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

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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 and 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 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 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 beliefs 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), as well as 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 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 such as which high school science courses to enroll in and in which extracurricular activities they participate (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.



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 was 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 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 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.



Table 1. Mean and standard deviations of the science self perception items for the fall and spring cohorts.

Item	Fall (N = 242)		Spring (N = 228)	
	Mean	SD	Mean	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.

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 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 didn't 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 apriori assumption about the number of latent classes. To fit LCA models, a series of models with differing number of latent classes are 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, 1998-2012). 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 used 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 (Wasserman, 2000), 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 the 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 (Bakk & Vermunt, 2016; Bolck, Croon, & Hagnaars, 2004), a preferred method for estimating distal outcome means (Asparouhov & Muthén, 2014). Class-specific means of science interested were tested for equality across the emergent latent classes using a series of Wald tests.

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.

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 student's attitudes toward science.

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.



Table 2. Fit indices for fall and spring LCA models

	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.



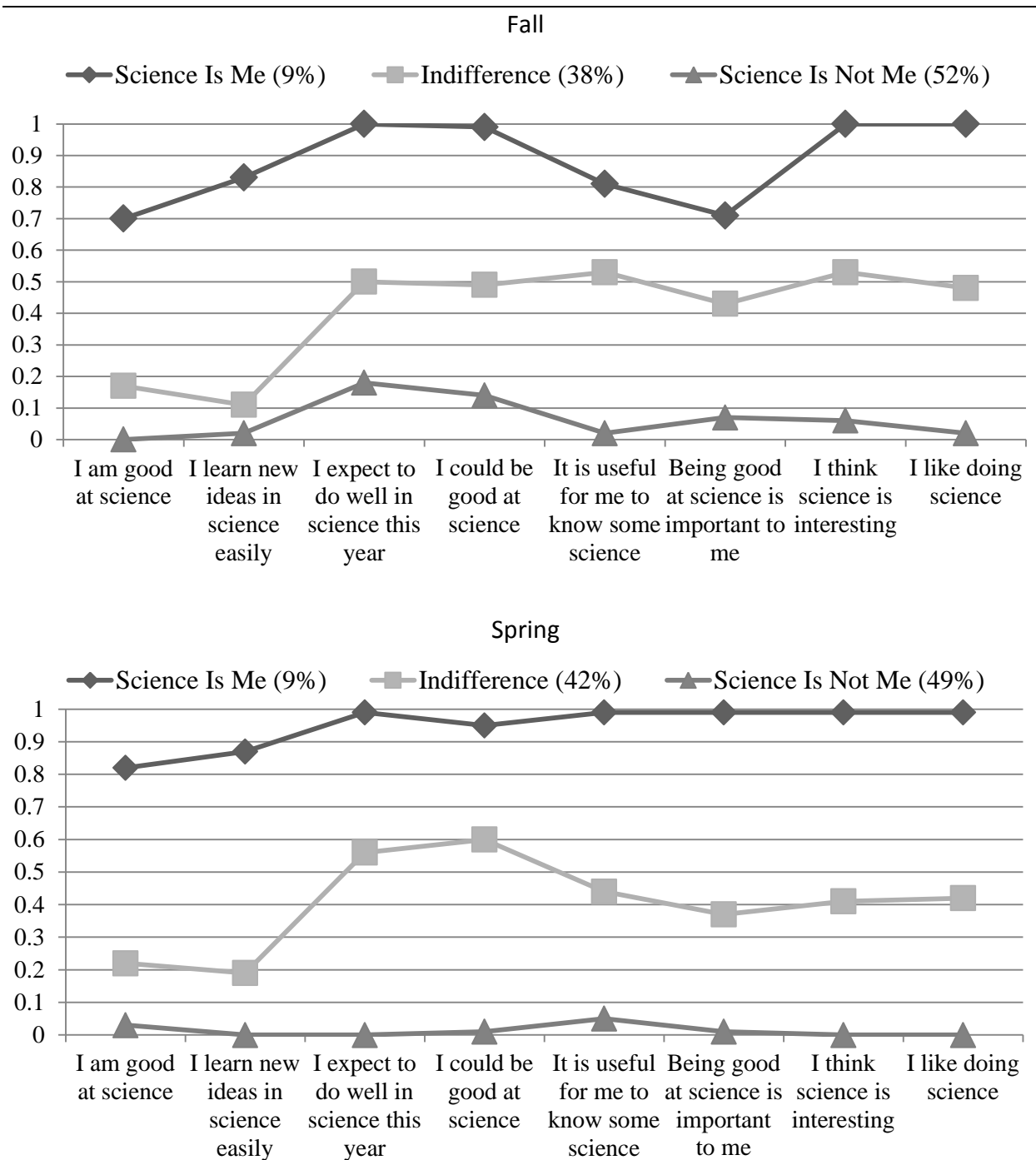


Figure 1. Item probability plots for fall (top) and spring (bottom) cohort LCAs.



DISCUSSION & CONCLUSIONS

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 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.



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