Journal of School Psychology 83 (2020) 1–24

Contents lists available at ScienceDirect

Journal of School Psychology

journal homepage: www.elsevier.com/locate/jschpsyc

The role of cost in adolescent students' maladaptive academic outcomes

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ARTICLE INFO

Action Editor: Nick Benson

Keywords:
Cost
Value
Expectancy-value theory
Motivation
Achievement

ABSTRACT

Motivation wields a tangible impact on students' academic functioning. Among the theoretical frameworks used to explain students' motivation to learn, Eccles et al.'s expectancy-value theory (1983) is one of the most influential. It has been used to investigate students' competence- and value-related beliefs and how they are associated with academic-related choices, learning behaviors, and achievement. In the learning context, cost has mostly been discussed under the expectancy-value framework as a sub-dimension of task value and conceptualized as reflecting the negative aspects of task engagement. The issue of cost has recently attracted growing interest among scholars, providing a way to explain the dynamics of student motivation. However, cost is still underexplored in the empirical literature. In the present study, we assessed adolescent students' perceived cost (i.e., effort cost, opportunity cost, ego cost, and emotional cost) of studying math and examined its unique relations with academic motivation and achievement. Across a series of three studies, we found that cost is empirically distinct from the utility, attainment, and interest components of task value and is closely related to students' maladaptive academic outcomes. In particular, cost showed unique associations with adolescent students' test anxiety, disorganization, adoption of avoidance goals, avoidance intentions, and academic achievement. The present study's findings highlight the importance of including cost as a unique construct alongside value to more fully capture students' motivational dynamics in school.

Approach-avoidance motivation is a fundamental driver of complex human behaviors (e.g., Carver, 2006). The distinction between approach and avoidance motivation is rooted in the concept of valence; attractive or desirable events or possibilities have a positive valence which elicits approach motivation, whereas aversive or undesirable events or possibilities have a negative valence which elicits avoidance motivation (e.g., Atkinson, 1964; Lewin, 1938). Whereas approach motivation helps individuals thrive, avoidance motivation has a more fundamental role in enabling individuals to survive (Elliot & Covington, 2001). Although this is obviously of great benefit for avoiding serious dangers, avoidance motivation is also recognized as leading to unwanted consequences, such as lower performance, resource depletion, and reduced well-being (Roskes et al., 2014).

In the school context, many factors have been linked to the development of avoidance motivation, including cost perceptions, fear of failure, low competence expectancies, and fear of rejection (e.g., Barron & Hulleman, 2015; Elliot & Covington, 2001). Of these factors, cost may be the key determinant of avoidance motivation because it is guided by negative-valence-focused evaluation processes (e.g., Eccles et al., 1983; Feather, 1992) and thus captures the core psychological mechanism of active avoidance. In

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https://doi.org/10.1016/j.jsp.2020.08.004
Received 24 July 2019; Received in revised form 9 May 2020; Accepted 10 August 2020
Available online 29 September 2020

general, cost refers to the negative aspects of engaging in a task. It is widely considered a sub-dimension of task value within the expectancy-value model (Eccles et al., 1983). Specifically, the expectancy-value model differentiates between negatively-valenced cost and positively-valenced interest, attainment, and utility values.

There is a wealth of empirical evidence that students' perceptions of the value of a task play a key role in predicting their academic-related choices and subsequent persistence (Eccles, 2005; Eccles & Wigfield, 2002). In contrast, the role of cost in predicting students' academic outcomes remains largely under-explored. Recently, researchers have begun to place renewed emphasis on the role of cost in students' academic functioning because cost may be a force that undermines students' motivation and likely changes students' academic behavior in ways that differ from value (Wigfield et al., 2017). In the present study, we explored the potential unique role of cost in students' maladaptive academic outcomes.

1. Understanding cost

The expectancy-value model (Eccles et al., 1983) is one of the most influential frameworks used to investigate students' academic-related choices, learning behaviors, and achievement. The task value component in the expectancy-value model has been defined as the qualities of an achievement task that influence individuals' evaluations about whether to choose to engage with the task (Eccles, 2005; Eccles et al., 1983). Eccles et al. (1983) used the term *subjective task value* to describe the subjectively perceived positive and negative characteristics of achievement tasks. Specifically, Eccles et al. (1983) proposed that task value is influenced by four major components: interest value, attainment value, utility value, and cost.

The role of cost within expectancy-value theory has been debated in recent years (Barron & Hulleman, 2015; Wigfield et al., 2017). When initially proposing the modern expectancy-value framework, Eccles et al. (1983) wrote about cost as an influence on task value, noting that they "conceptualized the influence of cost on the value of an activity in terms of a cost/benefit ratio" (p. 93). This phrasing indicates that cost and values influence student motivation and behavior independently. However, most studies within the expectancy-value framework have assessed task value either excluding cost or combining it with other value components into a composite task value score (e.g., Buehl & Alexander, 2005; Feather, 1988; Jacobs et al., 2002). Combining cost with other value components to create a composite task value score may be problematic, because the nature of cost is negative, whereas interest, attainment, and utility values are typically considered positive. From an expectancy-value perspective, all four components (i.e., interest value, utility value, attainment value, and cost) operate at the same psychological level to enhance or undermine students' overall task value. Empirically, several recent studies have found that cost forms a separate factor from interest, attainment, and utility values (e.g., Gaspard et al., 2015; Luttrell et al., 2010; Trautwein et al., 2012). However, researchers have not reached clear consensus on the role of cost versus task value to date.

In the expectancy-value model, cost is considered a multifaceted construct. Initially, three types of cost were hypothesized: negative appraisals of the effort required to complete the task (effort cost), forgone opportunities to engage in other valued tasks (opportunity cost), and the ego threats associated with potential failure in the task (psychological cost or ego cost). Recently, researchers have determined that the anticipated negative emotions associated with engaging in a task (emotional cost) also need to be included as a type of cost (e.g., Flake et al., 2015; Gaspard et al., 2015; Luttrell et al., 2010; Zhu & Chen, 2013).

2. Importance of cost in motivation and learning

Eccles et al.'s (1983) expectancy-value model was originally developed to explain gender differences in students' mathematics-related choices, engagement, and achievement. Subsequently, researchers have devoted a great amount of attention to studying the relations between task value and related outcomes in the subject of math. For example, researchers have found that students who report higher levels of task value in math exhibit better math achievement (Berndt & Miller, 1990), stronger course enrollment intentions (Meece et al., 1990), and a higher number of math courses taken (Simpkins et al., 2006).

In their original writing of the expectancy-value model, Eccles et al. (1983) proposed that students weigh costs against values to produce an overall task value to direct action. Researchers studying approach and avoidance motivation also have stated that, in directing their behavior, students consider both positive and negative factors in order to produce an overall judgment regarding whether they should act (see Corr, 2013, for review). Thus, cost and value might exhibit distinct patterns when predicting approach-related versus avoidance-related outcomes. Value is an affirming motivational construct that can induce approach motivation, whereas cost is an undermining motivational construct that can induce avoidance motivation (Atkinson, 1964; Lewin, 1938).

Empirical work that has been done suggests that cost predicts students' outcomes in the subject of math. For example, cost was negatively related to college students' level of participation in the math courses (Luttrell et al., 2010) and positively predicted college students' drop-out intentions from a STEM (i.e., science, technology, engineering, and mathematics) major (Perez et al., 2014). Using cluster analyses on variables from expectancy-value theory and achievement goals theory, Conley (2012) found that cost played a vital role in distinguishing middle-school students' motivation patterns for math learning and predicting their achievement and affective outcomes. In addition, Gaspard, Wigfield, et al. (2017) found negative correlations between cost and adolescent students' grades across multiple domains (i.e., math, biology, and German). Jiang et al. (2018) found that cost emerged as an important predictor of adolescents' maladaptive academic functioning in math learning. Thus, taking these findings together, cost could provide essential information about students' avoidance motivation and maladaptive academic outcomes in math.

3. The present study

Despite its importance in student academic functioning, cost is underexplored in the empirical literature. There were limited measures of cost related to learning before 2010, and thus, only a few researchers included cost when investigating academic motivation from an expectancy-value perspective (Wigfield et al., 2016). There remains a great need to systematically examine the role of cost in students' academic motivation and achievement. In the present study, we investigated the role of cost in adolescent students' mathematics maladaptive outcomes across three independent studies. In Study 1, we aimed to develop a new scale to assess students' perceived cost of studying math. We also evaluated the psychometric properties of the scale and provided validation evidence. In Study 2, we examined the relation between cost and value and tested whether and how these two constructs might be differently related to students' academic outcomes in math. In Study 3, we investigated the relative predictive power of cost and value on students' academic motivation and achievement in math. In particular, we were interested in whether cost could predict students' maladaptive academic outcomes, above and beyond what could be predicted by value.

We focused on adolescent students in the present research because recent empirical evidence has shown that students' cost perceptions increase throughout secondary school. Specifically, students in higher grades had higher means on cost perceptions (i.e., effort, opportunity, and emotional costs) toward studying (Gaspard, Häfner, et al., 2017). Mathematics was selected as the target subject as it is the most commonly selected subject in studies investigating the expectancy-value framework (Wigfield & Cambria, 2010). Moreover, mathematics is typically perceived to be difficult, highly demanding, and frustrating. Researchers have found an increasing number of students are afraid of engaging in math-related activities (e.g., Simpkins et al., 2006), indicating that cost perceptions related to studying math could be salient to students.

4. Study 1

Several empirical studies have attempted to develop a cost scale but have largely fallen short of capturing the multiple facets of this construct. For instance, Kosovich et al. (2015) developed an expectancy-value-cost (EVC) scale for student motivation, but this only covered opportunity cost. Likewise, Conley (2012) developed two items about opportunity cost to determine middle-school students' motivational profiles for math. Other scales have included multiple facets of cost, but exhibited suboptimal psychometric properties. For instance, Battle and Wigfield (2003) developed the Value of Education (VOE) scale, which covers three types of cost (personal effort, opportunity cost, and psychological cost of failure). However, many of the cost items exhibited cross-loadings in a factor analysis. In a study that attempted to further specify and measure cost components in the expectancy-value model, Flake et al. (2015) developed four independent scales measuring task effort cost, outside effort cost, loss of valued alternatives, and emotional cost. However, the correlations between these sub-scales were extremely high ($.83 \leq rs \leq .95$), indicating that the scale validity needs further improvement. Moreover, all of these measures focused on students from Western cultures. According to the expectancy-value model, individuals' task values are influenced by the cultural environment (Eccles et al., 1983; Eccles & Wigfield, 2002). For example, whether individuals are socialized in a culture oriented toward individualism or collectivism informs their value beliefs (Markus & Kitayama, 1991; Tonks et al., 2018). To advance research on expectancy-value theory, it is important to develop a valid cost measure for students from non-Western cultures and explore the role of cost in their academic functioning.

The aim of Study 1, therefore, was to assess Korean adolescent students' perceived cost of studying math. The overall process occurred in two phases. First, the primary aim of Study 1 was to craft items assessing different types of cost. Second, empirical tests of the psychometric fitness, internal consistency, and factor structure of the items were conducted. Specifically, an exploratory factor analysis (EFA) was first conducted to uncover the latent factor structure of the items, identify potentially problematic items, and help build a model for a confirmatory factor analysis (CFA). Then, using a second independent sample, a CFA was conducted to test the item functioning and identify the latent constructs among the items. Concurrent validity was tested by examining the correlations of the new cost scale with existing cost scales. Construct validity was also examined by exploring the correlations of the new cost scale with value and two indexes of avoidance tendency, namely avoidance of help seeking and task disengagement.

4.1. Item crafting

In accordance with expectancy-value theory (Eccles et al., 1983), we specified four types of cost: (a) perceived aversion to and lack on value placed on the personal effort required to be successful (*effort cost*), (b) forgone opportunities to engage in other valuable tasks in order to be successful (*opportunity cost*), (c) ego threats associated with potential failure in learning (*ego cost*), and (d) anticipated negative emotional states associated with learning (*emotional cost*). We adopted the merits of recently published cost scales when developing the items. As suggested by Flake et al. (2015), to activate cost, students should have negative appraisals of effort, loss of valued alternatives, and their emotional state. Thus, we intentionally used negative wording like “too much,” “not worthwhile,” “give up,” “sacrifice,” “embarrassed,” “suffer,” “stressful,” “annoyed” and so on when we wrote the items. We also adapted some items from existing cost measures. For instance, some existing items focusing on “math class” (i.e., “Taking math classes scares me” from Luttrell et al., 2010 and “This class is too exhausting” from Flake et al., 2015) were adapted to focus on studying math (“Studying math scares me”; “Studying math exhausts me”). In total, we constructed a pool of 20 items (five items for each type of cost). All items were developed in Korean.

Ten research scientists who were familiar with the concept of motivation were asked to rate the clarity of the items using a seven-point Likert scale ranging from 1 (*poor*) to 7 (*excellent*). They were provided with descriptions of each type of cost and were asked to suggest possible revisions. All items were assessed in Korean. The scientists' ratings of item clarity ranged from 3 to 7 ($M = 6.03$,

Table 1
Developed cost items and factor loadings from the EFA and CFA in Study 1.

Item		Factor			
		1	2	3	4
EFC01	**Doing well in math requires more effort than I want to put into it.**				**0.70/0.76**
EFC02	I think it demands too much effort to do well in math.				0.61/0.66
EFC03	**It requires too much effort for me to get a good grade in math.**				**0.64/0.83**
EFC04	What I gain is smaller compared to the amount of effort I put in to do well in math.	0.52/−			0.29/0.61
EFC05	I need to spend a great amount of energy to do well in math.				0.59/0.85
EFC06	**It takes too much of effort for me to do well in math.**				**0.76/0.85**
EFC07	I think the effort for studying math well is not worthwhile.	0.57/−			−0.19/0.31
OPC01	**I have to give up other activities that I like to do well in math.**		**0.87/0.83**		
OPC02	**I have to sacrifice a lot of free time to be good at math.**		**0.80/0.82**		
OPC03	I have to sacrifice opportunities of engaging in other interesting activities to be good at math.		0.62/0.88		
OPC04	**To do well in math requires that I give up other activities I enjoy.**		**0.71/0.93**		
OPC05	I cannot do other activities that I want in order to do well in math.		0.76/0.90		
EGC01	I would be embarrassed if I failed to do well in math.			0.67/0.71	
EGC02	My self-esteem would suffer if I was unsuccessful in math.			0.69/0.74	
EGC03	**Others would think worse of me if I failed to do well in math.**			**0.74/0.79**	
EGC04	**Others would think I am incompetent if I get low grades in math.**			**0.66/0.79**	
EGC05	**Others would be disappointed in me if I performed poorly in math.**			**0.76/0.83**	
EMC01	**Studying math scares me.**	**0.67/0.82**			
EMC02	**Studying math makes me feel stress.**	**0.80/0.86**			
EMC03	Studying math makes me anxious.	0.73/0.76			
EMC04	**Studying math makes me annoyed.**	**0.87/0.86**			
EMC05	Studying math exhausts me.	0.85/0.86			
EMC06	I feel burned out after studying for math.	0.79/0.80			

Note. Items in bold indicate final cost items. Pattern matrix coefficients from the EFA are presented first, followed by standardized factor loadings from the CFA. EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost.

SD = 0.37). Items judged to be unclear were revised (e.g., “To get a good grade in math demands too much effort” was revised as “It requires too much effort for me to get a good grade in math” in order to clarify that cost represents one's subjective perception) and three items (two effort cost items “It takes too much of effort for me to do well in math”, “I think the effort for studying math well is not worthwhile”; and one emotional cost item “I feel burned out after studying for math”) were added based on the scientists' recommendations. Table 1 presents the 23 developed items. Two content experts were then invited to evaluate item clarity and the representativeness of the complete item pool for each type of cost. Their evaluations were also based on a seven-point Likert scale. The expert evaluations of item clarity ranged from 4 to 7 (M = 6.00, SD = 0.55). The degree to which each complete item pool represented the respective type of cost was rated as follows: effort cost: (M = 6.00, SD = 0.00), opportunity cost (M = 6.50, SD = 0.71), ego cost (M = 6.50, SD = 0.71), and emotional cost (M = 5.50, SD = 0.71).

4.2. Empirical test of item functioning

Based on independent samples, EFA and CFA analyses were conducted for cost items. All analyses were conducted in Mplus 7.4. We used the robust maximum likelihood estimator (MLR) and the design-based correction of standard errors (with type = complex) to account for the potential nonindependence of data due to the nesting of students within classes (McNeish et al., 2017). To deal with the missing data, we used the full information maximum likelihood (FIML) approach implemented in Mplus, which takes all available information into account when estimating the model parameters (Schafer & Graham, 2002).

Several indexes were consulted to determine the goodness of fit of the model: the chi-square (χ^2) value and the degrees of freedom, the Tucker-Lewis index (TLI), the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root-mean-squared residual (SRMR). Values of TLI and CFI above 0.90 and values of RMSEA and SRMR below 0.08 were taken to indicate a reasonable model fit (Kline, 2010).

4.3. EFA

4.3.1. Participants and statistical analyses

The sample comprised 206 students (mean age = 14.7 years, SD = .67) in Grade 8 from one public middle school for girls in Seoul, South Korea. The middle school that participated in the present study was a typical public school with students coming from middle-class families, which constitute the majority of Korean society. Korea implements a 6–3–3 system from elementary to high school, which is basically the same as the K-12 system in the US; Grade 7 is the first year of middle school.

The 23 developed cost items were assessed based on seven-point Likert scales ranging from 1 (*not true at all*) to 7 (*very true*). All items were written in Korean and referred to the subject of math. Students filled out the questionnaire during regular classroom hours, and the survey took approximately 5 min to complete. Missing values in the data were due to non-response on individual items

Table 2
Descriptive statistics of cost items in Study 1.

Item	EFA (N = 206)				CFA (N = 473)			
	M	SD	Skewness	Kurtosis	M	SD	Skewness	Kurtosis
EFC01	4.68	1.38	−.17	−.35	5.15	1.57	−.81	0.03
EFC02	4.51	1.37	−.19	−.40	5.17	1.48	−.69	−.12
EFC03	4.55	1.43	−.24	−.22	4.82	1.60	−.56	−.40
EFC04	4.06	1.42	0.08	−.23	4.13	1.78	−.13	−.97
EFC05	4.23	1.52	−.04	−.72	4.58	1.61	−.48	−.44
EFC06	4.72	1.41	−.08	−.49	4.92	1.56	−.66	−.19
EFC07	3.05	1.43	0.65	0.01	2.54	1.48	0.93	0.16
OPC01	3.49	1.42	0.31	−.44	4.03	1.80	−.17	−1.11
OPC02	3.83	1.45	0.02	−.63	4.30	1.73	−.32	−.92
OPC03	3.69	1.45	0.11	−.26	3.87	1.77	−.04	−1.01
OPC04	3.34	1.43	0.49	−.16	3.81	1.74	−.04	−1.03
OPC05	3.38	1.35	0.35	−.14	3.69	1.71	0.05	−.93
EGC01	4.39	1.32	−.36	−.09	4.49	1.65	−.55	−.61
EGC02	4.24	1.41	−.18	−.26	4.52	1.70	−.44	−.65
EGC03	3.52	1.38	0.13	−.29	3.45	1.79	0.28	−.96
EGC04	3.89	1.56	0.06	−.53	3.71	1.75	0.10	−1.01
EGC05	3.61	1.48	0.10	−.45	3.71	1.70	0.09	−.99
EMC01	3.84	1.44	0.24	−.70	3.66	1.82	0.22	−1.03
EMC02	4.21	1.50	−.01	−.81	4.38	1.78	−.27	−.85
EMC03	3.74	1.52	0.17	−.70	3.54	1.75	0.30	−.90
EMC04	4.09	1.58	−.03	−.68	4.17	1.79	−.13	−.89
EMC05	4.12	1.52	0.02	−.73	4.24	1.71	−.22	−.87
EMC06	4.16	1.54	0.09	−.58	4.25	1.68	−.20	−0.79

Note. EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost.

and were < 0.05% for each item. Little's MCAR test (Little, 1988) indicated that the missing mechanism could be assumed to be missing completely at random (MCAR; χ^2 = 154.268, df = 154, p = .48).

The psychometric fitness of the items was evaluated in terms of skewness, kurtosis, and inter-item correlation. Items with absolute values of skewness and kurtosis lower than 2 were considered to have good normality (Hopkins & Weeks, 1990). Inter-item correlations between the items for each type of cost were examined; those items with low inter-item correlations (r < .40) were considered for potential elimination. Parallel analysis was performed to determine the optimum number of latent factors (Horn, 1965). Parallel analysis generates eigenvalues from the original data along with the mean eigenvalues and eigenvalues representing the 95th percentile based on the random data, thus can minimize over-identification of factors due to sampling error. The optimum number of factors is the number of original data eigenvalues that are larger than the random data eigenvalues (Hayton et al., 2004). In the EFA, an oblimin rotation was performed because the factors were expected to be correlated. Based on recommendations in the literature (Thompson, 2004), the pattern coefficient for the principal factor was set at ≥.40 to detect the item functioning.

4.3.2. Results

Table 2 presents the descriptive statistics for the two data sets used in Study 1. All items demonstrated good normality. The inter-item correlations within each sub-dimension were adequate (rs ≥ .49), the only exception being effort cost (EFC07), which exhibited low inter-item correlations (rs ≤ .39, see Online Supplemental Materials for detailed results). Bartlett's test of sphericity, which tests the overall significance of the correlations within the correlation matrix, was significant, χ^2 (253) = 3022.23, p < .001, indicating that it was appropriate to use the factor analytic model on the EFA data. The Kaiser-Meyer-Olkin measure of sampling adequacy indicated that the strength of the relationships among variables was high (KMO = 0.90). Thus, it was acceptable to proceed with the EFA.

Parallel analysis indicated four factors from the raw data that were above the 95th percentile estimates created by the random data (Fig. 1). Consistent with theoretical assumptions, the four factors matched effort, opportunity, ego, and emotional cost dimensions after rotation. The four factors explained a total of 51.4% of the variance in the entire set of variables. The first factor was emotional cost, with a high eigenvalue of 9.09; it accounted for 18.7% of the variance in the data. However, two effort cost items (EFC04 and EFC07) loaded on the emotional cost dimension and were thus flagged for potential elimination. Factor two was opportunity cost, which had an eigenvalue of 2.71 and accounted for a further 12.4% of the total variance. The third factor was ego cost, with an eigenvalue of 1.97; it accounted for additional 10.8% of the total variance. The fourth factor was effort cost, which had an eigenvalue of 1.72 and accounted for a further 9.5% of the total variance. Standardized factor loadings are presented in Table 1. In terms of correlations among factors, emotional cost positively correlated with opportunity cost (r = .38), ego cost (r = .47), and effort cost (r = .47). Opportunity cost positively correlated with ego cost and effort cost (rs = .37 and .43, respectively). The correlation between ego cost and effort cost was also positive, with r = .33.

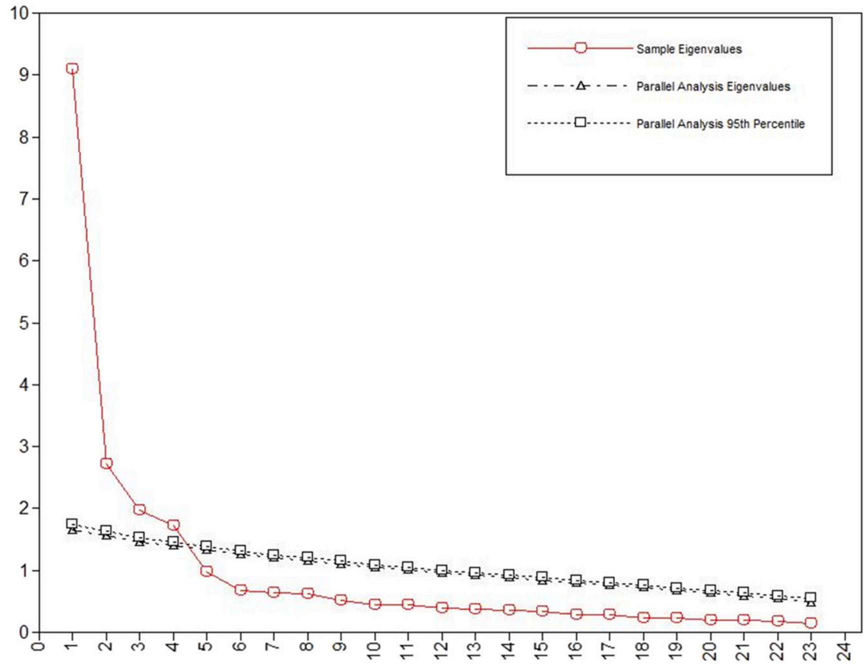

Fig. 1. Scree plot of Eigenvalues derived from the EFA data in Study 1 and 95th percentile Eigenvalue Estimates from the Parallel Analysis. The figure shows the visual results of a parallel analysis where eigenvalues from the sample compared to a Monte Carlo simulation of the data using permutations of the actual data. The plot clearly shows four factors above the 95th percentile line cutting the scree plot. Eigenvalues are on the y-axis.

4.4. CFA

4.4.1. Participants and statistical analyses

For the CFA, students were recruited from one middle school and one high school, both situated in Seoul, Soth Korea. Both schools were typical public schools with students from middle-class families. The sample comprised 473 students (327 girls, 271 8th graders, mean age = 14.1 years, *SD* = 0.40; 202 10th graders, mean age = 16.2 years, *SD* = 0.47). Again, the 23 developed cost items were assessed based on seven-point Likert scales ranging from 1 (*not true at all*) to 7 (*very true*). Students filled out the questionnaire during regular classroom hours and took approximately 10 min to complete. The percentage of missing data was low for all items (< 0.06%). We conducted two diagnostics tests to assess the level of randomness. First, Little's MCAR test indicated that the missing mechanism could not be assumed to be missing completely at random (χ^2 = 2180.688, df = 1836, 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).

A CFA model was estimated to identify the latent constructs among items. Based on the factor structure we observed in the EFA, a model containing four latent factors was set as the baseline model. Because cost is a multidimensional construct, a bifactor measurement model was also examined to test the instrument's dimensionality and model-based reliabilities (Reise, 2012; Reise et al., 2012). The bifactor model enables researchers to test the general factor, which presents the broad central construct an instrument intends to measure, while simultaneously allowing multidimensionality within the model, as group factors represent more conceptually specific sub-facet constructs. Once the CFA model was finalized, we conducted multi-group analyses to test for the invariance of the measurement model across gender and grade (i.e., middle school vs. high school). Measurement invariance is an important basis for determining whether an instrument can be used effectively to measure students' subjective perceptions across different groups (Vandenberg & Lance, 2000). Finding evidence of measurement invariance would provide support for the claim that the instrument is useful for measuring both male and female students' perceived cost of studying math across a wide range of age levels. Following the standard guidelines (Meredith, 1993; Vandenberg & Lance, 2000), we specified a series of nested models that hold increasing invariance constraints across groups, and examined changes in goodness of fit resulting from these invariance constraints. Specifically, we first built and tested a configural invariance model, which consisted of measurement models with identical loading patterns but no invariance in any parameters. Then, we tested whether weak (factor loadings invariant) and strong measurement invariance (factor loadings and item intercepts invariant) held across the groups (i.e., gender and grade).

4.4.2. Results

Based on the factor structure we observed in the EFA, a model containing four latent factors was tested first. The measurement model fits were: $\chi^2(224) = 873.318$, CFI = 0.907, TLI = 0.895, RMSEA = 0.078, 90% CI [0.073, 0.084], SRMR = 0.064. All factor loadings were significant at $p < .001$. The standardized factor loadings for the cost items were > 0.61, with the exception of one effort cost item (EFC07; factor loading = 0.31, see Table 1 for details). Although there are no golden rules regarding the optimal number of items for an instrument, researchers usually recommend that scales exhibit parsimony and have the minimum number of items to adequately capture the essence of the target construct (e.g., Boateng et al., 2018; Thorndike, 2005). It is suggested that a minimum of three items are required to adequately evaluate internal consistency reliabilities (Cook et al., 1981) and adequately perform factor analysis and structural equation modeling (SEM; Kline, 2010). Therefore, considering the factor loadings observed in both the EFA and CFA, as well as the inter-item correlations and item content,[1] three final items were selected for each type of cost (see Table 1).

Using the final items, the CFA model with four latent factors demonstrated good fit $\chi^2(48) = 114.420$, CFI = 0.979, TLI = 0.972, RMSEA = 0.054, 90% CI [0.041, 0.067], and SRMR = 0.033. The correlations between the four latent factors were all positive and significant at $p < .05$. Specifically, the correlations of effort cost with opportunity, ego, and emotional cost were $rs = 0.62$, 0.42, and 0.66, respectively. The correlations of opportunity cost with ego and emotional cost were $rs = 0.55$ and $r = 0.56$, respectively. The correlation between ego and emotional cost was $r = 0.37$.

4.4.2.1. Dimensionality and model-based reliability. Although the four-factor cost model demonstrated good model fit, the correlations between the four latent factors were relatively high ($.37 \le rs \le .66$), suggesting that a general factor might exist. We then conducted a bifactor CFA to ascertain the dimensionality and model-based reliabilities of the scales. The model fits were: $\chi^2(42) = 107.284$, CFI = 0.980, TLI = 0.968, RMSEA = 0.057, 90% CI [0.044, 0.071], and SRMR = 0.038. Using the Bifactor Indices Calculator (Dueber, 2017), we evaluated the psychometric properties of the bifactor model against several recommended criteria (Rodriguez et al., 2016).

Table 3 presents detailed results for the bifactor CFA. On the model level, the Percentage of Uncontaminated Variance (PUC) was .82, indicating that 82% of the covariance terms were reflected variance in the general cost factor. On the factor level, the Explained Common Variance (ECV) indicated that 54% of the total common variance was explained by the general cost factor. The amount of total common variance explained by the four specific costs ranged from 35% to 68%. The Omega statistic (ω) was .95 for general cost and the Omega Subscale (ωS) ranged from .86 to .91 for the four specific costs. These indicated that the cost scale demonstrated good internal reliability. Omega Hierarchical (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 .79. In contrast, Omega Hierarchical Subscale (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, was .29 for the effort cost, .35 for the opportunity cost, .58 for the ego cost, and .38 for the emotional cost.

According to recommended criteria (e.g., Reise, 2012; Reise et al., 2012), a ωH value exceeding 0.80 indicates that the scale is essentially unidimensional and a relative omega value (i.e., ωH or ωHS divided by ω) exceeding .50 indicates the factor accounts for a substantial proportion of reliable variance independently. In the present data, the ωH for general cost was .79 and relative omega for general cost and ego cost were .83 and .68, respectively. These results suggest that the scale is adequately described by a model consisting of general cost, but ego cost also exhibited interpretive relevance. Therefore, we used a bifactor approach to model the cost in the present study as it enables researchers to include both general and specific factors as independent variables and test the relationships of general and specific factors with external variables simultaneously (e.g., Chen et al., 2012; Gonzalez & Mackinnon, 2018).

4.4.2.2. Measurement invariance. We tested the measurement invariance of the bifactor cost model across gender and grade. For measurement invariance test, a decrease of < 0.01 in CFI and an increase of < 0.02 in the RMSEA should be taken as support for the more constrained model (e.g., Chen, 2007; Cheung & Rensvold, 2002). The separate analyses examining potential gender and grade differences yielded parallel results (see Table 4). First, the configural invariance model was shown to have good fit. Second, when constraining the factor loadings and further item intercepts to be invariant, no substantial changes in goodness of fit indices were found. Thus, the cost scale demonstrated strong measurement invariance across both gender and grade.

4.4.3. Scale validation

Correlations with theoretically relevant criteria constitute important evidence of validity (Clark & Watson, 1995). Therefore, in order to test the scale's validity, we surveyed variables which could be hypothesized to relate to the cost construct during CFA data collection. Two existing cost scales by Conley (2012) and Luttrell et al. (2010) were included to test concurrent validity (Thorndike,

[1] During the final item selection process, in addition to considering factor loadings obtained from empirical testing, we intentionally selected items for effort and opportunity cost with negative wordings like “too much”, “sacrifice”, and “give up” to ensure the items reflect students' negative appraisals. Therefore, we did not select effort cost item EFC05 “I need to spend a great amount of energy to do well in math” and opportunity cost item OPC05 “I cannot do other activities that I want in order to do well in math”, because these items may be endorsed by students who perceive studying math as demanding in terms of effort and time but have no negative appraisal. Item selection for ego cost was based purely on item factor loadings. For emotional cost, we did not select two items EMC05 and EMC06 referring to exhaustion/burnout about studying math. The reason was because items reflecting these negative feelings have been found to load on the effort cost dimension in previous studies (Flake et al., 2015; Gaspard et al., 2015) and thus may undermine the discriminant validity of the subscales.

Table 3
Standardized loading pattern for the final cost items bifactor CFA.

Item	GC	EFC	OPC	EGC	EMC	Residual
EFC01	.68/.62/.31	.33/.36/.72				.43/.48/.38
EFC03	.65/.66/.45	.63/.46/.78				.18/.38/.20
EFC06	.68/.65/.52	.46/.56/.69				.32/.26/.25
OPC01	.63/.64/.75		.64/.64/.40			.19/.18/.28
OPC02	.68/.69/.77		.51/.52/.44			.27/.25/.22
OPC04	.73/.71/.73		.46/.45/.61			.25/.30/.10
EGC03	.46/.46/.62			.67/.70/.58		.34/.30/.28
EGC04	.49/.49/.67			.68/.55/.58		.30/.46/.22
EGC05	.45/.51/.67			.68/.65/.64		.33/.32/.15
EMC01	.66/.61/.60				.49/.51/.55	.32/.38/.34
EMC02	.67/.59/.39				.61/.72/.85	.18/.13/.12
EMC04	.63/.53/.33				.58/.61/.87	.27/.35/.14

Psychometric properties	GC	EFC	OPC	EGC	EMC
$\omega/\omega S$	.95/.94/.96	.87/.83/.89	.91/.90/.92	.86/.84/.92	.90/.88/.92
$\omega H/\omega HS$	.79/.77/.72	.29/.27/.66	.35/.35/.27	.58/.53/.42	.38/.47/.69
PUC	.82/.82/.82				
ECV	.54/.53/.45	.35/.33/.74	.39/.39/.30	.68/.63/.46	.43/.54/.74

Note. Results from Study 1, 2, and 3 are presented sequentially. 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.

Table 4
Model fit statistics for bifactor models representing different degrees of invariance across gender and grades in Study 1.

Model	χ^2	*df*	CFI	TLI	RMSEA	ΔCFI	ΔTLI	ΔRMSEA
Gender								
Configural invariance	172.200	84	0.969	0.951	0.067	–	–	–
Weak measurement invariance	214.279	108	0.962	0.954	0.065	−.007	0.003	−.002
Strong measurement invariance	228.160	115	0.960	0.954	0.065	−.002	0.000	0.000
Grades								
Configural invariance	173.633	84	0.968	0.949	0.067	–	–	–
Weak measurement invariance	207.967	108	0.964	0.956	0.063	−.004	0.007	−.004
Strong measurement invariance	220.966	115	0.962	0.956	0.062	−.003	0.000	−.001

2005) and were expected to positively correlated with the new cost scale. Value, task disengagement, and avoidance of help seeking were included to test construct validity. According to expectancy-value theory, cost and value are typically negatively correlated with each other (Barron & Hulleman, 2015). By contrast, cost has been found to be positively related to task disengagement (Watkinson et al., 2005) and avoidance of help seeking (Lu et al., 2011).

4.4.4. Measures

All survey items were written in Korean and referred to the subject of math (see Appendix A). Scales that were originally developed in English were put through a translation-and back-translation procedure, as suggested by Brislin (1970). Items concerning value were based on a seven-point Likert scale ranging from 1 (*not true at all*) to 7 (*very true*), whereas for two existing cost scales (i.e., disengagement and avoidance of help seeking), items were based on a five-point Likert scale ranging from 1 (*not true at all*) to 5 (*very true*).

4.4.4.1. Personal cost. Seven items for personal cost were obtained from Luttrell et al. (2010). In their study, Luttrell and colleagues developed the Mathematics Value Inventory (MVI) and provided initial validation for the measure. Personal cost is a sub-scale of the MVI assessing negative effort- and emotion-related appraisals that would lead students to devalue math learning (e.g., “Trying to do math causes me a lot of anxiety”). This scale exhibited good reliability as $\alpha = .93$ in the original study. In the present study, the reliability coefficient of this scale was $\alpha = .95$.

4.4.4.2. Opportunity cost. Two items for opportunity cost were obtained from Conley (2012). This scale assessed students' perceptions of loss of valued alternatives due to studying math (e.g., “I have to give up a lot to do well in math”). In Conley's (2012) study, this scale exhibited reasonable reliability of $\alpha = .70$ in a group of adolescent students. The scale was also used successfully in a subsequent study with a group of different adolescent students (Safavian & Conley, 2016). In the present study, the Spearman-Brown coefficient for this two-item scale was $\rho = .87$.

Table 5
Descriptive statistics, reliabilities, and correlation coefficients among cost and validation scales in Study 1.

Variable	*M*	*SD*	α/ω	1	2	3	4	5	6	7	8	9
1. COST	4.17	0.91	.79[a]	–								
2. EFC	4.96	1.21	.29[b]	.79**	–							
3. OPC	4.04	1.55	.35[b]	.82**	.56**	–						
4. EGC	3.62	1.43	.58[b]	.70**	.36**	.47**	–					
5. EMC	4.07	1.51	.38[b]	.79**	.59**	.51**	.34**	–				
6. PC	4.29	1.47	.95[c]	.78**	.67**	.53**	.49**	.75**	–			
7. OC	3.81	1.69	.87[d]	.80**	.61**	.80**	.47**	.61**	.66**	–		
8. VALUE	4.22	0.92	.80[a]	−.30**	−.25**	−.12*	−.02	−.54**	−.41**	−.27**	–	
9. DENG	2.58	0.88	.88[c]	.46**	.37**	.30**	.19**	.56**	.50**	.39**	−.41**	–
10. AHS	2.28	0.89	.90[c]	.35**	.25**	.22**	.15**	.44**	.38**	.34**	−.36**	.59**

Note. COST = general cost; EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost; PC = personal cost; OC = opportunity cost (Conley, 2012); DENG = disengagement; AHS = avoidance of help seeking.

[a] Omega hierarchical.
[b] Omega hierarchical subscale.
[c] Cronbach's alpha.
[d] Spearman-Brown coefficient for two-item scale.
* $p < .05$.
** $p < .01$.

4.4.4.3. Value. Six items measuring value were adopted from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991). In the present study, we were interested in comparing the cost to positively-valenced components of task value. This goal aligned well with the MSLQ value scale, which measures utility value (e.g., "I think math is useful for me to learn"), attainment value (e.g., "It is important for me to learn math"), and interest value (e.g., "I like math"), but does not measure cost. This scale has been used successfully to investigate value in prior research with different groups of Korean adolescent students (e.g., Bong, 2001, 2004). Because this scale consists of three sub-dimensions, we examined the model-based reliability. The results revealed that the PUC was .80 on the model level, indicating that 80% of covariance terms merely reflect variance from the general factor. In addition, the ωH for the general value was .80, whereas the ωHS for the three specific factors ranged from .20 to .39. Thus, value was better explained by the general factor.

4.4.4.4. Disengagement. Three items for task disengagement were obtained from Liem et al. (2008). This scale was developed based on the effort regulation sub-scale of the MSLQ (Pintrich et al., 1991) and reflects the degree to which students disengage in math tasks when they find the tasks too difficult or boring (e.g., "When the work in Math is difficult, I give up"). The scale showed reasonable internal consistency in the original study, with $\alpha = .81$. The reliability coefficient of this scale in the present study was $\alpha = .88$.

4.4.4.5. Avoidance of help seeking. Five items were adopted from Ryan and Pintrich (1997). These items assessed students' tendency to avoid seeking help in math class even when needed (e.g., "When I don't understand my math work, I often guess instead of asking someone for help"). In that previous work, the reliability coefficient of this scale was $\alpha = .76$. In the present study, the reliability coefficient of this scale was $\alpha = .90$.

4.4.5. Results

Table 5 presents the descriptive statistics, reliabilities, and zero-order correlations among variables. The general cost and the four specific costs were all significantly correlated with the two existing cost scales ($.47 \le rs \le .80$, $p < .01$), suggesting that the new scale had good concurrent validity. Construct validity was supported by the significant correlations of cost with value, disengagement, and avoidance of help seeking. Specifically, the general cost and the four specific costs were all positively correlated with disengagement ($.19 \le rs \le .56$, $p < .01$) and avoidance of help seeking ($.15 \le rs \le .44$, $p < .01$). The general cost and three specific costs (i.e., effort, opportunity, and emotional cost) were also negatively correlated with value ($-.54 \le rs \le -.12$, $p < .05$). Exceptions were observed in the ego cost as its correlation with value was nonsignificant.

4.5. Discussion

In Study 1, we finalized a 12-item cost scale to assess Korean adolescent students' perceived cost of studying math. All items displayed strong psychometric properties and the scale's reliability coefficient indicated strong internal consistency. Correlations between the cost and validation scales provided evidence for concurrent and construct validity. Moreover, the cost scale displayed strong measurement invariance across gender and grade, indicating that this scale can function adaptively for various samples.

A four-factor model for cost was supported by the CFA results, suggesting that the different types of cost are empirically distinct. Similar findings have been witnessed in several recently published papers developing cost scales (e.g., Flake et al., 2015; Gaspard et al., 2015). This evidence suggests that, as Eccles et al. (1983) stated, students differentiate between different types of cost. Nonetheless, results from the bifactor cost model also revealed that the data can be adequately explained by a factor consisting of general cost. These results are compatible with those reported by Flake et al. (2015), who also found that both the model on the specific costs level and the model on the general cost level exhibited adequate model fit. As discussed by Flake et al. (2015), the way of modeling cost, whether using a multi-dimensional or uni-dimensional approach, may depend on the specific research question. We concur with this argument and further suggest that the chosen method of modeling cost should take into consideration the instrument's model-based reliability based on specific data (Reise et al., 2012). Researchers have argued that conventional indications of a scale's psychometric properties (e.g., Cronbach's alpha) do not provide an accurate estimation of the psychometric properties of multidimensional construct (Widhiarso & Ravand, 2014). It is necessary to provide model-based reliability evidence that the general factor or specific sub-factors of the multidimensional scale truly represent the target construct of interest (McDonald, 1999).

In addition, it is important to evaluate the interpretive relevance of the factors from multifaceted constructs (e.g., Benson et al., 2018). Results based on the current data revealed that although the cost scale can be described well by a model consisting of general cost, ego cost still accounted for a substantial proportion of reliable variance independent of the general cost. In the correlation analysis, we also found that ego cost was not significantly correlated with value. This may be because ego cost arises from individuals' fear of receiving a negative evaluation that damages their self-worth, so it is not necessarily negatively correlated with value. For example, Harter (1992) argued that failure only undermines self-esteem among those who value the task; thus, failure in a valued task might even strengthen the self-worth threat. In the present study, we refrained from discussing the three other specific costs because their reliability coefficients were low after accounting for general cost. We suggest that future studies continuously test the model-based reliability of cost instruments covering multiple sub-dimensions instead of taking the uni-dimensional or multi-dimensional approach for granted.

5. Study 2

Maladaptive academic outcomes, such as procrastination, disorganization, and excessive test anxiety, are major impediments to academic success and have received significant attention from educational researchers (Urdan & Midgley, 2001). Given that maladaptive academic outcomes are a manifestation of avoidance motives, cost may be a key antecedent, as it provokes the desire to avoid (Atkinson, 1964; Feather, 1992; Lewin, 1938). For instance, procrastination, which has been defined as the tendency to postpone necessary learning behaviors, is a well-known hindrance to academic success (Steel, 2007). In academic settings, cost may be closely related to procrastination. Because cost perceptions can prompt students to pay attention to adverse aspects of the energy and time required for studying, they may be less likely to start the task. Cost perceptions may also activate self-worth threat, which can lead to procrastination because a primary cause of procrastination is fear of appearing incompetent (Urdan & Midgley, 2001).

Cost may also function as a direct determinant of disorganization in a learning context. Disorganization refers to students' difficulty in establishing or maintaining a structured, organized approach to studying (Entwistle, 1987). Disorganization is associated with a failure of time and environment management. Studies investigating motivational conflict theory have found that cost elicited motivational interference, which subsequently impaired students' learning and performance (e.g., Fries & Dietz, 2007; Grund & Fries, 2012). This may be because cost perceptions can cause students to perceive the effort and time required for learning task as aversive, which is very likely to lead to disorganization. In addition, cost perceptions like self-worth threat and negative affective memories associated with studying can also create a psychological burden that may interfere with organized learning behavior.

Test anxiety, commonly defined as the fear of evaluation during examination situations, also undermines academic success (Spielberger & Vagg, 1995). Liebert and Morris (1967) proposed that test anxiety consists of two primary components: worry and emotionality. Cost may be closely related to test anxiety because it is closely related to both the worry and emotionality components of test anxiety. On one hand, both cost and test anxiety concern the threat to self-worth from potential failure. On the other hand, cost is rooted in negative affect, which becomes more apparent in test situations and can lead to higher levels of anxiety. Thus, cost perceptions are very likely to provoke anxiety in test conditions.

Compared to the extensive research documenting the important role of value in students' adaptive academic outcomes such as higher future choice intentions and persistence in learning (Eccles, 2005; Wigfield et al., 2017), much less research has explored how cost may be related to students' maladaptive academic outcomes. Part of the reason for this may be because researchers have not reached clear consensus on whether cost should be modeled as its own construct or as part of task value. The majority of empirical studies on expectancy-value theory have either excluded cost or combined it with other value components when assessing task value (e.g., Buehl & Alexander, 2005; Jacobs et al., 2002). In Study 2, we explicitly examined the dimensionality of cost and value and tested whether these two constructs exhibited unique relationships with academic outcomes. We hypothesized that cost and value would be empirically distinguishable. We also hypothesized that value would be more closely related to adaptive academic outcomes, such as future choice intentions and persistence, whereas cost would be more closely related to maladaptive academic outcomes like procrastination, disorganization, and test anxiety.

5.1. Method

5.1.1. Participants and procedures

The sample comprised 637 students (290 boys, 346 girls, one did not indicate sex; 294 8^{th} graders, mean age = 14.2 years, *SD* = 0.48; 343 11^{th} graders, mean age = 17.1 years, *SD* = 0.47) from two public schools located in Seoul, South Korea. Most students at these two schools come from middle-class families. The survey took approximately 15 min to complete; students filled out the survey during regular class hours. As in Study 1, all analyses were conducted in Mplus 7.4. Missing values were < 1.3% for each item. Similar to Study 1's CFA data, the propensity for data to be missing was found to be related to some of the observed data so the missingness mechanism was assumed as MAR. Missing values were analyzed using FIML approach. The MLR estimator and the design-based correction of standard errors were used to account for the nonindependence of data due to the nesting of students within classes (McNeish et al., 2017).

5.1.2. Measures

All survey items were written in Korean and referred to the subject of math (see the Appendix A). Items for cost, value, persistence, test anxiety, and disorganization were answered on a seven-point Likert scale ranging from 1 (*not true at all*) to 7 (*very true*), whereas items for procrastination and future choice intentions were answered on a five-point Likert scale ranging from 1 (*not true at all*) to 5 (*very true*). As in Study 1, items that were originally developed in English were put through a translation and back-translation procedure (Brislin, 1970).

5.1.2.1. Cost. The twelve items finalized in Study 1 were used to measure students' cost perceptions. As in Study 1, a bifactor CFA was performed to evaluate the model-based reliability of the cost scale. Table 3 presents the detailed results. For general cost, the PUC was .82 on the model level and the ECV was .53 on the factor level. The ωH for general cost was .77 and the ωHS for the four specific costs ranged from .27 to .53. Specifically, ego cost had ωHS = .53 and relative omega = .63. These results indicate that although general factor appears to adequately explain the cost scale, ego cost also demonstrated some interpretive relevance in the current data.

5.1.2.2. Value. Six items assessing value were identical to those used in Study 1. We also examined the model-based reliability because this scale is multidimensional. The results from the bifactor CFA revealed that the PUC was .80 and the ECV was .64 for general value. In the meantime, ωH was .72 for the general value, whereas the ωHS for three specific values were ≤ .33. These suggested that the scale is better described through a general value factor (Rodriguez et al., 2016).

5.1.2.3. Future choice intentions. Two items measured academic-related future choice intentions, defined as the degree to which students wanted to pursue future math-related courses and majors (e.g., “I'd like to choose a Math-related major at university”). Items were adapted from measures by Bong (2001) and Meece et al. (1990). The Spearman-Brown reliability coefficient for the two-item scale was ρ = .79 in the present study.

5.1.2.4. Test anxiety. Three items on test anxiety were adopted from the test anxiety sub-scale of the MSLQ (Pintrich et al., 1991), which was modified by Bong (2009). These items concerned worry and cognitive interferences during math test (e.g., “I am so nervous during a math test that I cannot remember things I have learned”). The Korean version of this scale has proven internally consistent among adolescent students (Bong et al., 2014). In the present study, the reliability coefficient of this scale was α = 0.81.

5.1.2.5. Persistence. Four items related to persistence were obtained from Elliot et al. (1999). Items assessed the degree to which students would continue in studying math in spite of difficulty (e.g., “When I become confused about something on math, I go back and try to figure it out”). Elliot and colleagues conducted a series of pilot studies, including factor analysis, to verify the psychometric properties of this scale. In that previous work, this scale showed reasonable reliability, α = .78. In the present study, the reliability coefficient of this scale was α = .88.

5.1.2.6. Disorganization. Five items for disorganization were also obtained from Elliot et al. (1999). The scale consisted of newly developed items as well as revised MSLQ learning strategy items measuring students' inability to establish an organized approach to studying (e.g., “I'm not sure how to study for math”). The scale showed reasonable reliability in the original study, with α = .74. The reliability coefficient of this scale in the present study was even higher, α = .92.

5.1.2.7. Procrastination. Five items for passive academic procrastination were adapted and revised from the Melbourne Decision Making Questionnaire (Mann et al., 1998). The original measure was designed to assess procrastination in decision-making and was shown to be both reliable and valid. In the present study, the items were revised to assess procrastination with respect to studying math (e.g., “I waste a lot of time on trivial matters before getting to study math”). The reliability coefficient was α = .91.

5.2. Results

5.2.1. Descriptive statistics and CFA

Table 6 presents the descriptive statistics, reliability coefficients, and zero-order correlations among variables. All variables demonstrated acceptable reliability. According to expectancy-value theory (Eccles et al., 1983; Wigfield et al., 2016), cost should be negatively correlated with value, future choice intentions, and persistence, and positively correlated with maladaptive academic outcomes such as test anxiety, disorganization, and procrastination. In contrast, value should be positively correlated with future choice intentions and persistence but negatively correlated with maladaptive academic outcomes. In addition, the three maladaptive academic outcomes should be positively correlated with each other but negatively correlated with both future choice intentions and persistence (Urdan & Midgley, 2001). The correlation patterns among variables in the present study were consistent with theoretical expectations and the empirical literature.

We first explored the dimensionality of cost and value by testing a bifactor model treating these two constructs as sub-dimensions

Table 6
Descriptive statistics, reliabilities, and correlation coefficients among variables in Study 2.

Variable	*M*	*SD*	α/ω	1	2	3	4	5	6	7	8	9	10
1. COST	3.88	.90	.77[a]	–									
2. EFC	4.63	1.17	.27[b]	.79**	–								
3. OPC	3.88	1.55	.35[b]	.81**	.57**	–							
4. EGC	3.25	1.27	.53[b]	.71**	.34**	.47**	–						
5. EMC	3.74	1.43	.47[b]	.77**	.54**	.41**	.38**	–					
6. VALUE	4.31	.94	.79[a]	−.22**	−.14**	−.01	−.01	−.52**	–				
7. FCI	2.75	1.05	.79[d]	−.19**	−.16**	−.03	.04	−.42**	.68**	–			
8. PER	4.57	.96	.88[c]	−.10*	−.08	.14*	.04	−.40**	.62**	.43**	–		
9. ANX	4.01	1.17	.81[c]	.51**	.45**	.30**	.37**	.45**	−.12**	−.12**	−.09	–	
10. DSO	3.81	1.08	.92[c]	.45**	.42**	.20**	.25**	.53**	−.27**	−.19**	−.37**	.46**	–
11. PROC	2.78	.87	.91[c]	.44**	.34**	.23**	.27**	.50**	−.33**	−.26**	−.40**	.36**	.58**

Note. COST = general cost; EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost; FCI = future choice intentions; PER = persistence; ANX = test anxiety, DSO = disorganization; PROC = procrastination.
[a] Omega hierarchical.
[b] Omega hierarchical subscale.
[c] Cronbach's alpha.
[d] Spearman-Brown coefficient for two-item scale.
* $p < .05$.
** $p < .01$.

of a general factor (Reise et al., 2012). As shown in Table 7, the PUC on the model level was .47, indicating that 47% of covariance terms merely reflect variance from the general factor. On the factor level, the ECV was .38, indicating that 38% of the common variance across items was explained by the general factor. Finally, the ωH for the general factor was .14, which means only 14% of total score variance can be attributed to the general factor after accounting for the two specific factors. In contrast, the ωHS were .54 for cost and .67 for value. Moreover, the relative omega for cost and value were .57 and .71, respectively. Hence, according to evaluation criteria (Rodriguez et al., 2016), cost and value should be treated as distinct constructs.

Table 7
Standardized loading pattern for the cost and value items bifactor CFA in Study 2.

Item	GF	COST	VALUE	Residual
COST01	.49	.53		.48
COST02	.46	.64		.37
COST03	.50	.69		.28
COST04	.34	.83		.20
COST05	.39	.78		.24
COST06	.41	.73		.31
COST07	.35	.75		.31
COST08	.33	.66		.46
COST09	.31	.77		.31
COST10	.78	.56		.09
COST11	.87	.09		.24
COST12	.87	−.09		.23
VALUE01	−.31		.58	.56
VALUE02	−.46		.89	.01
VALUE03	−.62		.60	.26
VALUE04	−.64		.78	.02
VALUE05	−.28		.70	.43
VALUE06	−.39		.73	.31

Psychometric Properties	GF	COST	VALUE
ω/ωS	.94	.96	.94
ωH/ωHS	.14	.54	.67
PUC	.47		
ECV	.38	.58	.70

Note. All factor loadings included in the table are significant at $p < .001$. GF = general factor. 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.

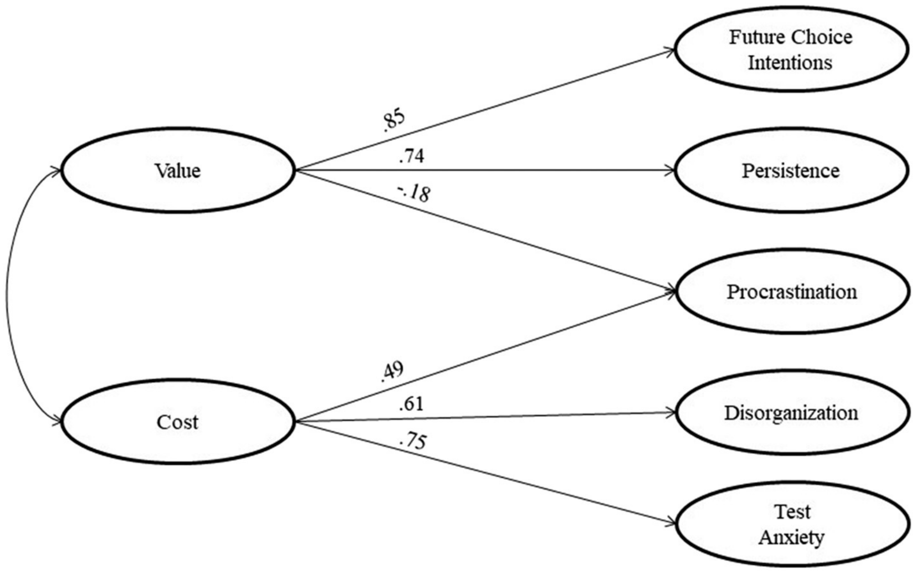

Fig. 2. Standardized path coefficients from the SEM model tested in Study 2. Only the paths significant at $p < .05$ are presented. Control variables and disturbance terms are not presented for clarity.

5.2.2. SEM

In the SEM model, both cost and value were modeled using a bifactor approach. Before running the SEM model, we confirmed that our measurement model exhibited an adequate fit: χ^2 (595) = 1646.067, CFI = 0.917, TLI = 0.907, RMSEA = 0.053, 90% CI [0.050, 0.056], SRMR = 0.084. All factor loadings were significant at $p < .001$, indicating that latent variables were represented well by their respective indicators. We then proceeded to test the SEM model. Demographic variables (i.e., sex and age) were included as control variables in the SEM model because gender- and age-related differences in cost and value perceptions toward math exist (e.g., Gaspard et al., 2015; Watt, 2004); moreover, demographic variables have been found to predict students' mathematics achievement and aspirations (Guo et al., 2015). However, these differences were not the focus of the present study. This approach is consistent with that of previous researchers (e.g., Jiang et al., 2018; Trautwein et al., 2012) investigating the role of value and cost in students' academic outcomes.

In the SEM model, we regressed each outcome variable on cost, value, and two control variables. The disturbances for three maladaptive academic outcomes as well as measurement errors of procrastination (Items 4 and 5) and disorganization (Items 2 and 3) were covaried based on theoretical considerations and modification indexes. The model fit statistics indicated a reasonable fit: χ^2(646) = 1694.906, CFI = 0.921, TLI = 0.909, RMSEA = 0.050, 90% CI [0.048, 0.053], and SRMR = 0.085. As shown in Fig. 2, only value significantly predicted future choice intentions (β = 0.85) and persistence (β = 0.74). In contrast, only cost significantly predicted test anxiety (β = 0.75) and disorganization (β = 0.61). Both value and cost significantly predicted procrastination (βs = −0.18 and 0.49, respectively).

We noticed that some path coefficients in the SEM model were somewhat high, indicating that a statistical suppression effect may exist (MacKinnon et al., 2000). A suppression effect is typically defined as increasing the predictive validity of one variable by including another variable in the regression model (Tzelgov & Henik, 1991). A close examination revealed that including value increased the path coefficient of test anxiety on cost (from 0.68 to 0.75). Thus, value may have suppressed the part of variance in cost that is unrelated to test anxiety, which resulted in an increase in the magnitude of the path coefficient. Nevertheless, the path coefficients had consistent signs, indicating that the suppression effect was not strong. We then included ego cost as an additional predictor in the SEM model to test whether and how ego cost would predict academic outcomes over and above general cost. However, there was no significant path from ego cost.

5.3. Discussion

The findings from Study 2 suggest that cost plays an important role in understanding adolescent students' maladaptive academic outcomes. First, we found that the internal structural of cost and value is not unidimensional. Eccles et al. (1983) wrote about cost originally as an influence on task value. In their later writings, however, cost was categorized as a component of task value (Eccles, 2005; Wigfield & Eccles, 1992). Many researchers have adopted this perspective and combined cost with other value components to create a composite task value score (e.g., Buehl & Alexander, 2005; Safavian & Conley, 2016). Our results suggest that cost should not be considered as equivalent to a lowering force on value. Other recent empirical studies have also shown that cost separates into its own factor rather than being subsumed under the value dimension (Battle & Wigfield, 2003; Luttrell et al., 2010; Perez et al., 2014; Trautwein et al., 2012). Therefore, cost and value should be considered as distinct constructs.

In addition, cost was more closely related to maladaptive academic outcomes than value. Our results revealed that when cost and value were both included as independent variables, only cost explained maladaptive academic outcomes such as test anxiety and disorganization. The observed close relations between cost and maladaptive outcomes were 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 maladaptive academic functioning (Feather, 1992; Urdan & Midgley, 2001). Empirically, cost has been found to positively relate to avoidance of help seeking and task disengagement (Lu et al., 2011; Watkinson et al., 2005) and to lead to greater drop-out intentions and actual drop-out behavior (de la Varre et al., 2014; Perez et al., 2014). Value, though less important in explaining maladaptive academic outcomes, was highly related to students' future choice intentions and persistence. These results are compatible with previous findings that value beliefs account for the greatest variance in students' academic choice and subsequent persistence (see Eccles & Wigfield, 2002; Wigfield & Cambria, 2010 for reviews).

6. Study 3

Study 2 revealed that cost can play a key role in understanding adolescent students' maladaptive academic outcomes. However, Study 2 included only cross-sectional data. In Study 3, we collected data from multiple time points and explored the predictive utility of cost for different academic outcomes. We were specifically interested in how cost is related to achievement goal adoption, which in turn is associated with students' classroom engagement, avoidance intentions, and academic achievement.

6.1. Relating cost to achievement goals

Achievement goals theory explains students' underlying purposes 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). Based on differences in motivational valences (i.e., approach vs. avoidance), achievement goal researchers have further divided each type of achievement goals, resulting in a 2 × 2 framework (Elliot & McGregor, 2001). Students who adopt mastery-approach goals seek to improve their intraindividual competence, whereas students who adopt mastery-avoidance goals seek to avoid intraindividual incompetence. Students who adopt performance-approach goals are interested in demonstrating normative competence, whereas students who adopt performance-avoidance goals are interested in avoiding normative incompetence.

Task values have been considered direct determinants of an individual's goals for engaging in a specific academic task (Wigfield, 1994). Elliot and Thrash (2001) suggested that students' task values are likely to exert a direct effect on their achievement goals. Similarly, Miller and Brickman (2004) argued that whether students perceive an academic task to be valuable could be consequential for the proximal achievement goals they adopt. Empirically, researchers have found that utility value and composite task value (including intrinsic, attainment, and utility value) positively predict students' adoption of mastery goals (e.g., Greene et al., 2004; Liem et al., 2008). As previously demonstrated, cost and value are empirically distinct and both have an independent influence on students' academic functioning. In particular, because cost involves negative appraisals related to learning, which have been posited to influence avoidance motivation, we expect that it will be positively related to students' adoption of avoidance goals.

6.2. Relating cost to classroom engagement, avoidance intentions, and achievement

Classroom engagement is considered crucial for academic achievement, yet evidence has shown that students become more disengaged from class as they move into higher grades (Marks, 2000). Because cost plays a critical role in motivating avoidance behaviors (Atkinson, 1964; Lewin, 1938), it may function as an important determinant of student disengagement in the classroom. For instance, perceived cost may cause concern that the effort and time spent on a target activity are not worthwhile, thus undermining engagement. Perceived cost also relates to the negative affective perceptions associated with a task, so higher levels of perceived cost will invariably lead students to avoid engaging in the target activity.

Similarly, researchers have emphasized that cost perceptions toward an ongoing task will induce avoidance (Inzlicht & Schmeichel, 2012). Several studies have demonstrated that cost predicts students' dropout intentions (Luttrell et al., 2010; Perez et al., 2014). Concerning the relationship between cost and achievement, Gaspard, Wigfield, et al. (2017) found negative correlations between 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 had detrimental effects on their performance. Therefore, it seems more than reasonable that cost perceptions will affect general avoidance intentions and lower students' academic achievement.

Meanwhile, the relationship between cost and engagement, avoidance intentions, and achievement may be largely mediated by the specific achievement goals a student adopts. According to the hierarchical model of achievement motivation (Elliot & Church, 1997; Elliot & Thrash, 2001), students' task values are more likely to exert a direct effect on their achievement goals, which in turn serve as a proximal precursor to academic functioning. Thus, cost may first influence the specific achievement goals students adopt in class and subsequently determine their levels of engagement and achievement.

In summary, we tested whether cost exhibits unique predictive utility for adolescent students' achievement goals, classroom engagement, avoidance intentions, and achievement. We examined the relative predictive strength of cost and value on each outcome. We hypothesized that cost would positively predict avoidance goals and avoidance intentions but would negatively predict classroom engagement and achievement. We did not make specific hypotheses regarding the relationships between cost and approach goals due to the lack of sufficient prior research on this topic.

6.3. Method

6.3.1. Participants and survey procedures

Data were collected from a group of Grade 8 students at a public middle school located in Seoul, South Korea. The school was a typical public school with students from middle-class families. Students' responses were collected at three points in time. The first wave of the survey (T1) was administered during regular classroom hours in the first week of the school year, during which the students' perceptions of cost and value were assessed. The second wave of the survey (T2) was conducted during regular classroom hours in the seventh week of the school year, two weeks before midterm examinations. At this measurement point, students reported their achievement goals, classroom engagement, and avoidance intentions. Both waves of the survey took approximately 25 min to complete. In week 10 of the schoolyear, the students' midterm exam scores were obtained as a measure of achievement (T3).

Two-hundred forty-five students participated in the T1 survey and 239 students participated in the T2 survey. The final sample consisted of 211 students who participated in both waves of data collection (107 boys; mean age = 13.5 years, $SD = 0.62$). The data for this study were collected as part of a broader research project investigating the role of students' perceptions in value transmission from teachers to students (Han, 2015). Missing values accounted for < 1.7% of the responses for each item on the T1 survey and < 1.4% of the responses for each item on the T2 survey. Little's MCAR test indicated that the missing mechanism was assumed as MCAR ($\chi^2 = 542.680$, $df = 494$, $p = .06$). As in Study 1 and 2, missing values were analyzed using FIML approach and the MLR estimator and the design-based correction of standard errors were used to account for the nonindependence of data due to the nesting of students within classes (McNeish et al., 2017).

6.3.2. Measures

As with Study 1 and Study 2, all survey items were written in Korean and referred to the subject of math (see the Appendix A). All survey items were based on a seven-point Likert scale ranging from 1 (*not true at all*) to 7 (*very true*). Items that were originally developed in English were put through a translation and back-translation procedure (Brislin, 1970).

6.3.2.1. Cost (T1). The twelve items finalized in Study 1 were used to measure students' cost perceptions. The model-based reliabilities of the cost scale are presented in Table 3. For general cost, the PUC was. 82 and ECV was .45. The ωH was .72 for general cost and the ωHS were .66 for effort cost, .27 for opportunity cost, .42 for ego cost, and .69 for emotional cost. The relative omegas for general cost, effort cost, and emotional cost were .75, .74, and .75, respectively. According to the evaluation criteria proposed by Reise (2012), general cost appears to adequately explain the scale, yet effort cost and emotional cost also have interpretive relevance in the current data.

6.3.2.2. Value (T1). Six items assessing value, identical to those used in Study 1 and Study 2, were used. The model-based reliability coefficient was $\omega\text{H} = .81$ for the general value; consequently, the scale can be considered as essentially unidimensional (Reise et al., 2012).

6.3.2.3. Achievement goals (T2). Nine items based on a 2 × 2 achievement goal framework were adopted from Elliot and McGregor (2001). The scale assessed students' (a) wanting to develop skill or competence in math class (Mastery-approach goals; e.g., "I want to learn as much as possible from math class"), (b) wanting to demonstrate skill or competence (Performance-approach goals; e.g., "It is important for me to do better than other students in math class"), and (c) not wanting to demonstrate a lack of skill or competence (Performance-avoidance goals; e.g., "I just want to avoid doing poorly in math class"). Mastery-avoidance goals were excluded due to their theoretical ambiguity. The Korean version of this scale previously demonstrated good internal consistency among Korean middle school students (e.g., Lee & Bong, 2016). In the present study, the reliability coefficients were $\alpha = .89$ for mastery-approach goals, $\alpha = .90$ for performance-approach goals, and $\alpha = .78$ for performance-avoidance goals.

6.3.2.4. Engagement (T2). Five items for engagement in the classroom were obtained from Skinner et al. (2009). Items of this scale reflected the actions of engaging in math class (e.g., "In Math class, I work as hard as I can"). This scale had been used successfully in prior research with Korean adolescent students (Jang et al., 2016). The reliability coefficient of this scale in the present study was $\alpha = .95$.

6.3.2.5. Avoidance intentions (T2). Avoidance intentions were measured with two researcher-developed items measuring the degree to which students did not want to engage in math class. The Spearman-Brown reliability coefficient for two-item scale was $\rho = .88$ in the present study.

6.3.2.6. Achievement (T3). Students' midterm exam score in math was used as an achievement index. The midterm exam was developed by math teachers at the school and consisted of both multiple-choice and open-ended questions. All students took the same exam and were scored equivalently based on a standard criterion. The scores ranged from 1 to 100.

6.4. Results

6.4.1. Descriptive statistics and measurement model

Table 8 presents the descriptive statistics, reliability coefficients, and zero-order correlations among variables. According to

Table 8
Descriptive statistics, reliabilities, and correlation coefficients among variables in Study 3.

Variable	*M*	*SD*	*α/ω*	1	2	3	4	5	6	7	8	9	10	11
1. COST	3.80	1.08	.72[a]	–										
2. EFC	4.89	1.15	.66[b]	.67**	–									
3. OPC	3.13	1.45	.27[b]	.80**	.38**	–								
4. EGC	3.33	1.41	.42[b]	.76**	.29**	.59**	–							
5. EMC	3.85	1.33	.69[b]	.71**	.38**	.35**	.32**	–						
6. VALUE	4.62	.60	.81[a]	−.17*	−.05	−.03	.01	−.42**	–					
7. MAP	4.95	1.16	.89[c]	−.11	−.04	−.02	.00	−.27**	.55**	–				
8. PAP	4.62	1.18	.90[c]	.22**	.07	.20**	.26**	.09	.26**	.55**	–			
9. PAV	4.35	1.08	.78[c]	.25**	.11**	.16**	.24**	.21**	.03	.26**	.64**	–		
10. ENG	5.09	1.13	.95[c]	−.12	−.08	−.09	−.00	−.18*	.38**	.55**	.37**	.22**	–	
11. AI	3.65	1.58	.88[d]	.31**	.21**	.18**	.12*	.40**	−.34**	−.31**	−.03	.23**	−.31**	–
12. ACH	71.89	32.46	–	−.23**	−.23*	−.07	−.07	−.31**	.45**	.27**	.14*	−.03	.27**	−.35**

Note. COST = general cost; EFC = effort cost; OPC = opportunity cost; EGC = ego cost; EMC = emotional cost; MAP = mastery-approach goals; PAP = performance-approach goals; PAV = performance-avoidance goals; ENG = engagement; AI = avoidance intentions; ACH = achievement.
[a] Omega hierarchical.
[b] Omega hierarchical subscale.
[c] Cronbach's alpha.
[d] Spearman-Brown coefficient for two-item scale.
* $p < .05$.
** $p < .01$.

achievement goals theory (Ames & Archer, 1988; Elliot & McGregor, 2001), mastery-approach goals are typically positively correlated with performance-approach goals, and performance-approach goals are typically positively correlated with performance-avoidance goals. In addition, both mastery-approach and performance-approach goals are usually positively correlated with achievement (Hulleman et al., 2010). Based on the extant literature, achievement should be positively related to engagement (Skinner et al., 2009) but negatively related to avoidance intentions (Elliot & Covington, 2001). As shown in Table 8, the correlation patterns observed in the present study were consistent with theoretical expectations and the existing literature. Before testing the structural paths of interest, we first fit the measurement model with all variables. The measurement model demonstrated an adequate fit: χ^2 (521) = 894.176, CFI = 0.919, TLI = 0.908, RMSEA = 0.058, 90% CI [0.052, 0.065], SRMR = 0.093. All factor loadings were significant at $p < .001$, indicating that the latent variables were represented well by their respective indicators.

6.4.2. SEM

We compared the relative importance of cost and value in predicting different outcomes in the SEM model. As with Study 1 and Study 2, both cost and value were modeled using bifactor approach. We also tested whether and how effort cost and emotional cost would predict outcomes over and above general cost. Demographic variables (i.e., sex and age) were included as control variables. The disturbance terms for the three achievement goals and for engagement and avoidance intentions were covaried based on theoretical considerations and the modification indexes. The final model fit statistics were: χ^2(561) = 958.432, CFI = 0.918, TLI = 0.902, RMSEA = 0.058, 90% CI [0.052, 0.064], SRMR = 0.092.

Fig. 3 displays the significant paths among latent variables. Value positively predicted mastery-approach goals (β = 0.65), performance-approach goals (β = 0.32), and achievement (β = 0.45). In contrast, cost positively predicted two types of performance goals (βs = 0.26 and 23 for approach and avoidance goals, respectively) and avoidance intention (β = 0.26). Of the other variables, mastery-approach goals positively predicted engagement (β = 0.52). Performance-approach goals negatively predicted avoidance intention (β = −0.23), whereas performance-avoidance goals positively predicted avoidance intentions (β = 0.46). Finally, avoidance intentions negatively predicted achievement (β = −0.19).

There were three significant indirect paths in the SEM model. Indirect effects were tested using 1000 bootstrapped samples to generate non-symmetric confidence intervals (CI). Specifically, students with higher value perceptions were more likely to adopt mastery-approach goals, which in turn enhanced classroom engagement (β = 0.33, *SE* = 0.09, 90% CI [0.19, 0.48]). In contrast, students with higher cost perceptions were more likely to adopt performance-avoidance goals, which in turn enhanced avoidance intentions (β = 0.11, *SE* = 0.03, 90% CI [0.03, 0.21]). Higher cost perceptions also led to higher avoidance intentions, which in turn undermined achievement (β = −0.05, *SE* = 0.02, 90% CI [−0.12, −0.02]).

Finally, adding effort cost and emotional cost as additional predictors in the SEM model yielded three significant direct paths. Specifically, effort cost negatively predicted achievement (β = −0.18), whereas emotional cost positively predicted performance-avoidance goals (β = 0.19) and avoidance intentions (β = 0.28).

6.5. Discussion

We aimed to explore how students' perceptions of cost are associated with their academic motivation and achievement. The results demonstrated that cost was an important predictor of students' adoption of achievement goals, avoidance intentions, and achievement. In particular, when cost and value were simultaneously included as separate predictors in the SEM model, only cost

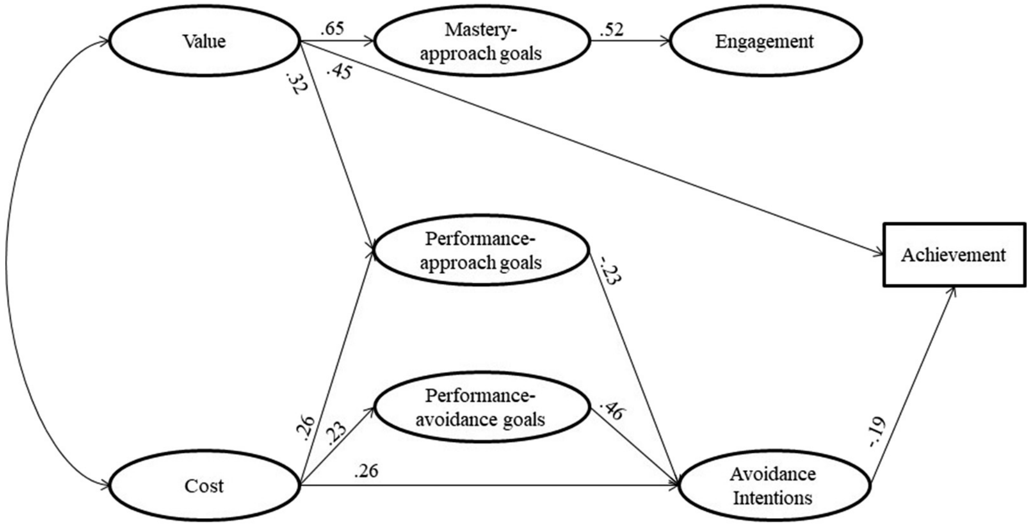

Fig. 3. Standardized path coefficients from the SEM model tested in Study 3. Only the paths significant at $p < .05$ are presented. Control variables and disturbance terms are not presented for clarity.

significantly predicted performance-avoidance goals and avoidance intentions. These results were in accord with previous findings that cost leads to the adoption of avoidance goals and the intention to quit (Jiang et al., 2018; Perez et al., 2014). As argued by Battle and Wigfield (2003), students will choose to avoid an activity when it is seen as involving too much cost even when the activity is deemed to be valuable. Thus, cost could have unique predictive utility on academic outcomes compared to value, thereby more strongly predicting the constructs related to students' avoidance motivation.

We also found that cost leads to stronger avoidance intentions, which then subsequently undermine achievement. This finding is consistent with several recent studies showing negative relations between cost and academic achievement (e.g., Gaspard, Wigfield, et al., 2017; Perez et al., 2019). The pattern of our results suggests that cost may influence students' motivational beliefs in important ways that can affect their academic achievement. Cost perceptions can induce aversive experiences toward learning and are very likely to undermine persistence and induce avoidance intentions; this may impair subsequent achievement. Therefore, it is important for educators to help their students overcome cost perceptions in order to keep them motivated and help them achieve academic success.

The one outcome that cost did not relate to in the present study was classroom engagement; only value was associated with this outcome. Specifically, students with higher value perceptions were more likely to adopt mastery-approach goals, which were then positively related to classroom engagement. This finding lends support to the perspective that achievement goals mediate the relationship between task values and classroom engagement (Elliot & Church, 1997). Observing no relations between cost and classroom engagement contradicts our hypotheses, as we assumed that cost perceptions were likely to exert a direct effect on students' achievement goals, which in turn serve as a proximal precursor to classroom engagement. We recommend that future researchers continue to examine whether there are some circumstances in which cost might be negatively associated with students' classroom engagement.

Using the bifactor approach enabled us to examine the unique roles of specific types of cost in predicting adolescent students' academic motivation and achievement. Specifically, we found that emotional cost positively predicted both performance-avoidance goals and avoidance intentions. These results are compatible with previous findings that emotional cost constitutes a main reason for students' dropping out of school (e.g., de la Varre et al., 2014; Zhu & Chen, 2013). Meanwhile, effort cost negatively predicted academic achievement. Previous studies also reported a significant negative correlation between effort cost and academic achievement across various samples and subject domains (Gaspard, Wigfield, et al., 2017; Perez et al., 2014). Thus, when students perceive high effort cost in learning, they are more likely to feel the effort required for success is not worthwhile. This feeling is very likely to undermine their academic achievement.

7. General discussion

In the learning context, cost has mostly been discussed under the framework of modern expectancy-value theory (Eccles et al., 1983). Compared to the extensive body of research on the interest, importance, and utility aspects of task value, there has been much less empirical work on cost. In the present study, we developed a scale to assess Korean adolescent students' perceived cost of studying math, examined the relations between cost and value, and explored the unique role of cost in students' maladaptive academic outcomes.

7.1. Cost as a unique construct distinct from value

The concept of cost has attracted growing interest as a way of explaining dynamics in student motivation. However, researchers debate the precise relationship between cost and value (Barron & Hulleman, 2015; Wigfield et al., 2017). Some researchers posit that cost acts primarily as an influence on task value, with students weighing cost against values to determine motivation (e.g., Eccles et al., 1983; Wigfield & Eccles, 1992). Other researchers have argued that cost affects task values in powerful ways and can therefore be considered a third primary factor influencing students' academic motivation (i.e., an expectancy-value-cost model, Barron & Hulleman, 2015). However, regardless of how exactly it fits into the relevant theoretical framework, researchers suggest that it is better to treat cost as a construct independent of values (Wigfield et al., 2017).

Theoretically, cost and values (i.e., interest, utility, and attainment values) operate at the same psychological level to enhance or undermine an individual's overall task value. Yet cost and the values differ in motivational valence. Cost has negative motivational valence and is associated with avoidance motivation, whereas values have positive motivational valence and are associated with approach motivation (Atkinson, 1964; Feather, 1992). Empirically, studies have shown that cost and values are separate factors (e.g., Gaspard et al., 2015; Perez et al., 2014; Trautwein et al., 2012). Moreover, in a recent study, Jiang et al. (2018) found that categorizing cost as a subtractive force on value rather than as its own construct can make predictive models less efficient and accurate in explaining students' academic functioning. In the present study, we also found that the internal structural of cost and value is not unidimensional and that cost is empirically distinct from value.

Additionally, if cost is to be included in expectancy-value models, researchers need to explore whether it should be included as a general factor or as specific sub-factors. In the present study, both a four-factor model representing different types of cost and a higher-order model representing general cost fit the empirical data well. Several prior studies have reported that students differentiate between different types of cost (e.g., Flake et al., 2015; Gaspard et al., 2015). Nevertheless, we suggest that the method of modeling cost should be based on model-based reliability evidence (McDonald, 1999). Only when specific types of cost have sufficient reliabilities after accounting for general cost should researchers apply the multi-dimensional approach to explore the roles of specific types of cost.

7.2. Unique role of cost in maladaptive academic outcomes

Findings from the present study revealed that cost plays a unique role in understanding adolescent students' avoidance motivation and maladaptive academic outcomes. When cost and value were both included in the SEM models, only cost was associated with maladaptive academic outcomes, specifically test anxiety and disorganization, as well as avoidance motivation, specifically performance-avoidance goals and avoidance intentions. These findings provide clear evidence in support of the approach-avoidance distinction. The approach-avoidance distinction is shaped by a valence-based evaluation process in which positive stimuli encourage approach motivation and negative stimuli lead to avoidance motivation (Atkinson, 1964). On the one hand, numerous studies have shown that value positively influences students' academic-related choices and subsequent learning (Wigfield et al., 2016). On the other hand, there is growing evidence that cost can negatively influence student academic functioning (e.g., Jiang et al., 2018; Perez et al., 2014, 2019). Essentially, value is associated with the "bright" side whereas cost is associated with the "dark" side of students' academic functioning. Evidence has revealed an age-related decline in adolescent students' motivation and achievement in various subject domains over the course of their school years (see Wigfield & Eccles, 2002, for a review). As a consequence, students become more disengaged from school as they progress to higher grades (Marks, 2000). Given the unique role of cost in maladaptive academic outcomes, it could serve as a critical factor to help educators explain this maladaptive development trend.

When examining how students' motivation affects their academic outcomes from an expectancy-value perspective, it would be useful to include cost in order to explain these outcomes more accurately. Empirical findings have suggested that cost plays an important role independently of values in predicting students' motivation and achievement. For example, Conley (2012) found that cost assumes a vital role in distinguishing middle school students' motivation patterns and predicting their achievement and affective outcomes even after accounting for values. Cost has also been found to predict college students' drop-out intentions beyond what could be predicted by expectancies and values (Battle & Wigfield, 2003; Perez et al., 2014). Furthermore, it is important that cost be included as its own construct, not simply as part of value, because the latter conflate the separate influences of cost and value on adaptive and maladaptive academic outcomes (Jiang et al., 2018).

7.3. Theoretical and practical implications

The expectancy-value model proposed by Eccles et al. (1983) has been widely used to investigate students' academic-related choices and achievement. The current results complement the expectancy-value framework by highlighting the unique and critical role of cost in avoidance motivation and maladaptive academic outcomes. Knowing what prevents students from engaging in learning is critical for educators to motivate students and promote educational outcomes. Educators have successfully enhanced students' interest and performance in math and science by promoting their sense of utility value (e.g., Hulleman & Harackiewicz, 2009). Nevertheless, even if students know studying is important and useful, they may still decide not to engage in it if they have strong negative appraisals of studying (Battle & Wigfield, 2003). Therefore, reducing cost may be as important as promoting value for helping students develop adaptive learning behavior and improve their achievement.

To the best of our knowledge, Rosenzweig et al. (2020) is the only study that developed and tested an intervention directly targeting students' cost perceptions. In that study, the authors developed a cost reduction intervention by asking college students to read quotations about how other students overcome challenges in their physics courses. This intervention program successfully helped students perceive the challenges of their physics course as less costly and achieve better course performance. Interestingly, their results also revealed that the cost reduction intervention was particularly effective for students with lower levels of initial performance. Lower performing students are more likely to be identified as lacking competence and are less likely to develop adaptive effort-focused attribution strategies (Weiner, 1985). Therefore, it can be a useful strategy for educators to provide students, particularly students with lower competence levels, with examples and information about how other students also struggled with studying but successfully overcame this difficulty with personal effort in order to reduce their cost perceptions toward studying.

Although not directly targeting cost, some interventions to promote values may unintentionally buffer students against the potential undermining effects of cost. For example, Walkington (2013) successfully promoted middle school students' math performance using adaptive learning technologies to personalize instruction to individual students. Walkington noted that technology-based personalization utilized students' interest and was a powerful way to support learning. Although it does not directly target cost, such interest-based interventions may simultaneously reduce perceived cost. Recently, researchers have found that interest value can buffer effort cost and subsequently enhance middle school students' engagement in math (Song et al., 2019). Moreover, interest entails positive feelings and thus may also reduce emotional cost. Thus, practically-speaking, educators should make learning content more interesting or use interactive teaching strategies to create a vivid leaning environment because these strategies can reduce students' negative appraisals of studying and support learning.

In a similar vein, interventions focused on affirming personal values are also likely to influence cost (e.g., Cohen et al., 2006; Harackiewicz et al., 2014; Miyake et al., 2010). For instance, by asking college students to write about personally important values (such as friends and family), Miyake and colleagues aimed to enhance their social belonging experiences associated with participation in physics class. This value affirmation strategy led to significant improvements in achievement, especially among women, who are often subject to negative stereotypes in the field of science. Enhancing social belonging can buffer against identity threat (Cohen & Sherman, 2014). In this sense, the intervention may mitigate students' ego cost perceptions because the essential mechanism of ego cost is fear of self-worth threat associated with potential failure. Nowadays, school environments are highly competitive due to the prevalence of norm-referenced and inter-individual comparisons (Eccles et al., 1993). Students in such highly competitive environments are more likely to experience self-worth threat. Therefore, creating an environment in which the development of ability rather than social comparison is emphasized will be helpful at reducing perceived cost. Guiding students to assess their learning process using a self-referenced evaluation rather than a normative comparison should help to foster mastery experiences and keep students motivated. In summary, more investigations are needed to provide direct evidence of the benefit of minimizing cost for students and to develop potential interventions that can reduce students' cost perceptions in the learning context.

7.4. Limitations and future directions

A number of limitations, as well as suggestions for future research, need to be addressed. First, our studies were conducted with students from several Korean middle and high schools. The EFA sample in Study 1, in particular, was recruited from one middle school for girls. Moreover, we did not assess socioeconomic status. Although all of these schools are regular public schools in which students come from middle-class families, this was nevertheless not a fully representative sample of Korean students. Our limited sample means that we cannot conclusively infer that our results are generalizable to other samples. Future research should test whether and how cost is related to academic outcomes across students of different ages and cultures.

Second, all three studies focused on the single domain of math. Therefore, the relations of cost with value and academic outcomes cannot be generalized to other domains at this stage. Although expectancy-value theory was originally developed to explain students' gendered choices and achievement in math, it has been widely applied in other subject domains as well. Cost perceptions toward math may differ from those in other academic domains such as writing or language learning. Future research should test whether the newly developed cost scale is also suitable in other subject domains and examine the relations between cost and other constructs in those domains.

Third, our results are correlational, which do not allow us to identify casual relationships between variables. Future research could clarify the causal direction between cost and other variables using experimental designs or longitudinal data with proper time intervals and controlling for stability in the constructs of interest. In addition, the correlational nature of the data means that alternative models could also explain the current pattern of results because any associations observed between cost and a given variable may reflect different directions of effects. For example, the SEM model tested in Study 3 was based on the hierarchical model of achievement motivation (Elliot & Thrash, 2001), and we hypothesized that cost perceptions are likely to predict students' adoption of achievement goals. However, it is also possible that the achievement goals students adopt affect their cost perceptions. Thus, the relations between cost and achievement goals may be reciprocal in nature. We were not able to test this alternative model in Study 3 because we collected cost data earlier than data on the other constructs in order to explore the predictive utility of cost for academic outcomes. Future studies should explore the potential relations between cost and other constructs more comprehensively.

Fourth, we mainly discussed cost in general throughout this study because the model-based reliability estimates consistently suggested that the general cost model fit the current data sets better. However, we also witnessed some interpretive relevance of specific costs and found that these specific costs were able to predict academic outcomes, over and above general cost (i.e., effort and emotional cost in Study 3). It is clear 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) could have distinct relationships with academic outcomes. For example, Perez et al. (2014, 2019) found that effort cost was more related to achievement than opportunity and psychological cost in the domain of science. More studies are needed to explore the potential unique effect of different types of cost on academic outcomes. Moreover, we focused on examining the relationships between cost and general value throughout this study. It is possible that the interest, attainment, and utility components of task value may have different relationships with cost. The present study cannot shed light on this possibility; however, it is a crucial topic for future work to investigate in order to better understand cost and its relation with task value.

Finally, we focused on examining the relationships between cost and value in the present study and did not include expectancy beliefs. Therefore, we did not explore whether and how cost may be related to expectancy beliefs. Some empirical work has found that cost is more strongly related to expectancy than to values (e.g., Flake et al., 2015). More studies are needed to explore this topic further.

7.5. Conclusion

Across three independent studies, we successfully assessed Korean adolescent students' cost perceptions toward studying math and explored the role of cost in academic outcomes. Cost showed a distinctive relation with value and demonstrated close associations with adolescent students' maladaptive academic outcomes in math. More research regarding the definition, measurement, and potential predictive utility of cost is needed in order to draw a comprehensive conclusion regarding the role of cost in students' academic motivation and achievement.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsp.2020.08.004.

Acknowledgements

This paper was funded by the Peak Discipline Construction Project of Education at East China Normal University. The work of Yi Jiang was also supported by the Program for Professor of Special Appointment (Eastern Scholar) at Shanghai Institutions of Higher Learning.

Appendix A. Items of scales used in the present study

Cost (final version, Study 1, 2, 3)
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.

Value (Study 1, 2, 3)
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.

Personal cost (Luttrell et al., 2010; Study 1)
1. Math exams scare me.
2. Trying to do math causes me a lot of anxiety.
3. Taking math classes scares me.
4. I worry about getting low grades in my math courses.
5. I have to study much harder for math than for other courses.
6. Mathematical symbols confuse me.
7. Solving math problems is too difficult for me.

Opportunity cost (Conley, 2012; Study 1)
1. I have to give up a lot to do well in math.
2. Success in math requires that I give up other activities I enjoy.

Disengagement (Study 1)
1. When the work in Math is difficult, I give up.
2. When the work in Math is dull and boring, I stop doing it even if it is incomplete.
3. I often feel bored when doing the work in Math that I quit before I finish what I planned to do.

Avoidance of help seeking (Study 1)
1. When I don't understand my math work, I often guess instead of asking someone for help.
2. I don't ask questions in math class, even when I don't understand the lesson.
3. When I don't understand my math work, I often put down any answer rather than ask for help.
4. I usually don't ask for help with my math work, even if the work is too hard to do on my own.
5. If my math work is too hard for me, I just don't do it rather than ask for help.

Future choice intentions (Study 2)
1. I'd like to take math class if I have the choice to choose what class I want to take.
2. I'd like to choose a Math-related major at university.

Test anxiety (Study 2)
1. I am so nervous during the math test that I cannot remember facts I have learned.
2. I worry a great deal about math tests.
3. When I take a math test I think about how poorly I am doing.

Persistence (Study 2)
1. When I become confused about something on math, I go back and try to figure it out.
2. Regardless of whether or not I like the math, I work my hardest to learn it.
3. When something that I am studying on math gets difficult, I spend extra time and effort trying to understand it.
4. I try to learn all of the testable material on math "inside and out," even if it is boring.

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.

Mastery-approach goals (Study 3)
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 3)
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 3)
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.

Engagement (Study 3)
1. I try hard to do well in Math class.
2. In Math class, I work as hard as I can.
3. When I'm in Math class, I participate in class discussions.
4. I pay attention in Math class.
5. When I'm in Math class, I listen very carefully.

Avoidance intentions (Study 3)
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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