-perceptions to interest in science. Findings suggest that there is a positive relationship between students' science self-perceptions and interest in science which is consistent with previous research (see for example, Aschbacher, Ing, & Tsai, 2014). The relationship between self-perceptions and interest in science was similar regardless of gender or ethnicity. Despite study limitations, self-perceptions should be considered valuable because teachers have influence on both learning activities and a students' sense of self as a science learner. These results underscore the importance of preparing teachers to foster student desire to learn more science in the future. In organizing the data using this particular methodology, information is provided in a potentially powerful way to target specific interventions or support.

Introduction

Given the importance of science, technology, engineering, and mathematics (STEM) training to the quality of a nation's workforce, there is much attention around understanding persistence in STEM fields. There is some consensus that achievement alone does not explain the lack of persistence in STEM fields and that other approaches are needed to understand and support students' STEM-related aspirations. The expectancy-value theory of achievement motivation provides a potentially useful approach to studying students' career aspirations by incorporating people's beliefs about how well they will do on the task and the extent to which they value the task (Atkinson, 1957; Eccles, Adler, Futterman, Goff, Kaczala, Meece, & Midgley, 1983; Wigfield, 1994; Wigfield & Eccles, 1992, 2000). The theory includes three interrelated constructs: ability belief, expectancy, and value. Ability belief and expectancy are both related to an individual's perceptions of how they do on a task or in a particular subject area currently (ability) or at some point in the future (expectancy). Value includes "attainment value or importance, intrinsic value, utility value or usefulness of the task and cost" (Wigfield & Eccles, 2000, p. 72). Variation in children's ability-expectancy beliefs is domain specific (Eccles et al., 1983; Wigfield, Eccles, Mac Iver, Reuman, & Midgley, 1991). For example, positive attitudes about ability beliefs and values in science are different from ability beliefs and values in art.

In studies specific to math and science, research indicates a positive association between perceived value, ability and achievement in mathematics and science (Wigfield et al., 1991), participation in out-of-school mathematics and science activities (Simpkins, Davis-Kean, & Eccles, 2006), and reported intention to enroll in mathematics and science courses (Atwater, Wiggins, & Gardner, 1995). In other words, those students who see themselves as being good at science, or expect to do well and continue studying science, tend to have higher achievement and participation in science-related activities than those who do not see themselves so.

This particular theory of achievement-motivation informs our work through its emphasis on student beliefs about whether they can and want to learn science and whether or not they see themselves as having a job in the future which utilizes science-specific learning. This framework is particularly applicable to middle school students' perceptions as this is a critical time for making decisions on which high school science courses to enroll in and which extracurricular activities to participate in (Wigfield, Eccles, Yoon, Harold, Argreton, Freedman-Doan, & Blumenfeld, 1997).

This study extends research by organizing information about students' expectancy-value achievement motivation in a way that helps parents and teachers identify specific entry points to encourage and support students' science aspirations. This study uses latent class analysis to describe underlying differences in ability beliefs and task values, and links these science-self-perceptions to interest in science. In organizing the data using this particular methodology, information is provided in a potentially powerful way to target specific interventions or support.

Method

Participants

Students enrolled in eighth grade physical science courses in a Southeast state were recruited for participation by their science teachers. All participating science teachers were part of the Laying the Foundation (LTF) professional development program that includes comprehensive teacher training and student support to boost enrollment and success in Advanced Placement (AP®) courses in mathematics, science and English, and the rigorous courses that lead up to AP. Science teachers volunteered to participate in the professional development program and agreed to gather information about program implementation using surveys and teacher logs. A subset of the science teachers were also observed teaching one of the LTF program-developed lessons.

Demographic data were available for a subset of participating teachers (8/10 teachers for whom we received at least one set of student surveys). There were six females and two males with an average age of 35.5 years and an average number of 8.5 years of teaching experience. Six teachers had three or more years' experience teaching science and two teachers had between 1-2 years' experience teaching science. All but one teacher was participating in the LTF program for the first time during the study year.

Survey

Participants completed a two-page survey on science self-perceptions. Packages with 40 paper copies of the student science self-perception surveys were mailed to participating science teachers ($n = 19$) in the fall (2015) and spring (2016). Teachers administered and returned the surveys once complete. There was a 42% response rate of teachers ($n = 8$) in the fall ($n = 268$ student surveys) and 32% response rate of teachers ($n = 6$) in the spring ($n = 241$ student surveys). The number of student surveys returned per teacher ranged from 17 to 66, with an average of 36 returned surveys. Four teachers returned surveys in both fall and spring.

Eight survey items which focused on students' science self-perceptions, were included in this study (Table 1). Survey items were based on the expectancy-value achievement motivation theory framework (described above) which suggests that student performance and persistence are influenced by students' beliefs in their abilities and the extent to which they value the activities in which they engaged in (Atwater et al., 1995; Simpkins et al., 2006; Wigfield et al., 1991). The original items included four response options (strongly disagree, disagree, agree, strongly agree). However, due to skewed distributions, with most students selecting that they strongly disagree or strongly agree, we collapsed the response options from four to two. Thus, the two response options included in our analyses were strongly agree (1) and other (0) which included disagree, strongly disagree, agree.

The three items related to students' interest in science included in this study were: I would like to work in a career involving science, I would like to take more science courses in high school, I would like to study science after high school. Responses to these items were also collapsed to dichotomous response options (strongly agree and other). A composite score to indicate interest in science was created by adding up the scores for these three items (fall: $M = 1.68$, $SD = 1.23$; spring: $M = 1.76$, $SD = 1.25$).

To gather validity evidence related to the survey, a non-random sample of 16 students was interviewed about their science self-perceptions. Interview items were first pilot tested with middle school students in a non-study school district (in California). Questions were revised based on feedback from the pilot test. In addition, two members of the research team listened to audio recordings of all the interviews and revised the protocol before gathering data from the study students. The structured interview protocol included the same items administered on the survey with some additional probes. For example: Please read this statement aloud. "I think science is interesting. With additional structured probes including: What makes something interesting to you? What makes something interesting in science? Does this statement (the one read aloud) describe you? Why/why not?

There is evidence that student interpretation of the interview items focused primarily on their experiences with school science and that being good at science was primarily focused on getting good grades and scoring well on tests. In addition, there was evidence that students thought that being good at science indicated that it came easy for them and that to be good at something meant you did not need to work that hard to succeed.

Analysis

Latent Class Analysis (LCA; Goodman, 1974; Magidson & Vermunt, 2004; Muthén, 2001) is a model-based cluster analysis technique that was used to identify subgroups of students based on their science attitudes. LCA is an exploratory method, meaning that there is not an a priori assumption about the number of latent classes. To fit LCA models, a series of models with differing number of latent classes were run and model fit is compared, along with substantive theory, to determine the number of latent classes which best describe the heterogeneity in students' science attitudes. All models were run in Mplus (Muthén & Muthén, 1998-2015). Fall and spring LCAs were run independently because it was not possible to link student responses from the fall and spring in our dataset (students responded to the surveys anonymously).

We used the commonly accepted fit statistics to evaluate fit for LCA models (Nylund, Asparouhov, & Muthén, 2007). This includes the Bayesian Information Criteria (BIC) and Adjusted BIC (ABIC), where lower values indicate a better fit. Two likelihood based indices were used, the Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT) and the Bootstrap Likelihood Ratio Test (BLRT). These tests provided a p-value that was used to compare models with one class difference. For more information on the BLRT and fit statistics for LCA see Nylund et al. (2007). Two quasi-Bayesian information-heuristic model fit indices were also used to compare LCA models (Masyn, 2013). The Bayes Factor (BF) is a pairwise comparison of relative fit between two models, where a ratio of the probability of each model being true is computed. This ratio is compared to the Jeffery's Scale of Evident (Kass & Raftery, 1997), for which $1 < BF < 3$ is considered weak evidence for the model with fewer classes, $3 < BF < 10$ is moderate evidence for the model with fewer classes, and $BF > 10$ is strong evidence. The correct Model Probability (cmP) estimates the probability that each of latent class analysis models being considered is correct, assuming the "true" model is among the models being considered. The model with the largest cmP value is the model chosen by the cmP because it has the highest probability of being correct. See Masyn (2013) for more on these two fit comparisons and their calculations. In addition to the fit indices listed above, the substantive interpretability of the modeling results is used as well to help decide on the final model (Muthén, 2003).

Once the best fitting model was decided, two covariates (gender and ethnicity) and one distal outcome (interest in science) were included. Class-specific means of the distal outcomes were estimated using the BCH method (Bolck, Croon, Hagenaars, 2004; Bakk & Vermunt, 2016), a preferred method for estimating distal outcome means (Asparouhov & Muthén, 2014). Class-specific means of science interests were tested for equality across the emergent latent classes using a series of Wald tests.

Item	Fall ($N = 242$) Mean	Fall SD	Spring ($N = 228$) Mean	Spring SD
I am good at science	0.13	0.34	0.19	0.39
I learn new ideas in science easily	0.13	0.34	0.17	0.37
I expect to do well in science this year	0.38	0.49	0.34	0.47
I could be good at science	0.36	0.48	0.39	0.49
It is useful for me to know some science	0.29	0.46	0.31	0.46
Being good at science is important to me	0.27	0.44	0.26	0.44
I think science is interesting	0.33	0.47	0.28	0.45
I like doing science	0.29	0.45	0.28	0.45

Note. Mean represents proportion of students who strongly endorsed the item.

Table 1. Mean and Standard Deviation of the Science Self-Perception Items for the Fall and Spring Cohorts.

Results

Student self-perceptions were similar in the fall and spring (Table 1). Based on a composite score for student self-perceptions, there were no gender differences in the fall, $t(266) = 1.13$, $p = .26$, or spring, $t(239) = -0.10$, $p = .92$. There were also no differences by ethnicity for either the fall, $t(266) = 1.76$, $p = .08$, or spring, $t(239) = -1.16$, $p = .25$.

Classes of Science Attitudes

We fit a series of LCA models with different number of classes and collected model fit statistics which is presented in Table 2. Model fit for fall and spring are included in the same table for models with 1-7 latent classes. First considering the LCAs for fall, we observe that the BIC was lowest for the three class model (1924.91) and the ABIC was essentially equally low between the 3-and 4-class model (1842.49). The Bayes Factor (BF) identified the 3-class model as well. Both the LRM-LRT and BLRT pointed towards a 2-class model. Thus, both the 2- and 3-class models were examined. Upon a closer look at the item profile plot, the 3-class solution was retained because the addition of the third class provided further distinction between the students with lower item profile plots. Figure 1 presents the item probability plots with the fall LCA classes presented on the top panel and spring on the bottom panel. Looking at the plot, we can label the three emergent latent classes. One class was characterized by having high probabilities of endorsing all the science attitude items. This class (which represented 9% of the sample) was labeled the *Science is me* class. A second class, characterized by having moderate item endorsement, was labeled the *Indifference* class. This group of students (38% of the sample) indicated neither strong positive or negative feelings of endorsement of science attitude items. The last class (52% of the sample) was characterized as having low probabilities of endorsing the science attitude items and was labeled the Science is *not me* class.

	Classes	LL	# of parameters	BIC	ABIC	LMR-LRT	BLRT	BF	cmP
Fall	1	-1092.92	8	2229.75	2204.39	--	--	0.00	--
	2	-922.49	17	1938.29	1884.40	**0.00**	**0.00**	0.00	0.00
	3	-891.10	26	**1924.91**	1842.49	0.57	0.58	**1536472.86**	**1.00**
	4	-880.64	35	1953.40	1842.45	0.87	0.88	19220731.11	0.00
	5	-872.71	44	1986.94	1847.47	0.11	0.10	11941138.34	0.00
	6	-864.31	53	2019.53	1851.53	0.48	0.48	116803080.25	0.00
	7	-858.19	62	2056.68	1860.16	0.65	0.65	--	0.00
Spring	1	-1052.24	8	2147.91	2122.55	--	--	0.00	--
	2	-837.12	17	1766.55	1712.67	0.15	0.15	0.00	0.00
	3	-792.29	26	**1725.74**	1643.33	0.13	0.14	**4027.90**	**1.00**
	4	-776.16	35	1742.34	**1631.41**	0.72	0.72	124741.64	0.00
	5	-763.46	44	1765.81	1626.36	0.71	0.71	42456899.93	0.00
	6	-756.59	53	1800.93	1632.96	0.45	0.45	14894461.64	0.00
	7	-748.67	62	1833.97	1637.47	0.66	0.66	--	0.00

Note. Bolded values indicate the class solution which was identified by the specific fit indicia. LL=log likelihood; # of parms= number of parameters; BIC= Bayesian Information Criterion; ABIC= Adjusted BIC; LMR-LRT=Lo-Mendel-Rubin Likelihood Ratio Test; BLRT= bootstrap likelihood ratio test; BF= Bayes Factor; cmP=Correct model probability.

Table 2. Fit Indices for Fall and Spring LCA Models

Considering the spring LCA fit information presented in Table 2, we observe that the 3-class model had the lowest BIC value (1725.74), the BF and cmP both identify the 3-class model as best (4027.90 and 1.0, respectively). The ABIC does not reach a minimum among the models we considered, there are diminishing returns by adding extra classes after 3 classes. The LMR-LRT and the BLRT never did have a significant *p*-value, thus did not provide any useful information for model fit. We did consider the 4-class solution, but the additional fourth class was small and not particularly meaningful. Taken together, this information pointed toward the 3-class solution for describing the heterogeneity in students' attitudes toward science.

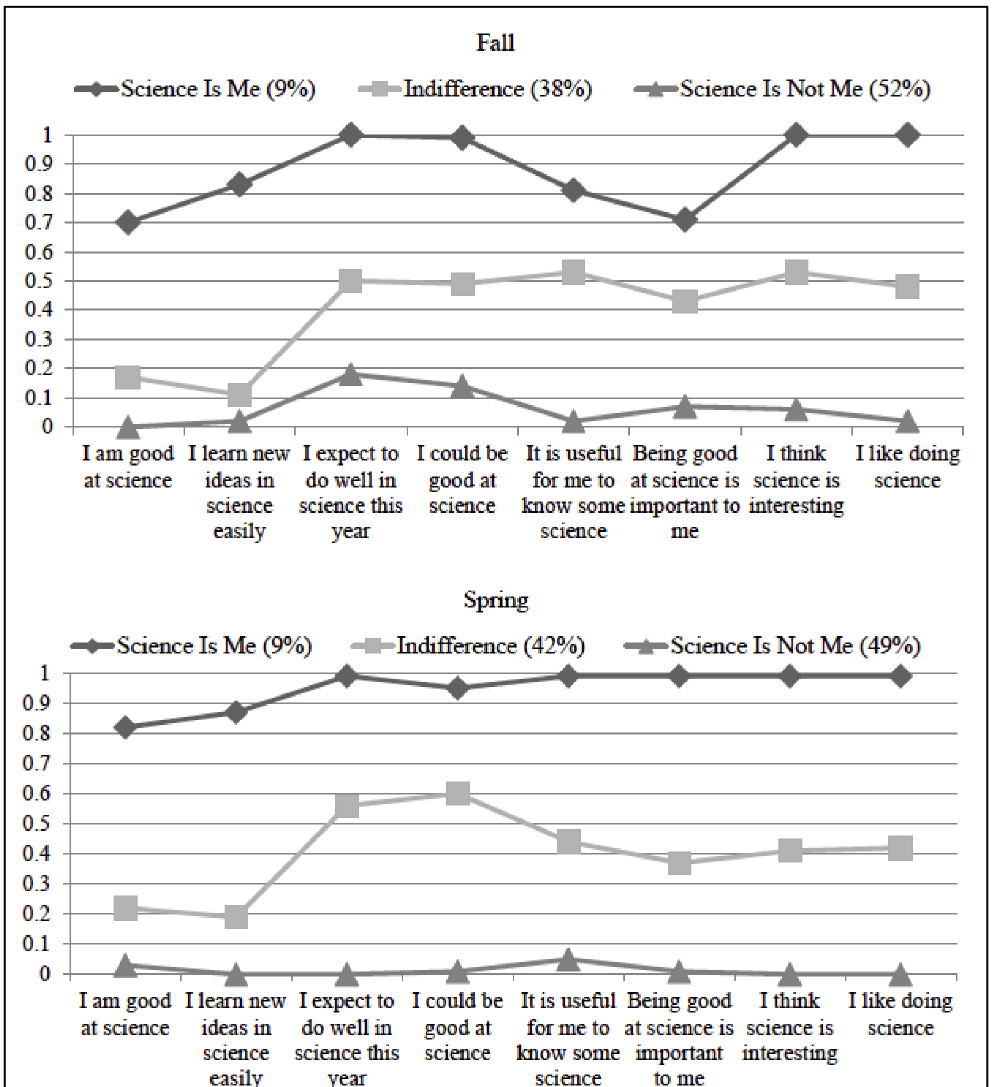

Figure 1. Item probability plots for fall (top) and spring (bottom) cohort LCAs.

We examined the item probability plot for the spring LCA in the lower panel of Figure 1 to label the classes, which ended up being similar to the 3-class solution for the Fall LCAs. Because the resulting classes were so similar to the ones in the fall, we labeled the classes the same, *Science is me* (9%), *Indifference* (42%), and *Science is not me* (49%).

Differences in Gender, Ethnicity and Desire to Take More Science

Once we identified the best number of classes for both the fall and spring LCAs, we added covariates and distal outcomes to the model to better understand class demographic composition. With respect to gender and ethnicity, there were no significant differences across the classes for either fall or spring. Boys and girls were equally likely to be in all three of the science attitude class for fall and spring. Additionally, White and non-White students are equally likely to be in each of the latent classes for both fall and spring.

With respect to the distal outcome, as expected the students in the *Science is me* class had significantly higher means on the distal outcome variable for both fall ($M = 2.09$, $SD = 1.16$) and spring ($M = 2.41$, $SD = 0.93$) cohorts, indicating that students in this class are significantly more interested in continuing to take more science courses. The other two classes, *Indifference* and *Science is not me* had lower means than the *Science is me* class for both the fall and spring cohorts.

Discussion

Findings suggest that there is a positive relationship between students' science self-perceptions and interest in science which is consistent with previous research (see for example, Aschbacher, Ing, & Tsai, 2014). The relationship between self-perceptions and interest in science was similar regardless of gender or ethnicity. However, the lack of differences in science self-perceptions for different gender and ethnicity groups is inconsistent with prior research in this area that suggests that males are more often than females to have more positive attitudes towards science and tend to participate more in science-related activities (Archer, DeWitt, Osborne, Dillon, Willis, & Wong, 2012; Aschbacher, Li, Roth, 2010; Eccles, 1984; Simpkins et al., 2006).

There are several limitations of the findings reported here. First and foremost, we were unable to match student responses on the two survey measures. And so, while the fall and spring samples come from the same population of teachers who participated in the same professional development program, the students of those teachers might change from the fall to the spring. This limits our ability to discuss growth or change between the fall and spring. To attempt to address this limitation, we ran analyses for teachers with student responses in both the fall and spring (and found similar relationships between the variables), but we do not have student-level information to compare how the same students responded in the fall and spring. This attempt might also not be sufficient because only four teachers who submitted completed student surveys were the same in the fall and spring.

Second, we were not able to link student responses to administrative or student outcome data. Without this information, we could not validate student reports of gender, or ethnicity. We were also not able to confirm whether or not students who reported that they were good at science were actually the same students who received high grades in science or who had high scores on standardized science achievement measures. Without being able to validate the data, the self-report nature of the study data is limiting.

Finally, although we statistically adjusted for differences between classrooms, these analyses do not include classroom or teacher-level characteristics that might help explain the variation between classrooms. This limits our ability to attribute differences in student interests to specific teacher characteristics (such as how well the teacher implemented the professional development program).

Despite these limitations, self-perceptions should be considered valuable because teachers have influence on both learning activities and students' sense of self as a science learner; these results underscore the importance of preparing teachers to foster student desire to learn more science in the future. One way in which this information could be potentially useful is to connect students' self-perceptions with particular resources that support students' interests and persistence in STEM fields. For example, current research in the area of educational technology designs has identified resources such as social media tools that allow students to capture their everyday life (in pictures and other media) and connect their interests with broader online communities (see for example, Ahn, Clegg, Bonsignore, & Pauw, et al., in press). Analyses like the ones reported here can help identify students who do not see science as something that is relevant to their everyday life (the *Indifference* or *Science is not me* classes), and then this type of social media tool could be introduced to these students as a way of encouraging students to see science as something relevant and useful both in their everyday lives and for future careers. This study provides an approach to help target limited resources where it is most needed to best support students' interests and dispositions towards science, with the aim on enhancing persistence within the field in the future.

References

Ahn, J., Clegg, T., Yip, J., Bonsignore, E., & Pauw, D., et al. (in press). Seeing the unseen learner: Designing and using social media to recognize children's science dispositions in action. *Learning, Media, and Technology*. doi: 10.1080/17439884.2014.964254

Archer, L., DeWitt, J., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2012). Science aspirations, capital, and family habitus: How families shape children's engagement and identification with science. *American Educational Research Journal, 49*(5), 881-908. doi: 10.3102/0002831211433290

Aschbacher, P., Li, E., & Roth, E. J. (2010). Is science me? High school students' identities, participation and aspirations in science, engineering, and medicine. *Journal of Research in Science Teaching, 47*(5), 564-582. doi: 10.1002/tea.20353

Aschbacher, P., Ing, M., & Tsai, S. (2014). Is science me? Exploring middle school students' STE-M career aspirations. *Journal of Science Education and Technology, 23*(6), 735-743. doi: 10.1007/s10956-014-9504-x

Asparouhov, T., & Muthén, B. (2014). *Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary second model* (Web note 21). Los Angeles, CA: Muthén & Muthén.

Atkinson, J. W. (1957). Motivational determinants of risk taking behavior. *Psychological Review, 64*, 359-372. doi: 10.1037/h0043445

Atwater, M. M., Wiggins, J., & Gardner, C. M. (1995). A study of urban middle school student with high and low attitudes toward science. *Journal of Research in Science Teaching, 32*(6), 665-677. doi: 10.1002/tea.3660320610

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling: An interdisciplinary journal, 23*(1), 20-31. doi: 10.1080/10705511.2014.955104

Bolck, A., Croon, M. A., & Hagenaars, J. A. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis, 12*, 3-27. doi: 10.1093/pan/mph001

Eccles, J. S. (1984). Sex differences in achievement patterns. In T. Sonderegger (Ed.), Nebraska *Symposium on Motivation* (Vol. 32, pp. 97-132). Lincoln, NE: University of Nebraska Press.

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation* (pp. 74-146). San Francisco, CA: W. H. Freeman.

Goodman, L. A. (1974). Exploratory latent structure analysis using both identifiable and unidentifiable models. *Biometrika, 61*(2), 215-231. doi: 10.2307/2334349

Kass, R. E.& Raftery, A.E. (1995). Bayes Factors. *Journal of the American Statistical Association, 90*(430), 773-795.

Magidson, J., & Vermunt, J. K. (2004). Latent class models. In D. Kaplan (Ed.), *The Sage Handbook of Quantitative Methodology for the Social Sciences* (pp. 175-198). Thousand Oaks, CA: Sage Publications.

Masyn, K. (2013). Latent class analysis and finite mixture modeling. In T. Little (Ed.), *The Oxford handbook of quantitative methods in psychology (*Vol. 2, pp. 375–393). Oxford, UK: Oxford University Press.

Muthén, B. (2001). Latent variable mixture modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *New Developments and Techniques in Structural Equation Modeling* (pp. 1-33). Mahwah, NJ: Lawrence Erlbaum Associates.

Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling. *Psychological Methods, 8*, 369–377. doi: 10.1037/1082-989x.8.3.369

Muthén, L. K., & Muthén, B. O. (1998 – 2015). *Mplus: Statistical analysis with latent variables (Version 7.11)* [Computer software]. Los Angeles, CA: Muthén & Muthén.

Nylund, K. L., Asparouhov, T., & Muthén, B.O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling, 14*, 535–569. doi: 10.1080/10705510701575396

Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivations: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology, 42*(1), 70-83. doi: 10.1037/0012-1649.42.1.70

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review, 6*(1), 49-78. doi: 10.1007/bf02209024

Wigfield, A., & Eccles, J. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review, 12*(3), 265-310. doi: 10.1016/0273-2297(92)90011-p

Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology, 25*(1), 68-81. doi: 10.1006/ceps.1999.1015

Wigfield, A., Eccles, J., Mac Iver, D., Reuman, D., & Midgley, C. (1991). Transitions at early adolescence: Changes in children's domain-specific self-perceptions and general self-esteem across the transition to junior high school. *Developmental Psychology, 27*(4), 552-565. doi: 10.1037/0012-1649.27.4.552

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A., Freedman-Doan, K., & Blumenfeld, P. C. (1997). Changes in children's competence beliefs and subjective task values across the elementary school years: A three year study. *Journal of Educational Psychology, 89*(3), 451-469. doi: 10.1037/0022-0663.89.3.451

Julia Phelan is a Senior Research Scientist at National Center for Research on Evaluation, Standards and Student Testing at the University of California, Los Angeles. She has extensive experience and expertise in the design and management of large-scale projects focused on K-16 educational assessment and standards, incorporating a wide range of quantitative and qualitative methodologies and coordinating with multiple stakeholders. Her experience includes developing curriculum; integrating Common Core State Standards in both math and literacy into multiple types of assessment format and strategies such as performance-based assessments; and evaluating the efficacy of adaptive quizzing for improving student learning.

Marsha Ing is an associate professor in the Graduate School of Education at the University of California, Riverside. Her research interests include measurement and assessment within the realm of teaching and learning. She is particularly interested in how various research methods are used to inform decisions about improving STEM teaching and learning.

Karen Nylund-Gibson is an associate professor in the Gevritz School at the University of California, Santa Barbara. Her focus is on latent variable models, specifically mixture models and she has published many articles and book chapters on developments, best practices, and applications of latent class analysis, latent transition analysis, and growth mixture modeling. Her research helps to bridge the gap between advanced statistical literature and application of these models to substantive issues.

Richard S. Brown is the Chief Research Scientist at the National Math and Science Initiative and a fellow with the Strategic Data Project at the Center for Education Policy Research at Harvard University. He is a former associate research professor at the University of Southern California's Rossier School of Education; assistant professor of education and director of the Center for Research in Educational Assessment and Measurement at the University of California, Irvine; and senior researcher at the National Center for Research on Evaluation, Standards and Student Testing at the University of California, Los Angeles.