INTEREST AND EMOTION PREDICTORS OF MOTIVATION IN SECONDARY MATHEMATICS CLASSROOMS

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This paper uses data from a large study of US high school mathematics engagement to quantitatively examine how different aspects of affect—interest, positive emotions, and negative emotions—influence different aspects of motivation—mastery goal orientation, performance goal orientation, and self-efficacy—in the context of mathematics classrooms. The results of a latent path analysis suggest that whereas interest was significantly associated with each of the different types of motivation, positive and negative emotions were only associated with self-efficacy. Implications for differentiating between the influence of different types of affect in learning contexts are discussed.

INTRODUCTION

Students' motivation to learn and do mathematics in the US is volatile during the first few years of high school. For example, in a recent study, many ninth graders interested in pursuing math-intensive career paths were found to be no longer interested two years later. By contrast, some who were previously uninterested became interested by eleventh grade (Mangu, Middleton, & Lee, 2016). However, the reasons behind such volatility are not well understood. Given the importance of mathematics for many careers, and that secondary education may be the last opportunity for students to opt in to mathematics-related pursuits, it is important to understand the complex nature of motivation for mathematics during this phase of their development.

Motivation in the Classroom.

Three types of motivation variables have consistently been shown to impact student engagement in mathematics: mastery goal orientation—in which students are motivated to understand the content; performance goal orientation—in which students are motivated to gain favourable judgement and avoid unfavourable; and self-efficacy—the belief that one has the capability to succeed. Mastery goal orientation is associated with more effective learning strategies, such as adapting one's strategies and seeking out help, whereas performance goal orientation is associated with somewhat less effective learning strategies, such as avoiding the appearance of incompetence (e.g., Elliot & Dweck, 2005, Harackiewicz et al., 2002). Mathematics self-efficacy, for its part, is associated with increased math performance and with choosing a mathematics-related major (Hackett & Betz, 1989).

Although these three commonly studied components of motivation are somewhat distinct, they are also related and may influence the expression of each other. For

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instance, mastery goal orientation and high self-efficacy together appear to be related to students' ability to muster the resources necessary to persevere in mathematics, as learners with this combined motivational profile tend to be more adept at coping with failure (Meyer, Turner, & Spencer, 1997).

Affect and Motivation.

Affect is also a key aspect of students' experiences with mathematics and has important relationships with motivation. Specifically, positive emotions (such as relief, hope, and joy) improve motivational outcomes such as effort and self-efficacy, whereas negative emotions (such as shame, hopelessness, and anger) typically lead to avoidance responses such as decreased self-efficacy (Pekrun et al., 2004, Akin & Kurbanoglu, 2011). Yet negative and positive emotions are rarely considered simultaneously with another component of affect, interest, which is associated with increased attention, academic goals, and higher levels of learning (Hidi & Renninger, 2006). Notably, math interest includes not only positive emotions in the moment (i.e., *situational interest*), but also a stored sense of value and desire to seek out repeated engagement with mathematics over time (i.e., *personal interest,* Hidi & Renninger, 2006).

The Present Project.

In the present project, we examine the simultaneous relationship between each of the three components of affect in the mathematics classroom—positive emotions, negative emotions, and math interest, which are conceptualized as predictors and as mediators between classroom experiences and students' academic history—and the influence of these affective variables on motivation—mastery goal orientation, performance goal orientation, and self-efficacy, which are conceptualized as outcomes in the present study. The study is part of a longitudinal approach to measuring students' mathematics engagement. As such, it reports early results on the cross-sectional relationships among these variables. Longitudinal relationships will be modelled in subsequent years.

Hypotheses.

From the research, we identified three hypotheses that are tested in this study: (1) significant, negative relationships should exist between *negative emotions* and mastery goal orientation, self-efficacy, and performance goal orientation, (2) significant positive relationships should exist between *positive emotions* and mastery goal orientation, self-efficacy, and performance goal orientation, (3) significant positive relationships should exist between *math interest* and mastery goal orientation, self-efficacy, and performance goal orientation. Correlations are hypothesized to exist among affective variables (specifically, math interest was hypothesized to be positively correlated with positive emotions, but both interest and positive emotions were expected to be negatively correlated with negative emotions), and motivation variables (specifically, mastery goals were hypothesized to be positively related with self-efficacy, and negatively related to performance goals. Performance goals were expected to show a low-to-moderate correlation with self-efficacy).

METHOD

Participants

As part of a larger study on mathematics engagement in secondary classrooms, 296 students enrolled in first-year mathematics classes across three high schools each in Delaware and Arizona were recruited to take a 91-item survey in Spring 2018.

Instrument

The survey used was developed by a team of five researchers with expertise in mathematics learning. They adapted items from previous surveys to reflect four major conceptual dimensions of mathematics engagement: cognitive engagement, behavioural engagement, affective engagement, and social engagement. Preliminary psychometric analyses on this instrument using the pilot data from the present study suggest that the instrument has a seven-factor structure for the Likert items, and a two-factor structure for the categorical emotion items (see Zhang, in prep).

Measures

Emotions were measured using a checklist in which a student was asked to select from a list of 28 emotions, which he or she commonly felt during mathematics class. N*egative emotions* comprised thirteen binary response items, *positive emotions* comprised ten binary response items. *Math interest* was comprised of thirteen 7-point Likert scale items. Motivational constructs were measured on a 7-point Likert scale: mathematics *mastery goal orientation* comprised thirteen items, mathematics *performance goal orientation* comprised five 7-point Likert scale items, and mathematics *self-efficacy* comprised eighteen 7-point Likert scale items (see Zhang, in prep for the wording and source of all items). Each of these constructs was treated as a latent variable in our analyses, thus helping to correct for attenuation in the estimates of our path coefficients due to measurement error.

Analysis

The pertinent variables for this study comprised 69 items, 23 binary and 46 Likert scale. Because of the difference in level of the variables, we treated all responses as ordinal, thus using polychoric correlations and WLSMV estimations with theta parameterization. We used pairwise deletion to handle missing data in our analyses, yielding a final sample size of 296 in each analysis.

First, we estimated the fit of our measurement model using a confirmatory factor model to examine whether our expected latent variables adequately captured common variance in our measured variables (see Figure 1).

Then, we examined the fit of our structural model using a hypothesized latent variable path model to see whether the expected relationships between each of the affective latent predictors (math interest, negative emotions, and positive emotions) and each of the motivational latent outcomes (mastery goal orientation, performance goal orientation, and self-efficacy) fit the data well (see Figure 2). However, because our hypothesized path model was saturated, we did not expect to see a difference in fit from our CFA model. Instead, we were interested in examining and interpreting theoretically relevant path coefficients.

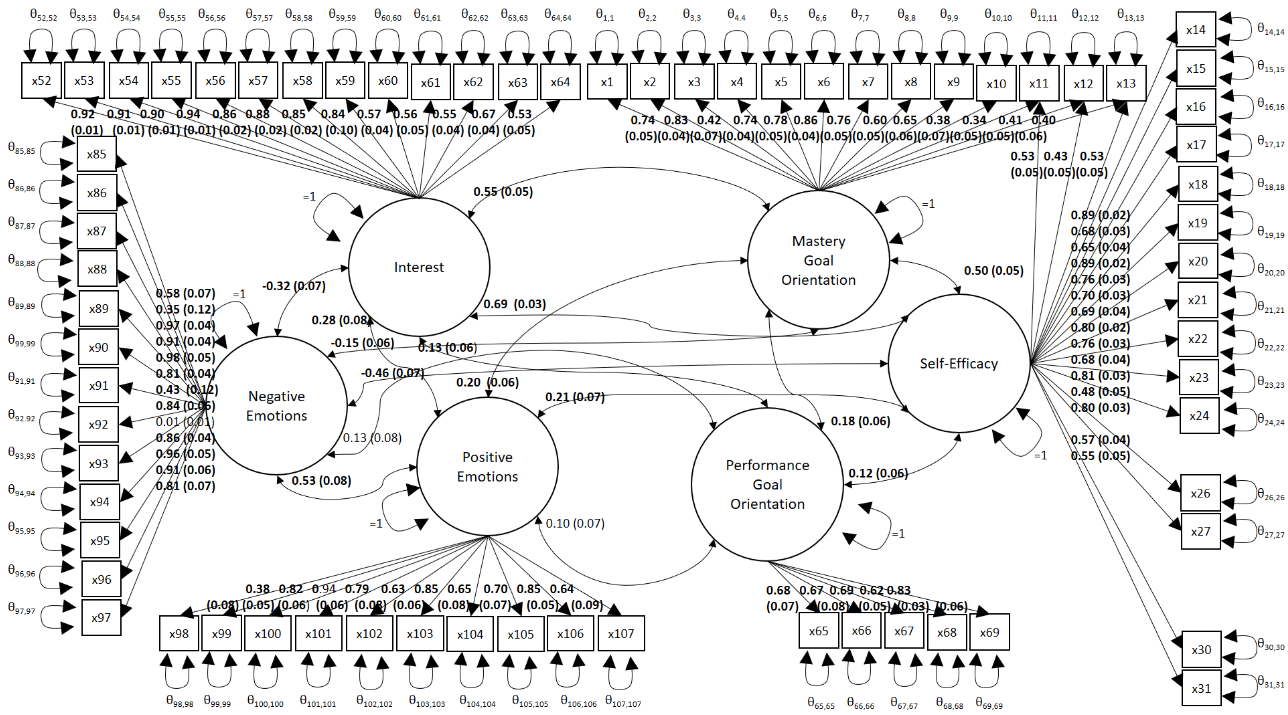

Figure 1. Parameter Estimates for the Confirmatory Factor Model.

Bolded values are significant at the p < .05 level. Standard errors are in parentheses. Results reflect standardized output.

Note also that in the latent path model, there were some significant expected correlations between each of the affective latent predictors (math interest, negative emotions, and positive emotions) and between each of the motivational latent outcomes (mastery goal orientation, self-efficacy, and performance goal orientation), consistent with theoretical conceptualizations of these constructs. All other possible correlations between latent variables were fixed to zero.

For ease of interpretation, we reported the fully standardized results from our output. All models were estimated in MPlus Version 8 (Muthen & Muthen, 2017).

RESULTS

Confirmatory Factor Model

Overall, the confirmatory factor model fit relatively well (see Table 1 for fit statistics). Although our chi square was significant [$\chi^2(2259) = 3800.56$, $p < 0.001$], the rule of thumb that χ^2/df be less than 3 shows that our model has adequate fit. The RMSEA was 0.048 with a 90% confidence interval between 0.045 and 0.051, which indicated relatively good model fit (Browne & Cudeck, 1993; Hu & Bentler, 1999). Moreover, CFI and TLI were also good by standard cutoffs (0.90 - 0.95) (Brown, 2006). However, note that given our use of WLSMV estimation, these estimates may be somewhat artificially high for CFI and TLI and artificially low for RMSEA (Xia & Yang, 2018). Nevertheless, overall, our fit indices suggested that our measurement model fit the data reasonably well. Because the factor structure of these items is addressed elsewhere (Zhang, in prep), we do not interpret factor loadings and parameters estimates here. We instead fit the hypothesized latent variable path model, interpreting parameter estimates.

Model	**Goodness of Fit Index**	**Estimate**
CFA	χ^2	3800.56 (p<.0001)
	df	2259
	RMSEA	0.048 (0.045, 0.051)
	CFI	0.91
	TLI	0.91
Path Model	χ^2	3800.56 (p<.0001)
	Df	2259
	RMSEA	0.048 (0.045, 0.051)
	CFI	0.91
	TLI	0.91

Table 1. Goodness of fit indices for the CFA and Latent Path Models

Hypothesized Path Model

Overall, the hypothesized latent variable path model fit the same as the CFA model (see Table 1 for fit statistics, and Table 2 and Figure 2 for parameter estimates). Together, this suggests that the proposed structural model fit the data well. This is not surprising given the saturated nature of the model at the path (but not measurement) level.

Accordingly, we interpret standardized regression coefficients and correlations between the latent variables, which are theoretically relevant to our research questions (See Table 2 and Figure 2).

The relationships among latent variables are presented at the top of Table 2. In the hypothesized model, there was a significant, positive standardized regression coefficient between math interest and all three motivation variables (mastery goal orientation, performance goal orientation, and self-efficacy). This suggests the potential importance of math interest in terms of supporting multiple components of motivation in secondary math classrooms.

There was also a significant, strong, *negative* standardized regression coefficient between negative emotions and self-efficacy, and a moderate positive coefficient between positive emotions and self-efficacy. Standardized regression coefficients between both emotion factors and the mastery goal and performance goal motivation outcomes were not statistically significant.

Next, we discuss the correlations among the affective variables. There was a significant negative correlation between math interest and negative emotions and a significant positive correlation between math interest and positive emotions, as might be expected. However, contrary to expectations, there was a large significant *positive* correlation between negative and positive emotions.

For the motivation variables, we found a significant, small, positive correlation between mastery goal orientation and self-efficacy, and between mastery goal orientation and performance goal orientation. However, the correlation between and between self-efficacy and performance goal orientation was not significant.

Standardized Regression Coefficients			
	Interest	*Positive Emotions*	*Negative Emotions*
Mastery Goals	0.53***	0.05	-0.01
Performance Goals	0.25**	-0.11	0.27
Self-Efficacy	0.42*	0.37*	-0.52**
Correlations Among Affective Variables			
	Interest	*Positive Emotions*	
Positive Emotions	0.28***		
Negative Emotions	-0.32***	0.53***	
Correlations Among Motivation Variables			
	Mastery Goals	*Performance Goals*	
Performance Goals	0.14*		
Self-Efficacy	0.22**	0.07	

Table 2. Relationships Among Latent Variables

DISCUSSION

In this project, we examined the relationship between three components of affect in the mathematics classroom: positive emotions, negative emotions, and math interest, and three commonly measured aspects of motivation: mastery goal orientation, performance goal orientation, and self-efficacy. Although we expected that negative emotions would be significantly negatively related to mastery goal orientation, performance goal orientation, and self-efficacy, whereas positive emotions and math interest would be significantly positively related to mastery goal orientation, performance goal orientation, and self-efficacy, our hypotheses were only partially supported. Specifically, we found that math interest was significantly positively associated with each of the three motivational outcomes—mastery goal orientation, self-efficacy, and performance goal orientation—as predicted.

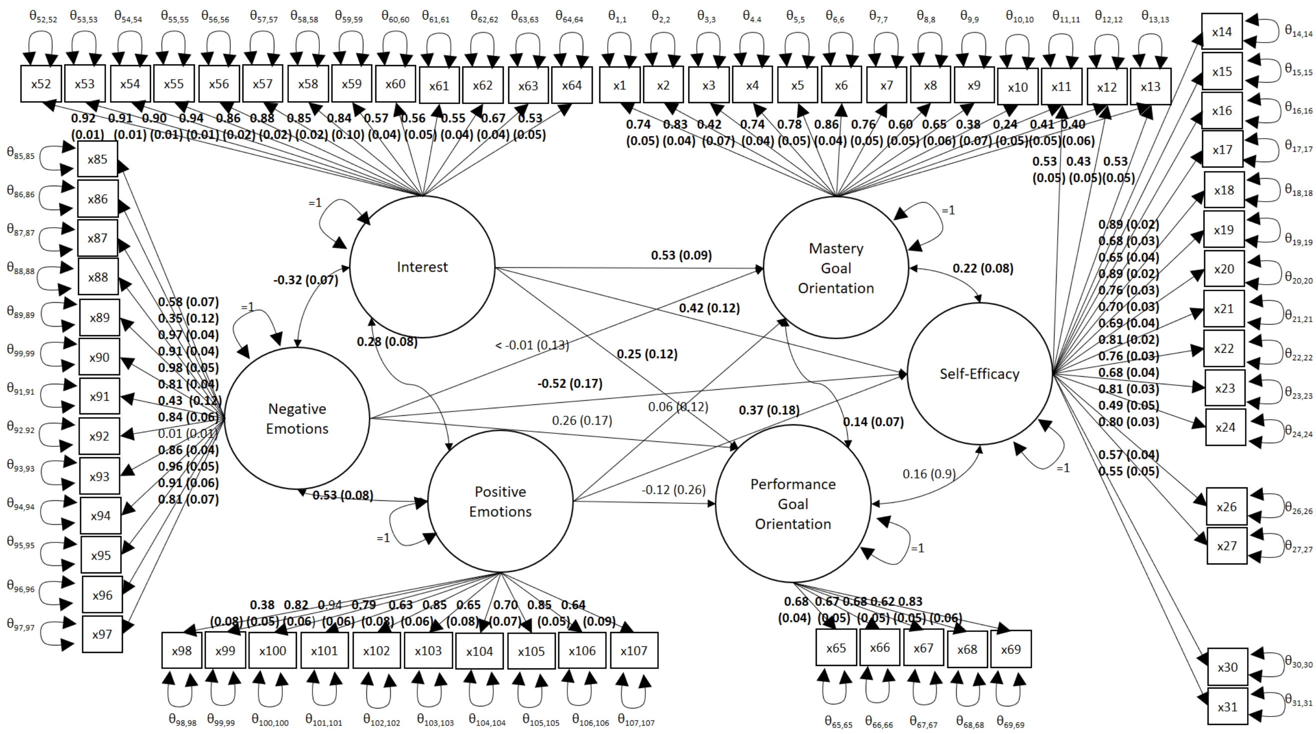

Figure 2. Parameter Estimates for the Hypothesized Latent Variable Path Model

Bolded values are significant at the p < .05 level. Standard errors are in parentheses.

However, our two emotion variables did not quite perform as expected—positive and negative emotions only showed significant relationships with self-efficacy. Specifically, in our sample, positive emotions were positively associated with self-efficacy, whereas negative emotions were somewhat more strongly negatively associated with self-efficacy. Although this is consistent with some prior research (Pekrun et al., 2004, Akin & Kurbanoglu, 2011), it is notable that math interest, which involves a math-specific knowledge structure (Hidi & Renninger, 2006) appeared to be more broadly related to motivation in math classrooms than did positive and negative emotions in our study.

This may be because our measures of emotions were relatively general. Specifically, we operationalized emotions using an item that asked participants to "think about a typical math experience" and indicate which among a list of emotions they felt during that experience. In responding to this question, students may have reflected not only on their feelings about math, but also on their feelings about other agents in the math classroom, such as teachers or classmates, which may have had conflicting influences on mathematics motivation. Indeed, if students were considering a variety of possible sources of math affect, this may help make sense of the unexpected positive correlation between positive and negative emotions in our sample (r = 0.53, p < 0.001). For instance, it may have been that when reflecting on their feelings about a typical math class, students had negative emotions about the math but positive emotions about their peers, or vice versa, thus allowing both positive and negative emotions to correlate when measured in the form of a single, undifferentiated self-report measure.

Whereas our results suggest the importance of disentangling different aspects of math affect, our findings also suggest that future research may benefit from taking this even further by disentangling whether positive and negative emotions felt about the math task, teachers, or classmates also have differing effects on motivation in the classroom. Such work may help us better understand how to foster richer affective and motivational secondary math experiences.

REFERENCES

Akin, A. & Kubanoglu, I. N. (2011). The relationships between math anxiety, math attitudes, and self-efficacy, a structural equation model. *Studia Psychologica, 53*(3), 263-273.

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

Browne, M. W., & Cudek, R. (1993). Alternate ways of assessing model fit. In K.A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136–162). Newbury Park, CA: Sage.

Elliot, A. J., & Dweck, C. S. (2005). Competence and motivation. In A. Elliot & C. Dweck (Eds*.), Handbook of competence and motivation* (pp. 3-12). New York: Guilford Press.

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

Harackiewicz, J. M., Barron, K. E., Pintrich, P., Elliott, A. J., & Thrash, T. M. (2002). Revision of achievement goal theory: Necessary and illuminating. *Journal of Educational Psychology, 94,* 638-645.

Hidi, S., & Renninger, K. A. (2006). The Four-Phase Model of Interest Development. *Educational Psychologist*, *41*(2), 111–127.

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

Mangu, D., Middleton, J. A., & Lee, A. (2016). A longitudinal study of mathematics and science motivation patterns for STEM intending high schoolers in the US. Paper presented at the International Congress for Mathematics Education, July, Hamburg, Germany.

Muthén, L. K., & Muthen, B. O. (2017). Mplus. Los Angeles: Muthen & Muthen.

Pekrun, R., Goetz, T., Perry, R. p., Kramer, K., Hochstadt, M., & Molfenter, S. (2004). Beyond test anxiety: Development and validation of the Test Emotions Questionnaire (TEQ). *Anxiety, Stress & Coping, 17(*3), 287–316.

Xia, Y. & Yang,Y. (2018). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods*, 1-20.

Zhang, X. V. (in prep). *Development and validation of a pilot survey instrument to measure math interest among high school students.* Arizona State University. Unpublished manuscript.