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Relative importance of students' expectancy–value beliefs as predictors of academic success in gateway math courses

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Abstract

Math-intensive fields in postsecondary education, such as physics and math, often struggle with high student dropout rates. Motivational declines after the transition to postsecondary education are a key factor underlying students' achievement difficulties and decisions to leave these fields. A better understanding of which motivational factors play a particularly central role in predicting achievement difficulties and dropout decisions is needed to inform potential interventions. Thus, drawing on Eccles' expectancy–value theory, we examined changes in the relative importance of students' expected success and different task values as unique or joint predictors of students' academic success and course dropout across three time points within a semester. Data were collected in gatekeeper math courses for physics and math majors ($N = 811$). Commonality analyses showed an increasing overlap in the predictive effects of students' expectancies and values on later academic outcomes, which indicates convergence in these motivational beliefs, as they likely influence each other over time. A significant shift in the relative importance of students' expectancies and values occurred after the transition to postsecondary education, highlighting a sensitive time point for interventions. Pre-existing achievement, socioeconomic, and gender differences lost some of their unique predictive power toward the midpoint of the semester.

KEYWORDS
academic success, commonality analysis, motivation, physics, situated expectancy–value theory, STEM

INTRODUCTION

There are national and international concerns about the high levels of student dropout in math-intensive study programs in the domains of science, technology, engineering, and mathematics (STEM).[1–3] In Germany, where the present research was conducted, about half of all students enrolled in a math or science program leave their program without obtaining a degree (for similar statistics in the United States, see Ref. 1).[4] The most math-intensive programs, such as physics and math, are typically most severely affected (59–60% student dropout).[4] Motivational declines and achievement difficulties in gateway math courses after the transition to postsecondary education have been identified as key contributors to these dropout rates.[1,5,6] However, a better understanding of which motivational factors may play a particularly central role in shaping students' dropout decisions, as well as their achievement and academic well-being (e.g., study program satisfaction) is needed to inform potential interventions. Accordingly, the present study used commonality analyses to examine the relative importance of different motivational factors as unique or joint predictors of students' academic success in gateway math courses for students enrolled in physics or math programs.[7] Students' background characteristics (e.g., gender, socioeconomic status [SES], and previous achievement) were also taken into account because they can influence both students' motivational beliefs and later academic success.[1,6,8]

Eccles and colleagues' situated expectancy–value theory (SEVT) is one of the most prominent theoretical frameworks in the motivation literature used to explain students' achievement-related outcomes and choices, including their exam performance and decisions to persist in or drop out of math-intensive fields.[8,9] Students' expectancy of success ("Can I do this?") and subjective task values ("Do I want to do this?") are powerful motivational predictors of these choices, even after controlling for students' prior achievement and cognitive abilities.[10] The theory further suggests that students' overall valuing of a given task or domain is differentiated into positively-valenced (e.g., intrinsic interest and the perceived utility of studying assigned course content) and negatively-valenced task values (i.e., costs), which are the perceived drawbacks of engaging in a task (e.g., the effort needed to be successful; perceived stress).[8] Students' math- or science-related expectancy–value beliefs have consistently emerged as important predictors of their academic achievement, retention, and career attainment in math-intensive fields.[11–14] Eccles' SEVT has also provided the foundation for interventions designed to improve students' academic achievement and persistence in their respective fields of study.[15–18] These interventions typically target selected motivational beliefs and mainly focus on increasing students' perceived utility of the learning material (e.g., for one's studies or future career) or on reducing the perceived costs of engaging with the material (e.g., dealing with challenging coursework).[15] Which types of motivational beliefs—uniquely or jointly—have the greatest predictive power on students' achievement-related choices and behaviors, and whether their predictive power may change over time, is still not well understood.[8,10]

To improve students' academic achievement and retention in math-intensive fields, it is important to identify which motivational beliefs are most likely to affect students' academic outcomes at critical points in their educational careers. Previous research generally suggests that students' expectancy of success is the strongest motivational predictor of their academic achievement, whereas students' valuing of a given domain is the strongest predictor of their decision to engage and persist in that domain.[8,10] However, these analyses have focused almost exclusively on the unique incremental predictive effects of different motivational beliefs, without considering their potential joint predictive effects or their overlap with other relevant factors, such as prior achievement. Because students' motivational beliefs and achievement are intertwined and influence each other over time, failing to account for such shared effects (i.e., commonalities, see Ref. 7) can underestimate the relative importance of different constructs as predictors of students' academic success and decision-making.[7] For instance, the unique predictive effects of students' expectancy on later achievement-related outcomes may be comparatively smaller than those of students' task values when differences in achievement are controlled for. This is because the conceptual and empirical links between expectancy and achievement are typically stronger, which is likely to boost their shared and reduce their unique predictive effects. However, the relative importance of students' expectancies and task values as predictors of later academic success may be comparable when both unique and shared predictive effects (i.e., commonalities between expectancy, task values, and previous achievement) are considered. Therefore, in this study, we considered not only unique but also joint predictive effects in analyses of relative importance.[7]

In addition, situation-specific fluctuations and shifts in students' weighting of different motivational beliefs might be particularly likely after the transition to postsecondary education and may result in corresponding shifts in relative importance. Prior research suggests that students' motivational beliefs decline shortly after the transition to postsecondary education and that these short-term declines significantly predict later academic struggles and dropout tendencies.[11,19,20] Furthermore, different beliefs may shift at different rates and may be more or less salient at different time points. Whereas students' interest in a given domain (e.g., math or physics) may be particularly important for choosing a college major, for instance, students may assign a greater weight to the perceived costs of studying when they face the high demands of studying in math-intensive programs.[21]

Thus, in the present study, we expand upon previous evidence by conducting commonality analyses to examine which expectancy and task value facets have the highest relative importance for students' end-of-term academic success in gateway math courses in physics and math study programs (i.e., for students' study program satisfaction, exam performance, and course dropout) and whether the relative importance of students' motivational beliefs changes over time. Three research questions (*RQs*), focusing on students' study program satisfaction (*RQ1*), exam performance (*RQ2*), and course dropout (*RQ3*) guided our analyses. For each outcome, we asked: First, which expectancy–value facets have the strongest unique predictive effects, controlling for differences in students' background characteristics (gender, prior achievement, and SES)? Second, which expectancy–value facets have the highest relative importance (unique *and* shared predictive effects) in the prediction of students' academic success and satisfaction? Third, does the estimated relative importance of different expectancy–value facets change systematically across students' first semester in postsecondary education, such that some factors may gain predictive power, whereas others may lose it? Commonality analyses allowed us to examine both unique and joint predictive effects of students' motivational beliefs in predicting their academic success as a means to determine their relative importance for students' academic success, which may have been underestimated in previous research focusing mostly on the unique incremental effects of these motivational beliefs (e.g., after accounting for prior achievement).[a]

[a] We conducted additional commonality analyses separately for female and male students to examine whether there are gender differences in the unique and shared predictive effects of students' motivational beliefs on their end-of-term academic success. The main results that we describe here were consistent across both groups. A few meaningful differences emerged beyond these main results and are reported in the Supplementary Material.

MATERIALS AND METHODS

Participants and procedure

Two cohorts of physics (n = 366) and math students (n = 445) who were enrolled in required gateway math courses for their study program at a German university participated in this study (N_{total} = 811, n = 231 female). This study is part of a larger research project described in Benden and Lauermann.[11] The research questions and analyses of the present study have not been addressed previously and are unique. Here, we focus on physics and math students because, as noted earlier, physics and math study programs face particularly severe student dropout rates. Most students were in their first year at the university (89%), were born in Germany (89%), and indicated German as the main language spoken at home (86%). Students completed paper-and-pencil questionnaires at the beginning (T1, Week 2), midpoint (T2, Week 8), and end of the semester (T3, Week 15). Participation was voluntary.

Measures

Students reported their personal characteristics at the beginning of the semester and answered questions about their expectancy–value beliefs at the beginning, midpoint, and end of the semester. Additionally, students rated their study program satisfaction at the end of the semester. All items and references to the original scales from which they were adapted are reported in the Supplementary Material.

Students' personal characteristics

Students reported their gender (31% female), family background, high school grade point average (GPA), and participation in voluntary math preparatory courses prior to enrollment (67% participation). The students' family background was operationalized via student-reported parental occupations. The occupations were coded according to the German Classification of Occupations (KldB), which differentiates between four job skill levels (1 = *requiring little or no education* to 4 = *requiring an advanced degree*).[22] Most students (63%) had at least one parent with an advanced degree; less than 1% had parents whose occupation required little or no education. Therefore, this variable was dichotomized into 0 = *low socioeconomic status* (*SES;* for job skill levels 1–3) and 1 = *high SES* (for job skill level 4). Students' high school GPA was recoded to facilitate the interpretation of results so that higher scores reflected higher achievement (M = 3.19, SD = 0.64, range from 1 to 4).

Expectancy–value beliefs

Students' course-specific *expectancy of success* was measured with three items (e.g., "Based on my experiences in this class so far, I think I will do well on the exam"). Two-item scales assessed students' *intrinsic value* (e.g., "Doing the coursework and the assignments for this class is something I enjoy"), *utility value* (e.g., "Doing the coursework and the assignments for this class is useful for my future"), *psychological cost* (e.g., "Doing the coursework and the assignments for this class is stressful for me"), and *effort cost* (e.g., "Doing the coursework and the assignments for this class drains a lot of my energy"). All items were assessed on a 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. The internal consistencies ranged from α = 0.69 to 0.93 across the three time points (Table 1). For the main analyses, three scale scores were computed for students' expectancy of success, values (intrinsic and utility values), and costs (psychological and effort costs).

Indicators of students' academic success and well-being

Students' study program satisfaction was measured at the end of the semester with five items, which were averaged for the subsequent analyses. Two items assessed students' certainty about their study choice (e.g., "I am certain that my study program is the right choice for me," from 1 = *very uncertain* to 6 = *very certain*); one item measured students' dropout intentions ("I oftentimes think about dropping out of or switching my study program," reverse-scored, from 1 = *completely disagree* to 6 = *completely agree*), and two items captured students' overall satisfaction with their studies (e.g., "In general, I am very satisfied with my study program," from 1 = *completely disagree* to 6 = *completely agree*). The internal consistency of the scale was α = 0.90.

The students' course dropout (i.e., nonattendance at the end of the semester) was recorded by a research assistant and the final exam scores were obtained from the instructor. As is typical for these fields of study, the rates of course dropout were quite high (36%). Students provided written consent to link their survey data with their grades at the midpoint or end of the semester; we used anonymized codes to link their survey data across time points. Overall, 82% of the students who were present at the midpoint or end of the semester gave consent to access their grades. Students who stopped attending the course by the end of the semester did not have performance data. Students in one physics cohort received only pass-fail grades. Accordingly, we conducted a series of commonality analyses predicting different indicators of study success: study program satisfaction, final exam performance (number of points on the exam, which was z-standardized within each math course), whether the student passed or failed the exam, and course dropout. Due to length constraints, we present the results for study program satisfaction, exam performance, and course dropout in the main results section and report additional analyses of pass-fail grades in the Supplementary Material. Our results are consistent across different achievement indicators.

Statistical analyses

Preliminary analyses focused on bivariate correlations among all variables and missing data patterns. Commonality analyses in Mplus 8.6 estimated the proportion of variance in students' study program satisfaction, exam performance, and course dropout that was explained

TABLE 1 Descriptive statistics and observed bivariate correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Female	–																	
2. Socioeconomic status (SES)	0.09*	–																
3. High school GPA	0.04	0.19**	–															
4. Preparatory course	0.07	0.09*	0.19**	–														
5. Instructor-specific dummy 1	−0.04	0.03	0.18**	0.06	–													
6. Instructor-specific dummy 2	−0.03	0.06	0.16**	0.04	−0.38**	–												
7. Expectancy T1	−0.18**	0.04	0.17**	−0.03	−0.01	−0.06	–											
8. Value T1	0.04	−0.01	0.09*	0.07	−0.08*	−0.20**	0.41**	–										
9. Cost T1	0.09*	−0.04	−0.06	−0.03	0.04	0.16**	−0.52**	−0.28**	–									
10. Expectancy T2	−0.22**	0.01	0.24**	0.00	0.15**	−0.14**	0.66**	0.29**	−0.47**	–								
11. Value T2	−0.06	0.02	0.19**	0.04	0.15**	−0.21**	0.37**	0.58**	−0.28**	0.53**	–							
12. Cost T2	0.12**	−0.05	−0.21**	−0.05	−0.07	0.03	−0.36**	−0.12**	0.60**	−0.50**	−0.22**	–						
13. Expectancy T3	−0.18**	−0.03	0.19**	−0.04	0.01	−0.12*	0.62**	0.31**	−0.43**	0.78**	0.39**	−0.45**	–					
14 Value T3	−0.03	0.09	0.14**	0.03	0.01	−0.22**	0.31**	0.51**	−0.25**	0.46**	0.69**	−0.26**	0.46**	–				
15. Cost T3	0.09	−0.06	−0.13**	−0.04	−0.03	0.00	−0.37**	−0.18**	0.59**	−0.49**	−0.23**	0.73**	−0.50**	−0.21**	–			
16. Study program satisfaction T3	−0.11*	0.01	0.19**	0.02	0.03	−0.13**	0.46**	0.39**	−0.40**	0.55**	0.50**	−0.42**	0.58**	0.57**	−0.41**	–		
17. Exam performance	−0.12*	0.06	0.45**	−0.03	0.00	0.00	0.28**	0.19**	−0.33**	0.40**	0.31**	−0.31**	0.44**	0.26**	−0.34**	0.37**	–	
18. Course dropout	−0.06	−0.12**	−0.40**	−0.26**	−0.12**	−0.05	−0.12**	−0.05	0.13**	−0.22**	−0.21**	0.14**	[a]	[a]	[a]	[a]	[a]	–
M	0.31	0.62	3.19	0.67	0.28	0.26	3.74	4.72	3.67	3.42	4.39	4.03	3.43	4.39	3.98	4.46	0.00	0.36
SD	0.46	0.49	0.64	0.47	0.45	0.44	0.87	0.72	1.05	0.96	0.83	1.01	1.01	0.80	0.99	0.95	1.00	0.48
N	751	658	725	655	811	811	719	730	730	569	571	571	449	451	451	451	312	811
Skewness			−0.56				0.10	−0.92	0.01	−0.13	−0.75	−0.33	−0.16	−0.77	−0.10	−0.89	0.03	
Kurtosis			−0.48				0.25	2.12	−0.40	0.14	1.22	−0.14	0.13	1.31	−0.25	0.87	−0.61	
Cronbach's α							0.89	0.69	0.85	0.93	0.75	0.87	0.92	0.76	0.86	0.90		

Abbreviations: T1, beginning of the semester (Week 2); T2, midpoint of the semester (Week 8); T3, end of the semester (Week 15).
[a]Course dropout implies that the students were not present at the end-of-semester data collection and did not take the exam; thus, no motivation and performance data were available to compute correlations.
*$p < 0.05$.
**$p < 0.01$.

uniquely or jointly by the different expectancy–value facets as well as students' personal characteristics.[7,23,24] Commonality analysis is a method of partitioning the explained variance in a multiple regression into unique and common effects of the predictor variables. Unique effects indicate the amount of explained variance that is unique to a predictor variable, whereas common (or joint) effects indicate how much variance is jointly explained by a set of predictors. Commonality analysis thus allows researchers to quantify how much explanatory power is unique to a given predictor as well as shared among (interrelated) predictors.

Students' expectancy of success, values (intrinsic and utility values), perceived costs (psychological and effort costs), and students' personal characteristics were entered individually and jointly as predictors of students' study program satisfaction, exam performance, and course dropout to determine changes in the amount of explained variance attributable to each individual or joint set of predictors. Maximum likelihood estimation with robust standard errors was used across all models. Full information maximum likelihood (FIML) estimation was used to account for missing data. All models were fully saturated (i.e., included all possible predictive paths and associations between the included motivational beliefs, student characteristics, and outcome variables). Instructor-specific dummy variables were included as control variables in all analyses.

RESULTS

Descriptive statistics and bivariate correlations are shown in Table 1. All correlations between students' motivational beliefs and outcomes were in the expected direction: students who reported comparatively higher expectancies and values as well as lower perceived costs were more satisfied with their study program, performed better on the final exam, and were less likely to drop out of their math course. Attrition from the math course (i.e., course dropout) was linked to lower high

TABLE 2 Total unique and common effects of students' expectancy, value, cost, and student characteristics in predicting their study program satisfaction, exam performance, and course dropout

Variables	Study program satisfaction																	
	T1 (R^2 = 0.367)						T2 (R^2 = 0.455)						T3 (R^2 = 0.498)					
	Unique	% of R^2	Common	% of R^2	Total	% of R^2	Unique	% of R^2	Common	% of R^2	Total	% of R^2	Unique	% of R^2	Common	% of R^2	Total	% of R^2
Expectancy	0.045	12.3	0.205	55.9	0.250	68.1	0.051	11.2	0.288	63.3	0.339	74.5	0.052	10.4	0.304	61.0	0.356	71.5
Value	0.049	13.4	0.148	40.3	0.197	53.7	0.078	17.1	0.229	50.3	0.307	67.5	0.107	21.5	0.232	46.6	0.339	68.1
Cost	0.021	5.7	0.155	42.2	0.176	48.0	0.019	4.2	0.185	40.7	0.204	44.8	0.020	4.0	0.174	34.9	0.194	39.0
Student characteristics	0.027	7.4	0.073	19.9	0.100	27.2	0.008	1.8	0.092	20.2	0.100	22.0	0.007	1.4	0.093	18.7	0.100	20.1
	Exam performance																	
	T1 (R^2 = 0.408)						T2 (R^2 = 0.439)						T3 (R^2 = 0.430)					
	Unique	% of R^2	Common	% of R^2	Total	% of R^2	Unique	% of R^2	Common	% of R^2	Total	% of R^2	Unique	% of R^2	Common	% of R^2	Total	% of R^2
Expectancy	0.017	4.2	0.116	28.4	0.133	32.6	0.027	6.2	0.189	43.1	0.216	49.2	0.049	11.4	0.189	44.0	0.238	55.3
Value	0.000	0.0	0.058	14.2	0.058	14.2	0.014	3.2	0.142	32.3	0.156	35.5	0.002	0.5	0.108	25.1	0.110	25.6
Cost	0.028	6.9	0.108	26.5	0.136	33.3	0.011	2.5	0.111	25.3	0.122	27.8	0.006	1.4	0.116	27.0	0.122	28.4
Student characteristics	0.226	55.4	0.075	18.4	0.301	73.8	0.180	41.0	0.121	27.6	0.301	68.6	0.171	39.8	0.130	30.2	0.301	70.0
	Course dropout																	
	T1 (R^2 = 0.289)						T2 (R^2 = 0.320)						T3[a]					
	Unique	% of R^2	Common	% of R^2	Total	% of R^2	Unique	% of R^2	Common	% of R^2	Total	% of R^2						
Expectancy	0.000	0.0	0.058	20.1	0.058	20.1	0.012	3.8	0.106	33.1	0.118	36.9						
Value	0.000	0.0	0.047	16.3	0.047	16.3	0.010	3.1	0.104	32.5	0.114	35.6						
Cost	0.013	4.5	0.059	20.4	0.072	24.9	0.001	0.3	0.072	22.5	0.073	22.8						
Student characteristics	0.209	72.3	0.058	20.1	0.267	92.4	0.173	54.1	0.094	29.4	0.267	83.4						

Notes: Student characteristics were students' gender, high school GPA, SES, and participation in math preparatory courses prior to enrollment. Negative commonalities were close to zero (> −0.005) and fixed to zero. See the Supplementary Material for an overview of all unique and common effects.

Abbreviations: common, sum of all common effects of a predictor; total, unique + common; % of R^2, total effect divided by multiple R^2; T1, T2, T3, course-specific assessments at the beginning (Week 2), midpoint (Week 8), and end of the semester (Week 15), respectively; unique, unique effect of a predictor.

[a]Course dropout implies that the students were not present at the end-of-semester data collection; thus, no motivation data were available to predict course dropout for these students.

school GPA ($r = -0.40$, $p < 0.001$), lower SES ($r = -0.12$, $p < 0.001$), and a lower likelihood of participation in math preparatory courses ($r = -0.26$, $p < 0.001$). Thus, students' personal characteristics were included as auxiliary or control variables in all models to aid the FIML approach.[25,26]

As shown in Table 2, our analyses revealed that students' motivational beliefs, personal characteristics (i.e., gender, high school GPA, SES, and participation in math preparatory courses), and instructor-specific dummy variables explained 37–50% of the variance in students' study program satisfaction, 41–44% of the variance in their final exam performance, and 29–32% of the variance in course dropout.[b] There was a greater increase in the overall amount of explained variance for students' study program satisfaction over time than for their exam performance and course dropout. However, as we show subsequently, there were shifts in the relative importance of different predictor variables for all three indicators of academic success.

Regarding *RQ1*, the commonality analyses revealed that students' valuing of the course material (i.e., the positively-valenced task values) was the strongest *unique* motivational predictor of their study program satisfaction (13–22% of the total explained variance; see Table 2), whereas students' expectancy of success had the highest *relative importance* across the three time points (contributing between 68% and 72% of the overall explained variance). However, the relative importance (i.e., unique *and* shared predictive effects) of students' values increased across the semester and was comparable to their expectancy beliefs by the end of the semester (54–68% of the overall explained variance; Table 2 and Figure 1). This increase was driven both by increases in the *unique* predictive effect of students' values and by increases in the *joint* predictive effects of students' expectancies and values on their study program satisfaction. Thus, analyses that focus only on incremental predictive effects may underestimate the predictive power of individual motivational beliefs, especially at later time points during the semester.

For *RQ2*, we found that students' expectancy of success was the strongest *unique* motivational predictor of their exam performance at T2 and T3, whereas both expectancy and perceived costs had similar *unique* predictive effects on exam performance at T1 (4–11% of the explained variance; Table 2). Similarly, students' expectancy generally had the highest *relative importance* compared to the other motivational constructs at T2 and T3 (49–55% of the total explained variance), whereas both expectancy and costs had similar levels of relative importance at T1 (33%). Finally, whereas the relative importance of students' expectancy and values for the prediction of students' exam performance increased across the semester, the relative importance of students' costs remained relatively stable (Table 2 and Figure 1). At the same time, the *unique* predictive effects of students' personal characteristics (including high school GPA) declined over time (55–40%). These results suggest that students' personal characteristics lost some of their unique predictive effects on students' exam performance, whereas students' motivational beliefs, and in particular their expectancy of success, gained importance.

[b] The instructor-specific dummy variables explained 1.9%, 0.1%, and 3.4% of the variance in students' study program satisfaction, exam performance, and course dropout, respectively.

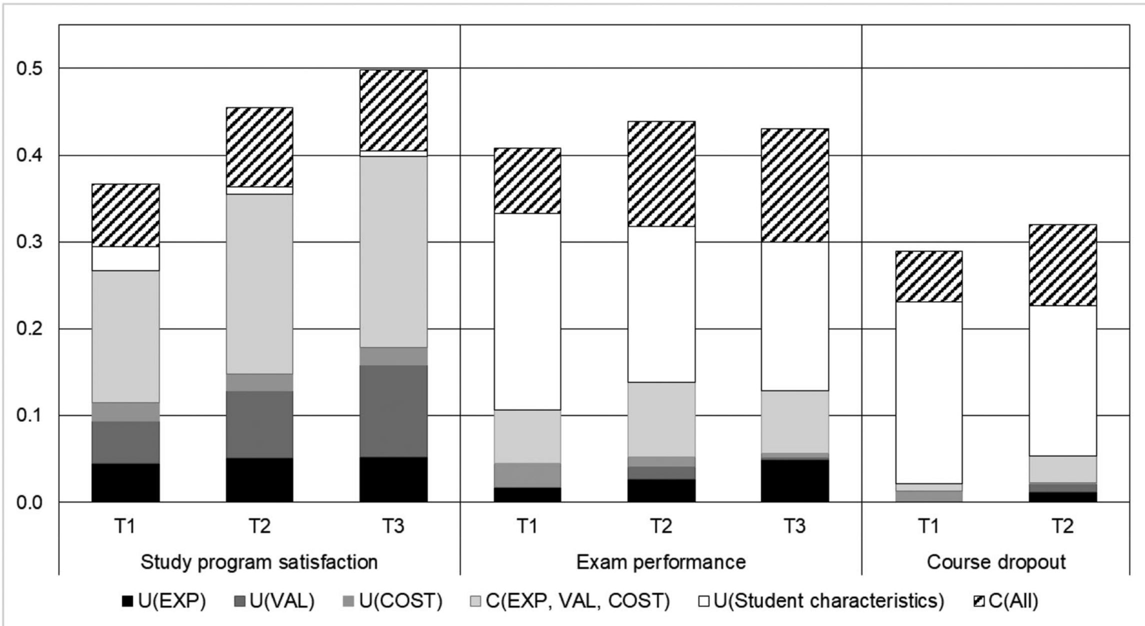

FIGURE 1 Unique and common variance in students' study program satisfaction, exam performance, and course dropout explained by motivational beliefs and students' personal characteristics. Abbreviations: C, sum of all common effects of a predictor; COST, psychological and effort cost; EXP, expectancy; T1, T2, T3, course-specific assessments at the beginning (Week 2), midpoint (Week 8), and end of the semester (Week 15), respectively; U, unique effect of a predictor; VAL, intrinsic and utility value. C(EXP, VAL, COST) = C(EXP, VAL) + C(EXP, COST) + C(VAL, COST) + C(EXP, VAL, COST), C(All) = C(EXP, Student characteristics) + C(VAL, Student characteristics) + C(COST, Student characteristics) + C(EXP, VAL, Student characteristics) + C(EXP, COST, Student characteristics) + C(VAL, COST, Student characteristics) + C(EXP, VAL, COST, Student characteristics). See the Supplementary Material for an overview of all unique and common effects.

Finally, we found similar results regarding students' course dropout (*RQ3*). Students' perceived costs had the strongest *unique* effect on course dropout at T1 compared to the other motivational factors, whereas their expectancy beliefs and values had the strongest *unique* predictive effects at T2 (3–5%; Table 2). Similarly, students' perceived costs had the highest *relative importance* for students' course dropout at T1, and students' expectancy and values had the highest *relative importance* at T2 (25–37%; Table 2). Lastly, the analyses revealed an increase in the *relative importance* of students' expectancy and values from the beginning toward the midpoint of the semester, accompanied by a decline in the *unique* predictive power of students' personal characteristics (Table 2 and Figure 1).

DISCUSSION

Motivational declines in gateway math courses are key contributors to students' achievement difficulties and subsequent student dropout in math-intensive study programs.[1,5,6] A better understanding of which motivational factors may play a particularly important role in shaping students' academic achievement and dropout after the transition to postsecondary education is needed to inform potential interventions. Accordingly, we conducted commonality analyses to examine the relative importance (i.e., predictive power) of different motivational factors for students' end-of-term academic success in gateway math courses for physics and math majors in their first semester in postsecondary education. Our study is the first to examine changes in the relative importance of students' expectancies, values, and costs shortly after the transition to math-intensive study programs in STEM. We summarize and discuss our key findings below.

First, our analyses of *unique* (i.e., incremental) predictive effects revealed that students' expectancy to be successful in their math course was the strongest unique motivational predictor of students' end-of-term exam performance, whereas students' valuing of their coursework (interest and utility values) was the strongest unique predictor of their end-of-term study program satisfaction. This pattern is consistent with our expectations and previous evidence.[12,13,27,28] Our results expand upon this evidence by showing that the unique predictive effects of students' expectancy (on exam performance) and values (on their study program satisfaction) increased over time, while students' background characteristics (e.g., gender, prior achievement, and SES) lost some of their unique predictive power. The increasing importance of students' motivations for their subsequent achievement and study program satisfaction is likely the result of an adaptation process at the beginning of postsecondary education. At the beginning of their studies, students' motivational beliefs may be influenced by unrealistic expectations.[29] Over time, as students gain more experience with their coursework, their expectancy of success likely becomes more realistic, thus leading to an increase in its unique predictive power for students' end-of-term academic achievement. A similar rationale applies to the development of students' valuing of their coursework, as these values become better aligned with students' context-specific experiences.

Second, regarding the *relative importance* of students' motivational beliefs (i.e., combined unique and joint predictive effects), we found that students' expectancies and values had comparable predictive effects on their study program satisfaction and course dropout, whereas students' expectancy had the highest relative importance for their end-of-term exam performance. These analyses expand upon prior research by showing that focusing only on the unique predictive effects of students' expectancy–value beliefs may underestimate their importance as predictors of achievement-related outcomes. Our commonality analyses showed that both students' expectancies and positively-valenced task values had similar predictive power in explaining students' decision-making and well-being in math-intensive fields when their shared effects were considered. Therefore, both types of beliefs should be taken into account to better support students' academic success in math-intensive fields. As noted earlier, most motivational interventions to date have focused on a single motivational belief but interventions targeting both students' expectancies of success and valuing of the course material may have a greater impact on student achievement, persistence, and well-being in STEM fields (e.g., see Ref. 30).[15] Students' perceived costs, by comparison, had smaller unique and shared predictive effects on their academic success (see also Ref. 13), possibly due to the high demands of gateway math courses for all students in STEM fields. Therefore, given that the instructional time for motivational interventions is limited, the effectiveness of such interventions targeting students' expectancy and positively-valenced task values (e.g., interest and utility values) should be compared to cost-reduction interventions in future research.[16–18]

Third, our analyses also revealed systematic *changes in the relative importance* of students' motivational beliefs and background characteristics over time. In line with Eccles and colleagues' assumption, we found time-specific shifts in the relative importance of different expectancy–value facets in the prediction of students' end-of-term academic success and well-being in demanding math courses shortly after the transition to postsecondary education.[8] The amount of variance that was jointly rather than uniquely explained by students' expectancy of success and their valuing of the course material (i.e., intrinsic and utility values) increased substantially across the semester. This finding indicates that students' expectancies and values likely influenced each other over time and that their predictive effects on students' academic success converged as students gained more experience in the new educational context (e.g., by receiving repeated performance feedback in their math courses). This finding further suggests that motivational declines shortly after the transition to postsecondary education that have been found in prior research are accompanied by an increasing overlap of students' expectancies and values in predicting their academic success.[11,19,20] Accordingly, motivational interventions might be particularly important in the early stages after the transition to postsecondary education before students' motivations start to decline and before their predictive effects converge toward the midterm.[15] Students' motivational beliefs may be more malleable at this time.

CONCLUSION

A key objective of the present study was to examine the relative importance of students' expectancy of success, values, and perceived costs for their academic success in gateway math courses for beginning physics and math majors while controlling for students' background characteristics (gender, prior achievement, and SES). Our analyses revealed a significant shift in the relative importance of students' math-related expectancy–value beliefs for their academic success shortly after the transition to postsecondary education. We found an increasing overlap between students' expectancies and values (but not costs) in predicting their end-of-term academic achievement, study program satisfaction, and course dropout, suggesting that the predictive effects of these motivational beliefs converged over time. At the same time, the unique predictive role of students' expectancy for their academic achievement and students' values for their study program satisfaction increased. Interventions to support students' motivation, achievement, and retention in STEM fields are thus needed in the early stages of students' postsecondary careers before these motivational beliefs converge and should target students' expectancies of success and valuing of the course material.

AUTHOR CONTRIBUTIONS

D.K.B. Conceptualization of theoretical framework and analysis; formal analysis; writing; review; editing. F.L. Conceptualization of theoretical framework and analysis; writing; review; editing.

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COMPETING INTERESTS

The authors declare no competing interests.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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