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Using cost to improve predictions of adolescent students' future choice intentions, avoidance intentions, and course grades in mathematics and English

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ABSTRACT

Understanding students' perceptions of the negative aspects of task engagement, known as cost, can provide new insights regarding how to predict outcomes related to students' learning behavior in school. The present study investigated the associations of cost, compared to and in interaction with self-efficacy and task value, with students' future choice intentions, avoidance intentions, and expected or actual course performance. Associations were assessed separately in two studies and focused on the subject areas of mathematics and English. Participants were students (N = 598 in Study 1 and N = 443 in Study 2) aged between 13 and 18 from two schools in Shanghai, China. For each subject domain in each study, three structural equation models were examined to test the unique associations of cost with outcomes, controlling for self-efficacy and task value. Latent moderated structural equation modeling was used to examine interaction effects among the motivational constructs. Results from two studies demonstrated that cost related negatively to students' course performance in both subject areas. In both studies, cost also interacted with task value in predicting avoidance intentions in both subject areas. Findings highlight the importance of including cost in the expectancy-value framework in order to capture more fully the factors that affect students' motivational dynamics in school.

1. Introduction

What drives some students to want to learn while other students avoid schoolwork? Among the theoretical frameworks used to explain students' motivation to learn, Eccles et al.'s (1983) expectancy-value theory provides one of the most comprehensive explanations of the factors that shape students' motivation and academic outcomes. The theory posits that two main forces influence academic motivation: the extent to which students expect to succeed on a task, and the extent to which they find the task to be valuable (i.e., whether it is important, interesting, and useful to them). According to the theory, students who expect to perform better in a given subject area and value their learning more in that area are more likely to pursue courses and activities related to it, engage more deeply with their learning in it, and achieve higher. Indeed, a large body of empirical research confirms that students' task value and expectancies (or related beliefs about competence, such as self-efficacy) are powerful predictors of academic engagement and performance (Bong et al., 2012; Durik et al., 2006; Musu-LeGallette et al., 2015; see Eccles & Wigfield, 2020, Rosenzweig et al., 2019, for reviews).

Although this evidence is helpful in understanding motivation, it is also limited. That is, there are many occasions where students value their learning and expect to succeed but still do not engage with a learning task because they have negative perceptions of it (e.g., they think the task will take too much time away from other activities). Motivation has both positively- and negatively-valenced components and both can influence students' academic outcomes (Atkinson, 1964). A major way that expectancy-value theory conceptualizes negatively-valenced motivational beliefs is in terms of *cost*, defined as perceptions of the negative consequences of engaging with a task (Wigfield & Eccles, 1992). Theoretically, cost has always been part of the expectancy-value theoretical model, but it has not received much empirical attention until recently (see Wigfield et al., 2017, for review). Emerging research suggests that cost may affect students' academic performance, intentions to major in certain fields, classroom affect, and avoidance-related behaviors in school (e.g., adoption of avoidance goals) (e.g., Battle & Wigfield, 2003; Conley, 2012; Flake et al., 2015; Jiang et al., 2018; Jiang et al., 2020; Perez et al., 2014). Additionally, theory suggests that students' perceptions of cost might affect their learning most strongly when students' task value is lower (Eccles, 2005). However, very little research has examined systemati-

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cally how cost relates to different types of learning outcomes, controlling for other constructs in expectancy-value theory; further, little work has explored whether cost interacts with task value and/or expectancies to predict learning outcomes. In the present study we examined these predictive relations across two subject areas and using two different data sets.

1.1. Understanding cost and its relation to learning

As noted above, cost refers to students' perceptions of the negative consequences of engaging with a task (Wigfield & Eccles, 1992). There are many negative consequences of task engagement and thus are many different types of costs, including not only costs that are associated with particular academic activities (e.g., doing mathematics homework) but also costs of participating in academics versus doing other things (e.g., working, Gorges, 2016). In the present study we focused on perceptions of cost for completing coursework in academics, rather than all possible types of cost; this is because in secondary school, participation in academics is typically compulsory. We were therefore interested in considering how students think about the negative consequences of the academic tasks they are required to complete while in school (e.g., coursework within a particular subject area). There are many types of negative consequences associated with tasks, and accordingly expectancy-value researchers study many different types of cost. The three most often studied are: perceptions of how much effort is required by a task, perceptions of valued alternative activities that one must give up to complete a task, and perceptions of negative emotional and psychological consequences of doing a task (Wigfield et al., 2017). Researchers working within expectancy-value theory sometimes measure and study cost as one overall construct reflecting the multiple types of negative consequences associated with a task (e.g., Guo et al., 2016; Jiang et al., 2018; Rosenzweig et al., 2019; Trautwein et al., 2012) and sometimes focus on the distinct dimensions of cost (e.g., Perez et al., 2014; Perez, Dai, et al., 2019).

Researchers debate the precise relationship of cost to expectancies and task value (Barron & Hulleman, 2015; Wigfield & Eccles, in press). Some researchers argue that cost should be considered an independent motivational construct from task value and expectancies, whereas others argue that cost primarily affects task value and as such should be considered part of the task value construct. More research is needed to determine which of these arguments holds more merit. However, both approaches agree in suggesting that cost (a) acts as a negative force on students' motivation to learn and (b) can be distinguished empirically from the other components of task value (i.e., intrinsic, utility, and attainment value). Consistent with those ideas, and in order to capture most fully the unique role of cost for influencing academic outcomes in this study, we chose to measure and assess cost separately from task value in this study.

Emerging research suggests that cost is influential in affecting adolescent students' academic behaviors and outcomes. Conley (2012) found that cost was the key variable discriminating middle-school students' motivational patterns in mathematics, with students whose motivational patterns included high cost performing worse in mathematics courses and reporting more negative classroom affect. Perez et al. (2014) found that college students who perceived higher cost for STEM majors reported higher intentions to leave STEM majors; similarly, Battle and Wigfield (2003) and Robinson et al. (2019) found that graduate students who perceived higher cost reported lower intentions to attend graduate school. Robinson et al. (2019) and Flake et al. (2015) reported that cost related negatively to college students' academic performance, although Perez et al. (2014) did not find significant relations of cost with performance. Finally, Jiang et al. (2018) found that cost predicted middle and high school students' adoption of avoidance goals, negative classroom affect, procrastination, intentions to avoid studying, and exam scores in mathematics.

These findings suggest that cost may predict a variety of academic outcomes (e.g., not just performance but also intentions to engage with certain fields and/or intentions to avoid doing schoolwork in certain fields). This idea is particularly important to explore because cost may not predict all academic outcomes equally well. Much research within expectancy-value theory suggests that the other motivational constructs from the theory show differential predictive patterns with different outcomes. That is, competence-related beliefs tend to predict strongly students' academic performance (e.g., Bong et al., 2012; Durik et al., 2006) but do not always predict students' intentions and/or actual decisions to take more courses or do activities related to specific subjects in the future; task value tends to show the opposite pattern (e.g., Durik et al., 2006; Musu-Gillette et al., 2015). It is possible that cost also shows differential predictive patterns. For example, perhaps cost predicts avoidance-related behaviors more consistently than it predicts intentions to engage with learning. It is difficult to assess this possibility directly using extant research, because the studies just noted differ in terms of not only outcomes assessed but also samples used and measures of cost. Additionally, many studies did not control for the other expectancy-value motivational constructs and thus did not isolate the predictive effects of cost.

Few researchers to date have investigated how cost relates to multiple different types of academic outcomes within one data set, while controlling for competence-related beliefs and task value. We know of only three studies that have evaluated this topic. Jiang et al. (2018) found that among middle and high school students, cost was a stronger predictor of procrastination and intentions to avoid studying mathematics compared to competence-related beliefs or task value; it also predicted performance but did so less strongly than competence-related beliefs. Similarly, Guo et al. (2016) reported that cost predicted negatively German high school students' achievement and teacher-rated classroom engagement; however, competence-related beliefs were the strongest predictors of these outcomes. Finally, Perez et al. (2014) found that effort cost was the strongest predictor (relative to competence-related beliefs or task value) of college students' intentions to leave STEM majors; however effort cost did not predict students' chemistry course grades. These studies suggest that cost may relate to performance, avoidance-related outcomes such as procrastination, and/or intentions to engage positively with learning, but these findings need to be replicated with more research. Additionally, all three studies were limited to the subject areas of mathematics and/or science; theoretically we expect cost to predict academic outcomes similarly across all domains, but it is important to confirm this proposition empirically by examining relations in other subject areas.

1.2. Interaction effects among cost, competence-related beliefs, and task value

In addition to considering how cost predicts different types of outcomes *compared to* competence-related beliefs and task value, it is also important to consider the possibility that cost might *interact with* competence-related beliefs or task value to predict outcomes. Eccles et al. have posited that there may be positive interactive effects of expectancy and task value in predicting academic performance and choices (Wigfield & Eccles, 1992). That is, if a student has very low expectancy for success on mathematics homework, thinking the homework is more useful (i.e., a value increase) might not be sufficient to motivate the student to complete the problems (Feather, 1982). The effect of low expectancy on performance might dampen the effect of task value on that outcome; conversely, students with high expectancy may perform much better, in a synergistic way, from thinking that the homework is more valuable. Extant empirical research is mixed in terms of whether researchers observe positive, negative, or no interactions between task value and competence-related beliefs on academic outcomes (see Wigfield et al., 2017, for review), but empirical research confirms that at least in some circumstances students' competence-related beliefs interact positively with their perceptions of task value in predicting academic performance, choice of courses, and intentions to pursue certain careers (Guo et al., 2015; Guo et al., 2017; Nagengast et al., 2011; Trautwein et al., 2012).

Cost might similarly interact with task value and/or competence-related beliefs in predicting academic outcomes. Theoretically, Eccles (2005) posited that individuals weigh cost against value in deciding which activities to pursue. This implies that cost would influence academic outcomes more strongly (and negatively) when students also perceive that their coursework has less value. In practical terms, a student may think their science coursework has high perceived value (e.g., it is interesting) but also perceive that the coursework has high cost (e.g., it will take too much time, it takes away from other enjoyable activities). If an educator tries to help that student perceive more value for the coursework, for example by making it more interesting, this value boost might not be as impactful as it would for a student who perceived lower cost and thus did not have to weigh cost against value as much in deciding whether to engage with the material.

Similarly, although Eccles et al.'s expectancy-value theoretical research does not touch on this idea, Barron and Hulleman (2015) posited that cost might influence the extent to which students' competence-related beliefs affect students' academic outcomes, or vice versa. That is, one may expect cost to affect academic outcomes more strongly when students' perceived competence is lower.

Understanding potential interactions among the expectancy-value constructs is imperative, because real students' motivational beliefs do not occur in a vacuum; any given student will experience competence-related beliefs, task value, and cost simultaneously. It is essential to understand how these variables function alongside one another, in addition to understanding each variable's independent impact, in order to determine most fully how changes to one motivational construct will affect their learning in real classrooms.

Few studies have explored interactions among cost and competence-related beliefs or task value. Conley (2012) and Perez, Wormington, et al. (2019) examined how competence-related beliefs, task value, and cost were patterned together within students and how those patterns influenced academic outcomes, but these person-centered studies do not allow researchers to model the nature of interactions among specific motivational variables. Besides that work, Trautwein et al. (2012) and Guo et al. (2016) both found interactions between students' competence-related beliefs and cost in predicting German adolescents' mathematics achievement, such that competence-related beliefs predicted achievement more strongly when perceptions of cost were lower. Similarly, Perez, Dai, et al. (2019) found an interaction between undergraduate students' expectancy beliefs and perceptions of effort cost in predicting biology achievement. These findings support theoretical hypotheses by Barron and Hulleman (2015) about the potential interaction of cost with competence-related beliefs and both pieces of evidence suggest that when students perceive lower cost, the effect of competence-related beliefs on performance may be stronger. Although informative, this topic necessitates more research given that the aforementioned studies focused only on relations with course performance, were limited to STEM domains, and did not include potential interactions between cost and task value.

One reason that more researchers have not studied interaction effects in expectancy-value research is because such effects typically are small, and a very large number of subjects may be needed to detect such interactions (Marsh et al., 2004). Even small effects can be informative in demonstrating how individuals' motivational beliefs interrelate to affect learning. Fortunately, new statistical approaches provide more power to examine multiplicative relations between constructs, such as the latent moderated structural equation approach (Kelava et al., 2011). We utilize this approach in the present study in order to maximize our capabilities to detect interactions among cost, expectancies and task value.

1.3. The present study

In the present study, using structural equation modeling (SEM), we examined how adolescent students' perceptions of cost related to their intentions to pursue future activities related to a given subject, their intentions to avoid engaging with a given subject, and their expected or actual course performance in two subject areas, mathematics and English. In order to isolate the unique effects of cost, we controlled for the other constructs in the expectancy-value model (i.e., competence-related beliefs and task value). We also tested for interaction effects among cost, competence-related beliefs, and task value.

We examined these research questions across two studies, one of which utilized cross-sectional data and the other which utilized longitudinal data. We hypothesized that cost would predict unique variance in all three learning outcomes in mathematics, as prior research has reported each of these relations (e.g., Battle & Wigfield, 2003; Jiang et al., 2018; Perez et al., 2014). Additionally, because the theoretical arguments behind the predictive utility of cost are not specific to particular academic domains according to the expectancy-value theory (e.g., Eccles et al., 1983; Wigfield & Eccles, 2000), we expected that we would find the same patterns of results for English as we observed for mathematics. Our hypotheses about the interactions of cost, competence-related beliefs, and task value were all tentative given the lack of systematic research examining cost predicting different academic outcomes. However, based on theoretical predictions (e.g., Eccles et al., 1983), we expected that cost and task value might interact negatively in predicting the three academic outcomes. Additionally, based on prior empirical research we expected that cost might interact negatively with competence-related beliefs in predicting the academic outcomes. For example, if a student had high task value or high competence-related beliefs, this may mitigate the undermining effect of cost on students' academic outcomes.

2. Study 1

The objective of Study 1 was to explore how students' perceptions of cost might predict their future choice intentions, avoidance intentions, and expected course grades in mathematics and English, both independently and in interaction with competence-related beliefs and task value. We tested our hypothetical models using cross-sectional data in this study. Nonetheless, we chose to model cost as a predictor of academic outcomes rather than modeling bidirectional relations between cost and the academic outcomes, because a growing body of evidence has shown cost to predict students' academic outcomes over time (e.g., Conley, 2012; Jiang et al., 2018, 2020; Perez et al., 2014), and because expectancy-value theory argues that cost predicts academic avoidance, engagement, and performance (e.g., Eccles et al., 1983; Wigfield et al., 2016; Wigfield et al., 2017).

2.1. Method

2.1.1. Participants and survey procedure

Participants were 598 students (318 boys, 272 girls, 8 did not indicate gender; Mean age = 14.8 years, *SD* = 1.61) from five seventh-grade classrooms, six eighth-grade classrooms, three tenth-grade classrooms, and four eleventh-grade classrooms in one school in Shanghai, China. The school was a bilingual school, and as such all students took both mathematics and English courses. Chinese secondary schools begin their academic year in September, and a typical semester lasts for about four months. Data were collected in October 2016,[2] midway through the semester. Participants completed paper surveys during classroom hours which were administered by teachers. All students consented to participate and were treated in accordance with APA ethical guidelines; all procedures were performed in compliance with all relevant institutional guidelines regarding human subjects protection. Institutional Review Board approval for this study was deemed not necessary under the guidelines of the university at which the research was conducted, due to the study not collecting identifying information and asking questions of no more than minimal risk to participants.

2.1.2. Measures

All survey items were administered in Chinese and referred to the subjects of mathematics and English (full list of items is provided in the Appendix). The same items were used to assess students' beliefs about mathematics as were used for English, with only the name of the subject differing. Items which were originally developed in English were put through a translation-and back-translation procedure suggested by Brislin (1970) to ensure that the Chinese translations were appropriate. All items used six-point Likert-type scales ranging from 1 (*completely disagree*) to 6 (*completely agree*).

2.1.2.1. Cost Twelve items measuring students' perceptions of cost were taken from a questionnaire developed by Jiang et al. (2020). The measure assesses four dimensions of cost: effort cost, opportunity cost, ego cost (or psychological cost), and emotional cost. These dimensions align with the three dimensions of cost most commonly studied in prior research, while breaking the psychological/emotional cost component into two separate dimensions. Results from confirmatory factor analyses (CFA) showed that a four-factor model treating each dimension of cost as a separate factor had reasonable model fit: $\chi^2(48) = 241.970$, CFI = 0.966, TLI = 0.953, RMSEA = 0.082, and SRMR = 0.030 for mathematics and $\chi^2(48) = 322.179$, CFI = 0.960, TLI = 0.944, RMSEA = 0.099, and SRMR = 0.028 for English. However, the correlations between the four latent factors representing the different cost dimensions were quite high in both subjects ($0.64 \leq rs \leq 0.86$ in mathematics and $0.75 \leq rs \leq 0.92$ in English). This suggested that a general factor might exist that would be useful for conceptualizing the predictive role of cost for academic outcomes.When modeling data with one general factor that includes several sub-factors, researchers often use one of two approaches. Researchers might treat the general factor as a second-order factor, with several sub-factors underneath it; in this case the sub-factors have their shared variance explained by the higher order factor, and any remaining variance in each sub-factor coming from particular survey items is reflected in what is known as a statistical "disturbance" for each sub-factor. Alternatively, researchers can use a bifactor model, which treats the overall factor as a distinct latent entity from its sub-factors and still reflects the shared variance among the sub-factors; however, the variance in each sub-factor not explained by the overall factor is modeled as a separate factor statistically. In recent years, many researchers have argued that for multidimensional scales, a bifactor model can provide a particularly useful structural representation compared to second-order factor models (e.g., Chen et al., 2006; Chen et al., 2012; Reise, 2012; Reise et al., 2012; Reise et al., 2013). For instance, the bifactor model tends to fit better when there are unmodeled complexities among items being modeled (e.g., cross-loadings, correlated errors). In the field of motivation research, several studies have already utilized bifactor models when investigating value-related beliefs within the expectancy-value framework (e.g., Guo et al., 2016; Jiang et al., 2020). Moreover, Part et al. (2020) have found that bifactor models demonstrated superior model fit than other competing models when representing task value beliefs. Given the relative benefits of a bifactor model relative to a higher-order factor model, as well as the fact that prior expectancy-value research has used a bifactor model, we chose to model cost using a bifactor approach in the present study.The bifactor model demonstrated good model fit: $\chi^2(42) = 193.459$, CFI = 0.973, TLI = 0.958, RMSEA = 0.078, and SRMR = 0.024 for mathematics and $\chi^2(44) = 251.855$, CFI = 0.969, TLI = 0.954, RMSEA = 0.090, and SRMR = 0.023 for English. Using the Bifactor Indices Calculator (Dueber, 2017), we evaluated the psychometric properties of the bifactor model against several recommended criteria (Rodriguez et al., 2016). In particular, we examined the model-based reliability of the general cost factor and of the four specific sub-factors representing the cost dimensions. Model-based reliability provides information about whether each component of the model (in this case, the general factor and the sub-factors) reliably represents the target constructs of interest after considering other aspects of the model. This is evaluated by using the coefficient omega hierarchical (ωH) and Omega Hierarchical subscale (ωHS). Specifically, ωH reflects variance explained by general factor after partialling out the variance explained by the specific sub-factors, whereas ωHS reflects variance explained by specific sub-factors after partialling out the variance explained by the general factor. Table 1 presents detailed results for the bifactor CFA. On the model level, the Percentage of Uncontaminated Variance (PUC), which represents the proportion of covariance terms that reflect variation from a general cost factor as opposed to the specific dimensions of cost, was 0.818 for both mathematics and English. On the factor level, the Explained Common Variance (ECV) indicated that 75% and 81% of the total common variance was explained by the general cost factor in mathematics and English, respectively. The ωH for general cost, an indicator of reliability expressed in terms of the variance explained by general cost after partialling out the variance explained by the four specific costs, was 0.89 in mathematics and 0.93 in English. In contrast, the ωHS, an indicator of reliability expressed in terms of the variance explained by specific costs after partialling out the variance explained by the general cost, ranged from 0.08 to 0.42 for the four specific costs across two subject domains. These tests indicated that the four specific dimensions of cost did not possess sufficient reliability after partialling out variance attributable to general cost in the bifactor model. Thus it was the general cost factor more so than the specific sub-factors of cost which was likely to be meaningful for interpreting the predictive utility of cost in the present data (e.g., Reise, 2012; Reise et al., 2012; Rodriguez et al., 2016). We therefore proceeded to interpret the predictive relations for only the general cost factor in the model to answer our research questions, as opposed to interpreting the predictive relations for both the general cost factor and the sub-factors representing each dimension of cost.

2.1.2.2. Task value Six items measuring task value were adopted from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991). In this study we were interested in comparing the predictive utility of the cost construct with that of the task value construct as it is conceptualized without considering cost. This goal aligned well with the MSLQ task value scale, which measures three dimensions of positively-valenced task value (utility, attainment, and interest value) and not perceived cost. This scale has been used by many previous researchers when investigating the effects of task value on academic motivation (e.g., Bong, 2001; Jacobs et al., 2002; Liem et al., 2008).Similar to the procedures used in assessing reliability for the cost scale, we conducted a bifactor CFA model to examine the model-based reliability of the task value scale. The model fits were:

[2] Portions of the data collected for this study (the measures of self-efficacy and cost in Study 1) were utilized in another paper which examined the cross-cultural validity of a value/cost scale in this sample, along with samples from Germany and South Korea (Gaspard et al., 2020). The research questions of these two studies are substantially different; as such the manuscripts represent quite distinct contributions to the motivation literature.

Table 1
Standardized loading pattern for the cost items bifactor CFA in Study 1.

Item	GC	EFC	OPC	EGC	EMC
EFC1	.64/.74	.27/.17			
EFC2	.73/.83	.52/.56			
EFC3	.84/.85	.33/.24			
OPC1	.74/.84		.34/.31		
OPC2	.74/.87		.29/.25		
OPC3	.80/.84		.48/.35		
EGC1	.64/.69			.49/.47	
EGC2	.58/.66			.63/.59	
EGC3	.55/.67			.59/.48	
EMC1	.83/.83				.33/.22
EMC2	.83/.85				.19/.06
EMC3	.80/.86				.42/.52
Psychometric Properties	GC	EFC	OPC	EGC	EMC
ω/ωS	.96/.97	.87/.91	.91/.93	.87/.88	.91/.93
ωH/ωHS	.89/.93	.18/.13	.16/.11	.42/.33	.12/.08
PUC	.818/.818	–/–	–/–	–/–	–/–
ECV	.750/.810	.051/.042	.049/.030	.112/.085	.037/.034

Note. Path coefficients in mathematics are presented to the left of the slash; those in English to the right. All factor loadings included in the table are significant at $p < .001$. GC = general cost; EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost. ω = omega coefficient for general factor; ωS = omega subscale coefficient for subscales; ωH = omega hierarchical coefficient for general factor; ωHS = omega hierarchical subscale coefficient for subscales; PUC = percent of uncontaminated variance; ECV = explained common variance.

$\chi^2(6) = 48.918$, CFI = 0.977, TLI = 0.944, RMSEA = 0.110, and SRMR = 0.024 for mathematics and $\chi^2(6) = 37.646$, CFI = 0.979, TLI = 0.946, RMSEA = 0.095, and SRMR = 0.028 for English. The results revealed that the PUC was 0.80 on the model level for both mathematics and English, indicating that 80% of covariance terms reflect variance from the general task factor as opposed to the specific dimensions of task value. In addition, the ωH for general task value was 0.85 for mathematics and 0.82 for English, whereas the ωHS for the three task value dimensions ranged from 0.18 to 0.40 across two subject domains. Thus, similar to the cost scale, only the general task value but not the specific dimensions of task value seemed to be meaningful for interpretation in the present data (e.g., Reise, 2012; Reise et al., 2012; Rodriguez et al., 2016). Like with the cost construct, we therefore chose to interpret the predictive relations only for the general value construct in this study.

2.1.2.3. Self-efficacy We measured students' self-efficacy, defined as their perceived capabilities to execute desired courses of action, for learning mathematics or English as an indicator of their competence-related beliefs for that subject. The constructs of self-efficacy and expectancies for success from expectancy-value theory are conceptually distinct (e.g., Wigfield & Eccles, 2000), but they overlap empirically (e.g., Bong & Skaalvik, 2003); as such we consider both constructs to be indicators falling under the umbrella term of competence-related beliefs. Six items measuring self-efficacy were adopted from the self-efficacy sub-scale of the MSLQ (Pintrich et al., 1991) and modified by Bong (2008) (αs = 0.90 mathematics; 0.93 English).

2.1.2.4. Future choice intentions Three items measured academic-related future choice intentions, defined as the degree to which students wanted to pursue future math- or English-related courses, majors, and/or careers (αs = 0.89 mathematics; 0.90 for English). All three items were adapted from measures by Bong (2001) and Meece et al. (1990).

2.1.2.5. Avoidance intentions Three items developed by Jiang et al. (2018) measured avoidance intentions, defined as the degree to which students tried to avoid engaging with their mathematics or English classes and coursework (αs = 0.93 mathematics; 0.94 English).

2.1.2.6. Expected course grades We asked students to report the grades that they expected to earn in their mathematics and English courses' final exams during the semester when they completed the surveys. Students rated these on a 0–100 scale. Expected course grades were reported approximately two months prior to students receiving their actual grades, and as such we consider this measure to be an indicator of students' future likely academic performance rather than a fully objective indicator of their course performance.

2.1.3. Statistical analyses

All analyses were conducted in Mplus 7.4. In this study, participants were recruited from 18 class sections. We thus created 17 dummy variables and used them as covariates to account for nonindependence of data due to the nesting of students within classes in the models. Demographic variables (i.e., gender and age) were included as control variables in these models because previous researchers have reported gender- and age-related differences in cost and task value perceptions toward mathematics and English (e.g., Gaspard et al., 2015; Watt, 2004; Yeung et al., 2011); moreover, demographic variables have been found to predict students' academic achievement and educational aspirations (Guo et al., 2015; Watt et al., 2012). The approach of controlling for gender and age is consistent with that of previous researchers (e.g., Jiang et al., 2018; Trautwein et al., 2012) who have investigated the role of cost and task value in students' academic outcomes. Missing data was relatively low (less than 1.7% for any item) and was addressed using full information maximum likelihood (FIML) estimation (Schafer & Graham, 2002).

We specified three SEM models, separately for each subject domain (mathematics or English). In Model 1, we regressed all three outcome variables (i.e., future choice intentions, avoidance intentions, and expected course grades) on self-efficacy, task value, and the control variables (gender, age, and the 17 dummy variables representing class section). The purpose of these models was to examine whether the associations of self-efficacy and task value with all outcomes were consistent with what has been found in prior literature. In Model 2, we added cost as an additional predictor to elucidate its unique association with each outcome. In Model 3, we added interactions between self-efficacy, task value, and cost as additional predictors.

To test for interaction effects, we applied the latent moderated structural (LMS) equation modeling approach, which was developed for the analysis of nonlinear structural equation models with latent interactions (Kelava et al., 2011; Maslowsky et al., 2015). An interaction effect in the LMS approach is estimated by modeling the implied non-normal distribution of the latent outcome variable and its indicators (Kelava et al., 2011). In Mplus, the latent interaction can be specified by a single command of "xwith". At suggestion of the literature (Marsh et al., 2013, 2004), we standardized all indicators before running the analyses in order to enhance the interpretability of the interaction results. This approach has been used by previous researchers investigating latent interactions within the expectancy-value framework (e.g., Guo et al., 2017; Trautwein et al., 2012).

We used several indexes to assess goodness-of-fit of all models and factor analyses, including the chi-square (χ^2) value, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root-mean-squared residual (SRMR). Values of RMSEA and SRMR below 0.08 indicated a reasonable model fit and values of CFI and TLI above 0.90 and 0.95 indicated acceptable and excellent model fit, respectively (Hu & Bentler, 1999; Kline, 2010). Because model fit indices are insensitive to nonlinear misspecifications (Mooijaart & Satorra, 2009), we do not present model fit indices for Model 3, which included latent interactions.

2.2. Results

2.2.1. Outliers

Before beginning analyses, we checked for univariate and multivariate outliers in the data. Specifically, univariate outliers were considered to be any values that represented a standardized score for the sample outside of the absolute value of 3.29 for a given variable (Tabachnick & Fidell, 2013). To detect multivariate outliers, we computed the Mahalanobis distance (MD) for the three motivational variables, which is the distance of a data point from the centroid shaped by the cloud of the majority of data points (Mahalanobis, 1930). The distances are interpreted using a $p < .001$ and the corresponding χ^2 value with the degrees of freedom equal to the number of variables. We conducted outlier diagnostic tests for the mathematics and English data separately.

The tests identified three outliers in the mathematics data and seven outliers in the English data. The final sample after excluding cases with outliers constituted 595 students (317 boys, 270 girls, 8 did not indicate gender; Mean age = 14.8 years, $SD = 1.61$) for mathematics and 591 students (317 boys, 266 girls, 8 did not indicate gender; Mean age = 14.8 years, $SD = 1.61$) for English.

2.2.2. Descriptive statistics and measurement model

Table 2 presents descriptive statistics, reliabilities, and correlation coefficients among variables; all correlations were in the expected directions. We first tested measurement models which included all variables before running three targeted SEM models for both subject domains. In all analyses, cost and task value were modeled as general factors using bifactor approaches. The measurement models demonstrated good fit in both subject domains: χ^2 (406) = 1320.768, CFI = 0.938, TLI = 0.929, RMSEA = 0.062, SRMR = 0.060 in mathematics, and χ^2 (407) = 1378.603, CFI = 0.937, TLI = 0.928, RMSEA = 0.064, SRMR = 0.056 in English. All factor loadings were significant at $p < .001$, indicating that the latent variables were represented well by their indicators.

2.2.3. SEM to examine relation of cost to outcomes

We proceeded to test the planned SEM models and all models demonstrated good fit (see Table 3). In Model 1, control variables (i.e., gender, age and class dummy covariates), self-efficacy, and task value significantly explained variance for all dependent variables in both subjects ($0.421 \le \Delta R^2 \le 0.607$, $ps < .01$). In Model 2, introducing cost into the SEM model significantly explained additional variance for avoidance intentions ($\Delta R^2 = 0.057$, $\triangle F(1, 572) = 86.48$, $p < .01$ in mathematics and $\Delta R^2 = 0.050$, $\triangle F(1, 568) = 67.78$, $p < .01$ in English) and expected course grades ($\Delta R^2 = 0.004$, $\triangle F(1, 572) = 5.88$, $p < .05$ in mathematics and $\Delta R^2 = 0.011$, $\triangle F(1, 568) = 16.23$, $p < .01$ in English), but not for future choice intentions in both subjects ($\Delta R^2 = 0.002$, $ps > .05$). Finally, in Model 3, adding interaction terms between self-efficacy, task value, and cost into the SEM model significantly explained additional variance for future choice intentions in both subjects ($\Delta R^2 = 0.086$, $\triangle F(3, 569) = 43.73$, $p < .01$ in mathematics and $\Delta R^2 = 0.050$, $\triangle F(3, 565) = 17.87$, $p < .01$ in English) as well as expected course grades in mathematics ($\Delta R^2 = 0.047$, $\triangle F(3, 569) = 26.07$, $p < .01$) and avoidance intentions in English ($\Delta R^2 = 0.034$, $\triangle F(3, 565) = 16.63$, $p < .01$).

In Model 1, when self-efficacy and task value were entered as independent variables, self-efficacy was the strongest predictor of expected course grades (βs = 0.29 and 0.30 for mathematics and English, respectively). However, self-efficacy did not predict future choice intentions or avoidance intentions in both subjects. Conversely, task value strongly predicted students' future choice intentions (βs = 0.73 and 0.62 for mathematics and English, respectively) and avoidance intentions (βs = −0.61 and −0.63 for mathematics and English, respectively). Task value also weakly predicted expected course grades in mathematics (β = 0.20), but not in English.

In Model 2, cost significantly negatively predicted expected course grades (βs = −0.11 and −0.14 for mathematics and English, respectively), and positively predicted avoidance intentions (βs = 0.37 and 0.29 for mathematics and English, respectively), but it did not predict future choice intentions. Task value remained the strongest predictor of both future choice intentions (βs = 0.72 and 0.62 for mathematics and English, respectively) and avoidance intentions (βs = −0.46 and −0.56

Table 2
Descriptive statistics, reliabilities, and correlation coefficients among latent variables in Study 1.

	Mathematics (N = 595)			English (N = 591)			1	2	3	4	5	6
	α/ωH	M	SD	α/ωH	M	SD						
1. Self-efficacy	.90 [a]	4.69	.97	.92 [a]	4.70	.96	–	.83	−.59	.54	−.58	.49
2. Task value	.85 [b]	4.52	1.09	.82 [b]	4.85	.95	.77	–	−.58	.63	−.70	.43
3. Cost	.89 [b]	2.97	1.26	.93 [b]	2.84	1.35	−.70	−.72	–	−.38	.61	−.45
4. Future choice intentions	.89 [a]	3.35	1.42	.90 [a]	3.64	1.41	.56	.73	−.53	–	−.51	.28
5. Avoidance intentions	.93 [a]	2.53	1.50	.94 [a]	2.31	1.39	−.60	−.73	.70	−.51	–	−.39
6. Expected course grades	–	88.95	12.75	–	87.27	11.92	.62	.61	−.55	.45	−.47	–

Note. Correlation coefficients from mathematics are below the diagonal; those from English are above the diagonal. All correlation coefficients were significant at $p < .01$.
[a] Cronbach's alpha.
[b] Omega hierarchical.

Table 3
Standardized path coefficients and model fit statistics from structural equation modeling in Study 1.
Expand

	Model 1			Model 2			Model 3		
	FCI	AI	ECG	FCI	AI	ECG	FCI	AI	ECG
Control variables									
Gender	**−.10**/.07	**−.08**/−.03	**−.07**/−.01	**−.10**/.07	**−.07**/−.02	**−.07**/−.02	**−.10**/.07	**−.08**/−.02	**−.07**/−.02
Age	−.05/−.14	.08/.04	−.10/**−.27**	−.04/−.14	.02/.02	−.09/**−.26**	.02/−.15	.03/.04	−.15/**−.25**
Self-efficacy	.01/.03	−.11/−.02	**.29/.30**	.00/.02	.02/.09	**.25/.26**	−.01/−.03	−.00/.11	**.25/.23**
Task value	**.73/.62**	**−.61/−.63**	**.20**/.01	**.72/.62**	**−.46/−.56**	**.16**/−.03	**.80/.72**	**−.45/−.60**	**.14**/−.07
Cost				−.03/−.01	**.37/.29**	**−.11/−.14**	.01/.01	**.35/.27**	−.07/**−.16**
Self-efficacy × task value							**.25/.09**	−.05/−.06	**−.23/−.10**
Self-efficacy × cost							**.22**/.14	.04/.09	**−.14**/.02
Task value × cost							−.02/−.08	**−.17/−.24**	**.15**/−.04
R^2	.539/.421	.566/.531	.607/.604	.541/.423	.623/.581	.611/.615	.627/.473	.623/.615	.658/.615
Model fit									
χ^2		1013.983/1009.770			2015.763/2009.899			n/a	
df		406/406			881/882			n/a	
CFI		.932/.931			.927/.930			n/a	
TLI		.911/.909			.912/.916			n/a	
RMSEA		.050/.050			.047/.047			n/a	
SRMR		.036/.033			.044/.040			n/a	

Note. Path coefficients in mathematics are presented to the left of the slash; those in English to the right. Path coefficients in bold were significant at $p < .05$. FCI = future choice intentions, AI = avoidance intentions, ECG = expected course grades. Traditional fit indices are not available (n/a) for models with latent product terms.

for mathematics and English, respectively) when cost was entered in the model. Self-efficacy remained the strongest predictor of expected course grades (βs = 0.25 and 0.26 for mathematics and English, respectively).

In Model 3, we observed a positive interactive effect between self-efficacy and task value on future choice intentions (Fig. 1), a negative interactive effect between self-efficacy and task value on expected course grades (Fig. 2), and a negative interactive effect between task value and cost on avoidance intentions (Fig. 3) in both subjects. As Fig. 1 depicts, consistent with our hypotheses, the positive association between task value and future choice intentions was stronger when students' self-efficacy for that subject increased. However, as Fig. 2 depicts, the positive association between task value and expected course grades was stronger as self-efficacy for that subject *decreased*. As Fig. 3 depicts, consistent with our hypotheses, for avoidance intentions the positive association between cost and avoidance intentions became stronger as students' task value decreased.

Finally, in mathematics, but not English, we found several additional interactions. Consistent with our hypotheses, there was a negative interactive effect of self-efficacy and cost on expected course grades, such that the effect of self-efficacy on grades went down as students perceived more cost. Contrary to hypotheses, self-efficacy and cost had a positive interactive effect on future choice intentions, such that self-efficacy had a stronger positive effect on this outcome when students' perceived cost was *higher*. There was also a positive interaction effect of task value with cost on expected course grades. In these models predicting expected course grades in mathematics including interactions, the direct predictive effect of cost on grades became non-significant.

2.3. Discussion

Findings from Study 1 revealed that the construct of cost is an important motivational force influencing students' learning, beyond what can be explained by competence-related beliefs and intrinsic, attainment, and utility value. That is, cost was a significant predictor of both expected course grades (negatively) and avoidance intentions (positively). An additional novel finding of the present study was that there was an interaction between cost and task value in predicting students' avoidance intentions in mathematics and English. One prior study has

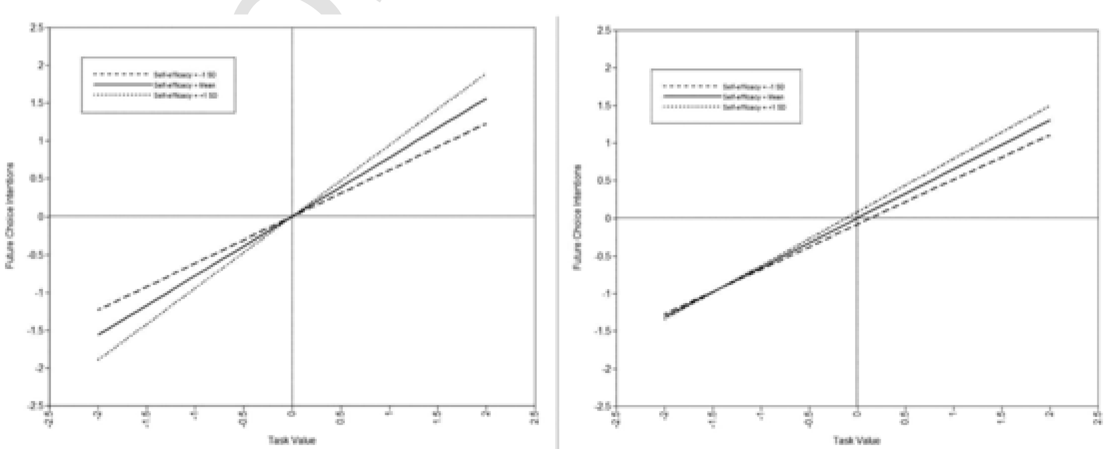

Fig. 1. Plots of interaction effect of self-efficacy and task value on future choice intentions in mathematics (left) and English (right) from Study 1.

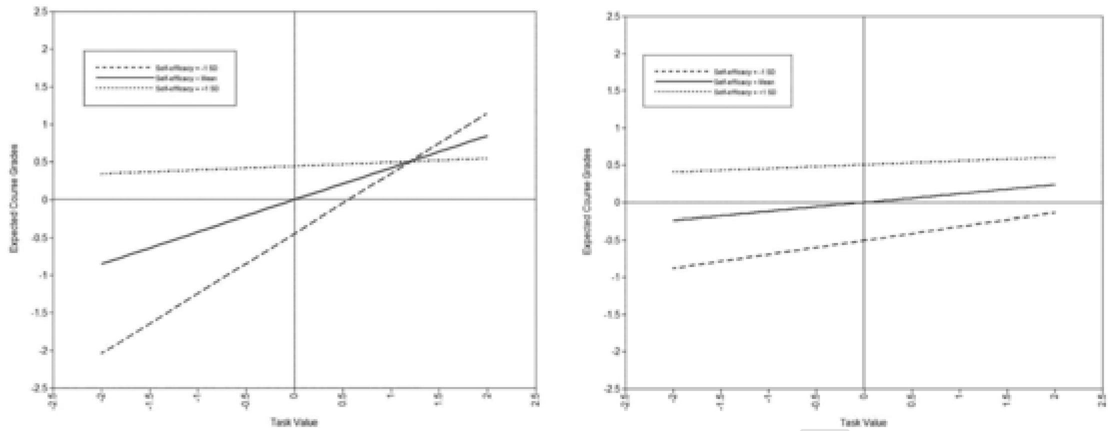

Fig. 2. Plots of interaction effect of self-efficacy and task value on expected course grades in mathematics (left) and English (right) from Study 1.

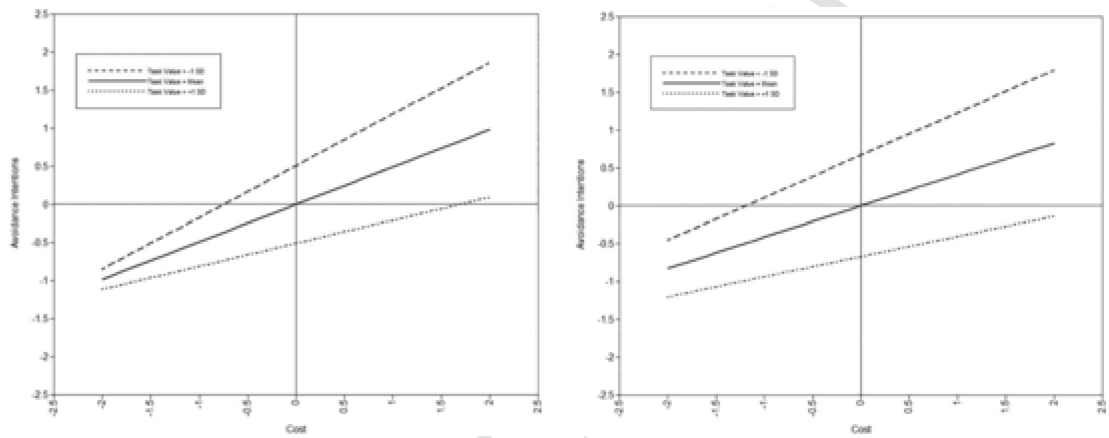

Fig. 3. Plots of interaction effect of task value and cost on avoidance intentions in mathematics (left) and English (right) from Study 1.

shown that the interaction of students' math competence beliefs and cost significantly predicted their achievement (Trautwein et al., 2012). We did not replicate this interaction, but we did find that having high task value mitigated the positive associations between cost and avoidance intentions. These results are important because they suggest that students' perceptions of cost influence how their values impact their academic functioning.

3. Study 2

Results from Study 1 revealed that cost could successfully predict adolescent students' avoidance intentions and expected course grades in both mathematics and English, beyond what could be predicted by self-efficacy and task value. However, Study 1 included only cross-sectional data and a self-reported measure of student course performance. In Study 2, we examined the same research questions using a longitudinal data set and including students' actual course grades as an achievement index. This study complemented Study 1 by exploring how cost affects academic outcomes over time.

3.1. Method

3.1.1. Participants and survey procedure

Data were collected from 8th graders at a public middle school located in Shanghai, China. Like with Study 1, this school was a bilingual school and students were required to take both mathematics and English courses. Students' responses were collected at three time points in 2019. The first wave survey (T1) was administered in the second week of September which was at the beginning of the semester. During the eighth week of the semester and one week before midterm examinations, the second wave survey (T2) was administered. Both T1 and T2 surveys were based on a paper-and-pencil format and students completed surveys during regular classroom hours. After the midterm examinations during the tenth week of the semester, students' midterm examination scores in mathematics and English were obtained from the school (T3). The study was approved by East China Normal University's Institutional Review Board for human participants. A total of 577 students participated in the T1 survey and 469 students' participated in the T2 survey. There were 443 students who participated in both waves of data collection (222 boys, 221 girls; Mean age = 14.1 years, *SD* = 0.35).

3.1.2. Measures

All survey items were identical to those used in Study 1 and were administered in Chinese and referred to the subjects of mathematics and English. All items used six-point Likert-type scales ranging from 1 (*completely disagree*) to 6 (*completely agree*).

3.1.2.1. Cost (T1) As in Study 1, CFA analysis of the cost measure showed that a four-factor correlated model had reasonable model fit: $\chi^2(48) = 142.800$, CFI = 0.974, TLI = 0.964, RMSEA = 0.068, and SRMR = 0.029 for mathematics and $\chi^2(48) = 237.921$, CFI = 0.973, TLI = 0.962, RMSEA = 0.095, and SRMR = 0.022 for English. However, also as in Study 1, the correlations between the four cost dimensions were quite high in both subjects ($0.47 \le rs \le 0.73$ in mathematics and $0.59 \le rs \le 0.80$ in English), suggesting that a general factor might exist. We thus again chose to use a bifactor modeling approach. Table 4 presents the detailed results evaluating the model-based reliability of the bifactor model for the cost scale. Again similar to Study 1, for general cost, the PUC was 0.82 for both mathematics and English on the

Table 4
Standardized loading pattern for the cost items bifactor CFA in Study 2.
Expand

Item	GC	EFC	OPC	EGC	EMC
EFC1	.65/.71	.32/.50			
EFC2	.69/.77	.57/.58			
EFC3	.80/.82	.31/.42			
OPC1	.72/.91		.47/.30		
OPC2	.73/.92		.45/.30		
OPC3	.67/.89		.59/.28		
EGC1	.52/.75			.73/.58	
EGC2	.51/.72			.86/.64	
EGC3	.45/.68			.64/.65	
EMC1	.63/.70				.58/.67
EMC2	.61/.68				.51/.62
EMC3	.55/.66				.63/.66

Psychometric Properties	GC	EFC	OPC	EGC	EMC
ω/ωS	.96/.99	.86/.94	.90/.97	.92/.97	.87/.96
ωH/ωHS	.79/.88	.21/.28	.30/.09	.64/.42	.42/.46
PUC	.818/.818	–	–	–	–
ECV	.549/.674	.059/.072	.088/.024	.191/.110	.113/.120

Note. Path coefficients in mathematics are presented to the left of the slash; those in English to the right. All factor loadings included in the table are significant at $p < .001$. GC = general cost; EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost. ω = omega coefficient for general factor; ωS = omega subscale coefficient for subscales; ωH = omega hierarchical coefficient for general factor; ωHS = omega hierarchical subscale coefficient for subscales; PUC = percent of uncontaminated variance; ECV = explained common variance.

model level and the ECV was 0.55 for mathematics and 0.68 for English on the factor level. The ωH for general cost was 0.79 and 0.88 for mathematics and English respectively. In contrast, the ωHS for the four specific costs ranged from 0.09 to 0.64 across two subject domains. These results indicate that just like in Study 1, it was the general cost factor rather than the specific sub-factors of cost which were meaningful for interpreting the predictive utility of cost in the present data (Reise, 2012; Reise et al., 2012; Rodriguez et al., 2016).

3.1.2.2. Task value (T1) We also examined the model-based reliability for the task value scale. The results from the bifactor CFA revealed that the PUC was 0.80 for both mathematics and English on the model level and the ECV was 0.50 in mathematics and 0.68 in English for general value. In the meantime, ωH was 0.71 and 0.86 for the general task value in mathematics and English, respectively. In contrast, the ωHS for three specific values ranged from 0.13 to 0.64 across two subject domains. Like with the data for cost scale, data from these analyses suggested that the general task value factor was the most meaningful for interpretation in the present study (Reise, 2012; Reise et al., 2012; Rodriguez et al., 2016).

3.1.2.3. Self-efficacy (T1) The reliability coefficients of this scale were $\alpha = 0.88$ for mathematics and $\alpha = 0.90$ for English.

3.1.2.4. Future choice intentions (T1 & T2) The reliability coefficients of this scale were $\alpha = 0.86$ for T1 and $\alpha = 0.90$ for T2 in mathematics and $\alpha = 0.89$ for T1 and $\alpha = 0.91$ for T2 in English.

3.1.2.5. Avoidance intentions (T1 & T2) The reliability coefficients of this scale were $\alpha = 0.87$ for T1 and $\alpha = 0.92$ for T2 in mathematics and $\alpha = 0.93$ for T1 and $\alpha = 0.90$ for T2 in English.

3.1.2.6. Course grades (T3) Students' actual scores on their course midterm examination in mathematics and English were used as an outcome in this study rather than their self-reported expected course grades. The midterm exam was developed by teachers at the school and the content of the exam was a reflection of what students had learned in the class thus far. All students took the same exam and were scored equivalently based on a standard answer key. Scores ranged from 0 to 120.

3.1.3. Statistical analyses

All analyses were conducted in Mplus 7.4. We used the same models as were used in Study 1 with only minor changes to account for the different study design. Specifically, in Model 1, all three outcome variables (T2 future choice intentions, T2 avoidance intentions, T3 course grades) were regressed on T1 self-efficacy, T1 task value, and control variables (i.e., gender, age, class section dummy variables, and pretest scores on T1 future choice intentions or T1 avoidance intentions in their respective models). Because students were nested in 7 classes in this data set, we created 6 dummy variables and treated them as covariates in the models to account for the nested data structure. Like in Study 1, T1 cost was added as an additional predictor in Model 2 and interactions between T1 self-efficacy, T1 task value, and T1 cost were added as additional predictors in Model 3. All individual indicators were standardized for all SEM models.

3.2. Results

3.2.1. Descriptive statistics and measurement model

Using the same diagnostic tests as were used in Study 1, we identified ten outliers in the mathematics data and six outliers in the English data. The final sample was 433 students (216 boys, 217 girls; Mean age = 14.0 years, *SD* = 0.35) for mathematics and 437 students (217 boys, 220 girls; Mean age = 14.0 years, *SD* = 0.36) for English. Table 5 presents descriptive statistics, reliabilities, and correlation coefficients among variables. Again, all variables demonstrated good reliability and all correlations were in the expected directions. Before running our three targeted SEM models, we tested measurement models with all variables for both subject domains. Same as in Study 1, cost and task value were modeled using bifactor approaches, with us interpreting the predictive coefficients for the general factors of these constructs. Our measurement models demonstrated adequate fits in both subject domains: χ^2 (587) = 1297.264, CFI = 0.936, TLI = 0.928, RMSEA = 0.053, SRMR = 0.054 in mathematics, and χ^2 (587) = 1506.243, CFI = 0.941, TLI = 0.933, RMSEA = 0.060, SRMR = 0.066 in English. All factor loadings were significant at

Table 5
Descriptive statistics, reliabilities, and correlation coefficients among latent variables in Study 2.
Expand

	Mathematics (N = 433)			English (N = 437)			1	2	3	4	5	6	7	8
	α/ωH	*M*	*SD*	α/ωH	*M*	*SD*								
1. Self-efficacy (T1)	.88 [a]	4.29	.93	.90 [a]	4.14	1.01	–	.46	−.42	.64	−.29	.47	−.45	.40
2. Task value (T1)	.71 [b]	4.66	.89	.86 [b]	4.71	1.04	.73	–	−.43	.52	−.56	.53	−.49	.34
3. Cost (T1)	.79 [b]	3.07	1.08	.88 [b]	3.19	1.29	−.70	−.76	–	−.34	.50	−.29	.43	−.38
4. Future choice intentions (T1)	.86 [a]	3.40	1.27	.89 [a]	3.27	1.30	.62	.83	−.65	–	−.36	.53	−.55	.21
5. Avoidance intentions (T1)	.87 [a]	2.25	1.21	.93 [a]	2.70	1.47	−.40	−.64	.57	−.56	–	−.22	.50	−.30
6. Future choice intentions (T2)	.90 [a]	3.53	1.34	.91 [a]	3.70	1.34	.56	.64	−.60	.70	−.42	–	−.35	.19
7. Avoidance intentions (T2)	.92 [a]	2.35	1.30	.90 [a]	2.36	1.31	−.29	−.48	.40	−.42	.52	−.33	–	−.32
8. Course grades (T3)	–	90.44	22.63	–	93.14	20.83	.37	.34	−.43	.31	−.36	.36	−.32	–

Note. Correlation coefficients from mathematics are below the diagonal; those from English are above the diagonal. All correlation coefficients were significant at $p < .01$.
[a] Cronbach's alpha.
[b] Omega hierarchical.

$p < .001$, indicating that the latent variables were represented well by their indicators.

3.2.2. SEM to examine relation of cost to outcomes

As shown in the Table 6, all SEM models demonstrated adequate fit. In Model 1, the set of variables including control variables (i.e., gender, age, pretest measure, and class dummy covariates), T1 self-efficacy, and T1 task value significantly explained variance for all dependent variables in both subjects ($0.267 \leq \Delta R^2 \leq 0.541$, $ps < .01$). In Model 2, introducing T1 cost into the SEM model significantly explained additional variance for T3 course grades in both subjects ($\Delta R^2 = 0.039$, $\triangle F(1, 421) = 23.60$, $p < .01$ in mathematics and $\Delta R^2 = 0.022$, $\triangle F(1, 425) = 14.98$, $p < .01$ in English) as well as T2 future choice intentions in mathematics ($\Delta R^2 = 0.010$, $\triangle F(1, 420) = 9.35$, $p < .01$) and T2 avoidance intentions in English ($\Delta R^2 = 0.008$, AI $\triangle F(1, 424) = 5.73$, $p < .05$). Finally, in Model 3, adding interaction terms between T1 self-efficacy, T1 task value, and T1 cost into the SEM model significantly explained additional variance for T2 future choice intentions in both subjects ($\Delta R^2 = 0.015$, $\triangle F(3, 417) = 4.80$, $p < .01$ in mathematics and $\Delta R^2 = 0.049$, $\triangle F(3, 421) = 12.62$, $p < .01$ in English) as well as T2 avoidance intentions in English ($\Delta R^2 = 0.030$, $\triangle F(3, 421) = 7.49$, $p < .01$).

In Model 1, T1 self-efficacy consistently predicted T3 course grades (βs = 0.25 in both subjects). T1 self-efficacy also positively predicted T2 future choice intentions in mathematics (β = 0.16) and negatively predicted avoidance intentions in English (β = −0.30). T1 task value weakly predicted T3 course grades in English (β = 0.18) but not in mathematics. Task value also predicted T2 future choice intentions in English (β = 0.31) but not in mathematics. T1 task value predicted T2 avoidance intentions (βs = −0.34 and −0.16 for mathematics and English, respectively); however, these main effects did not hold up across all three models.

In Model 2, T1 cost significantly and negatively predicted T3 course grades in both subject domains (βs = −0.36 and −0.18 for mathemat-

Table 6
Standardized Path Coefficients and Model Fit Statistics from Structural Equation Modeling in Study 2.
Expand

	Model 1			Model 2			Model 3		
	FCI (T2)	AI (T2)	ACG (T3)	FCI (T2)	AI (T2)	ACG (T3)	FCI (T2)	AI (T2)	ACG (T3)
Control variables									
Gender	**−.12**/**−.13**	−.04/.02	**.10**/**.15**	**−.10**/**−.13**	−.05/.02	**.14**/**.14**	**−.10**/**−.12**	−.05/.03	**.13**/**.15**
Age	.00/.04	.03/.02	−.00/−.02	.01/.04	.02/.03	.00/−.03	.01/.04	.03/.03	.00/−.03
Control (T1)	**.55**/**.31**	**.28**/**.28**	–/–	**.52**/**.31**	**.29**/**.25**	–/–	**.48**/**.29**	**.30**/**.25**	–/–
Self-efficacy (T1)	**.16**/.12	.06/**−.30**	**.25**/**.25**	.12/.12	.05/**−.27**	**.20**/**.20**	.12/.09	.01/**−.31**	**.21**/**.19**
Task value (T1)	.01/**.31**	**−.34**/**−.16**	.16/**.18**	−.07/**.31**	**−.24**/**−.15**	−.11/**.13**	−.02/**.38**	−.20/−.09	−.09/**.12**
Cost (T1)				**−.18**/−.01	.10/.10	**−.36**/**−.18**	**−.18**/.01	.05/**.11**	**−.34**/**−.18**
Self-efficacy × task value (T1)							.05/.02	−.21/.03	−.15/**−.11**
Self-efficacy × cost (T1)							.02/.10	−.04/**.16**	−.08/−.04
Task value × cost (T1)							−.04/**−.19**	**−.22**/**−.16**	−.03/−.04
R^2	.541/.405	.333/.400	.267/.354	.551/.406	.333/.408	.306/.376	.566/.455	.340/.438	.306/.376
Model fit									
χ^2		880.109/1000.894			1692.014/1885.818			n/a	
df		400/400			823/823			n/a	
CFI		.934/.930			.924/.933			n/a	
TLI		.917/.913			.912/.922			n/a	
RMSEA		.053/.059			.049/.054			n/a	
SRMR		.041/.052			.049/.061			n/a	

Note. Path coefficients in mathematics are presented to the left of the slash; those in English to the right. Path coefficients in bold were significant at $p < .05$. FCI = future choice intentions, AI = avoidance intentions, ACG = actual course grades. Control (T1) represents future choice intentions (T1) and avoidance intentions (T1), respectively. Traditional fit indices are not available (n/a) for models with latent product terms.

ics and English, respectively), but it did not predict significantly avoidance intentions. It predicted students' future choice intentions in mathematics (β = −0.18) but not English. In Model 3, there was a negative interactive effect between T1 task value and T1 cost on T2 avoidance intentions in both subject domains. As Fig. 4 depicts, the positive association between cost and avoidance intentions became stronger as students' task value decreased.

In Model 3 in English, but not mathematics, we found several additional interactions. Specifically, T1 self-efficacy and T1 task value had a negative interactive effect on T3 course grades. In addition, T1 self-efficacy and T1 cost had a positive interactive effect on T2 avoidance intentions; and T1 task value and T1 cost had a negative interactive effect on T2 future choice intentions.

3.3. Discussion

Using longitudinal data, we found that cost successfully explained additional variance in adolescent students' course grades in both mathematics and English after controlling for self-efficacy and task value. These findings replicate those observed in Study 1 and extend them to include actual grades as opposed to self-reported grades. Among various motivational factors, self-efficacy is posited to be one of the strongest predictors of achievement (Lee & Stankov, 2013; Pajares, 1996). Researchers investigating academic motivation from an expectancy-value perspective argue that students' competence-related beliefs predict achievement more strongly than does task value (e.g., Wigfield & Eccles, 2000). Results from the current study do not refute this idea, but they do suggest that cost plays an important role in predicting adolescent students' achievement in addition to what can be predicted by self-efficacy. These findings are compatible with the results of several recent studies revealing that cost perceptions can impair students' subsequent achievement (e.g., Jiang et al., 2018; Perez, Dai, et al., 2019). In addition, and also replicating the results of Study 1, we found a negative interaction effect of task value and cost on avoidance intentions in both subjects. Specifically, the positive association between cost and avoidance intentions becomes weaker when students have higher task value. Thus, task value and cost beliefs can affect learning in an interactive manner rather than in a vacuum.

Not all findings were the same as those observed in Study 1. One difference is that in Study 1 the relations between cost and expected course grades were weaker than were the relations between cost and actual course grades in Study 2. Moreover, in Study 1 the significant relation between cost and expected course grade did not hold up in the mathematics domain after the interaction terms were added into the SEM model. Although it has been shown that the overall validity of self-reported grades is high (e.g., Cole & Gonyea, 2010) and the correlation between students' self-reported grades and their actual grades is typically high (e.g., $r = 0.84$; Kuncel et al., 2005), researchers still should be cautious in the use of students self-reported achievement outcomes.

A second difference is that in the domain of mathematics, cost significantly predicted future choice intentions after controlling for pretest scores of the measure, self-efficacy, and task value. In contrast, perceived task value failed to predict future choice intentions in the same models (these beliefs did predict future choice intentions in English in Study 2). Both findings differ from what was observed in Study 1. Students' task value beliefs have been shown to affect their choice intentions and actual choice behavior in the mathematics domain in other studies (for reviews, see Eccles, 2005; Wigfield et al., 2017). Our findings therefore suggest that the predictive relations of task value and cost to future choice intentions may be context and situational dependent; it also may be the case that predictive relations assessed using longitudinal differ from those observed using cross-sectional data. More studies are needed to continue to explore these relations more precisely.

4. General discussion

Results from two studies suggest that students' perceptions of cost are uniquely associated with their learning outcomes in the subject areas of mathematics and English. Consistent with our hypotheses, results demonstrated that across both data sets, and in both subject areas, perceived cost predicted negatively students' anticipated or actual course grades. Cost also interacted with task value to predict students' avoidance intentions across both subject areas and both data sets. Other results provided only mixed support for our hypotheses: Cost predicted directly students' avoidance intentions in both subject areas in Study 1 and predicted directly students' future choice intentions in mathematics in Study 2; however, both of these effects were either inconsistent or non-significant in the other data set. There was also some evidence of cost interacting with self-efficacy in predicting outcomes in both studies, but these interaction effects were not consistent across subject areas or studies.

4.1. Direct associations of cost with academic outcomes

Cost predicted negatively students' expected course grades in Study 1 and actual course grades in Study 2, across both mathematics and English. This pattern of results suggests that cost may influence students' motivational beliefs in important ways that can affect their academic achievement. Such a finding is consistent with several emerging studies which have shown negative relations between cost and students' academic performance (e.g., Flake et al., 2015; Jiang et al., 2018,

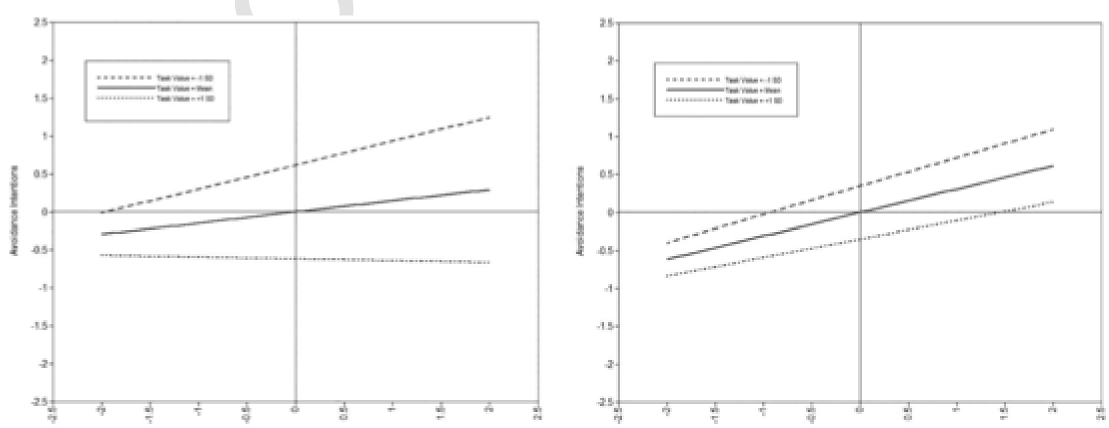

Fig. 4. Plots of interaction effect of task value and cost on avoidance intentions in mathematics (left) and English (right) from Study 2.

2020). Interestingly, cost was associated with course grades even after controlling for self-efficacy. Researchers have found that self-efficacy beliefs are among the strongest predictors of academic performance; for example, Lee and Stankov (2013) analyzed the Programme for International Student Assessment (PISA) data and found that self-efficacy was the strongest predictor of achievement after controlling for fourteen other variables (e.g., other motivational constructs, the use of learning strategies). The results of this study suggest that perceptions of cost may add explanatory power to understanding the determinants of students' performance beyond what can be explained by self-efficacy.

Evidence that cost predicted the other two outcomes directly was more mixed. In terms of avoidance intentions, in Study 1 cost predicted avoidance intentions in both subject areas; however, in Study 2 cost predicted avoidance intentions only in English, and only in the statistical model that included interactions between self-efficacy, task value, and cost. We conclude that there is mixed evidence of cost predicting avoidance intentions directly, although there are consistent *interactions* suggesting that cost predicts avoidance intentions by interacting with task value (see next section for discussion). Observing a relation between cost and avoidance intentions is both consistent with our hypotheses and in accordance with the psychological underpinnings of the cost construct. Theoretically, cost is a negatively-valenced construct that is likely to induce avoidance motivation (Atkinson, 1964; Feather, 1995; Lewin, 1938). Thus, we would expect that cost be closely related to avoidance-related behaviors in school settings. Previous studies have reported that cost perceptions predicted students' drop-out intentions, avoidance intentions, and actual drop out behaviors (de la Varre et al., 2014; Jiang et al., 2018; Perez et al., 2014). Results of the present study extend the evidence demonstrating relations between cost and avoidance-related academic behavior to the subject area of English. However, our results also suggest that such relations might depend on students' perceptions of task value (see next section). In terms of future choice intentions, cost did not show consistent predictive relations, predicting this outcome only in Study 2 and only in one subject area. Results of the present study suggest that perhaps cost is not a robust predictor of future choice intentions in all contexts. Alternatively, as previously discussed, these different patterns may also be because of the differences in data sources and analytical methods between two studies.

What is the relative predictive power of cost compared to the other constructs? Cost was an equally strong or stronger predictor of performance compared to competence-related beliefs in Study 2, but a less strong predictor in Study 1. Compared to perceptions of task value, cost was a less strong and less consistent predictor of avoidance intentions and intentions to engage with schoolwork in the models tested. However, the cost-value interactions were the strongest interactions observed. Together, results suggest that cost is not always the strongest predictor of any particular outcome compared to self-efficacy and task value, but including cost in predictive models within expectancy-value theory (particularly cost-value interactions) added additional explanatory power to each of the models tested. A researcher might assume that competence-related beliefs are the only factor predicting students' performance, and that task value is the only factor predicting intentions to engage with or avoid schoolwork, if the researcher does not consider cost. Results of this study demonstrate that this is not accurate; cost can also impact each of these outcomes and interacts with the other motivational constructs to do so. The results of the present study contribute to a growing base of evidence suggesting that including cost in expectancy-value theoretical models is useful for understanding students' course performance and avoidance behavior in school, above and beyond what can be learned by considering only competence-related beliefs and task value.

4.2. Latent interactions between self-efficacy, task value, and cost

We observed an interaction between task value and cost on avoidance intentions in both mathematics and English in both data sets. Specifically, perceiving high task value mitigated the positive associations between cost and avoidance intentions. Empirically, this is the first study to evaluate or report on potential cost-value interactions, and as such this finding helps shed light on how expectancy-value motivational constructs interact with one another to affect academic behavior. Theoretically, results support Eccles' (2005) argument that students weigh their perceptions of cost against their perceptions of task value in deciding what activities to pursue. It may be the case that when students value a task, the impact of perceived cost on avoidance intentions is lower because students believe that the negative consequences of task engagement are “worth it.” Alternatively, if students perceive high negative consequences of completing a task, having high value may not be sufficient to prevent students from wanting to avoid the unpleasant aspects of doing the task. Such findings suggest that either supporting task value or reducing cost in the classroom alone is not sufficient to ensure that students do not avoid learning activities; educators may need to consider both factors simultaneously in order to promote optimal learning.

It is worth noting that very similar cost-value interactions also occurred for the outcomes of course grades (in Study 1 in mathematics) and future choice intentions (in Study 2 in English), but they did not occur consistently across the models tested or across subject areas. Thus we do not draw strong conclusions about whether cost and task value interact to influence performance or future choice intentions and recommend that future researchers continue to explore these possibilities.

We observed mixed evidence to support our hypothesis that there might be interactions between perceptions of competence-related beliefs and perceptions of cost in predicting any outcomes: There was a positive interaction on future choice intentions in mathematics in Study 1, a negative interaction on expected course grades in mathematics in Study 1, and a positive interaction on avoidance intentions in English in Study 2. The interactions did not show consistent patterns or directions across different outcomes within or across data sets, across subject areas within a data set, or across data sets within a given subject area. Given the lack of consistency, we conclude that our observed results do not provide clear evidence about *how* cost and self-efficacy interact, although they suggest that these variables do interact to influence the three academic outcomes at least in some circumstances. These findings contradict those reported by Guo et al. (2016) and Trautwein et al. (2012), who both reported positive interactions between competence-related beliefs and cost on performance. Our results may differ from those of prior studies because this study utilized different measures of cost and competence-related beliefs compared to the two prior studies, or because this study included interactions between cost and task value. It also may be that the nature of interactions between the expectancy-value motivational constructs depends on the context in which students are learning certain subjects; we encourage researchers to continue exploring this topic to understand precisely why these discrepancies occurred.

Although assessing these relations was not part of our central study goals, we found significant interaction effects between self-efficacy and task value on students' future choice intentions and course grades in both subject areas in Study 1, as well as on course grades in English (but not math) in Study 2. The fact that we found interactions between self-efficacy and task value supports prior research which has also reported interaction effects between these constructs (e.g., Guo et al., 2015; Nagengast et al., 2011; Trautwein et al., 2012). However, prior findings and theory most often suggest *positive* interactions between competence-related beliefs and task value, such that if students have high competence-related beliefs for learning, this can strengthen the positive association between task value and intentions to engage with schoolwork or performance. In contrast, in this study the interactions for course grades for both data sets were negative, which would suggest that students with *lower* competence-related beliefs performed better as task value increased. Practically a negative interaction would suggest that boosting students' perceptions of task value may compensate for students' low perceptions of their competence, a finding that intervention research focusing on task value has reported before (e.g., Hulleman & Harackiewicz, 2009). It is also worth noting that other prior studies also have reported negative interactions between expectancy and task value on outcomes that are generally considered to be adaptive (see Wigfield et al., 2017, for discussion); thus the field has not clearly provided evidence that expectancy-value interactions are always positive. However, it is hard to draw clear conclusions about the nature of this interaction given that a number of prior studies have found opposite patterns of interactions between these constructs. Again, these different results may be due to the use of different measurement strategies or the inclusion of cost-value interactions, which were not included in prior studies.

These interaction effects along with the cost-self-efficacy interactions that we observed were complex. Such complexity demonstrates that much more research is needed to understand exactly how students' perceptions of expectancy, task value, and cost interrelate with one another to affect learning. We encourage researchers to avoid drawing overly strong conclusions about the nature of expectancy-value interaction effects until a larger body of research, examining multiple types of academic outcomes and including the different potential interrelations among expectancy-value constructs, has been done in different subject areas and has included perceptions of cost. However, we do believe that our findings provide important evidence that these motivational constructs often interact with one another to affect students' learning behavior and performance; thus researchers should continue to pursue study of this topic. In terms of practical implications, these findings suggest that educators and researchers should be aware that students do not experience perceptions of cost, competence, or task value independently of their other motivational beliefs. Rather, students' beliefs play off of one another to influence their interpretation of learning settings and the ways that they engage with their schoolwork.

4.3. Limitations and conclusion

We hope future researchers will address four important limitations of the current study. First, this study was based on a sample of Chinese adolescent students; the generalizability of findings to different-aged students or to other school contexts requires further investigation. Second, as noted earlier the first data set is correlational in nature and was collected at one time point; our conclusions about the directionality of relationships were based on prior theory, and the use of a second data set confirmed these findings using a longitudinal sample, but this design does not allow us to conduct strong tests of the directional relations among variables in Study 1.

Third, we discussed cost in general throughout this study because the model-based reliability suggested that a general cost factor was more interpretable than were the specific cost sub-factors in the bifactor model. When measuring multidimensional constructs, it is necessary to provide model-based reliability evidence that the general factor or specific sub-factors reliably represent the target construct of interest (McDonald, 1999). Results based on the current data showed that reliability coefficients of the specific types of cost and task value were low after accounting for general cost and task value, thus failing to demonstrate interpretive relevance. Therefore, we refrained from discussing specific types of cost and task value in the present study. It is clear that there are many types of cost and that cost is a multi-faceted construct (Eccles et al., 1983; Wigfield et al., 2017), and different types of cost (i.e., effort cost, opportunity cost, ego cost, and emotional cost) may have distinct relationships with academic outcomes in some circumstances (e.g., Perez et al., 2014). Our findings point to a broader concern with respect to needing more attention to the optimal measurement and interpretations of cost, to determine whether students of different ages and in different learning contexts perceive the different dimensions of cost to be distinct and to create measures which capture these distinctions fully. We recommend that researchers expand upon this work by considering best practices with respect to measurement of cost, which is a relatively new construct in expectancy-value research, and we recommend that researchers continue to explore the specific dimensions of cost and task value when model-based reliability can be guaranteed.

Finally, our study focused narrowly on students' perceptions of costs for two academic subject areas (mathematics and English) and did not consider students' broader perceptions of the costs of learning overall, or whether students would like to participate in academics at all. We made this choice because it was compulsory in our sample for students to engage in academics, but understanding broader conceptualizations of cost also might help researchers obtain a more complete picture of how individuals think about the negative consequences of academic engagement. We recommend that researchers complement the findings of this study by conducting work focused on perceptions of cost more broadly, perhaps with older populations of students who have autonomy over whether or not to engage in school.

Nonetheless, findings of the present study provide important evidence in understanding the relation of cost to academic outcomes across subject areas, by revealing that cost is uniquely associated with changes in adolescent students' course grades and (in interaction with task value) their avoidance intentions in school. Together findings build upon a growing body of research demonstrating that cost is important for affecting students' motivation and learning, both independently from and interaction with competence-related beliefs and task value. Based on these findings, we argue that it is vital to explore cost as a unique motivational construct, along with expectancy and task value, to capture most fully students' motivational dynamics in school.

Uncited reference

Benson et al., 2018

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