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Strategy Motivation and Strategy Use: Role of Student Appraisals of Utility and Cost

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Abstract
There is substantial evidence that students' use of self-regulated learning strategies is directly related to their motivation to achieve desired learning outcomes (designated outcome motivation: OM). Further, motivational beliefs about the strategies themselves (designated strategy motivation: SM) may also influence strategy use. In the absence of systematic analyses of SM, we examined beginning U.S. high school students' ($n = 253$) appraisals of the utility and cost of using cognitive, metacognitive and resource management strategies and their reported use of those strategies in mathematics classes. Students who appraised a strategy as higher in utility reported greater frequency of use, but perceived cost was only a weak inverse function of reported use. Mixed effects modeling used to examine relations across strategies within students also verified that strategy use was positively related to its perceived utility for most students. However, relations between reported strategy use and perceived cost varied considerably: inversely related, unrelated, and for a sizable proportion of students even positively related. We discuss the necessity of developing a model of SRL that includes SM as well as OM influences on learning strategy use and learning outcomes, and the importance of within-person in addition to between-person analytic approaches to understand self-regulated learning.

Keywords Outcome motivation · Strategy motivation · Self-regulated learning

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There is substantial evidence for the importance of self-regulated learning (SRL) in the learning process (e.g., Schunk and Greene 2018). Panadero (2017), for example, reviewed six models of SRL and designated them as “a core conceptual framework to understand the cognitive, motivational, and emotional aspects of learning” (p. 472). A prominent feature of seminal research in SRL (Pintrich and De Groot 1990; Zimmerman 2011; Zimmerman and Martinez-Pons 1986; Zimmerman and Moylan 2009) included motivation to activate such strategies as memorization, elaboration and metacognition. Pintrich focused on the “will and the skill” while Zimmerman included self-motivational beliefs (self-efficacy, outcome expectations, intrinsic interest/value, goal orientation) in the forethought phase of his model (Zimmerman 2000). Meta analyses consistently affirm the importance of motivation, especially self-efficacy, as a critical component of the SRL process (Dent and Koenka 2016; Dignath et al. 2008; Sitzmann and Ely 2011).

Numerous studies affirm that adaptively motivated learners are more likely to employ SRL strategies to accomplish their learning-related goals. For example, mastery-oriented students, those who expect to perform well and learners who value the goals they set, are more likely to employ cognitive, metacognitive and resource management strategies and to regulate their motivation when studying, completing assignments or preparing for exams (Berger and Karabenick 2011; Boekaerts and Cascallar 2006; Cleary and Kitsantas 2017; Karabenick and Berger 2013; Karlen 2016; Pintrich and Zusho 2007; Schiefele 1991; Weinstein, Husman, & Dierking, 2000; Wolters et al. 2011; Wolters and Hussain 2015; Wolters et al. 2005; Zusho et al. 2003).

The Source of Motivation: A Critical Distinction

Most generally, motivation is assumed a precursor that influences strategic activities although with somewhat varied positions situated in SRL models (Panadero 2017), and strategies are modeled as mediators between motivation and desirable learning and performance outcomes (e.g., Zusho 2017). Assumed but rarely explicitly stated is that the type and strength of motivation that influences strategy use emanates from *the outcome*s that strategies are intended to accomplish (e.g., Carver et al. 2000). For instance, the likelihood that students are motivated to memorize, organize their notes, or plan how they are going to study is considered a function of their interest in or importance of the course material, which we can designated as *outcome motivation* (OM). However, OM does not account for all of the motivational sources that affect strategy use given that relatively less recognized or assessed influences emanate from the motivational characteristics of the strategies themselves, which can be designated *strategy motivation* (SM).

SM has been generally considered a function of how useful, easy or difficult a strategy is to employ. Depending on the particular content one is required to learn, for example, memorization could be a relatively easy learning strategy, whereas students could find organizing the material more difficult. Most of the research on SM is found in the discourse involving deep strategies that are assumed more difficult to employ (e.g., elaboration) than such surface strategies (e.g., organization; Biggs et al. 2001). Furthermore, discussions of cognitive load theory have recently been the focus of connections between load and SRL, which may depend on different types of load: intrinsic, extrinsic or germane (Seufert 2018). The purpose of the present study is not to examine load and strategy use per se but rather to examine whether learners’ differentially perceive levels of benefit and cost of surface versus deep learning strategies, and the degree to which these perceptions are related to their reported use of those strategies.

Expectancy-Value Theory Applied to Strategy Motivation

Expectancy-Value Theory (EVT) provides an appropriate framework to examine SM as it has for OM, although with necessary modifications. Although they differ somewhat, in models of EVT, the value (also considered subjective task value) of pursuing an outcome is generally comprised of, and consistently assessed as interest, utility and attainment value (e.g., Eccles et al. 1983; Wigfield and Cambria 2010; Wigfield and Eccles 1992, 2000, 2020). Cost, initially considered primarily a function of effort and lost opportunities (Eccles et al. 1983), has expanded to include boredom, and the psychological consequences of failure (e.g., Battle and Wigfield 2003) as well as emotional cost (Flake et al. 2015) and fear of failure (Johnson and Safavian 2016; Perez et al. 2014). Cost has also been elevated to receive a separate designation in an expectancy-value-cost model (e.g., Barron and Hulleman 2015), and other studies have suggested a bifactor value that includes other ways of including cost (Part et al. 2020).

The features of value and expanded cost components have refined our models of OM but may not be directly transferable to SM. For example, the attainment value component of EVT, considered a function of one's personal identity, may be an important contributor to students' motivation to engage in a history course (i.e., their degree of OM) but not to decisions about whether to memorize or organize their course notes (i.e., SM). Similarly, such personal costs as stress and anxiety may be highly relevant to selecting a college major but less relevant to whether to spend time planning what to study versus engaging in elaboration. Most generally, we propose that SM consists primarily of specific strategies' perceived utility and cost. That is, students choose to engage strategies they value (Nolen 1988) and believe will be effective (Goetz and Palmer 1991), which is consistent with evidence that providing information about the value of strategies (i.e., telling students why they are effective) is known to increase the likelihood they will be used (Dignath et al. 2008; Schunk and Rice 1992). The cost of their use, such as the time and effort required also have relevance.

Indeed, considering SM from a cognitive load theory perspective, utility and cost are relevant determinants of learners' use of surface-level versus deep-level strategies (Biggs et al. 2001; Pintrich and De Groot 1990). Deep-level strategies, such as elaboration (e.g., paraphrasing information, generating metaphors, comparisons with other course material), are assumed to be more effective as learning tools (i.e., have higher utility), but are also assumed to require more cognitive effort than do such surface-level strategies as rehearsal (memorization; e.g., Borkowski et al. 2000). In sum, strategy level (surface versus deep) could be related to how an individual perceives the degree of SM cost.

The Present Study

To complement the literature affirming relations between OM and the use of learning strategies (e.g., Berger and Karabenick 2011), the present study assessed students' appraised benefits and costs of engaging in cognitive, metacognitive and resource management strategies and their associations with reported strategy use. Cognitive strategies included rehearsal (memorization), organization and elaboration; metacognition components included planning, monitoring and regulation; and resource management was represented by help seeking (Karabenick and Gonida 2018). Framed within EVT, the benefit of a strategy was assessed by its perceived utility. Perceived time and effort were used as indicators of strategy cost. Because of its importance as a gateway subject for subsequent success in numerous fields, especially in science, technology, engineering and mathematics (STEM) areas, we studied adolescent students in their mathematics classes. Given that mathematics curricula are relatively standard compared to other curricula, results obtained in the present study may thus be more generalizable that would be the case, for example, with social studies.

Owing to the present study's longitudinal design (students' perceptions of the utility, cost, and reported use of the seven strategies collected at two time points) a unique contribution of our study is an examination of utility-use and cost-use associations at the *intra-* and *inter-*individual levels. Accordingly, we examine whether an individual student who perceives a strategy as having more utility and cost *relative to the other strategies that they considered* is more likely to use that strategy (an *intra*-individual or within-student difference). We simultaneously examine whether students who perceive higher utility or cost *relative to other students* also tend to report using a strategy more (an *inter*-individual or between-student difference). Researchers cannot assume that an association that holds at the between student level, most commonly examined in the literature, necessarily holds at the within-student level. Considering associations at both levels allows for a fuller understanding of how perceived utility and cost are related to strategy use. Likewise researchers cannot assume that associations between utility and cost and subsequent strategy use are uniform across students (c.f., Johnson and Safavian 2016). We therefore examine the degree to which utility-use and cost-use associations vary across individual students.

Predictions

Generalizing from OM research and framed within EVT, we would expect that the frequency of strategy use would be directly related to its perceived strategy utility (H1). Based on the existing evidence it is also likely that cost would be inversely related to strategy use (H2); the more cost anticipated when using a strategy, the less frequently students would report using it (Battle and Wigfield 2003; Chiang et al. 2011; Karabenick and Berger 2013; Townsend and Hicks 1997). There is less confidence regarding H2, however, since recent analyses suggest that cost may also be perceived as beneficial (Johnson and Safavian 2016), in which case there may be some strategies, and for some individuals, for whom cost would be inverse and others where cost may even be positively related to use. The possibility for such variability requires a within-student analytic procedure, which is based in part on seminal work by Murayama and colleagues (Murayama 2003, 2006; Murayama et al. 2017) for determining the relations of perceived utility and cost to reported use. We approach this by examining within- as well as between-student covariance in the utility-use and cost-use associations. Between-student effects are based on how utility and cost are related to use for each strategy; e.g., whether, relative to other students, students that believe organization requires more time and effort are less likely than other students to use organization strategies. A within-student approach, by contrast, examines the utility-use and cost-use covariation across the seven strategies, which allows for examination of heterogeneity in the strength of this covariation across students.[1] An important outcome of the present study, therefore, is the degree of consistency between the between- and within-student approaches to the question of covariation in the perceived utility and cost of various strategies and their subsequent usage.

[1] Eccles (2005) proposed the importance of taking into consideration hierarchies of task values when predicting task choice, which in that case referred to OM, but is applied here to SM as well.

Method

Design and Participants

Students' judgments of the perceived utility, cost and reported use of cognitive, metacognitive and resource management strategies were assessed at the beginning (T1) and end (T2) of a single academic term. Participants were 306 ninth grade students (50% female, aged 13-14 years old based on national trends) enrolled in one of 15 algebra classes in a Midwest urban high school in the U.S (Berger and Karabenick 2011). Other than biological sex, we did not require students to report on other demographic characteristics given the long survey focused on seven different SRL strategies. We targeted students in mathematics that, as noted above, is considered an important gateway subject for subsequent success in numerous fields, especially those in STEM fields. Although not formally tracked, students were distributed in classes that varied in difficulty: (a) Algebra I support (16%), (b) Algebra I – 2/3 (7%) (material covered in three trimesters instead of the normal two), (c) Algebra I normal (42%), (d) Geometry advanced (30%), and (e) Algebra II (5%). In this two–wave study, 288 students were surveyed at T1 and 286 at T2 of a 12–week term. A total of 253 students completed surveys both at T1 and T2. Because students were unaware that the survey would be administered during a specific class session, we can assume that participation is unlikely to reflect unintended sample selectivity (e.g., students not attending class to avoid having to complete the survey) but rather a function of attendance on the day of testing. Only five students present during the sessions declined to participate.

Procedure

Surveys were administered by research personnel during regular class periods and required approximately 25 minutes of class time. Students were first provided with a brief explanation that the study concerned how students learn and feel about mathematics. This was followed by a required informed consent statement that: (a) emphasized the voluntary nature of participation, (b) gave students the option to not answer a question, (c) assured them of confidentiality, and (d) that their responses would not affect their mathematics grade. Names and student numbers were obtained to match data from T1 and T2 (but subsequently de-identified). Survey items were read aloud and administered by the same person at both testing sessions to standardize the procedure and help ensure consistency. To emphasize the promised confidentiality, especially that their teachers would not have access to their responses, completed surveys were placed in an envelope and sealed in a manner that was clearly visible to students.

Survey Contents and Format

Survey items were adapted from the college version of the MSLQ (Duncan and McKeachie 2005; Pintrich et al. 1991).[2] Several design principles were employed to improve learning strategy scales and their constituent items. Alterations were based on cognitive interviews, as

[2] According to Veenman (2011), the choice of obtaining evidence for research on self-regulated learning devolves to the approach that is appropriate for the research question. Since the purpose of the present study was to model students' subjective beliefs about the utility and cost that contribute to their decisions about strategy use across a wide range of content and tasks in mathematics classrooms, an off-line self-report approach was deemed most appropriate, which was echoed by the conclusion in the present instance by McCardle et al. (2017) that self-report data provide critical evidence for interpreting learners' regulatory profiles.

described in Karabenick et al. 2007) to render them easier for high school students to comprehend and to ensure that students understood the meaning of all terms used. For example, words such as "concept" were replaced, and "the material" was clarified by referencing "what I have/need to learn/know." In addition, items were made subject–specific to fit the context of mathematics learning in high school. References to reading activities were omitted and "lectures" was replaced by the word "class." Terms in items that referred to frequency or quantity (e.g., "each time", "often", "a lot") were eliminated since the response scale provided the necessary alternatives to capture that meaning. A more specific description of the design principles employed to improve the MSLQ self-regulation scale can be found in Berger and Karabenick (2016).

In addition to ensuring the understanding of terms, modifications were made to several learning strategy items with content that confounded learning strategies and motivational beliefs. For example, the item, "I try to understand the material in this class by making connections between the readings and the concepts from the lectures" was deleted given that "understanding" refers to a mastery goal as well an elaboration strategy. Items that implied two different strategies were also revised, such as "Before I study new course material thoroughly, I often skim it to see how it is organized," which potentially describes metacognitive planning in the first phrase and organization in the second. The final sets of items that measure cognitive, metacognitive and resource management strategies are provided in the Appendix.

The final survey with these modifications began with an introduction that described the purpose of the responses asked of students to the subsequent items. Strategy use (Ways you study) was introduced with "The following statements describe different ways that students study for math class. We would like to know how *you* study by indicating whether each statement is true of *you*." Ratings were requested using a standard 5-point Likert scale in response to "How true of you" with anchors of "Not at all true of me" and "Very true of me". Perceived utility was introduced as follows:

> We would also like to know how much you believe each way of studying would be useful for doing well in math class. If you believe that a way of studying would be very useful, circle 5. If you believe that a way of studying would not be at all useful, circle 1. If that way of studying would be more or less useful, find the number between 1 and 5 that best describes what you believe.

Ratings were requested in response to "How useful do you think it is?" The 5-point response scale was anchored with "Not at all useful " and "Very useful". Perceived cost was introduced with the instructions:

> We would also like to know how much you believe studying in different ways takes time and effort. If you believe that a way of studying takes a lot of time and effort, circle 5. If you believe that a way of studying takes very little time and effort, circle 1. If you believe that way of studying takes more or less time and effort, find the number between 1 and 5 that best describes what you believe.

Ratings were requested in response to "How much effort/time does it take?" The 5-point response scale was anchored with "Very little " and "A lot".

For each strategy item, students rated its utility and cost immediately after rating whether the use of that strategy was true of them. This procedure was considered more efficient than having students rate their use of all strategies then the utility and cost. That alternative would have (a) required students to read each item three times, (b) probably exceeded students' attention span, and (c) taken more time than allotted for the testing session.

Psychometric Analysis and Nesting

In addition to the Cronbach's alpha coefficients for the strategies at T1 and T2 shown in Table 1, we estimated the overall degree of internal consistency for utility, cost, and use by combining all strategies at both T1 and T2 for each variable. The resulting Cronbach's alphas are .91 for utility, .88 for cost, and .91 for strategy use, which provides relative confidence in the psychometric adequacy of these three higher-order constructs. Considering the time lapse, students were also fairly consistent in their ratings from T1 to T2, with average correlations of .54 for utility, .44 for cost, and .57 for reported strategy use. Given that the students are nested within-classes, modeling the variance not only at the individual-level but also at the class-level might be called for. Thus, intraclass correlation coefficients were computed to gauge the necessity of using a multilevel model. The coefficients ranged from .002 to .069 for T1 and from .002 to .043 for T2 variables depending on strategy. Accordingly, the variance in observed response stems almost exclusively from individual differences within rather than between classes and thus a negligible nesting effect. Therefore, the data were treated only at the individual level.

Analytical Approaches

As summarized above, we adopted two approaches to analyze relationships between SM and strategy use. The standard between-student approach was used to describe the relative perceived utility and cost of each strategy separately and relations of each strategy with use. In addition, since each student reported on multiple strategies at two time points, we used a within-student approach (Murayama 2003, 2006; Murayama et al. 2017; see also Rutherford 2017; Ruzek and Schenke 2019) to examine how, for each student, perceptions of the utility of a strategy and its cost were related to use of the strategy. We employed a mixed effects model to investigate variability in the within-student associations between, on the one hand, utility and use, and on the other hand, cost and use, among the beginning high school students in the sample.

To visualize the differences in perceived use, utility and cost for each of the strategy types (e.g., monitoring, help seeking, rehearsal), we estimated separate mixed effects models for use, utility, and cost. To estimate this and the subsequent model, we structured the data such that reports from each type of strategy and time point were collapsed making a long dataset, with students having up to 14 rows (7 strategies for each of the two time points). Thus, for a given

Table 1 Alpha reliabilities of each of the seven strategy scales at time 1 and time 2

	Utility		Cost		Use	
Strategy	T1	T2	T1	T2	T1	T2
Rehearsal	.66	.71	.70	.69	.70	.65
Organization	.70	.76	.67	.68	.70	.64
Elaboration	.53	.54	.62	.58	.57	.58
Planning	.77	.77	.73	.72	.75	.79
Monitoring	.71	.72	.57	.66	.78	.79
Regulation	.64	.73	.62	.64	.63	.64
Help seeking	.58	.57	.55	.62	.61	.52

student, each row of data contained their cost, utility, and use scale scores for a particular time point and strategy, the latter of which was coded as a multi-category dummy variable. The mixed effects model, estimated separately for use, utility, and cost, is given below:

$$y_{ijk}(use, utility, cost) = \beta_0 + \upsilon_{1j} + \upsilon_{2k} + \epsilon_{ijk} \quad (1)$$

Equation 1 has no predictors (equivalent to a variance components model) with two uncorrelated, non-nested random factors, one for strategy type (υ_{1j}) and one for student (υ_{2k}). These random factors are assumed to come from normal distributions with means of 0 and have their own estimated variance (σ^2). These models have superior fit to the data (based on AIC, BIC, and likelihood ratio tests) than variance components models with a single nested random intercept for students. From these variance components models, we predicted values and standard errors of the random strategy intercepts for use, utility, and cost using Empirical Bayes prediction for the purposes of visualizing the differences across strategy types.

Next, we examine the unique associations between perceptions of utility and use, on the one hand, and cost and use, on the other hand, with the following mixed effects model:

$$\mathrm{y_{ij}} = \beta_{0j} + \beta_{1j}\left(\mathrm{utility_{ij}}-\overline{utility}_{\mathrm{j}}\right) + \beta_{2j}\left(\mathrm{cost_{ij}}-\overline{cost}_{\mathrm{j}}\right) + \beta_{3ij}-\beta_{9ij}\left(\mathrm{strategy_{ij}}\right) + \mathrm{e_{ij}} \quad (2)$$

Intercept $\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\overline{utility}_j) + \gamma_{02}\,(\overline{cost}_j) + u_{0j}$, $[u_{0j} \sim N(0, \sigma^2_{u0})]$
Utility $\beta_{1j} = \gamma_{10} + u_{1j}$, $[u_{1j} \sim N(0, \sigma^2_{u1})]$
Cost $\beta_{2j} = \gamma_{20} + u_{2j}$, $[u_{2j} \sim N(0, \sigma^2_{u2})]$

In this model, perceived strategy use at occasion *i* for student *j* (y_{ij}) was a function of perceived utility (β_{1j}) and cost (β_{2j}), which were centered around each student's mean for utility and cost, respectively, and a set of seven indicators for the type of strategy (β_{3j}-β_{9j}). The random intercept (β_{0j}) was predicted by two person-level predictors: a student's mean utility across time points and strategies (γ_{01}) and their mean cost (γ_{02}). The utility (β_{1j}) and cost (β_{2j}) slopes were allowed to vary across students. We account for any potential influence of a student's teacher by including 0/1 indicators for three of the four teachers as fixed effect predictors.

This model allows us to test 1) whether the within- and between-person associations (utility-use and cost-use) are uniquely significant, 2) whether the two associations are different from each other, and 3) whether the associations between utility and strategy use and between cost and strategy use vary across individuals (random slopes). All analyses were conducted using the mixed command in *Stata15* (StataCorp, 2017) with unstructured variances and covariances.

Results

Perceived Utility, Perceived Cost and Reported-use of the Seven Strategies

To visualize how utility, cost, and use vary across the strategies, Fig. 1 shows the Empirical Bayes predictions from the non-nested variance components models (Eq. 1). A value of zero indicates that the prediction for the strategy is equivalent to the model estimated mean for either use, utility, or cost, which were 2.87, 3.35, and 3.02, respectively. Predictions greater than zero indicate that, relative to the model estimated mean, a strategy was perceived as more

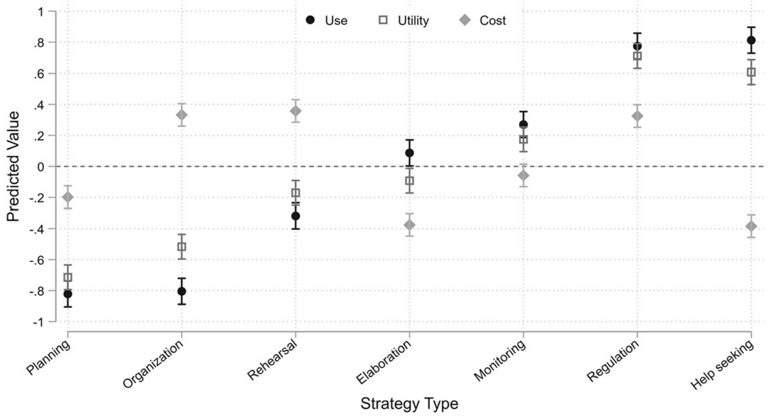

Fig. 1 Predicted use, utility, and cost means across strategies (T1 and T2 merged)

used/useful/costly whereas predictions less than zero indicate that, relative to the model estimated mean, a strategy was perceived as less used/useful/costly. The graph shows that use and utility for a given strategy tended to go in the same direction (i.e., if use was predicted to be positively endorsed for a strategy, utility was also predicted to be positively employed), but that cost was not closely paired with use.

We also estimated the within- and between-student correlations among the seven strategy scales for each of utility, cost, and use in Table 2. These correlations help to establish the distinctiveness of the seven strategies as they relate to use, cost, and utility. Notably and across all constructs, within-student correlations are smaller in size than their between-student counterparts.

Table 2 Within- and between-student correlations for the seven strategy scales at the within- and between-student level

Within-student correlations (n = 550)

Strategies	rehearsal	organization	elaboration	planning	monitoring	regulation
organization	.27/.51/.22					
elaboration	.21/.27/.06	.34/.32/.13				
planning	.36/.22/.36	.50/.38/.32	.38/.38/.23			
monitoring	.25/.23/.18	.31/.25/.12	.38/.33/.30	.45/.47/.43		
regulation	.24/.18/.08	.22/.24/.06	.28/.13/.26	.30/.22/.25	.41/.37/.34	
help seeking	.11/.03/.08	.22/.18/.03	.34/.23/.21	.13/.24/.19	.24/.24/.28	.31/.20/.33

Between-student correlations (n = 302)

Strategies	rehearsal	organization	elaboration	planning	monitoring	regulation
organization	.51/.67/.53					
elaboration	.35/.67/.30	.41/.41/.33				
planning	.50/.52/.54	.62/.58/.57	.46/.59/.42			
monitoring	.47/.55/.50	.45/.53/.43	.60/.53/.52	.52/.62/.61		
regulation	.43/.45/.43	.33/.38/.32	.53/.30/.47	.26/.34/.34	.66/.63/.64	
help seeking	.42/.27/.37	.28/.27/.30	.46/.37/.35	.28/.29/.25	.54/.49/.40	.68/.38/.59

Note: Correlations are presented in the order of utility/cost/use.

Within- and Between-person Associations from Mixed Effects Model

Results from the mixed model examining within- and between-person associations of utility-use and cost-use are shown in Table 3. Utility and cost were person mean centered and represent within-student effects. Further, we included utility and cost person means in the model, which are the average of utility and cost reports respectively for each student and represent between-student effects. Adjusting for strategy type (the reference strategy is planning), perceived utility positively predicted strategy use; the within-person association between utility and use is b (SE) = .67(.01), $p < .001$. Thus, when a student perceived higher utility than their average perception of utility, they tended to report using the related strategy, with the coefficient corresponding to an approximately one standard deviation *increase* in use. The between-person association between utility and use was $b(SE)$ = .75(.05), $p < .001$, indicating that students who tended to perceive higher utility across all strategies and occasions, compared to other students, also tended to use those strategies more (H1). The within- and between-person associations between utility and use were not significantly different from each other. The association between cost and use was such that, at the within-person level, on occasions when a student perceived higher cost they used a strategy slightly less often (H2) (b(SE) = -.05(.01), $p < .01$). This represents approximately .06 of a standard deviation *decrease* in use. The between-person cost-use association (b(SE) = -.09(.05), $p > .05$) was not statistically different from the within-person association.

In addition to these average within-student associations, we examined whether the utility-use and cost-use slopes varied across students. Model fit indices (AIC and BIC) indicated that the more complex random slopes model, which allows for heterogeneity in the utility-use and cost-use associations across students, was a better fit to the data than the more parsimonious random

Table 3 Mixed effects model results from within-person analyses predicting strategy use with random coefficients for utility and cost

Predictor	*b*	*(se)*	*95% CI*
Utility (within-person)	.68***	(.02)	[.64, .71]
Utility-person mean	.72***	(.05)	[.63, .81]
Cost (within-person)	- .05*	(.02)	[-.09, -.02]
Cost-person mean	- .07	(.05)	[-.17, .02]
Strategy type (reference is planning)			
Organization	- .07*	(.03)	[-.14, -.01]
Rehearsal	.17***	(.03)	[.11, .24]
Elaboration	.46***	(.03)	[.40, .52]
Monitoring	.47***	(.03)	[.40, .53]
Regulation	.63***	(.04)	[.55, .70]
Help seeking	.69***	(.04)	[.62, .76]
Intercept	.45*	(.18)	[.10, .80]
Random effect variances and covariances			
Utility slope	.03	(.01)	[.02, .05]
Cost slope	.03	(.01)	[.02, .04]
Intercept	.15	(.01)	[.13, .18]
Covariance (utility, cost)	- .01	(.00)	[-.02, .00]
Covariance (utility, intercept)	.03	(.01)	[.01, .04]
Covariance (cost, intercept)	.01	(.01)	[-.00, .03]
Residual	.26	(.01)	[.25, .27]

*$p < .05$ **$p < .01$ ***$p < .001$. Also included are 0/1 indicators for a student's teacher.

intercept-only model. These results provide strong evidence that the associations between utility and use, on the one hand, and cost and use, on the other hand, vary across students.

Sensitivity of Mixed Effect Model Results

Reported use, perceived utility, and perceived cost scales for elaboration and help seeking had slightly lower internal reliabilities than use, utility, and cost scales for the other five strategies. To determine whether the mixed effects model results for the within-person associations of utility and cost on use were sensitive to the lower reliabilities of these two strategies, we re-ran the model excluding all data points associated with the use, utility, and cost for elaboration and help seeking. Model results were nearly identical, with parameter estimates differing by less than .01. Thus we would draw the same conclusions as we did from the models with all strategies included. We take this as additional evidence that the reported results are robust to any variation in the reliabilities of the strategies.

Description of Within-Students Relations

To help interpret the effects from the mixed models, we also estimated the within-student correlations between utility-use, cost-use, and utility-cost, and provide the distributions of these within-student correlations of utility, cost and use. As shown in Fig. 2, for most students the correlations are generally positive at both time points, and the distributions are negatively skewed, also strongly supporting H1. The distributions of cost-use correlations shown in Fig. 3, however, are very different. For some students cost is negatively associated with use whereas for others, cost is either negatively associated with use or unrelated. In line with this, the mean within-person cost-use slope in the mixed effect model (Table 3) was -.05 and the 95% prediction interval for this slope at the between-student level was [-.34, .30], suggesting a fair degree of variability in the association but that a greater proportion of students are expected to use a strategy somewhat less when they perceive the cost as higher. The distribution of correlations between utility and cost are presented in Fig. 4. To further illustrate the difference between utility and cost distributions, scatterplots of a randomly selected sample of 30 students

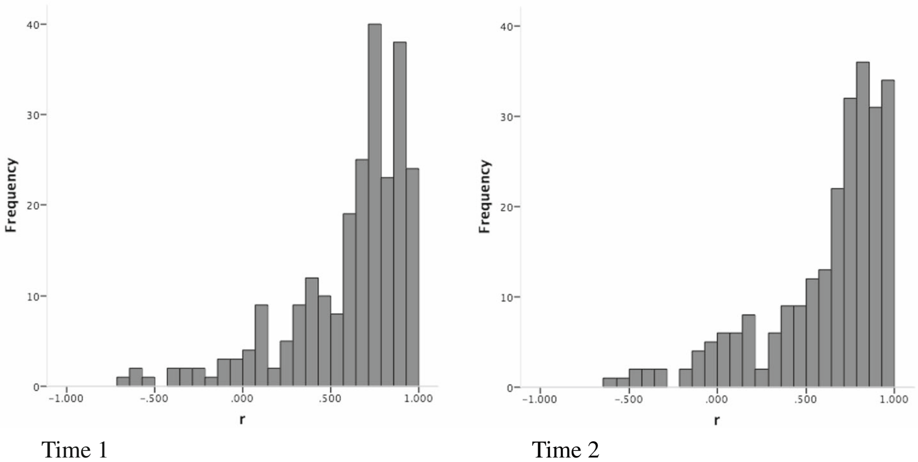

Fig. 2 Distribution of within-person correlations between utility and reported use at T1 (left) and T2 (right)

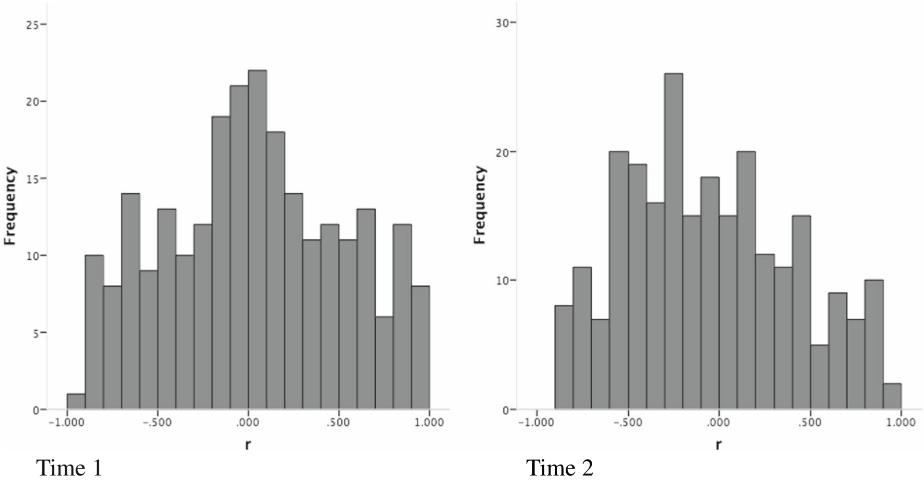

Fig. 3 Distribution of within-person correlations between cost and reported use at T1 (left) and T2 (right)

are shown for utility-use in Fig. 5 and cost-use in Fig. 6. The utility-use relations in Fig. 5 are consistently positive, whereas the cost-use correlations in Fig. 6 vary from negative to positive. Simply stated, the association between cost and use, although negative on average, varies considerably across students. A non-trivial portion of students report using a strategy more despite perceiving it as being more costly than other strategies.

Discussion

Building on previous research that documented the role of outcome motivation in self-regulated learning (e.g., Berger and Karabenick 2011; Karlen 2016; Pintrich 1999; Pintrich and De Groot 1990; Pintrich and Zusho 2002, 2007; Pressley and Harris 2006; Schiefele 1991;

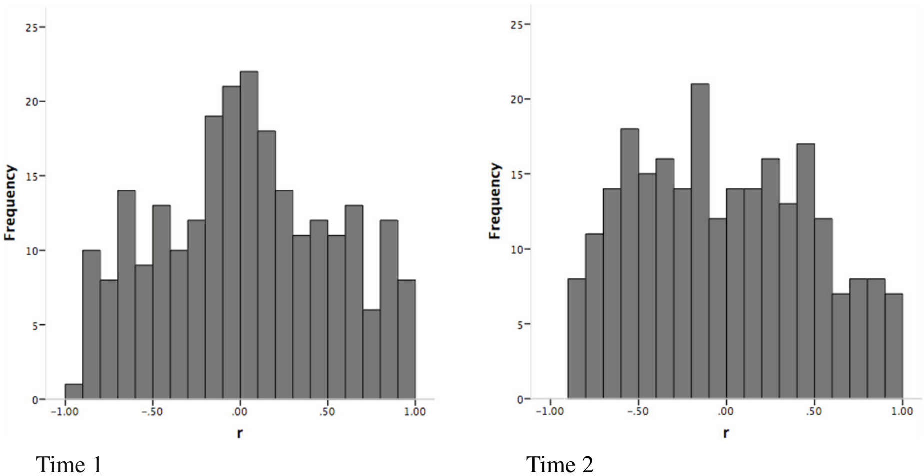

Fig. 4 Distribution of within-person correlations between utility and cost at T1 (left) and T2 (right)

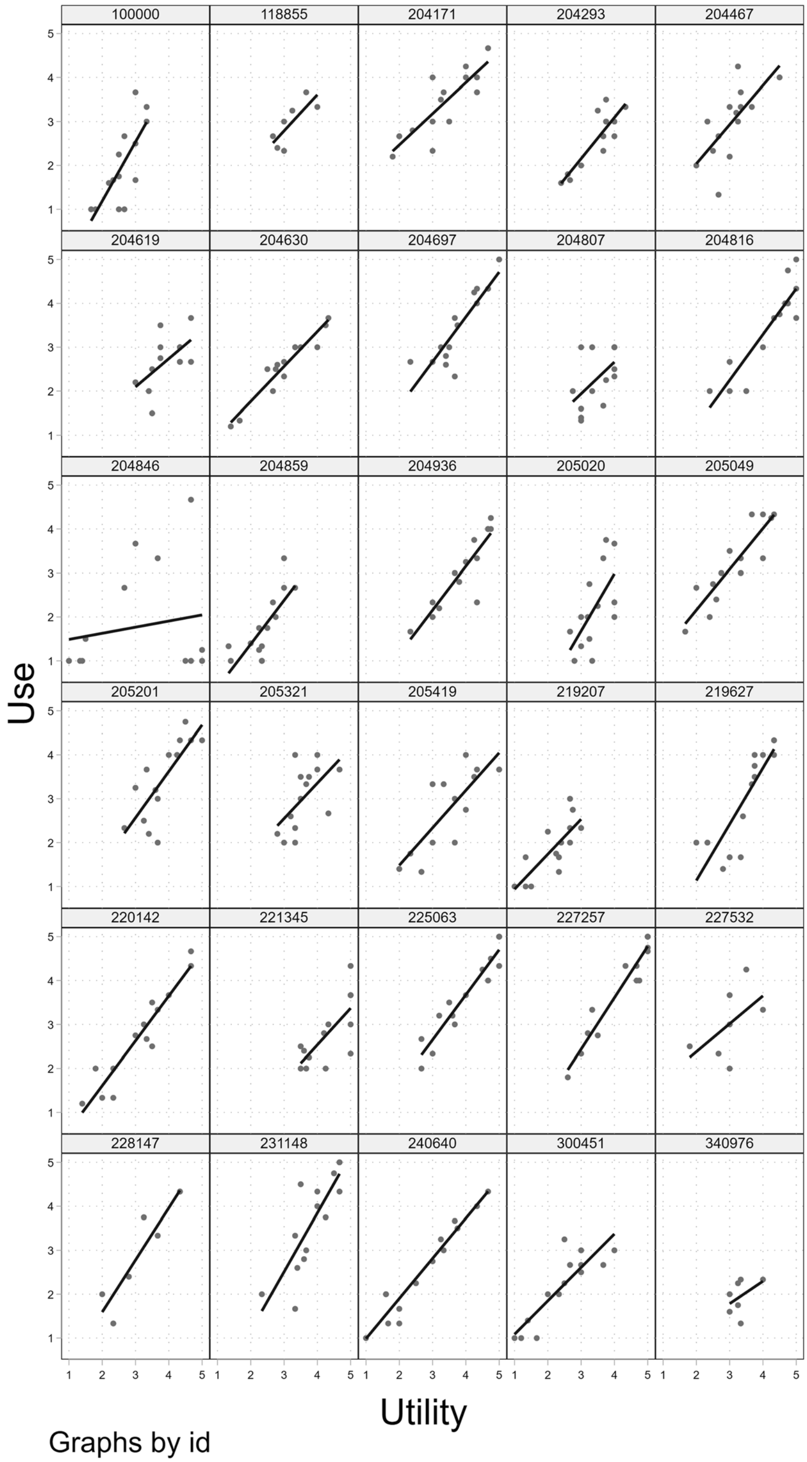

Fig. 5 Utility-Use relations for a randomly selected set of students (T1 and T2 inclusive)

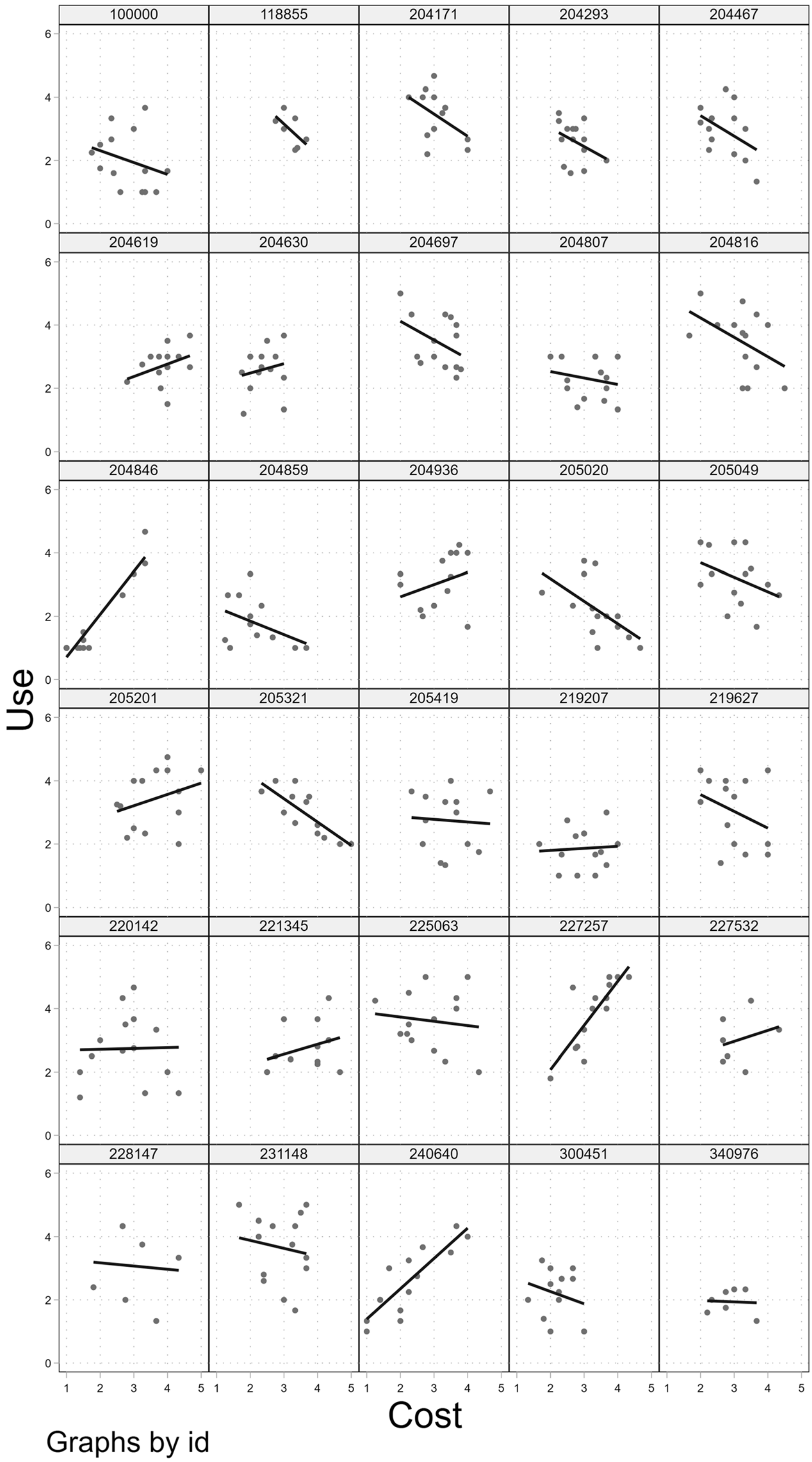

Fig. 6 Cost-Use relations for a randomly selected set of students (T1 and T2 inclusive)

Wolters and Hussain 2015; Wolters et al. 2005; Wolters et al. 2011), the present study adopted a benefit-cost approach to systematically examine the strategy motivational determinants of reported use across a range of learning strategies. Framed within EVT, we assessed beginning high school students' SM in terms of their perceived utility and time and effort cost of employing cognitive, metacognitive and resource management strategies and their reported use in mathematics classes at the beginning and end of an academic term; in essence, the first such examination of SM.

There was sufficient evidence based on the existing OM and SM literature to predict a relatively strong positive relation between strategy use and perceived utility (H1), although less was known, and inconsistent, to justify a definite prediction about the relation between cost and use, although theoretically it should be inverse (H2) (Battle and Wigfield 2003; Berger and Karabenick 2011; Chiang et al. 2011; Conley 2012; Townsend and Hicks 1997). The within-person approach (Murayama 2003, 2006; Murayama et al. 2017), based on the correlations between utility, cost and use estimates across the seven strategies and on a multilevel modeling approach, showed that, for most students, the strategies most often used were also those considered most useful, supporting H1.

However, strategy reported use was only slightly inversely related to perceived time and effort cost, and as shown in the cost-use correlation distributions, while for some students the relations are inverse, for some they are relatively unrelated, and for others the relations are even positive—higher cost associated with higher use. In sum, the results reflect the uncertainty of support for H2 and provide initial evidence that there are individual differences in the association between perceived cost and strategy use. Another explanation regarding the large range of possible perceived cost-reported use association lies in the potential lack of knowledge about the cost of using a strategy. Ninth grade students might more easily judge how useful a strategy is, but be more uncertain about how costly it is. Upon using a strategy, students can quickly observe whether it helps them, but be less considerate of the cost associated with its use. This explanation relies on the concept of metacognitive conditional knowledge (Pintrich 2002). Utility and cost correlations are similar to those for cost-use. In some respects, the cost-use relations (and the utility-cost relations) are revealing given recent examinations of the potential positive features of cost (Flake et al. 2015; Johnson and Safavian 2016), most evidently displayed here by the within-person correlation frequency distributions. Although most students are more likely to use a strategy when they perceive it as useful, some students report being more likely to use a strategy even when they perceive it as costly.

We also found that the associations between utility, cost, and use varied across the strategies. Namely, the pattern of perception of use and utility were more closely aligned for some strategies than they were for others. Students perceived help seeking, regulation, and monitoring as more used/useful than planning, organization, and rehearsal. These differences in students' perceptions of utility, cost, and use may be explained by students' perceptions of what strategies have worked for them in the past or what self-regulated learning strategies seem more obvious to adolescents. The relatively high perceived cost of planning and organization compared to their low perceived utility and reported use might reveal why students do not engage much in the processes that take place mostly at the beginning of the SRL process. In contrast, the results concerning help seeking presented a different profile revealing a low perceived cost relative to other strategies and a high perceived utility and reported use. Accordingly, help seeking may be among the most obvious strategies students think about when they believe a task might be difficult to accomplish. In other words, our results suggest why students default to help seeking instead of putting effort and time in planning and organizing.

The evidence of cost-use variability raises a number of questions and directions for future research. Most immediately is whether cost-use relations we found in math would be present for other subjects (e.g., social sciences, language arts), and become more consistently negative as students have more experiences with school generally. Would we have found the same results with college students? In other words, as they mature as strategic learners, would students become more strategically calibrated regarding cost as they manifestly are for utility? Although not included in the present study, it would also be important to understand how strategy motivation influences students' regulation of their motivation (Wolters 1998, 2003; Wolters et al. 2011), which would involve examining the perceived benefits and costs of such strategies as goal-oriented self-talk and interest enhancement.

We can also speculate about whether and how cost-use relations may depend on moderator variables such as interest in the subject or even teacher's approaches to instruction. Such variables could help explain the individual differences in the correlations among cost and use we found and may even present opportunities for intervening on students' SM. The results also raise intriguing questions that could motivate new lines of inquiry. For example, would cost-use relations be more consistent with teachers who focused on between-student competition rather than on learning and understanding? In addition, are there complex combinatorial influences that involve both mediation and moderation, which increases the complexity of current SRL models (Panadero 2017)?

Further Suggestions

The addition of systematic evidence for the effects of SM has implications for interventions that familiarize and support strategic knowledge and use (Berger et al. 2008; Pressley and Harris 2006). As summarized by Dignath et al. (2008), for example, effective self-regulation interventions convey to students the benefits and costs of strategy use in addition to knowledge about cognitive, metacognitive (especially planning) and motivational strategies. Results of the present study suggest that additional motivation-related information would also be important, such as the way students' perceptions of SM are influenced by how learners are introduced to and adopt strategies in classroom settings (e.g., Perry and Rahim 2011).

Furthermore, we need to propose and test models that would add SM effects on strategy use to previously established effects of outcome motivation (e.g., the value of math). Are OM and SM additive such as the utility of rehearsal adding to the utility of mathematics, and/or would the cost of rehearsal negate some of the tendency to rehearse despite the utility of math? To complicate matters further, it is possible that such combined effects might vary across strategies. In addition to the existence of such combinations is the extent of their influence on strategy use; that is, their relative effect sizes, which may also vary across strategies and depend on other person and context variables.

We may also consider how SM acts as a mediator of OM influences on educational outcomes. For instance, would the value and perceived cost of organization alter its use and diminish the influence of math utility on math performance? The present study opens the door to a host of potential influences and invites further exploration of strategy motivational effects. This includes ways that SM changes over time as students use strategies and the impact of those changes on strategy use. In summary, we have provided initial evidence regarding SM. That does not imply that strategy motivation exists in isolation from its OM counterpart but rather is embedded within that framework of relations with outcome influences (Berger and Karabenick 2011; Nolen 1988), especially the person and situation variables that moderate the heterogeneity of cost-use relationships.

Study Limitations

We fully recognize the limitations of self-reported strategy use, an ongoing issue in the study of SRL. Additional studies might include cognitive interviews (e.g., Karabenick et al. 2007), diary studies (Schmitz et al. 2011), direct observation of strategy use, think alouds, other qualitative approaches (Wolters et al. 2011), or even trace data (Winne and Perry 2000). Each of these has advantages and disadvantages in terms of their relative ecological validity, measurement obtrusion, or even reliability and validity concerns (Winne 2020). Observing students as they learn may obviate concerns about the accuracy of recall but may not yield important information provided by self-report with all of its limitations. Further methodological triangulation is clearly called for.

We also note that some of our scales did not meet the standards with regards to reliability, ranging from .53 to .78 depending on the construct and the time point. The low reliabilities may be due to the low number of items we used to assess each construct (ranging from 3 to 5). This was done purposefully to ensure that there was appropriate coverage of the various SBM constructs. To ameliorate concerns and see if our results were sensitive to these low reliabilities, we included additional analyses described in the results section and found that we are still able to draw the same conclusions.

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Dr. Stuart Karabenick passed away on August 1, 2020 at the age of 80. He was a supportive and inspiring mentor to his coauthors on this manuscript and to many colleagues, graduate students, and friends during his long career. As a scholar, he left an indelible mark on the fields of help seeking, selfregulated learning, teacher motivation, and computer-mediated instruction. In 2019 he was the keynote speaker at EARLI (https://youtu.be/lA55kxn3ssM) and in 2014, the keynote speaker at the Self-Regulated Learning SIG at AERA (https://www.aera.net/Portals/38/Users/149/21/99221/SKKeynote.pdf). Recently, he shared his acquired wisdom from a five-decade career in Education Review (https://edrev.asu.edu/index.php/ER/article/view/2965).

No financial interest or benefit has arisen from the direct applications of this research.

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Compliance with ethical standards

Conflict of Interest The authors attest that they have no conflict of interest.

Ethical Principles The research conducted was approved by the University of Michigan Institutional Review Board regarding treatment of human subjects, including appropriate informed consent and subject privacy.

Appendix 1

Learning Strategies Scales and Items

Cognitive Strategies

Rehearsal

- When I study math, I memorize what I need to learn by repeating it over and over to myself.
- I study math by doing the practice problems over and over again to memorize them.
- When I study math, I write down the formulas and definitions many times in order to memorize them.

Organization

- When I study math, I make outlines to organize what I have to learn.
- I study math by highlighting or underlining to organize what I need to know.
- I study math by making charts, diagrams, or tables to organize what I need to learn.

Elaboration

- I connect what I learn in math to what I am learning in some other classes.
- When studying math, I try to connect new material to what I already know.
- When I study math, I translate the formulas or definitions in the textbook into my own words.
- I make connections between how I solve one math problem with the way I could solve others.

Metacognitive Strategies

Planning

- I plan how I am going to study new math topics before I begin.
- Before I begin studying math I think about what and how I am going to learn.
- Before I study math, I plan how much time I will need to learn a topic.
- When I learn new topics in math, I first figure out the best way to study.
- Before I study math, I set goals for myself to help me learn.

Monitoring

- When I study math, I ask myself questions to make sure I know what I have been learning.
- When studying math I try to determine how well I have learned what I need to know.
- When I'm studying math I test myself to see whether I know the material.
- I check whether I have learned what I am studying in math.

Regulation

- If I get confused with something I'm studying in math, I go back and try to figure it out.

- If the math I am studying is difficult to learn, I slow down and take my time.
- If I think I don't know my math well enough, I make sure I learn it before going to the next topic.

Resource Management Strategy

Help Seeking

- If I don't understand something in math I ask my teacher for help.
- If I don't understand something in math I ask other students for help.
- If I don't understand something in math I ask for help to better understand general ideas or principles.

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