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An expectancy-value-cost approach in predicting adolescent students' academic motivation and achievement☆

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ABSTRACT

In the context of learning, cost has mostly been discussed under the expectancy-value framework and defined as the perceived negative consequences of task engagement. The issue of cost has recently attracted growing interest among scholars, because it may provide insights regarding how to predict students' avoidance motivation and behavior. In the present study, we investigated the potential benefits of an expectancy-value-cost approach for predicting outcomes related to adolescent students' academic motivation and achievement in math. Using two data sets ($N = 637$ and $N = 211$) of middle and high school students, we found that cost could successfully explain additional variance in multiple different variables related to academic motivation and achievement, beyond what could be predicted by expectancy and value. In particular, cost emerged as an important factor in predicting adolescent students' adoption of avoidance goals, negative classroom affect, maladaptive academic outcomes, and exam scores. Findings of the present study extend the scope of expectancy-value theory by highlighting the importance of using expectancy, task value, and cost together to predict students' academic motivation and educational outcomes.

1. Introduction

Among the different antecedents of academic behavior, motivation is one of the most important, playing a crucial role in impacting students' choices, engagement, and achievement in school (e.g., Schunk, Printrich, & Meece, 2008). In educational psychology, Eccles et al.'s (1983) expectancy-value model is one of the most influential frameworks that has been used to investigate students' motivation and how it relates to academic-related choices, learning behaviors, and achievement. In general, researchers working within this theory posit that when students have high competence beliefs and value for an academic task, they are more likely to engage with it and to have higher achievement (Wigfield & Eccles, 2000). Students' competence beliefs, which include their self-efficacy, beliefs about ability, or expectations about future success, have been found to predict positively their engagement and achievement in various academic subjects (see Pajares, 1996; Schunk, 1991, for reviews). Students' perceptions of the value of a task also have been found to predict reliably their intentions and actual decisions to take more courses in specific subjects and to complete activities related to those subjects (e.g., Eccles, 2005; Wigfield, Rosenzweig, & Eccles, 2017). Most expectancy-value researchers posit that task value has at least three components, which refer to the extent to which a student thinks a task is interesting (i.e., intrinsic value), personally meaningful and important (i.e., attainment value) or useful (i.e., utility value).

Although research shows many links between competence beliefs, task value, and students' academic outcomes, these factors do not explain fully whether students engage adaptively with their schoolwork or not. In particular, researchers have recently begun to explore the construct of cost as another potential factor that affects students' academic outcomes in school. Cost refers to students' perceptions regarding the negative consequences of engaging in a task (Wigfield & Eccles, 1992) and captures a dimension of motivation that is more negative in nature than competence beliefs and task value. The construct of cost has not received much attention in empirical research to date. However, cost is likely to predict students' motivation and

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academic outcomes, in particular their maladaptive academic choices and behaviors, in ways that cannot be explained by competence beliefs and task value. In the present study, we explored whether and how adding cost to an expectancy-value model could improve the prediction of a variety of adaptive and maladaptive motivational variables and academic outcomes.

1.1. Role of cost in expectancy-value theory

Cost is defined as the negative consequences of engaging in a task. According to expectancy-value theory, cost is a multifaceted construct consisting of effort required to perform a task successfully, forgone opportunities to engage in other valued tasks, ego threats associated with potential task failure, and negative emotions associated with task engagement (Barron & Hulleman, 2015; Eccles et al., 1983; Wigfield et al., 2017).

Cost has always been part of expectancy-value theory, but its role within the theory has been debated in recent years (Barron & Hulleman, 2015; Wigfield et al., 2017). Eccles et al. (1983) wrote about cost originally as an influence on task value, arguing that students "conceptualized the influence of cost on the value of an activity in terms of a cost/benefit ratio." (p. 93). If the cost of a task was too high, an individual would not engage with it. This phrasing indicates that to some extent, cost and task value both have independent influences on students' motivation and behavior in academic settings. In later expectancy-value researchers' writings, however, cost was categorized as a component of task value (Wigfield & Eccles, 1992; Eccles, 2005). Many researchers have adopted this perspective and most researchers who have assessed task value either have excluded cost altogether or have combined cost with other components of task value to create a composite task value score (e.g., Buehl & Alexander, 2005; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002; Safavian & Conley, 2016). This perspective suggests that cost is one factor that determines value, but it does not have any separate impact on students' motivation or behavior beyond its impact on value.

Considering cost to be part of the task value construct may be problematic, because the nature of cost is negative whereas task value is typically thought to be positive. Researchers have argued that the term "valence" is useful to describe both positive and negative characteristics of a specific task or activity (Feather, 1992, 1995). From an expectancy-value perspective, cost has negative valence, whereas the other components of task value (i.e., attainment, intrinsic, and utility value) have positive valence. In achievement settings, both positive and negative valences influence individuals' approach- or avoidance-oriented behavior, both consciously and unconsciously (Elliot & Covington, 2001; Pintrich, 2003). Thus, students may be affected by both cost and task value, separately, rather than cost impacting students only as a function of its influence on task value. Recently, some researchers have expressed support for this perspective on cost and suggested that cost is a unique construct that differs from task value (Barron & Hulleman, 2015). Also, empirically, in several recent studies cost has formed a separate factor from other dimensions of task value (e.g., Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Gaspard et al., 2015a; Jiang, 2015; Luttrell, et al., 2010; Perez, Cromley, & Kaplan, 2014). However, researchers have not reached clear consensus on the role of cost versus task value to date.

1.2. Role of cost in predicting academic motivation and behavior

Compared to task value, which has been extensively investigated, the role of cost in predicting students' academic motivation and achievement remains largely under-explored. Few researchers had developed measures of cost prior to 2010 and thus few researchers included cost in studies that explored motivation from an expectancy-value perspective (Wigfield, Tonks, & Klauda, 2016). The work that has been done suggests that cost predicts students' outcomes. Conley (2012) found that cost assumed a vital role in discriminating middle school students' patterns of motivation for learning math and in predicting their subsequent achievement and classroom affect. Cost also was found to predict college students' drop-out intentions beyond what could be predicted by expectancies and task values (Perez et al., 2014). However, researchers have not systematically explored whether adding cost to the expectancy-value model can predict additional variance in multiple different academic outcomes. This is important to explore because including cost may help predict more variance in these outcomes than could be predicted with only expectancy and task value.

Additionally, if cost is to be included in expectancy-value models, researchers need to explore whether it should be included as its own construct or as part of the task value construct. One aspect of this debate is theoretical, as was discussed above. Another aspect of this debate, the aspect on which we focus in the present study, relates to predictive utility. Considering cost and task value to be separate constructs might increase the predictive accuracy of expectancy-value models. This is because cost and task value might show very different patterns when predicting approach-related versus avoidance-related outcomes. In particular, task value is an affirming motivational construct associated with students' approach motivation, whereas cost is an undermining motivational construct associated with students' avoidance motivation (Atkinson, 1964; Lewin, 1938; McClelland, Atkinson, Clark, & Lowell, 1953). Lack of value would predict a student lacking approach motivation, but this would not necessarily lead to avoidance-related behaviors, because the worst outcome that a low-value task would bring is the absence of a reward. In contrast, perceiving cost would lead to individuals having avoidance motivation. Thus individuals might engage in behaviors to escape the negative consequences they perceive regarding a task. Taken together, this argument would suggest that cost might influence different types of behavior than does task value.

If researchers include cost as part of the task value construct, this might conflate the separate predictive relationships of cost and task value on approach and avoidance behaviors. This would reduce the ability of models to predict accurately behaviors that are related to approach or avoidance in school, compared to if cost was included as a separate construct from task value. For example, procrastination is an avoidance-related behavior that is likely to be most strongly related to students' cost perceptions. A student with moderate task value and high cost may be equally likely to procrastinate as is a student with low task value and high cost. When cost is treated independently from task value, the two students would be found to be equally likely to procrastinate. However, if cost is treated as part of the task value construct, the student with moderate task value and high cost would have a higher overall task value score than would the student with low task value and high cost. That first student would be predicted to be less likely to procrastinate, which in this example would not be an accurate conclusion.

1.3. The present study

In this study, we investigated the utility of using an expectancy-value-cost approach to predict a variety of motivation and educational outcomes for adolescent students. We focused on adolescent students because academic motivation declines over secondary school and students' cost perceptions in many subjects increase over this time period (e.g., Gaspard, Häfner, Parrisius, Trautwein, & Nagengast, 2017). These trends put many students at risk for lower achievement and poor school adjustment. We also focused on assessing outcomes associated with both approach and avoidance in school. This was because, as noted above, cost may be particularly strongly related to avoidance-related outcomes and may relate differently to these outcomes than does task value.

Using hierarchical multiple regression, we tested whether adding cost as an independent variable would significantly explain additional variance in several outcomes that are important for students' academic functioning, beyond what could be predicted by students' competence beliefs and task value. In addition, we directly compared the predictive utility of an expectancy-value-cost approach with an expectancy-value approach that subsumed cost under task value, to test whether cost should be considered an independent predictor from task value in these models. In the expectancy-value-cost models, we examined the relative predictive power of cost versus self-efficacy and task value on each outcome to explore whether cost showed unique predictive relationships with the outcomes as compared to the other two constructs. We tested these relations in two independent data sets. In Study 1, we used a cross-sectional dataset of middle and high school students to test the predictive power of self-efficacy, task value, and cost on the outcomes of achievement goals and classroom affect. In Study 2, we used a longitudinal dataset of middle school students to test the predictive power of self-efficacy, task value, and cost on the outcomes of students' maladaptive academic beliefs (i.e., procrastination, disorganization, and avoidance intentions) and academic achievement.

The subject domain of math was selected for the present study because math is a fundamental subject in school learning. It plays a critical role in developing students' logical thinking and creativity and many teachers and parents emphasize its importance. Yet the subject of math is typically perceived as difficult and highly demanding (e.g., Brown, Brown, & Bibby, 2008; Stodolsky, Salk, & Glaessner, 1991). Researchers have found that more and more students are starting to feel afraid of engaging in math-related activities (e.g., Gaspard, Häfner, et al., 2017; Simpkins, Davis-Kean, & Eccles, 2006), indicating that cost perceptions about studying math could be very salient to students.

2. Study 1

In Study 1, we evaluated the predictive utility of an expectancy-value-cost approach in explaining adolescent students' achievement goals and positive or negative classroom affect. Achievement goals refer to the underlying purposes that students have for engaging in achievement-related work (Dweck & Leggett, 1988). Achievement goals were originally dichotomized into two different types: mastery and performance goals (e.g., Ames & Archer, 1988; Dweck & Leggett, 1988; Nicholls, 1984). Contemporary achievement goal researchers have further divided performance goals into performance approach and performance avoidance goals (e.g., Elliot, 1999). Students who adopt mastery goals are interested in mastering the learning task and improving their competence. Students who adopt performance approach goals are interested in demonstrating their ability and gaining approval from others, whereas students who adopt performance avoidance goals are interested in avoiding incompetent appearances or losing the approval of others. Besides these three types of achievement goals, researchers also have proposed another goal orientation toward learning called work avoidance goals (e.g., Meece, Blumenfeld, & Hoyle, 1988). These reflect students' negative attitudes toward school work and students who adopt work avoidance goals usually try to get work done with a minimum amount of effort.

Researchers have posited that competence beliefs such as self-efficacy are an antecedent of achievement goals (e.g., Elliot, & Church, 1997). Specifically, individuals with high self-efficacy are more likely to adopt stronger mastery and performance approach goals, whereas individuals with low self-efficacy are more likely to adopt stronger performance avoidance goals. Wigfield (1994) also suggested that competence beliefs can have a proximal influence on an individual's adoption of achievement goals. Empirical evidence has confirmed that students' competence beliefs such as self-efficacy positively predicted their mastery and performance approach goal adoption and negatively predicted their performance avoidance goal adoption (e.g., Bong, Hwang, Noh, & Kim, 2014; Liem, Lau, & Nie, 2008).

In a similar vein, task value also is thought to be a precursor of students' achievement goals (Wigfield, 1994). Based on the model of future-oriented motivation and self-regulation, Miller and Brickman (2004) argued that high task value perceptions could encourage students to adopt stronger mastery goals. Empirically, researchers have found that task value positively predicted students' adoption of mastery goals, but did not predict their adoption of performance goals (e.g., Greene, Miller, Crowson, Duke, & Akey, 2004; Liem et al., 2008). It is also reasonable to expect that cost could influence students' adoption of achievement goals. As mentioned earlier, cost involves negative appraisals related to learning which have been posited to influence avoidance motivation (e.g., Atkinson, 1964; Lewin, 1938; McClelland et al., 1953). Therefore, one might expect cost to influence positively whether students adopt avoidance goals (i.e., performance avoidance and work avoidance goals).

We also considered the outcomes of students' positive and negative classroom affect in this study, in order to understand how cost relates to the outcome of students' subjective well-being in school. Positive classroom affect reflects students' level of pleasurable engagement with the classroom environment. In contrast, negative classroom affect reflects students' subjective distress in the classroom and encompasses a broad range of negative mood states such as fear, anxiety, and disgust (e.g., Watson, Clark, & Tellegen, 1988). Students who have higher positive affect tend to show benefits including higher school satisfaction, stronger self-efficacy beliefs, and better academic achievement (e.g., Suldo & Huebner, 2006). Unfortunately, evidence has shown that students report decreased positive affect in school as they move to higher grades (see Eccles et al., 1993; Wigfield, Eccles, Fredricks, Simpkins, Roeser, & Schiefele, 2015, for reviews). Thus it is important to explore what predicts students' classroom affect in order to understand how to improve it. Previous research has shown that competence beliefs and task value predict students' affective experiences in academic settings (e.g., Goetz, Pekrun, Hall, & Haag, 2006; Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010). Cost reflects negative aspects of learning which can induce negative affect, so we hypothesized that cost might predict strongly students' negative affect in the classroom.

We were interested whether including cost in predictive models would increase their predictive utility for these outcomes beyond what could be predicted by competence beliefs and task value. We also were interested in how cost predicted these outcomes compared to task value and to competence beliefs. We hypothesized that cost would explain additional variance in students' avoidance goals and in their negative classroom affect. We did not make specific hypotheses about the predictive power of cost on the other outcomes or the relative predictive power of cost versus task value.

2.1. Method

2.1.1. Participants

Data were collected from 652 students (302 8th graders and 350 11th graders) at two public schools located in Seoul, South Korea. Students came from middle-class families, which constitute the majority of Korean society. Respondents ($n = 15$) who provided insincere responses (e.g., pattern drawing) were excluded from the analyses. The final sample consisted of 637 students (290 males, 346 females, one did not indicate gender; 294 8th graders, Mean age = 14.2 years, $SD = 0.48$; 343 11th graders, Mean age = 17.1 years, $SD = 0.47$). The data from this study was collected as part of a broader research project asking students about their motivation to learn. In a prior doctoral dissertation study, Jiang (2015) used data from the project to develop a cost scale and to explore the relationships between specific dimensions of cost and students' academic outcomes. The present study thus utilizes the same data for perceptions of cost and classroom affect that was used in the Jiang (2015) project, but to address different research aims.

2.1.2. Measures

All survey items were written in Korean and referred to students' math class or math as a subject domain. The items that referred to math class were those measuring self-efficacy, achievement goals, and classroom affect. The items that dealt with math as a subject domain were those measuring cost. For the measure of task value, one item referred to math class whereas others referred to math as a subject domain. We adapted all items from previously-used scales, so our choice to measure items at the class- versus the domain-level was based on how these constructs have typically been assessed in the literature (e.g., Bong, 2001; Gaspard et al., 2015a; Liem et al., 2008). Items measuring self-efficacy, task value, cost, and achievement goals were based on seven-point Likert scales ranging from 1 (*not true at all*) to 7 (*very true*), whereas items measuring classroom affect were based on five-point Likert scales ranging from 1 (*not true at all*) to 5 (*very true*). Items which were originally developed in English were put through a translation-and back-translation procedure suggested by Brislin (1970). Cronbach's alpha coefficients were used to examine the reliabilities of the measures. All survey items are presented in Appendix A.

2.1.2.1. Self-efficacy. Six items measuring self-efficacy were adopted from the self-efficacy sub-scale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991) and modified by Bong (2008). The reliability coefficient was $\alpha = .94$.

2.1.2.2. Task value. Six items about task value were adopted from the MSLQ (Pintrich et al., 1991). The scale measured three components of task value including utility, attainment, and interest value, with two items for each component. For the purpose of exploring the utility of the expectancy-value-cost approach, we were interested in investigating the effect of an overall task value construct on academic motivation rather than on the individual components of task value. This approach is consistent with that of previous researchers (e.g., Bong, 2001; Liem et al., 2008; Jacobs et al., 2002). The reliability coefficient was $\alpha = .87$.

2.1.2.3. Cost. Twelve items were used to measure cost based on a questionnaire developed by Jiang, Kim, and Bong, (2016). The cost scale measured four sub-facets of cost with three items for each sub-facet: effort, opportunity, ego, and emotional cost. For the research questions of interest in the present study, we used an overall cost score to test the utility of the expectancy-value-cost approach. The reliability coefficient was $\alpha = .89$.

2.1.2.4. Achievement goals. Nine items based on the 2 × 2 achievement goal framework were adopted from items used by Elliot and McGregor (2001). We only measured mastery approach, performance approach, and performance avoidance goals from Elliot and McGregor (2001). Mastery avoidance goals were excluded in the present study due to their theoretical ambiguity. Mastery avoidance goals are those in which students are focused on avoiding intraindividual incompetence, such as failing to master the task as completely as possible (Elliot & McGregor, 2001). Researchers have argued that it may be rare for adolescent students who are still improving their competence to pursue mastery avoidance goals (Elliot, 2005). In a recent study using open-ended questions, Lee and Bong (2016) found that among 1146 adolescent students' spontaneous responses of reasons for achievement striving, no responses reflected mastery avoidance goals. Thus, mastery avoidance goals might be a statistical artifact in forced-choice surveys. The reliability coefficients were $\alpha = .75$ for mastery approach goals, $\alpha = .87$ for performance approach goals, and $\alpha = .66$ for performance avoidance goals. In addition, five work avoidance goal items were adapted from Meece and Miller (2001). The reliability coefficient was $\alpha = .83$.

2.1.2.5. Classroom affect. Three items for positive affect and four for negative affect in school were adopted from Kaplan and Maher (1999). Items were revised to assess positive and negative affect in math classes. Both revised scales had been used successfully in prior research with different groups of Korean students of varying ages (Jiang, Bong, & Kim, 2015). The reliability coefficients for positive and negative classroom affect were $\alpha = .93$ and .87, respectively.

2.1.3. Intraclass correlations and missing value analysis

Students in the present study were nested within 21 classes from two schools. Because of the nested nature of our data, we checked intraclass correlation coefficients (ICCs) to evaluate whether a large proportion of variance in the outcome variables stemmed from students' nesting within classes and schools. ICCs for these variables as a function of nesting within classes ranged from .01 to .07, and ICCs as a function of nesting within schools ranged from .01 to .08, indicating that only little variance in the outcome variables was explained by this nesting (Kreft & de Leeuw, 1998). However, we conducted all analyses in Mplus 7.4 with the robust maximum likelihood estimator (MLR) and the design-based correction of standard errors (with type = complex) to account for any potential nonindependence of data due to the nesting of students within classes (McNeish, Stapleton, & Silverman, 2017).

Missing values in the data were due to non-response on individual items and were less than 1.7% for each item. We conducted two tests to assess the level of randomness in the missing data. First, Little's MCAR test (Little, 1988) indicated that the missing mechanism could not be assumed to be missing completely at random ($\chi^2 = 2796.730$, $df = 2357$, $p < .001$). We then tested whether the propensity for data points to be missing was related to some of the observed variables. *T*-tests revealed that the missingness on some variables was related to the values of other observed variables. Thus, we assumed the missingness mechanism to be missing at random (MAR). For MAR data, a growing body of research has recommended using the multiple imputation (MI) approach to deal with missing values (e.g., Graham, 2009). We thus used Mplus 7.4 software to conduct multiple imputation for missing data. All variables (including gender and age) were included in the imputation model. For the data whose missingness is less than 3%, researchers have claimed that good inferences can be made with 3–5 imputed data sets (Graham, Olchowski, & Gilreath, 2007). Therefore, we generated five imputed data sets for the present study. We then used these five imputed data sets for our statistical analyses in Mplus and reported the average results over five data sets.

2.1.4. Overview of data analysis

We first conducted confirmatory factor analyses (CFA) to examine the fit of the questionnaire measuring cost, task value, and classroom affect, as well as to examine the factor structure of items measuring cost and task value. Several indexes were consulted to determine goodness-of-fit in these analyses: the chi-square (χ^2) value and the degrees of freedom, 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). In specific, values of RMSEA and SRMR below .08 indicate a reasonable model fit and values of CFI and TLI above .90 and .95 indicate acceptable and excellent model fit, respectively (Hu & Bentler, 1999; Kline, 2010; Marsh, Hau, & Wen, 2004).

To investigate the utility of an expectancy-value-cost approach in predicting student's academic outcomes, a three-step hierarchical multiple regression was conducted with each type of achievement goal and classroom affect as dependent variables. Mean scores of the variables were used for the analyses. Demographic variables (i.e., gender and age) were entered as control variables at step one. Self-efficacy and task value were entered at step two. Cost was entered at step three.

In addition to the overall regression, we conducted an additional set of regression analyses in order to compare more directly the predictive utility of an expectancy-value versus an expectancy-value-cost approach. We tested a series of models in which we subsumed cost under task value to produce one composite value score that included cost. To do so, we subtracted students' cost scores from their task value scores. We then conducted a two-step hierarchical multiple regression for each dependent variable using the composite value scores and self-efficacy as predictors, comparing results to those that treated cost, self-efficacy, and task value as three separate predictors.

2.2. Results

2.2.1. CFA and descriptive statistics

For the structure of the items measuring cost and task value, CFA results revealed that a higher-order factor model in which the three components of task value functioned as indictors of a general task value factor demonstrated good model fit (χ^2 (6) = 14.48, CFI = .994, TLI = .985, RMSEA = .047, SRMR = .019). Similarly, the higher-order factor model in which the four sub-facets of cost functioned as indicators of a general cost factor also demonstrated reasonable model fit (χ^2 (50) = 189.45, CFI = .955, TLI = .941, RMSEA = .066, SRMR = .053). Thus, it was appropriate to create composite value and cost scores to represent students' overall task value and cost perceptions. We next conducted CFA analyses including items from both the cost and task value scales together. Results showed that a two-factor model, with one factor representing task value (having three sub-factors as latent indicators) and the second factor representing cost (having four sub-factors as latent indicators), showed considerably better model fit (χ^2 (123) = 357.12, CFI = .956, TLI = .946, RMSEA = .055, SRMR = .069) than a single-factor model with seven latent sub-factors representing the components of task value and cost (χ^2 (128) = 1136.62, CFI = .812, TLI = .776, RMSEA = .111, SRMR = .245). These results suggest that cost is an empirically unique construct from task value.

For the structure of classroom affect items, CFA analysis showed that a two-factor model with one factor representing positive affect and the second factor representing negative affect (χ^2 (13) = 94.92, CFI = .964, TLI = .943, RMSEA = .099, SRMR = .070) showed better model fit than a single-factor model representing overall classroom affect (χ^2 (14) = 886.81, CFI = .621, TLI = .432, RMSEA = .313, SRMR = .210). This indicated that positive and negative classroom affect were two unique constructs.

Finally, we tested a CFA model including items from the task value, cost, and two classroom affect scales. The results revealed an acceptable model fit (χ^2 (259) = 858.26, CFI = .933, TLI = .923, RMSEA = .060, SRMR = .088), indicating that positive and negative classroom affect were separable from task value and cost.

Table 1 presents descriptive statistics, Cronbach's alpha coefficients, and zero-order correlation coefficients among variables. All variables demonstrated acceptable reliability with $a \geq .66$ and good normality with absolute values of skewness and kurtosis less than 1. Self-efficacy correlated positively with task value ($r = .67, p < .01$) and correlated negatively with cost ($r = -.24, p < .01$). Task value also correlated negatively with cost ($r = -.23, p < .01$). Correlations of self-efficacy, task value, and cost with other motivational variables were consistent with what has been shown in the empirical literature. Specifically, self-efficacy and task value correlated positively with mastery approach goals, performance approach goals, and positive classroom affect ($.31 \leq rs \leq .67$, $ps < .01$). They correlated negatively with work avoidance goals and negative classroom affect ($-.42 \leq rs \leq -.33$, $ps < .01$). Cost correlated positively with both types of performance goals, work avoidance goals, and negative classroom affect ($.16 \leq rs \leq .53$, $ps < .01$) but it correlated negatively with positive classroom affect ($r = -.23$, $p < .01$).

2.2.2. Hierarchical multiple regression

As shown in Table 2, control variables contributed significantly to all of the regression models except for the work avoidance goals model ($\Delta R^2 \geq .01$, $ps < .05$). Introducing self-efficacy and task value significantly explained additional variance for all dependent variables except for performance avoidance goals ($\Delta R^2 \geq .14$, $ps < .01$). Finally, adding cost into the regression model significantly explained additional variance for all dependent variables ($\Delta R^2 \geq .01$, $ps < .01$).

In particular, the addition of cost to the regression model explained additional variance in performance avoidance goals, work avoidance goals, and negative classroom affect ($\Delta R^2 \geq .18$). When all independent variables were included in the regression model, cost emerged as the strongest predictor of the two types of avoidance goals (β = 0.45 and 0.46 for performance avoidance goals and work avoidance goals, respectively) and of negative classroom affect (β = 0.47). Task value, in contrast, emerged as the strongest predictor of mastery approach goals (β = 0.42) and positive classroom affect (β = 0.56), but it did not predict performance avoidance goals.

We then tested a model subsuming cost under task value rather than including it as its own predictor. As Table 3 shows, the combined value score significantly predicted all dependent variables in the final regression model. Yet the total explained variances of dependent variables were less than they were using the approach that treated competence beliefs, task value, and cost separately ($\Delta R^2 \geq .02$). In addition, the information about whether cost or task value was a relatively stronger predictor of any outcome was lost when subsuming cost as part of task value. For example, the combined value construct appeared to predict performance avoidance goals negatively. However, this finding masks the fact that only cost had predicted the outcome and task value had not in the other set model. Finally, some findings using the combined value score were misleading. For example, the combined value score negatively predicted two types of performance goals, which is different from what was observed in the regressions treating cost and task value as separate constructs.

2.3. Discussion

We aimed to explore the utility of an expectancy-value-cost approach in predicting adolescent students' math achievement goals and classroom affect. We found that cost explained additional variance in all of these outcomes beyond what expectancy and value could predict. Cost also showed unique predictive patterns with the outcomes as

Table 1
Descriptive statistics, Cronbach's alpha, and zero-order correlation coefficients among variables in study 1.

Variable	*M*	*SD*	S	K	*a*	1	2	3	4	5	6	7	8
1. Self-efficacy	4.25	1.33	−0.09	−0.27	.94	–							
2. Task value	4.31	1.28	−0.20	−0.14	.87	.67**	–						
3. Cost	3.88	1.16	−0.13	−0.19	.89	−.24**	−.23**	–					
4. Mastery approach goals	4.77	1.21	−0.30	−0.02	.75	.59**	.62**	−.04	–				
5. Performance approach goals	4.35	1.38	−0.16	−0.18	.87	.40**	.31**	.16**	.50**	–			
6. Performance avoidance goals	4.00	1.20	−0.10	0.37	.66	.06	.05	.40**	.23**	.62**	–		
7. Work avoidance goals	4.02	1.21	0.05	0.13	.83	−.33**	−.39**	.51**	−.18**	.13**	.45**	–	
8. Positive classroom affect	2.57	1.06	0.17	−0.58	.93	.54**	.67**	−.23**	.46**	.21**	.01	−.40**	–
9. Negative classroom affect	2.47	0.99	0.38	−0.35	.87	−.42**	−.39**	.53**	−.25**	−.06	.22**	.48**	−.38**

Note. S = Skweness, K = Kurtosis.
* $p < .05$.
** $p < .01$.

Table 2
Hierarchical multiple regression analyses in Study 1.

	Mastery approach goals			Performance approach goals			Performance avoidance goals			Work avoidance goals			Positive classroom affect			Negative classroom affect		
	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE
Step 1	.05** [$\Delta F(2, 634) = 16.68$]			.03** [$\Delta F(2, 634) = 9.80$]			.01* [$\Delta F(2, 634) = 3.20$]			.00[$\Delta F(2, 634) = 1.45$]			.04** [$\Delta F(2, 634) = 13.21$]			.02** [$\Delta F(2, 634) = 6.47$]		
Gender		−.04	0.04		−.07	0.03		.03	0.03		.04	0.04		−.13**	0.04		.11*	0.03
Age		.21**	0.05		.17**	0.04		.10*	0.04		−.05	0.05		.15*	0.06		−.11**	0.04
Step 2	.40** [$\Delta F(2, 632) = 229.82$]			.14** [$\Delta F(2, 632) = 53.30$]			.00[$\Delta F(2, 632) = 0.71$]			.16** [$\Delta F(2, 632) = 60.19$]			.43** [$\Delta F(2, 632) = 256.38$]			.18** [$\Delta F(2, 632) = 71.10$]		
Gender		.05*	0.02		−.00	0.03		.03	0.03		−.02	0.03		−.04	0.03		.04	0.03
Age		.08**	0.03		.08*	0.04		.08*	0.04		.03	0.04		.02	0.04		−.02	0.04
Self-efficacy		.31**	0.05		.33**	0.07		.04	0.07		−.14*	0.07		.15**	0.05		−.29**	0.07
Task value		.40**	0.06		.08	0.06		.02	0.07		−.30**	0.05		.57**	0.04		−.19**	0.06
Step 3	.01** [$\Delta F(1, 631) = 11.69$]			.07** [$\Delta F(1, 631) = 58.12$]			.18** [$\Delta F(1, 631) = 140.22$]			.19** [$\Delta F(1, 631) = 184.45$]			.01** [$\Delta F(1, 631) = 12.13$]			.19** [$\Delta F(1, 631) = 196.54$]		
Gender		.05	0.02		−.02	0.03		.01	0.03		−.04	0.03		−.04	0.03		.01	0.03
Age		.05	0.03		.02	0.03		−.01	0.03		−.07	0.04		.03	0.04		−.11**	0.04
Self-efficacy		.34**	0.05		.39**	0.07		.13*	0.05		−.05	0.06		.14**	0.05		−.19**	0.06
Task value		.42**	0.05		.11	0.06		.07	0.06		−.25**	0.05		.56**	0.04		−.14**	0.04
Cost		.12*	0.05		.28**	0.05		.45**	0.05		.46**	0.04		−.07	0.04		.47**	0.04
Total R^2	.46**			.24**			.19**			.35**			.48**			.39**		

Note.
* $p < .05$.
** $p < .01$.

Table 3
Hierarchical multiple regression analyses with composite value score in Study 1.

	Mastery approach goals			Performance approach goals			Performance avoidance goals			Work avoidance goals			Positive classroom affect			Negative classroom affect		
	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE
Step 1	.05** [$\Delta F(2, 634) = 16.68$]			.03** [$\Delta F(2, 634) = 9.80$]			.01* [$\Delta F(2, 634) = 3.20$]			.00[$\Delta F(2, 634) = 1.45$]			.04** [$\Delta F(2, 634) = 13.21$]			.02** [$\Delta F(2, 634) = 6.47$]		
Gender		−.04	0.04		−.07	0.03		.03	0.03		.04	0.04		−.13**	0.04		.11*	0.03
Age		.21**	0.05		.17**	0.04		.10*	0.04		−.05	0.05		.15*	0.06		−.11**	0.04
Step 2	.33** [$\Delta F(2, 632) = 168.19$]			.16** [$\Delta F(2, 632) = 62.42$]			.09** [$\Delta F(2, 632) = 31.60$]			.33** [$\Delta F(2, 632) = 155.64$]			.37** [$\Delta F(2, 632) = 198.17$]			.33** [$\Delta F(2, 632) = 160.43$]		
Gender		.06*	0.03		−.01	0.03		.02	0.03		−.04	0.03		−.03	0.02		.02	0.03
Age		.11**	0.04		.06	0.04		.04	0.04		−.05	0.04		.08	0.04		−.08	0.04
Self-efficacy		.49**	0.05		.50**	0.06		.28**	0.05		.02	0.06		.26**	0.05		−.09	0.07
Composite value		.16*	0.07		−.19**	0.05		−.37**	0.06		−.59**	0.03		.43**	0.05		−.52**	0.05
Total R^2	.38**			.19**			.10**			.33**			.41**			.35**		

Note.
* $p < .05$.
** $p < .01$.

compared to task value, predicting more strongly constructs related to students' negative affect and avoidance goals. These results are in accordance with the psychological underpinnings of cost, as it is thought to be related to avoidance motivation (Atkinson, 1964; Lewin, 1938).

In terms of achievement goals, adding cost into the regression significantly improved the proportion of explained variance for all four types of achievement goals. Additionally, whereas self-efficacy and task value were stronger predictors of approach goals, cost emerged as the strongest predictor of avoidance goals. These regression models, however, should be interpreted cautiously: The regression coefficients from cost to performance goals (i.e., βs = .28 and .45 for performance approach and avoidance goals, respectively) were greater than the zero-order correlations between cost and performance goals (i.e., *r*s = .16 and .40 for performance approach and avoidance goals, respectively). Thus, there may exist statistical suppression effect in these models (MacKinnon, Krull, & Lockwood, 2000). Nevertheless, the sign of regression coefficients were consistent with the sign of correlations for all models unless otherwise noted, indicating the suppression effects likely were not strong. Additionally, the reliability for performance avoidance goals was somewhat low in this study ($\alpha = .66$), but this scale has been used reliably in prior research with different groups of Korean adolescent students (Jiang et al., 2015). The relatively low alpha for performance avoidance goals in the present study may be because of the low inter-item correlations among two performance avoidance goals items (items 1 and 3, $r = .25$, $p < .001$). We conclude that although more work is needed, our findings suggest that cost plays an important role in understanding students' avoidance motivation in school.

An unexpected finding was that cost also positively predicted approach goals. In terms of mastery approach goals, cost was a significant positive predictor in the final regression model, but overall there was a negative correlation of cost with mastery approach goals. Therefore this positive path is probably due to a suppression effect in the regression model. In terms of performance approach goals, one possible explanation for why cost predicted these goals positively is that both cost and performance approach goals are tied to East Asian students' perceptions of self-worth. One important sub-facet of cost is ego cost, which is self-worth threat associated with potential failure (Eccles et al., 1983). Ego threat is usually perceived as particularly salient among East Asian students, because they often perceive academic achievement as being central to their sense of identity (Markus & Kitayama, 1991). Meanwhile, performance approach goals emphasize normative superiority relative to competitors (e.g., Elliot & McGregor, 2001), which can serve as an effective way to enhance self-worth beliefs. It is possible that a student who perceives higher ego cost might also adopt stronger performance approach goals in order to maintain self-worth. However, more studies are needed to further explore this possibility.

In the present study, we also found that cost was the strongest predictor of negative classroom affect whereas task value was the strongest predictor of positive classroom affect. These findings support the idea that cost and task value relate differently to the approach and avoidance dimensions of motivation and their associated outcomes. Students who reported high task value were more likely to pursue approach goals and to have more positive affect. In contrast, students with high cost perceptions were more likely to pursue avoidance goals and to have more negative affect. This finding supports the importance of studying cost separately from task value in expectancy-value predictive models. Including cost as a subtractive force on task value, or omitting it from the expectancy-value models altogether, loses important information regarding how to predict both approach and avoidance behavior in school.

3. Study 2

Findings from Study 1 revealed that cost could successfully predict additional variance in adolescent students' achievement goals and classroom affect, beyond what could be predicted by competence beliefs and task value. However, Study 1 included only cross-sectional data. In Study 2, we tested the predictive utility of the expectancy-value-cost approach using a longitudinal data set and with different academic outcomes: disorganization, procrastination, avoidance intentions, and academic achievement.

Researchers have suggested that one of the primary antecedents of maladaptive academic behaviors such as procrastination and disorganization is having low competence beliefs (Urdan & Midgley, 2001). However, it is possible that cost might explain additional variance in these maladaptive academic outcomes beyond what could be predicted by self-efficacy and task value. It is likely that because these outcomes are relevant to avoidance behaviors in school, cost might predict them strongly.

We also assessed students' avoidance intentions toward math class in Study 2. It has been well established that task value is a stronger predictor than competence beliefs for students' academic choices and intentions to engage in certain academic behaviors (see Eccles & Wigfield, 2002; Wigfield & Cambria, 2010 for reviews). An accumulating body of research indicates that cost also might play an important role in understanding individuals' academic choices and intentions. For example, researchers have found that cost negatively predicted college women's intentions to pursue graduate study (Battle & Wigfield, 2003) and positively predicted college students' drop-out intentions from a STEM major (Perez et al., 2014). Luttrell et al. (2010) also found that a general sense of cost negatively related to students' level of course participation in college. We therefore tested whether cost could obtain significant predictive utility on adolescent students' avoidance intentions beyond what would be predicted by task value and competence beliefs.

Finally, we aimed to explore the utility of an expectancy-value-cost approach in predicting academic achievement. Competence beliefs like self-efficacy are one of the most powerful predictors of student achievement in various academic domains (Pajares, 1996). Lee and Stankov (2013) analyzed the Programme for International Student Assessment (PISA) data and found that self-efficacy not only correlated more strongly with mathematics achievement than other self-beliefs did, but it also remained the strongest predictor of achievement after controlling for fourteen other variables, which ranged widely from motivation to the use of learning strategies. Within the expectancy-value model, competence beliefs are considered to be a more powerful predictor of achievement than task value (see Wigfield et al., 2016 for review).

To date, little empirical research has examined the relation between cost and achievement. However, based on the work that has been done, it seems possible that cost would predict negatively students' achievement in the learning context. Flake et al. (2015) reported significant negative correlations between three types of cost (i.e., effort, opportunity, and emotional cost) and undergraduate students' academic achievement. Gaspard et al. (2017) found negative correlations between cost (i.e., effort & emotional cost and opportunity cost) and students' grades in multiple domains (i.e., Math, Biology, and German). In an experimental study, Fries and Dietz (2007) showed that raising high school students' perceptions of cost (i.e., opportunity cost) had detrimental effects on their performance. In this study, we were interested in whether cost could explain additional variance in adolescents' math achievement, beyond what could be predicted by self-efficacy and task value.

We aimed to test whether cost could obtain extra predictive utility on students' maladaptive academic beliefs and achievement beyond what could be predicted by students' corresponding pretest scores on a given measure, self-efficacy, and task value. We also wanted to examine the relative predictive strength of cost, self-efficacy, and task value on each outcome. We hypothesized that cost would explain additional variance in all of the outcomes but did not make hypotheses about the relative predictive strength of each of the three motivational constructs on any outcomes.

3.1. Method

3.1.1. Participants and survey procedure

Data were collected from 8th graders at a public middle school located in Seoul, South Korea. The school is a typical academic-track school with students from middle-class families, who constitute the majority of Korean society. Korean secondary schools begin their academic year in March, and a typical semester lasts for about four months. In order to test the research questions of the present study, students' responses were collected at three time points. The first wave survey (T1) was administered during regular classroom hours in the first week of the school year. During the seventh week of the school year and two weeks before midterm examinations, the second wave survey (T2) was administered during regular classroom hours. After the midterm examinations during the ninth week of the semester, students' midterm examination scores were obtained from teachers (T3).

A total of 245 students participated in the T1 survey, 239 students participated in the T2 survey and 249 students' achievement scores were obtained at T3. For both T1 and T2 surveys, respondents who provided insincere responses (e.g., pattern drawing) were excluded. The final sample consisted of 211 8th graders who participated in both waves of data collection (107 males; Mean age = 13.5 years, *SD* = 0.61).

3.1.2. Measures

Similar to Study 1, all survey items were written in Korean and referred to either students' math class or to math as a subject domain. The items that referred to math class were self-efficacy and avoidance intentions. The items referred to math as a subject domain were task value, cost, disorganization, and procrastination. All items were based on seven-point Likert scales ranging from 1 (*not true at all*) to 7 (*very true*). As in Study 1, items which were originally developed in English were put through a translation-and back-translation procedure (Brislin, 1970). Cronbach's alpha coefficients were used to examine the reliabilities of the measures. For the scale which only had two items (i.e., avoidance intentions), a Spearman-Brown coefficient was used to examine reliability (Eisinga, Grotenhuis, & Pelzer, 2013). All survey items are presented in Appendix A.

3.1.2.1. Items assessing self-efficacy (T1), task value (T1), and cost (T1) were identical to those used in study 1. The reliability coefficients were α = .94 for self-efficacy, α = .87 for task value, and α = .89 for cost.

3.1.2.2. Disorganization (T1&T2). Five items on disorganization were adapted from Elliot, McGregor, and Gable (1999). The scale consisted of revised items from existing measures of cognitive/metacognitive study strategies (e.g., the MSLQ) as well as novel items generated by Elliot et al. (1999). A series of pilot studies including factor analysis were conducted by Elliot and his colleagues to derive the final items to measure disorganization. In that previous work, the final scale showed reasonable reliability, α = .74. In the present study, the reliability coefficients of this scale were even higher: α = .94 for T1 and α = .96 for T2.

3.1.2.3. Procrastination (T1&T2). Five items on procrastination were adopted and revised based on the Melbourne Decision Making Questionnaire (Mann, Burnett, Radford, & Ford, 1997). The original measure was designed to assess procrastination in decision-making and was shown to be both reliable and valid (Mann et al., 1997). In the present study, items were revised to assess procrastination specifically with respect to studying math. The reliability coefficients of this scale were α = .93 for T1 and α = .95 for T2.

3.1.2.4. Avoidance intentions (T1&T2). Avoidance intentions were measured by two researcher-developed items measuring the degree to which students did not want to engage with math class. The reliability coefficients were ρ[1] = .86 for T1 and ρ = .88 for T2.

3.1.2.5. Achievement (T3). Students' scores on their course midterm examinations in math were used as an achievement index in this study. The midterm exam consisted of both multiple-choice and open-ended questions, and it was developed by math teachers at the school. 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 100.

3.1.3. Intraclass correlations and missing value analysis

Students were nested within ten classes in this study, so we checked the ICCs of the dependent variables as a function of nesting within classes. The ICCs ranged from .00 to .01, indicating that the outcome variables did not differ much as a function of students' nesting within classes. However, just as we did in Study 1, we used a robust maximum likelihood estimator (MLR) with a design-based correction of standard errors (i.e., type = complex) in Mplus to account for the non-independence of data due to nesting of students within classes (McNeish et al., 2017). Missing values were less than 1.7% for each item. Similar to Study 1, the missingness mechanism in the present data was assumed as MAR. We again conducted multiple imputation for missing data, using the same processes as we did in Study 1 and pooling results across five imputed data sets for further statistical analyses.

3.1.4. Overview of data analysis

CFA analyses were conducted to ascertain the factor structure of items measuring cost and task value as well as to determine whether the outcome variables of procrastination, disorganization, and avoidance intentions formed a single factor empirically. For variables that were collected from both T1 and T2 (i.e., disorganization, procrastination, and avoidance intentions), multiple-occasion comparisons were conducted to test measurement invariance. We specified a series of nested models that put increasing invariance constraints across occasions, and examined changes in goodness of fit resulting from these invariance constraints. We began by fitting a configural invariance model, which consisted of measurement models with identical loading patterns but no invariance for any parameters. We then tested whether weak (factor loadings invariant) and strong (factor loadings and item intercepts invariant) measurement invariances held across the two survey waves. For tests of measurement invariance, literature suggests that a decrease of less than .01 in incremental fit indices such as CFI and TLI with respect to the fit of the more parsimonious model can be treated as support for the more constrained model (Chen, 2007; Cheung & Rensvold, 2002).

We then conducted three-step hierarchical multiple regression analyses with disorganization, procrastination, and avoidance intentions at T2 as dependent variables. The scores on each respective outcome at T1 and demographic variables (i.e., gender and age) were entered at step one as control variables. Self-efficacy and task value were entered at step two and cost at step three. For achievement, we only used gender and age for control variables, because we had no pretest measure of this outcome. Again, we also conducted a two-step hierarchical multiple regression using a composite value score that included cost as a predictor of each dependent variable, comparing its predictive utility with that of using cost and task value as separate predictors.

3.2. Results

3.2.1. CFA and descriptive statistics

In terms of the factor structure for items measuring cost and task

[1] Spearman-Brown reliability coefficient for two-item scale.

Table 4
Model fit statistics for models representing different degrees of invariance across two survey waves.

Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔTLI
Configural invariance	475.90	237	.931	.920	.069	.042	/	/
Weak measurement invariance	486.25	246	.931	.923	.068	.043	0	.003
Strong measurement invariance	521.00	255	.924	.917	.070	.045	−.007	−.006

value, CFA results again revealed that a two-factor model, including one factor representing task value (with three sub-factors as latent indicators) and the second factor representing cost (with four sub-factors as latent indicators) showed better model fit (χ^2 (123) = 261.17, CFI = .938, TLI = .922, RMSEA = .073, SRMR = .091) than a single factor model with seven latent sub-factors of task value and cost as indicators (χ^2 (128) = 452.37, CFI = .854, TLI = .825, RMSEA = .110, SRMR = .214). This confirmed the empirically distinct relationship between cost and task value. Regarding the structure of the disorganization, procrastination, and avoidance intentions, results indicated that a CFA model with three independent latent factors (χ^2 (51) = 125.20, CFI = .946, TLI = .930, RMSEA = .083, SRMR = .036 for T1 and χ^2 (51) = 104.21, CFI = .952, TLI = .938, RMSEA = .070, SRMR = .035 for T2) demonstrated considerably better model fit than a CFA model with one latent factor (χ^2 (54) = 419.35, CFI = .734, TLI = .675, RMSEA = .179, SRMR = .080 for T1 and χ^2 (54) = 222.60, CFI = .849, TLI = .816, RMSEA = .122, SRMR = .059 for T2). These suggest that procrastination, disorganization, and avoidance intentions can be considered to be independent constructs.

In terms of testing measurement invariance, Table 4 presents fit statistics for models representing different degrees of invariance across two survey waves. In conducting these analyses, we found first that the configural invariance model demonstrated a reasonable fit (χ^2 (237) = 475.90, CFI = .931, TLI = .920, RMSEA = .069, SRMR = .042). Second, we found no decrease in goodness-of-fit indices when constraining the factor loadings to be invariant (ΔCFI = 0, ΔTLI = .003). Third, when additionally constraining the item intercepts to be invariant, comparison with the weak measurement invariance model revealed only small decreases in goodness-of-fit indices (ΔCFI = −.007, ΔTLI = −.006). Together this evidence can be taken to indicate strong measurement invariance across the two survey waves (e.g., Chen, 2007; Cheung & Rensvold, 2002).

Table 5 presents descriptive statistics, reliabilities, and zero-order correlation coefficients among variables. Again, all variables demonstrated good reliability with $\alpha \geq .86$ and good normality with absolute values of skewness and kurtosis less than 1. Similar to Study 1, cost correlated negatively with both self-efficacy ($r = -.15$, $p < .05$) and task value ($r = -.17$, $p < .05$), whereas self-efficacy and task value correlated positively with each other ($r = .74$, $p < .01$). Self-efficacy and task value correlated negatively with all maladaptive academic outcomes at both time points ($-.53 \leq rs \leq -.28$, $ps < .01$). In contrast, cost correlated positively with all maladaptive academic outcomes at both time points ($.30 \leq rs \leq .45$, $ps < .01$). In terms of correlations with achievement, self-efficacy and task value correlated positively with achievement ($rs = .51$ and .45, respectively, $ps < .01$) whereas cost correlated negatively with achievement ($r = -.23$, $p < .01$).

3.2.2. Hierarchical multiple regression

As Table 6 shows, the pretest measure accounted for the largest proportion of variance in each regression model that included it ($\Delta R^2 \geq .22$, $ps < .01$). Nevertheless, adding self-efficacy and task value significantly explained additional variance in each dependent variable ($\Delta R^2 \geq .04$, $ps < .01$). The addition of cost into the model also explained significant additional variance in each dependent variable ($\Delta R^2 \geq .01$, $ps < .05$). When all independent variables were included in the regression models, self-efficacy positively predicted achievement (β = 0.38) and negatively predicted disorganization (β = −0.24), procrastination (β = −0.26), and avoidance intentions (β = −0.31). Cost also emerged as a significant predictor of achievement, procrastination and avoidance intentions (βs = −0.12, 0.19, and 0.14, respectively). Task value failed to demonstrate any significant predictive associations in the final regression models.

We also evaluated results using regression models that subsumed cost under task value as a single predictor instead of treating them separately. As shown in Table 7, these models explained less variance in procrastination and avoidance intentions than did the models using cost and task value as separate predictors. Moreover, the relative predictive power of cost versus task value on all outcomes could not be observed when combining the two constructs into one predictor term. For example, it appeared that the combined value score predicted the outcomes of grades and procrastination. However, in the other set of regressions it could be observed that cost had predicted these outcomes, whereas task value had not. Additionally, the combined value construct failed to predict avoidance intentions whereas cost did predict significantly avoidance intentions when it was treated as a separate construct from task value.

Table 5
Descriptive statistics, reliability, and zero-order correlation coefficients among variables in Study 2.

Variable	*M*	*SD*	S	K	α	1	2	3	4	5	6	7	8	9
1. Self-efficacy (T1)	4.16	1.40	0.07	−0.30	.94[a]	–								
2. Task value (T1)	4.62	1.26	−0.20	0.20	.87[a]	.74**	–							
3. Cost (T1)	3.80	1.15	0.10	−0.31	.89[a]	−.15*	−.17*	–						
4. Disorganization (T1)	3.92	1.53	−0.03	−0.60	.94[a]	−.53**	−.35**	.45**	–					
5. Procrastination (T1)	4.03	1.46	−0.06	−0.32	.93[a]	−.41**	−.28**	.38**	.72**	–				
6. Avoidance intentions (T1)	3.43	1.67	0.43	−0.45	.86[b]	−.51**	−.48**	.39**	.59**	.58**	–			
7. Disorganization (T2)	3.80	1.46	−0.34	−0.35	.96[a]	−.43**	−.32**	.33**	.52**	.43**	.32**	–		
8. Procrastination (T2)	3.79	1.44	−0.35	−0.32	.95[a]	−.43**	−.33**	.38**	.51**	.53**	.36**	.86**	–	
9. Avoidance intentions (T2)	3.65	1.51	−0.14	−0.46	.88[b]	−.43**	−.34**	.30**	.49**	.45**	.43**	.69**	.78**	–
10. Achievement (T3)	71.89	27.27	−0.71	−0.84	/	.51**	.45**	−.23**	−.42**	−.36**	−.31**	−.35**	−.38**	−.35**

Note. S = Skweness, K = Kurtosis.
[a] Cronbach's alpha.
[b] Spearman-Brown coefficient for two-item scale.
* $p < .05$.
** $p < .01$.

Table 6
Hierarchical multiple regression analyses in Study 2.

	Disorganization (T2)			Procrastination (T2)			Avoidance intentions (T2)			Achievement (T3)		
	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE
Step 1	.27** [ΔF(3, 207) = 25.52]			.30** [ΔF(3, 207) = 29.57]			.22** [ΔF(3, 207) = 19.46]			.03* [ΔF(2, 208) = 3.22]		
Gender		−.05	0.04		−.09	0.05		−.08	0.07		−.01	0.06
Age		.06	0.06		.10	0.06		.14*	0.06		−.17*	0.08
Control (T1)		.51**	0.07		.53**	0.06		.43**	0.05		/	/
Step 2	.04** [ΔF(2, 205) = 5.94]			.06** [ΔF(2, 205) = 9.61]			.06** [ΔF(2, 205) = 8.42]			.26** [ΔF(2, 206) = 37.72]		
Gender		−.07	0.03		−.12*	0.05		−.11	0.07		.06	0.06
Age		.05	0.06		.08	0.07		.12	0.07		−.10	0.08
Control (T1)		.39**	0.08		.43**	0.05		.29**	0.07		/	/
Self-efficacy (T1)		−.21**	0.07		−.24*	0.09		−.30**	0.08		.39**	0.15
Task value (T1)		−.03	0.09		−.03	0.07		.02	0.10		.16	0.15
Step 3	.01* [ΔF(1, 204) = 3.00]			.03** [ΔF(1, 204) = 10.03]			.01* [ΔF(1, 204) = 2.87]			.01* [ΔF(1, 205) = 2.93]		
Gender		−.06	0.04		−.11*	0.05		−.10	0.07		.06	0.06
Age		.03	0.06		.06	0.06		.09	0.06		−.08	0.08
Control (T1)		.33**	0.11		.35**	0.06		.23**	0.08		/	/
Self-efficacy (T1)		−.24**	0.07		−.26**	0.09		−.31**	0.08		.38**	0.15
Task value (T1)		−.01	0.08		−.01	0.07		.02	0.10		.15	0.16
Cost (T1)		.13	0.09		.19**	0.06		.14**	0.05		−.12*	0.06
Total R^2	.32**			.39**			.29**			.30**		

Note. Control (T1) represents disorganization (T1), procrastination (T1), and avoidance intentions (T1), respectively.
* $p < .05$.
** $p < .01$.

3.3. Discussion

Self-efficacy and task value are known to predict academic-related behaviors and achievement, but the present study aimed to explore the potential role of cost in explaining additional variance in these outcomes. Using longitudinal data, we found that cost successfully explained additional variance in disorganization, procrastination, and avoidance intentions, after controlling for pretest scores on these measures, self-efficacy, and task value. Interestingly, when all these independent variables were included in the regression model, cost significantly predicted procrastination and avoidance intentions whereas task value failed to predict these outcomes. These findings indicate that compared to task value, cost was a more powerful predictor of outcomes related to adolescent students' maladaptive academic outcomes in math. This is reasonable since conceptually, cost is a negatively-valenced construct, which functions as an energizer of avoidance motivation and related behaviors. Evidence has revealed that students usually become more disengaged from learning math as they progress to higher grades (Simpkins et al., 2006). Meanwhile, students in higher grades also have reported higher cost perceptions toward math (Gaspard et al., 2017). This pattern of results is important because it suggests that studying cost could be critical to help educators understand why and how students develop avoidance tendencies toward math.

Cost also successfully explained additional variance in adolescent students' math achievement after controlling for self-efficacy and task value. Self-efficacy is thought to be the strongest motivational predictor of achievement (Pajares, 1996). Researchers have found that self-efficacy predicts achievement more strongly than other motivation variables such as task value (Lee & Stankov, 2013; Wigfield & Eccles, 2000). Our finding suggests that cost plays an important role in predicting adolescent students' math achievement in addition to self-efficacy. Cost perceptions can induce avoidance behaviors in math, which may impair subsequent achievement.

4. General discussion

The concept of cost has attracted growing interest as a way of

Table 7
Hierarchical multiple regression analyses with composite value score in Study 2.

	Disorganization (T2)			Procrastination (T2)			Avoidance Intentions (T2)			Achievement (T3)		
	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE	ΔR^2	β	SE
Step 1	.27** [ΔF(3, 207) = 25.52]			.30** [ΔF(3, 207) = 29.57]			.22** [ΔF(3, 207) = 19.46]			.03* [ΔF(2, 208) = 3.22]		
Gender		−.05	0.04		−.09	0.05		−.08	0.07		−.01	0.06
Age		.06	0.06		.10	0.06		.14*	0.06		−.17*	0.08
Control (T1)		.51**	0.07		.53**	0.06		.43**	0.05		/	/
Step 2	.05** [ΔF(2, 205) = 7.54]			.08** [ΔF(2, 205) = 13.23]			.06** [ΔF(2, 205) = 8.54]			.27** [ΔF(2, 206) = 39.73]		
Gender		−.06	0.03		−.11*	0.05		−.10	0.07		.06	0.06
Age		.04	0.06		.06	0.07		.10	0.06		−.08	0.08
Control (T1)		.36**	0.10		.38**	0.06		.25**	0.08		/	/
Self-efficacy (T1)		−.17**	0.07		−.17	0.10		−.23**	0.07		.39**	0.09
Composite value (T1)		−.13	0.11		−.19*	0.09		−.13	0.09		.20*	0.08
Total R^2	.32**			.38**			.28**			.30**		

Note. Control (T1) represents disorganization (T1), procrastination (T1), and avoidance intentions (T1), respectively.
* $p < .05$.
** $p < .01$.

explaining dynamics in student motivation (Barron & Hulleman, 2015). In the context of learning, cost has mostly been discussed under the modern expectancy-value framework (Eccles et al., 1983). However, cost had rarely been studied in empirical motivation literature until recently. In the present study, we utilized an expectancy-value-cost approach to investigate whether cost could predict additional variance in adolescent students' motivation and achievement in math beyond what would be predicted by self-efficacy and task value. We found that cost successfully predicted additional variance in different outcomes related to math, including students' achievement goals, classroom affect, maladaptive academic outcomes, and achievement. Moreover, we found that the predictive utility of cost held when controlling for pretest scores on the outcomes, when those scores were available.

4.1. Theoretical and practical implications

Our findings have extended the literature by revealing that including cost in models with competence beliefs and task value can improve researchers' abilities to predict adolescent students' academic outcomes. In particular, both competence beliefs and task value showed limited predictive utility for avoidance goals. Task value also failed to predict achievement and maladaptive academic outcomes such as procrastination and avoidance intentions. Cost, in contrast, demonstrated significant predictive utility on all of these outcome variables.

In addition, we directly compared the predictive utility of an expectancy-value-cost approach with an expectancy-value approach in which cost was subsumed under task value to produce one composite value score. Our results revealed that the expectancy-value-cost approach could explain more variance in achievement goals, classroom affect, and maladaptive academic beliefs including disorganization and procrastination. Moreover, the predictive patterns using the expectancy-value-cost approach were more informative than what was observed with the expectancy-value approach, because the relative predictive power of cost versus task value on various dependent variables could be observed. We recommend that researchers include cost as a separate construct in models exploring how expectancy and value beliefs relate to academic motivation and achievement. Adding cost into the expectancy-value framework seems to be especially useful to understand students' avoidance-oriented academic behavior and maladaptive academic beliefs.

It is worth noting that cost predicted negatively math achievement even when controlling for self-efficacy and task value. These findings are important as they revealed that adolescent students with high cost might be at risk for lower achievement in math, even if they have high competence beliefs and task value. It is critical to understand the factors that prevent adolescent students from learning math in order for educators to promote their school adjustment. Educators have successfully enhanced students' math and science interest and performance by promoting their sense of utility value (e,g., Gaspard et al., 2015b; Hulleman & Harackiewicz, 2009). Given the critical role of cost in determining avoidance motivation and behaviors, reducing cost may be an additional important way to promote students' achievement and persistence in these fields. More investigations are needed to explore potential interventions that can reduce students' cost perceptions in math.

4.2. Limitations and future directions

Despite the important findings witnessed in the present study, several limitations as well as suggestions for future research need to be addressed. First, this work was based on results from self-report surveys and our findings are correlational. A logical next step for future research would be to clarify the causal direction between cost and other variables by using longitudinal or experimental designs with appropriate controls for prior achievement.

Second, our studies were based on students from three Korean middle schools. Although these are regular schools, this was not a fully representative sample of Korean students. Therefore, the generalizability of our findings to students in other school contexts requires further investigation. Similarly, our studies focused only on the domain of math. Although we believe that our findings are likely to be generalizable to other academic domains, this should be tested in future research.

Third, the surveys we used in the present studies measured motivation in a general manner, referring to students' overall beliefs about a particular academic subject. Although we believe these analyses provide important information, they do not capture fully students' motivation for a given subject because motivation also can vary depending on specific situations (e.g., Ratelle, Baldwin, Vallerand, 2005; Vallerand, 1997). Individuals' competence beliefs, task value, and cost may fluctuate depending on the specific tasks and conditions they encounter and are likely to change over the course of a semester and at different points in a given lesson (e.g., Dietrich, Viljaranta, Moeller, & Kracke, 2017; Perez et al., 2014). It would be useful to replicate our findings regarding the predictive utility of the expectancy-value-cost approach by exploring these perceptions with respect to specific situations or by using designs that account for situation-specific variations in these perceptions. An additional measurement limitation in this study is that some constructs were assessed at the math class level whereas some others were assessed the math subject level. We measured different constructs at different levels in order to be consistent with the measurement approaches of prior studies, and because the distinction between class and subject items was not central to our research questions. However, future studies should test whether the predictive utility of the expectancy-value-cost approach holds when all the constructs are assessed at the same level.

Fourth, we discussed cost in general throughout this study, but it is possible that specific dimensions of cost (i.e., effort cost versus opportunity cost versus ego cost versus emotional cost) predict differently students' academic outcomes compared to overall cost. It is also possible that various dimensions of cost overlap conceptually or empirically with certain classroom outcomes, which is a critical topic to explore further when considering how cost affects students' classroom behavior. For example, we found that general cost positively predicted negative classroom affect in this study. It is likely that of all of the dimensions of cost, emotional cost would show the strongest relationship with classroom affect because both emotional cost and negative affect are closely tied to the affective experience. It is also possible that some aspects of emotional cost overlap with some aspects of negative classroom affect. By definition, emotional cost focuses on anticipated negative affect associated with the specific task or activity, whereas negative affect focuses on experiencing negative emotions in the specific situation. Thus, experiencing negative affect per se is not equal to emotional cost. However, some negative affective experiences such as worry might be both an anticipation of negative affect and a negative affective experience in and of itself. The present study cannot shed light on these possibilities, but this topic is critical to study in future work in order to understand cost and its impact on student behavior more completely.

Finally, researchers have demonstrated that interactions between expectancy and value beliefs can predict students' academic outcomes in addition to students' overall levels of these constructs (e.g., Nagengast, Marsh, Scalas, Xu, Hau, & Tautwein, 2011; Trautwein, Marsh, Nagengast, & Lüdtke 2012). For example, Nagengast et al. (2011) found that the interaction of students' science competence beliefs and task value (i.e., interest value) predicted positively students' engagement in science activities and intentions of pursuing scientific careers. The present study suggests that cost is as important as task value in terms of predicting students' academic motivation and achievement. Thus, it would be an interesting topic to test the interactive effects of competence beliefs, task value, and cost on students' academic motivation and educational outcomes. Supporting this idea, Trautwein et al. (2012) have reported that the interaction of students' math competence beliefs and cost perceptions significantly predicted their achievement. More studies are needed to continue to explore this topic further.

4.3. Conclusion

Including cost as an independent construct in the expectancy-value model provided important additional information about adolescent students' academic motivation and achievement, especially their maladaptive academic outcomes. Based on these findings, we suggest that it is necessary to incorporate cost as an independent motivational construct in the expectancy-value framework and to measure expectancy, task value, and cost simultaneously in order to capture best the relations between students' motivation and their behavior and performance in school.

Appendix. . Items of scales used in the present study

Item
Self-efficacy (Study 1&2)
1. I'm certain that I can understand what is taught in math class.
2. I expect to do very well in math class.
3. I am sure that I can do an excellent job on the problems and tasks assigned for math class.
4. I know that I will be able to learn the material for math class.
5. My study skills are excellent in math class.
6. I think I will receive a good grade in math.
Task value (Study 1&2)
1. I think I will be able to use what I learn in math class in other places.
2. I think math is useful for me to learn.
3. Understanding math is very important to me.
4. It is important for me to learn math.
5. I am very interested in math.
6. I like math.
Cost (Study 1&2)
1. Doing well in math requires more effort than I want to put into it.
2. It requires too much effort for me to get a good grade in math.
3. It takes too much of effort for me to do well in math.
4. I have to give up other activities that I like to do well in math.
5. I have to sacrifice a lot of free time to be good at math.
6. To do well in math requires that I give up other activities I enjoy.
7. Others would think worse of me if I failed to do well in math.
8. Others would think I am incompetent if I get low grades in math.
9. Others would be disappointed in me if I performed poorly in math.
10. Studying math scares me.
11. Studying math makes me feel stress.
12. Studying math makes me annoyed.
Mastery approach goals (Study 1)
1. I want to learn as much as possible from math class.
2. It is important for me to understand the content of math course as thoroughly as possible.
3. I desire to completely master the material presented in math class.
Performance approach goals (Study 1)
1. It is important for me to do better than other students in math class.
2. It is important for me to do well compared to others in math class.
3. My goal in math class is to get a better grade than most of the other students.
Performance avoidance goals (Study 1)
1. I just want to avoid doing poorly in math class.
2. My goal in math class is to avoid performing poorly.
3. My fear of performing poorly in math class is often what motivates me.
Work avoidance goals (Study 1)
1. I wish I didn't have to do math class.
2. I just want to do what I am supposed to do in math class and get it done.
3. I want to do as little as possible in math class.
4. I want to get out of having to do much work in math class.
5. I want to do math class as easily as possible so I won't have to work very hard.
Positive classroom affect (Study 1)
1. Most of the time, being in math class puts me in a good mood.
2. I like being in math class.

Item
3. I am happier when I am in math class than when I am in other classes.
Negative classroom affect (Study 1)
1. I am often angry when I'm in math class.
2. I often feel frustrated when I am doing math work.
3. Math class often makes me feel bad.
4. I often feel bored in math class.
Disorganization (Study 2)
1. I'm not sure how to study for math.
2. I often find that I don't know what to study or where to start for math.
3. I find it difficult to develop a study plan for math.
4. I find it difficult to organize my study time for math effectively.
5. When I study for math, I have trouble figuring out what to do to learn the material.
Procrastination (Study 2)
1. I waste a lot of time on trivial matters before getting to study math.
2. Even after I have made a decision to study math I delay acting upon it.
3. When I have to study math I wait a long time before starting to study it.
4. I delay studying math until it is too late.
5. I put off studying math.
Avoidance intentions (Study 2)
1. I wish I didn't have to take math class.
2. I can't wait for math class to be over.

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