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Motivation and students' use of learning strategies: Evidence of unidirectional effects in mathematics classrooms

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Abstract

Considerable evidence indicates that student motivation and use of learning strategies are related. There is insufficient understanding, however, about their reciprocal effects—whether motivation affects strategy use, the converse, or whether the effects are bidirectional—and which components of motivation and strategies are involved. A two-wave longitudinal design was used to examine this issue among 9th grade students ($\underline{N}$ = 306) enrolled in high school mathematics classes during an academic term. A cross-lagged structural model found that students' self-efficacy in mathematics and value predicted their reported use of learning strategies. There was no evidence, however, that learning strategy use predicted motivation and, thus, support for unidirectional effect of motivation during that time interval. Implications for models of self-regulated learning and instruction are discussed.

Keywords: Learning strategies; Motivation; Cross-lagged correlation; Mathematics

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1. Introduction

Boekaerts (2010) has described motivation and self-regulation as "two close friends" that are inextricably related. That relationship is reflected in descriptions of self-regulated learning (SRL) as an active, constructive process that involves setting learning goals, then monitoring, regulating, and controlling motivation and behavior to accomplish them (Boekaerts, Pintrich, & Zeidner, 2000; Pintrich, 2000; Zimmerman, 2008). According to this view, motivation is among the components of SRL subject to regulation (Dansereau et al., 1979; Pintrich, 2000; Weinstein & Mayer, 1986; Wolters, 2003; Wolters, Pintrich, & Karabenick, 2005; Zimmerman, 2000). Recent models of SRL include motivational beliefs together with self-regulatory strategies; for example, the activation of task value as part of the forethought phase of Pintrich's SRL model (Pintrich, 2000).[1]

Rather than motivation being considered a component of self-regulation, others have focused on relations between motivation and self-regulatory strategies, most prominently operationalized by the Motivated Strategy for Learning Questionnaire (MSLQ; Pintrich, 1989; Pintrich, Smith, Garcia, & McKeachie, 1993). The MSLQ self-regulatory strategies are distinguished in cognitive (rehearsal, organization and elaboration), metacognitive (planning, monitoring and regulating), and resource management strategies (help seeking, time and study environment management) (Liu, 2009; Pintrich, et al., 1993; Pintrich, Wolters, & Baxter, 2000; Weinstein, Husman, & Dierking, 2000; Weinstein & Mayer, 1986; Wolters et al., 2005). By assessing different facets of motivation (e.g., expectancy, value, control beliefs), the MSLQ made it possible to examine associations between motivation and self-regulation with a greater degree of precision. There is now considerable support for the association between students' motivational beliefs and use of learning strategies (Elliot, McGregor, & Gable, 1999; Lens, Simons, & Dewitte, 2002; Pintrich, 1999; Pintrich & De Groot, 1990; Schiefele, 2001).

The direction of effects between motivation and strategy use, however, remains unresolved. First, there is the tacit assumption that since more motivated students are more likely to use learning strategies (Pintrich & De Groot, 1990), motivation predicts learners' self-regulatory strategies (or alternatively, that the motivational component of self-regulation predicts the use of strategies). That is, students who are more motivated to engage in learning tasks generally, or who become more motivationally engaged in given learning contexts such as a mathematics or science class, will opt to be more strategic. The converse assumption is that students' use of strategies predicts their motivation; that is, the successful application of rehearsal or elaboration, for example, could predict students' self-efficacy and, thus, their motivational engagement in mathematics or science.

One reason this issue remains unresolved is that studies examining motivation and strategy use have largely employed correlational cross-sectional designs. This approach inherently restricts inferences regarding the direction of effects, even with the use of structural equation modeling (SEM) and its directional assumptions. A stronger test of

[1] Note that the terms learning strategies and SRL are often used interchangeably (Dinsmore, Alexander, & Loughlin, 2008).

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directional effects would require a longitudinal study to test whether motivation affects students' use of learning strategies, and the converse, over time. Specifically, time-lagged effects in longitudinal models could determine whether motivation at an initial point in time predicts reported strategy use at a subsequent time point, controlling for initial strategy use, and the converse. Adopting this approach requires specification of an appropriate period of time needed for the detection of these effects. A plausible period is the interval of an academic term, which has a natural entry and end point. The research question would thus be whether motivation and strategy use assessed at the beginning of the term would affect each other during the term, detected as described above, by cross-lagged paths between the two time points.

1.1. SRL and expectancy-value theory

The above effects were examined through the lens of expectancy-value theory since this approach has been the basis of most of the previous work on motivation and SRL (cf. Wolters et al., 2005). In Eccles and Wigfield's expectancy-value model (Eccles et al., 1983; Wigfield & Eccles, 1992), expectancies for success and task value are the proximal determinants of such outcomes as effort, choice and persistence. Expectancy is represented by self-concept of ability and self-efficacy (Eccles & Wigfield, 1995). The four components of value are: (a) intrinsic interest, that is, the enjoyment gained from doing the task; (b) attainment value that captures the importance of doing well on the task; (c) utility, which is defined as how useful the task is for the student's future; and (d) cost, that is, the effort and lost opportunities for engagement in an activity.

According to Pintrich and Zusho (2002) and Zimmerman (2000), given that strategy use is an effortful and time-consuming activity, students who value a task or domain will be more likely to employ strategies to increase the likelihood of success, with such as cognitive and metacognitive strategies requiring more concentration, effort and self-reflection and, hence, higher levels of motivation. Conversely, learners would use fewer strategies when outcomes are not considered valuable (Zimmerman, 2000). Following Wigfield, Hoa, and Klauda (2008), the role of value in the use of learning strategies is to favor or restrain students' cognitive engagement in the task and the regulation of that engagement.

Among the components of value, perceived utility (or instrumentality) of an outcome predicts the use of deep-processing learning strategies (e.g., elaboration, critical thinking) even after controlling for the effect of achievement goals and perceived competence (Miller, Greene, Montalvo, Ravindran, & Nichols, 1996). Moreover, students choosing a class because of its relevance for their future (and for personal development) tend to use fewer surface-processing strategies and more deep-processing strategies than do students choosing a class in order to obtain extrinsic rewards (e.g., course credits) (Lens et al., 2002). College students' use of deep-processing strategies, but not rehearsal, organization, and time management, was positively and moderately related to intrinsic task interest (Schiefele, 1991).[2] To date, cost is the most understudied component of value (Wigfield & Cambria, 2010), including its relation to SRL. Cost may constrain

[2] Note that whereas Schiefele (1991) considered organization as a surface-processing strategy, Linnenbrink and Pintrich (2003) considered it as a deep-processing strategy.

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students' use of strategies to learn or guide them toward the use of more surface-processing strategies (e.g., rehearsal) that require less cognitive engagement even if it requires the same amount of time as higher-order strategies.

There is also considerable evidence for the relationship between expectancy for success (typically assessed as self-efficacy beliefs) and the adaptive use of cognitive and metacognitive strategies (Linnenbrink & Pintrich, 2003). Linnenbrink and Pintrich (2003) emphasized that in longitudinal studies self-efficacy explained additional variance over time in higher-order cognitive and metacognitive strategy use; that is, higher self-efficacy is related to an increased use of deep-processing strategies over time (Pintrich, 1999). Borkowski, Chan, and Muthukrishna (2000) have described reciprocal effects of motivational beliefs and cognitive and metacognitive strategy use in a heuristic developmental model. According to this model, self-efficacy beliefs lead to the efficient use of learning strategies and improve performance, including the increased use of metacognitive strategies (planning and monitoring). Furthermore, they propose that the effect of learning strategies on self-efficacy is mediated by performance and subsequent self- or teacher-provided feedback following performance. Zusho, Pintrich, and Coppola (2003) assessed the motivational beliefs at three points, and learning strategies twice, during a college chemistry course. Associations between efficacy, strategies and performance suggested support for the Borkowski et al. (2000) model, but analyses reported by Zusho et al. (2003) were not sufficient for a definitive test, and performance was only obtained at the end of the course.

1.2. The present study – Hypotheses

In sum, research to date indicates that motivation in the form of expectancy and value beliefs is related to the use of learning strategies. There is insufficient evidence, however, regarding the direction of effects, as well as an incomplete specification of the components of motivation involved, notably that of cost. Accordingly, we employed a two-wave longitudinal design that afforded a test for both direct and reciprocal effects of each set of variables within a single academic term in mathematics classes. As in prior studies (Linnenbrink & Pintrich, 2003; Pintrich & De Groot, 1990; Zusho et al., 2003), in addition to relations at the beginning and end of the term, it was possible to examine: (a) whether students' initial motivation toward mathematics predicted the use of learning strategies reported at the end of the term, controlling for use of learning strategies reported at the beginning of the term; (b) whether the initial use of learning strategies predicted the motivation reported at the end of the term, controlling for motivation reported at the beginning of the term; (c) the relative strength of these effects; (d) the stability of self-reported motivation and use of learning strategies; and (e) differences in the levels of motivation and strategy use from the beginning to the end of the term.

Framed within expectancy-value theory (Wigfield et al., 2008; Wigfield & Cambria, 2010), both initial self-efficacy and the three components of value (liking, utility, and importance) were expected to be directly related to and predict strategy use at the end of the term (Hypothesis 1). Given the sparse evidence regarding cost, however, no predictions were advanced. Concerning the effects of strategy use on motivation, based on Borkowski et al. (2000) and Linnenbrink and Pintrich (2003), it was expected that the self-reported use of cognitive and metacognitive strategies will predict students' mathematics-related self-efficacy at the end of the term; on the other hand, resource management strategies were not expected to predict mathematics-related self-efficacy (Hypothesis 2).

For continuity with prior research, the present study adopted the assessment of learning strategies used by Weinstein and Mayer (1986) and Pintrich and colleagues (Pintrich & De Groot, 1990; Pintrich et al., 1993; Wolters et al., 2003). This permitted testing effects of motivation on the complete set of cognitive, metacognitive and resource management strategies, as well as the potential effects of each strategy on each component of motivation. Taking into consideration the issues and limitations of current self-report inventories of learning strategies and SRL raised primarily by Winne and colleagues (Winne, Jamieson-Noel, & Muis, 2002; Winne & Perry, 2000), techniques to improve the assessment of self-reported learning strategies were employed by revising MSLQ scales to increase their construct validity, discriminant validity and, thus, the likelihood of detecting the predicted effects.

2. Method

2.1. Participants

Participants were 306 ninth grade students (50% female) enrolled in one of 15 algebra classes in a Midwest urban high school in the U.S.A. Although students are not formally tracked in the school system, they were distributed across the following types of classes that increased in difficulty, respectively: (a) Algebra I support (16%), (b) Algebra I - 2/3 (material covered in three trimesters instead of the normal two; 7%), (c) Algebra I normal (42%), (d) Geometry advanced (30%), and (e) Algebra II (5%). Of the whole sample, 288 were surveyed at the beginning (Time 1, designated as T1) and 286 at the end (Time 2, designated as T2) of a 12-week term. The final sample consisted of the 253 students who participated in both sessions.

Students were unaware that the survey would be administered during a specific class session, and thus participation was a function of attendance on the day of testing and unlikely to reflect unintended sample selectivity (e.g., students not attending class to avoid having to complete the survey). Of those who were present when assessment occurred only five students declined to participate.

2.2. Material

The 44-item survey was divided into sections that assessed students' use of learning strategies in their mathematics class (33 items), followed by their motivation for mathematics (11 items). Students responded to all items on a 5-point scale with anchors of 1 (Not at all true of me) and 5 (Very true of me). The scales were based on a selection of those in the college version of the MSLQ (Garcia Duncan & McKeachie, 2005; Pintrich, Smith, Garcia, & McKeachie, 1991), with modifications (described subsequently) for the present study.

2.2.1. General MSLQ item revision principles

Several design principles were employed in the present study to improve the MSLQ scales and their constituent items, including suggestions based on cognitive interviews of several motivation-related scales (Karabenick et al., 2007). First, several items were abbreviated to make them easier for high school students to comprehend. Second, words such as "concept" were removed, and "the material" was clarified by referencing "what I have/need to learn/know." Third, the items were made subject-specific to fit the context of mathematics learning in high school. Hence, references to reading activities were omitted and "lectures" was replaced by the word "class." Fourth, terms referring to frequency or quantity (e.g., "each time", "often", "a lot") were removed given that the response scale provided the necessary alternatives to capture that meaning.

2.2.2. Learning Strategies Scale

Several learning strategy items were judged by the authors to contain terms that potentially confounded learning strategies and motivational beliefs. For example, the statement "I find it hard to stick to a study schedule" which suggests self-efficacy regarding time and study environment management, was replaced with "I use a study schedule when preparing for math exams." In another example of an item in need of revision, "I try to understand the material in this class by making connections between the readings and the concepts from the lectures," the inclusion of understanding potentially focused attention on the motivational goal of mastery as well an elaboration strategy. Additional revision principles were employed for the cognitive and metacognitive learning strategy items in an effort to adhere as closely as possible to the theoretical constructs they were assumed to operationalize. For example, items that implied two different strategies were revised. For example, the statement "Before I study new course material thoroughly, I often skim it to see how it is organized," potentially describes metacognitive planning in the first phrase and organization in the second. The items included in the Learning Strategies Scale are given in Appendix A.

2.2.2.1 Cognitive strategies. Rehearsal was assessed by four items (e.g., "When I study math, I memorize what I need to learn by repeating it over and over to myself"). Organization was assessed by four items (e.g., "When I study math, I make outlines to organize what I have to learn"). Elaboration was assessed by four items (e.g., "I connect what I learn in math to what I am learning in some other classes").

2.2.2.2. Metacognitive strategies. Planning was assessed by five items (e.g., "I plan how I am going to study new math topics before I begin"). Monitoring was assessed by four items (e.g., "When I study math, I ask myself questions to make sure I know what I have been learning"). Regulation was assessed by four items (e.g., "If I get confused with something I'm studying in math, I go back and try to figure it out").

2.2.2.3. Resource management strategies. Time and study environment management was assessed by four items (e.g., "I make sure I have as few distractions as possible when I study math"). Help seeking was assessed by four items (e.g., "If I don't understand something in math I ask my teacher for help").

2.2.3 Motivation Scale

Items used to measure motivation were framed specifically for mathematics. Expectancy was assessed by three items selected from the self-efficacy scale of the MSLQ (e.g., "I'm certain I can understand the most difficult material presented in math.”). The four components of task value defined by Eccles (Eccles et al., 1983) were assessed with items adapted from Eccles and Wigfield (1995), that is, utility (3 items; e.g., “I believe that math is valuable because it will help me in the future”), attainment (3 items; e.g., “It is important to me to be the kind of person who is good at math”), interest (3 items; e.g., “I like math”), and cost (2 items; e.g., “I have to give up a lot to do well in math”). The items included in the Motivation Scale are given in Appendix B.

2.3. Procedure

Surveys were administered by research personnel during regular class periods and required approximately 25 minutes of class time. Following a brief explanation of the nature of the study—that it was concerned with how students learn and feel about mathematics—students were provided with an informed consent statement that emphasized the voluntary nature of participation, that they could refuse to answer any question, assured them of confidentiality and that their responses would not affect their mathematics grade. Names and student numbers were obtained to match data from the two survey administrations. Consent was required for participation. 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.

2.4. Statistical analyses

First, psychometric analyses were used beginning with confirmatory factor analysis (CFA) that was conducted separately for the items assessing expectancy-value components and those assessing learning strategy use. The CFAs were conducted in order to test for the fit of the factor structure. These were followed by CFA analyses to determine the extent of measurement invariance between assessments at the two time points, and thus confidence that we are measuring the same constructs at T1 and T2.

Then, a cross-lagged correlation (CLC) model (Kenny, 1975, 1979) was tested. This model included the same expectancy-value and learning strategies variables at T1 and T2. The CLC method is based on two assumptions (Kenny, 1975), namely synchronicity, which refers to the fact that the variables at each occasion are measured at the same time, and stationarity, which means that the presumed causal process did not change during the interval between the measurement occasions. Given that the design of the study satisfies the assumptions, it is an appropriate method to infer reciprocal causation in correlational data (Locascio, 1982). In addition, the method provides information about the stability of the variables over time. Although causality is not strictly proven with CLC, since the design is correlational, this approach can determine if the proposed directional model is consistent with the data, and more specifically, that the assumption of directionality is not disconfirmed (Bollen, 1989). The CLC employed observed variables corresponding to the mean score of the items loading their respective factors (i.e., unweighted composites). The scores were then corrected for measurement error. The use of manifest variables instead of latent variables was necessary given the large number of parameters included in the model, which otherwise would have resulted in large standard errors and non-significant parameters even with moderate effect sizes.

The Maximum Likelihood Robust Estimator (MLR) available in Mplus 5.0 was used in all analyses to take into account deviations from multivariate normality. The fit of each model was assessed using χ^2, the ratio of χ^2/df (when the p value associated to χ^2 was significant), the Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA) (cf. Schermelleh-Engel, Moosbrugger, & Müller, 2003). With regard to missing data, at T1, the highest percentage of missing values at the item level was 3.5% (10 students out of 288 did not answer an item), and at T2, 5.9% (17 students out of 286 did not answer an item). All analyses employed the Full Information Maximum Likelihood (FIML) procedure that is the most efficient method to estimate SEM models in presence of missing data (Enders, 2006).

3. Results

To check the adequacy of the expected factor structure, CFAs were conducted using the items as factor indicators, initially as separate analyses at T1 and T2.

3.1. Expectancy-value constructs

Correlations between utility, interest and attainment were all high and statistically significant both at T1 ($r > .45$, $p < .001$) and at T2 ($r > .41$, $p < .001$). Cost, however, was only slightly correlated with utility, interest and attainment at either T1 or T2. A model that consisted of the five first-order constructs (expectancy and the four components of value) and a second-order factor explaining utility, interest, and attainment fit the data adequately at T1, $\chi^2(71, N = 288) = 141.212$, $p < .001$, $\chi^2/df = 1.98$, CFI = .95, RMSEA = .06. All loadings were large (> .60) and highly significant ($p < .001$). The first order factors of utility, interest, and attainment were largely explained (all loadings > .71, $p < .001$) by the second-order factor that was designated as “value.” Consistent with the fact that cost was only slightly correlated with the other components of value, it was represented as a separate factor, distinct from value. No items were removed from the analysis. At T2, an identical model fit the data equally well, $\chi^2(71, N = 286) = 138.890$, $p <.001$, $\chi^2/df = 1.96$, CFI = .96, RMSEA = .06.

3.2. Learning strategies constructs

A model with nine first-order factors and one second-order factor explaining the metacognitive first-order factors (planning, monitoring, and regulation) fit the data adequately at T1, $\chi^2(329, N = 288) = 450.129$, $p < .001$, $\chi^2/df = 1.37$, CFI = .94, RMSEA = .04. All loadings were at least moderate (> .39) and highly significant ($p < .001$). The first-order factors of planning, monitoring, and regulation were largely explained (all loadings > .79, $p < .001$) by the second-order factor termed “metacognition.” An identical model fit the T2 data, although the indices were not as satisfactory as these were at T1, $\chi^2(329, N = 286) = 540.837$, $p < .001$, $\chi^2/df = 1.64$, CFI = .88, RMSEA = .05. As with the T1 factor solution, all loadings were at least moderate (> .49) and highly significant ($p < .001$). This factorial solution, however, required the removal of four items at both measurement occasions. Two items contained common words “the formulas or definitions” that apparently had overlapping meaning. One of these items was expected to assess rehearsal (“I study math by going over the formulas or definitions in order to memorize them”) and largely cross-loaded on the factor organization; the second item was designed to assess organization but cross-loaded on the rehearsal factor (“When I study math, I make a list of the formulas or definitions to organize what I need to know”). One item (“If I’m having trouble solving math problems I try other ways to solve them”), which was expected to assess regulation, did not significantly load on the expected factor. The last discarded item (“I use a study schedule when preparing for math exams”) was designed to assess time and study management but did not load on the factor; this seemed due to the fact that all the other items explained by this factor refer to strategies related to concentration and distraction.

3.3. Measurement invariance over time

Comparison of the same models at T1 and T2 reported above provided information regarding the configural invariance of the factorial solution. In order to provide a more stringent test of measurement invariance over time, we conducted a test of metric invariance, which consists of constraining the factor loadings to be equal across measurement occasions. All expectancy-value constructs were included in one analysis. Concerning learning strategies, however, given the large number of items and, therefore, number of parameters to be estimated in a single model, two separate models were estimated. One model consisted of the cognitive strategies (rehearsal, organization, elaboration and time and study environment management). The second consisted of metacognitive strategies (planning, monitoring and regulating) and help seeking.

3.3.1. Invariance in the measurement of expectancy-value components

The same five-factor model (four first-order and one second-order) was specified for both waves, with loadings constrained to be equal. The Satorra-Bentler scaled $\Delta\chi^2$ test (Satorra & Bentler, 1999) revealed that the fit of the constrained model (loadings constrained to be equal across time) was not significantly different, Satorra-Bentler scaled $\Delta\chi^2(9) = 8.006$, $\underline{p} = .53$, from the fit of the unconstrained model (loadings freely estimated). It can, therefore, be concluded that there was invariance in the factor loadings between T1 and T2.

3.3.2. Invariance in the measurement of learning strategies

For rehearsal, organization, elaboration, and time and study environment management strategies, the same four-factor model was specified for both waves, with loadings were constrained to be equal. The Satorra-Bentler scaled $\Delta\chi^2$ test revealed that the fit of the constrained model was not significantly different from the fit of the unconstrained model, Satorra-Bentler scaled $\Delta\chi^2(7) = 1.101$, $\underline{p} = .99$. It can, therefore, be concluded that there was invariance in the factor loadings between T1 and T2. For metacognition and help seeking strategies, the same five-factor model (four first-order factors and one second-order factor) was specified for both waves with the loadings constrained to be equal. As with the other models, it can be concluded that there is invariance in the factor loadings between T1 and T2, Satorra-Bentler scaled $\Delta\chi^2(11) =$

1.056, $p = .99$. Table 1 presents the descriptive statistics for the scales based on these analyses and the internal consistency estimates. Raykov's rho estimate of internal consistency (Raykov, 1997) was used given that this index has been shown to be a better estimate than Cronbach's alpha, as it does not assume tau-equivalence of the factor loadings.

Insert Table 1 about here.

3.4. Differences in motivation and strategy use over time

Separate ANOVAs tested both mean level differences and differential change of motivation and learning strategy use from T1 to T2. For each analysis, two within subjects factors were time and the type of expectancy-value component or strategy. The results revealed that the Time x Expectancy-Value component interaction was significant, $F(2, 251) = 9.17$, $p < .001$, partial $\eta^2 = .04$, which indicates that the mean expectancy-value components changed at different rates from T1 to T2. As shown in Table 1, whereas self-efficacy remained relatively stable, students valued mathematics less at the conclusion of the term and considered doing well more costly in terms of time, effort and lost opportunity. Moreover, a main effect of expectancy-value component was found, $F(2, 251) = 110.084$, $p < .001$, partial $\eta^2 = .30$, whereas no main effect of time was found, $F(1, 252) = 1.102$, $p = .30$. The Time x Strategy interaction was not statistically significant, $F(5, 248) = 1.703$, $p = .13$. Moreover, main effects of strategy type, $F(5, 248) = 222.757$, $p < .001$, partial $\eta^2 = .47$, and of time, $F(1, 252) = 12.059$, $p < .01$, partial $\eta^2 = .05$, were found. This indicates an overall decrease in strategy use over time. Nevertheless, univariate ANOVAs suggested that metacognition, help seeking, and time and study environment management decreased significantly whereas rehearsal, organization and elaboration did not. Although the extent of the mean changes is modest, the differences may be considered substantial given the short interval between the two measurement occasions and, thus, have practical implications as they probably cumulate over successive mathematics classes.

Table 2 presents the correlations between all measured variables. Concerning the correlations between learning strategy scales, the same pattern was found at T1 and T2, that is, all of the strategies were positively and moderately associated, with the highest correlations found between rehearsal and organization ($r = .51$, $p < .001$ and $r = .55$, $p < .001$, respectively at T1 and T2). The correlations between expectancy-value scales are equivalent at both time periods, except that value and cost were not significantly related at T2 ($r = -.05$) but were at T1 ($r = -.15$, $p < .05$). The correlations showed a clear pattern of association between motivation and self-regulation but also some differences at the two time points. In general, at both T1 and T2, students who believed themselves more capable in mathematics and who considered mathematics more valuable were more likely to use higher-order cognitive (elaboration) and metacognitive strategies, help seeking and time and study environment management, but were not more likely to rely on rehearsal or organization.

The same pattern prevailed for students who considered mathematics more valuable at T1 but not at T2 when mathematics value was also associated with rehearsal

($r = .30$, $p < .001$) and organization ($r = .23$, $p < .001$). Relations between cost and strategy use also showed a somewhat different pattern at the beginning and end of the term. The more students thought that doing well in mathematics was costly in terms of time and opportunities lost the more likely they were to report using rehearsal at both time points. At T2, however, cost was also associated with the use of organization ($r = .20$, $p < .01$) and time and study environment management ($r = .14$, $p < .05$). The correlation between self-efficacy and time and study management also tended to increase from T1 ($r = .19$, $p < .05$) to T2 ($r = .31$, $p < .001$). Taken together, the changes in relations suggest some shifts in how students with different motivational profiles allocate time and effort to the way they study and approach the course. It is these changes that are reflected in analyses that incorporate both time periods.

Insert Table 2 about here.

Except for elaboration that had lower correlations with rehearsal, organization, and metacognition in the present study, the correlations between learning strategy scales are approximately of the same magnitude as those in the primary validation study of the MSLQ with college students (Pintrich et al., 1993)[3]. It should also be noted that in the Pintrich and De Groot (1990) study of high school students only two scales were formed with the learning strategy items based on exploratory factor analyses, namely Cognitive Strategy Use that comprised all the items pertaining to the use of rehearsal, elaboration and organization, and Self-Regulation that comprised the metacognitive self-regulation strategies and effort management items. In contrast, results of the present study indicated that specific scales can be formed for cognitive and resource management strategies, respectively, whereas the three types of metacognitive strategies were explained by a single second-order factor.

3.5. Cross-lagged correlation (CLC) model and analyses

The cross-lagged correlations between several variables measured on several occasions were used in order to identify directional effects from passive observational longitudinal data (Kenny, 1975). Specifically, the presence of asymmetrical cross-lag paths would indicate a directional effect by rejecting the alternative hypothesis of spuriousness.

Based on the literature review and the hypotheses of the study, a general model of the expected cross-lag paths (represented by dotted lines) was proposed, shown in Figure 1. Each of the expectancy-value components at T1 might have an effect on strategy use at T2 whereas the use of learning strategies at T1 could have an effect on self-efficacy at T2. Moreover, no path linking different learning strategies at both time points was proposed since there was no theoretical rationale to expect cross-lagged effects from the use of any learning strategy at T1 on the use of any other learning strategy at T2. Both value and self-efficacy were expected to positively predict the level of learning strategies at T2, controlling for T1 levels of learning strategies. Given that the effect of cost on learning strategies is largely unknown, a question mark is shown to represent this

[3] That may be a function of elaboration's lower internal consistency in the present study ($\rho = .58$ and .59) compared to previous research (Cronbach's alpha = .75 in Pintrich et al., 1993).

exploratory part of the model. Moreover, a positive path was included from learning strategies at T1 to self-efficacy at T2, following the Borkowski et al.'s (2000) theoretical model. Finally, stability (represented by solid lines) over time was expected for the same variables from T1 to T2.

Insert Figure 1 about here

The CLC model tested included all of the learning strategy constructs and the expectancy-value constructs. Measurement error in the scores was corrected using the formula (1 - reliability) x variance to fix measurement error in the SEM model (Bollen, 1989). These corrections take into consideration the reliability of the scores resulting in more precise parameters. The results are shown in Figure 2. Only significant paths at the level of alpha = .05 were retained in the model. Since the correlations between the variables at T1 and between the variables at T2 are available in Table 2, they were not included here to increase readability.

The testing of the CLC model revealed a fit qualified as acceptable following Schermelleh-Engel et al.'s (2003) guidelines, $\chi^2(67, \underline{N} = 306) = 147.502$, $\underline{p} < .001$, $\chi^2/\underline{df} = 2.20$, CFI = .94, RMSEA = .06. However, based on suggested modification indices we added a path from value at T1 to self-efficacy at T2 ($\beta = .33$), suggesting that value predicts change in self-efficacy but not the reverse, $\chi^2(66, \underline{N} = 306) = 124.240$, $\underline{p} < .001$, $\chi^2/\underline{df} = 1.88$, CFI = .96, RMSEA = .05. Thus, the more the students indicated they valued mathematics at the beginning of the term the more efficacious they reported being at the end of the term, even after controlling for their level of self-efficacy beliefs at the beginning of the term. Addition of this path significantly improved the fit of the model, $\Delta\chi^2(1) = 23.26$, $\underline{p} < .01$.

As shown in Figure 2, the path coefficients indicated a moderate degree of stability in self-efficacy ($\beta = .59$) and cost ($\beta = .56$), and a high degree of stability of value from T1 to T2 ($\beta = .82$). At both time points the paths between constructs were of similar magnitude, that is, value was consistently strongly associated with self-efficacy but not with cost, and self-efficacy and cost were inversely related. The only cross-lagged path reaching significance within the set of motivation constructs was from value at T1 to self-efficacy at T2 ($\beta = .33$). The stability of learning strategies ranged from $\beta = .56$ (time and study environment management) to $\beta = .80$ (help seeking). Importantly, the moderate level of stability is both an indication of sufficient inter-individual variability yet with sufficient variance over time to be predicted by T1 levels of motivation and strategy use.

Insert Figure 2 about here.

As shown in Figure 2, there were several paths from motivation at T1 to learning strategies at T2 but none from strategy use at T1 to motivation at T2. First, the use of rehearsal as a learning strategy at T2 was positively predicted by both value ($\beta = .18$) and cost ($\beta = .21$) at T1, over and above the use of rehearsal at T1. In other words, the more students believed that mathematics is valuable (in terms of utility, interest, and attainment) and the more it costs for the students to learn mathematics, the more students increased (or the less students decreased) their use of rehearsal from T1 to T2. These effects were not expected. That the zero-order correlations show a similar pattern suggests these path values are not artifacts (e.g., due to various forms of suppression). Three learning strategies, namely elaboration, metacognition, and time and study environment management at T2 were significantly predicted by self-efficacy at T1 controlling for their level at T1. The path coefficients, which range from $\beta = .17$ and $\beta = .27$, were substantial given the short time interval (12 weeks) between the two time points.

The proportion of explained variance in expectancy-value constructs at T2 ranged from $\underline{R}^2 = .32$ (cost) to $\underline{R}^2 = .68$ (self-efficacy). For learning strategies, the proportion of explained variance at T2 was between $\underline{R}^2 = .37$ (time and study environment management) and $\underline{R}^2 = .64$ (help seeking). As a further test of these effects, we also conducted tests of separate models that included expectancy-value components, and a single learning strategy per model rather than all in a single model. These analyses revealed that the effects found in the global model were also present in the single-strategy models. This supports the validity of the global model by verifying that the cross-lagged effects are not due to suppressor effects.

4. Discussion

4.1. Motivation and learning strategies

The present study was designed to detect reciprocal effects of motivation and students' reported use of learning strategies during a single academic term in high school mathematics classes. Cross-lagged analyses indicated that both expectancy and value components of motivation significantly predicted students' reported use of learning strategies, therefore confirming Hypothesis 1. Rather than motivation in general, however, the effect must be stated conditionally given that only self-efficacy and value predicted the use of different strategies. Specifically, students' self-efficacy for mathematics at the beginning of the term predicted more frequent use of deep-processing strategies (elaboration, metacognition) and of time and study environment management, but self-efficacy did not predict rehearsal or organization. Given that the use of metacognition and time and study environment management strategies significantly decreased over the course of the term, the effects of self-efficacy can be interpreted as reducing the decrease in the use of those strategies. The effect of self-efficacy on strategy use is consistent with the results for elaboration and metacognition found in studies of middle school students (Pintrich, 1999) of similar age to those in the present study.

However, the results of the present study indicate that whereas being confident in one's ability to learn leads to the use of deeper, more sophisticated strategies, valuing the domain does not lead to similar higher-order self-regulation. Compared with their peers, students who initially considered mathematics more valuable—the combination of interesting, useful and important—were more likely to increase only their use of memorization during the term, controlling for beginning of term use of rehearsal. It is possible that value indirectly affected higher-order strategy use, however, given that the value of mathematics at the beginning of the term predicted students' reported levels of self-efficacy at the end of the term, which in turn affected the use of higher-order strategies.

The more the students perceived that being successful at mathematics is costly in terms of time, effort and lost opportunities the more likely they were to increase their use of rehearsal, which requires less time and effort than higher-order strategies do. Taken together, therefore, rehearsal was increasingly preferred by students who considered mathematics more valuable but that also required more of them (i.e., was considered more costly). Results of the role of cost is especially important given the dearth of information available to date (Wigfield & Cambria, 2010), and should spur additional efforts to study its effects on the use of learning strategies.

Students' use of cognitive and metacognitive strategies at the beginning of the term did not predict the levels of student motivation reported at the end of the term, controlling for strategy use at the beginning. Thus, there is absolutely no evidence in favor of Hypothesis 2, namely that learning strategy use predicts student motivation (self-efficacy, value or cost), and consequently no support for the Borkowski et al. (2000) model that proposed such effects. One reason for the absence of strategy effects may be that the temporal interval in the present study was too brief for the effects to be detected. Thus believing in the value of, or being confident in mathematics could affect the use of certain learning strategies in the short term, but the use of strategies may require more time before affecting motivational beliefs—strategy use is relatively modifiable whereas levels of motivation, in this instance regarding the domain of mathematics, are less so. Especially in the case of value, it would seem unreasonable to expect this component of motivation to change over that time period, as suggested by the high stability observed in the present study. What we can rule out is that the differences in predictability from motivation to learning strategies and from learning strategies to motivation are a function of differential stability over that interval. Except for value, the motivation components and learning strategy use were both comparably and moderately stable yet with sufficient variability (between 31% and 64% of the variance at T2 was explained by strategy use at T1) for systematic effects to occur.

Evidence from the present study also bears on the general consensus that the levels of value and efficacy decrease over a typical school term or college course (Eccles, Wigfield, & Schiefele, 1998; Pintrich & Schunk, 2002; Zusho et al., 2003). Consistent with this generalization, the mean level of value for mathematics decreased over the term, and the level of cost increased; however, the mean reported level of self-efficacy did not decline. Changes in the use of learning strategies also varied: only use of three strategies (metacognition, help seeking, and time and study environment management) decreased over the course of the term. These can be considered three of the most adaptive learning strategies (Pintrich, 1988; Weinstein et al., 2000), this suggests that, as a group, students became less self-regulated learners during the term. In comparison, the study by Zusho et al. (2003) found that the use of rehearsal and elaboration strategies decreased over the term whereas the use of organizational and metacognitive strategies increased. However, differences in student population and subject matter could explain the differences between studies.

4.2. Assessment of motivation and strategy use

With regard to revisions of the items and scales used to assess motivation and strategy use, confirmatory factor analyses indicated that the variance in students' responses could be explained by the proposed factors. The expectancy-value scales demonstrated very desirable properties in terms of construct validity and in terms of measurement invariance over time. The constructs of utility, interest, and attainment value (importance) were explained by a single value factor, whereas the construct of cost component of expectancy-value theory (Eccles et al., 1983) was considered distinct. That cost factored independently from interest, utility and importance suggests that it be treated separately rather than as just another component of task value.

The learning strategy factorial solution fit the data when analyzed together (i.e., all the items in a single CFA). Moreover, several factors representing distinct learning strategies were extracted, contrary to Pintrich and De Groot (1990) who found two learning strategy factors using the MSLQ, or Liu's (2009) learning strategy inventory that proposed three factors (cognitive, metacognitive, and behavioral strategies). However, the analyses of measurement invariance revealed that metacognition and help seeking resulted in a less adequate factorial solution (i.e., the CFI was under .90) than did the analysis of cognitive and resource management strategies (rehearsal, organization, elaboration, and time and study environment management), which suggests the need for further revision of these items. Furthermore, the reliability of several scales' scores was less than desired, suggesting that these scores should be corrected for measurement error, as was done in the present study. Globally, the CFAs indicated that the revisions and adaptations of the items used to measure high school students' use of learning strategies represent an improvement over those in previous versions of the MSLQ (i.e., increased discriminant validity for the learning strategy scales). Exploration of the validity and of how to better phrase these items is currently under investigation (Berger & Karabenick, 2010) using the cognitive interviewing approach suggested by Karabenick et al. (2007).

In general, the correlations between expectancy-value components and learning strategies corroborate those found by Pintrich et al. (1993). Notably, self-efficacy and task value are more strongly related to higher than to lower-order learning strategies. However, the present results revealed that expectancy-value components and learning strategies correlated less strongly than the values reported by Pintrich and De Groot (1990), that is, value was correlated with cognitive strategy use ($\underline{r} = .63$, $\underline{p} < .001$) and self-regulation ($\underline{r} = .73$, $\underline{p} < .001$), whereas self-efficacy was correlated with cognitive strategy use ($\underline{r} = .33$, $\underline{p} < .001$) and self-regulation ($\underline{r} = .43$, $\underline{p} < .001$). Compared with former studies, the results of our factor analyses and the correlations between expectancy-value and learning strategies are closer to those of Pintrich et al. (1993) based on college students than they from Pintrich and De Groot (1990) based on high school students.

4.3. Implications for education

A major implication of this study for learning and instruction is the need to consider value, cost and self-efficacy separately when examining the impact of motivation on the way students learn mathematics. It is clear from the results that self-efficacy should be a major focus since it is inversely related to cost, which predicts students' use of rehearsal rather than higher-order strategies. In addition, even though learning strategy use did not predict student self-efficacy, the presence of variance in learning strategy use suggests that learning strategies are malleable and may be changed by instruction, even in the relatively brief time period over which the present study was conducted.

The inclusion of the cost component of value (although here considered a distinct variable) broadens the set of motivational beliefs associated with learning strategy use and warrants expanding the assessment of cost to include more of its constituents. For example, cost may be divided into the extent to which liked activities have to be abandoned in order to do the task and the anticipated effort necessary to put into task completion (Wigfield & Cambria, 2010), since the two forms of cost may relate differently to learning strategies use. It is likely, for example, that cost as the anticipated effort needed for task completion would relate more strongly and negatively to the use of deep learning strategies than would opportunity cost that was assessed in the present study.

4.4. Limitations of the present study

Information regarding the effects of performance feedback (e.g., mid-term grades) would be useful in explicating changes in learning strategy and motivational beliefs, as performance feedback (e.g., test grades) could reinforce or discourage a student from using their approaches to learning, as well as influencing self-efficacy (Borkowski et al., 2000) or value. For example, students largely using rehearsal to learn mathematics and obtaining a poor intermediate grade on a mid-term test may decrease their self-efficacy beliefs and decide to change study habits with increased comprehension monitoring. Hence, a more precise picture of how the use of learning strategies changes over the course of a term is suggested, although inclusion of performance feedback would violate the CLC assumption of stationarity (Kenny, 1975) since the causal process under investigation would change between T1 and T2 and thus other structural models would be required to capture these effects.

Further research should also extend the two-wave longitudinal design, which would provide a more dynamic picture of the causal relations between motivation and learning strategies. Within a given term, as in the present study, more information would be desirable, although it would also increase the likelihood of assessment obtrusion. Longitudinal studies beyond a given term or even beyond one school year may also increase the probability of detecting the effects of motivation and learning strategy use, but the models' complexity would be greatly increased given changes in students' courses and teachers. Learning strategy or motivational interventions could also be used to demonstrate causal effects. However, experimental or quasi-experimental studies would have to take into consideration the degree of complexity in school learning and the multiple learning strategies available to students, and such designs would still require assessment that is sufficient to capture the dynamic interplay between motivation and strategy use (Zimmerman, 2008).

Of course we must point out the reliance in the present study on self-reported data to measure students' use of learning strategies. Direct observation may well bring a different and complementary picture of the relations between motivation and learning strategy use (Winne et al., 2002). However, that would be difficult given the natural settings (e.g., home, school) in which learning takes place. Experience sampling methodology may also be informative, although it too raises the potential for assessment obtrusion, even more so perhaps than multiple assessments within classroom settings. All methodological approaches have their costs and benefits. The present study's detection of directional effects—motivation predicts the use of learning strategies but learning strategies do not predict motivation—suggests that despite its need for improvement, as in the present study, the self-reported assessment of strategy use remains an important tool in the study of self-regulated learning.

Appendix A: Learning Strategies Scale 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 going over the formulas or definitions in order to memorize them.
- 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.
- When I study math, I make a list of the formulas or definitions to organize what I need to know.

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'm having trouble solving math problems I try other ways to solve them.
- 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 strategies

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.
- If I don't understand something in math I ask others for the answers I need to complete my work.

Time and study environment management

- I study math in a place where I can concentrate.
- I use a study schedule when preparing for math exams.
- I study math at a time when I can concentrate.
- I make sure I have as few distractions as possible when I study math.

Appendix B: Motivation Scale and items

Value

Interest

- I like math.
- I enjoy doing math.
- Math is exciting to me

Utility

- I believe that math is valuable because it will help me in the future.

Berger, J.-L., & Karabenick, S. A. (2011). Motivation and students' use of learning strategies: Evidence of unidirectional influences in mathematics classrooms. *Learning and Instruction, 21*, 416–428.

- I believe that math will be useful for me later in life.
- I believe that being good at math will be useful when I get a job or go to college.

Attainment Value (Importance)

- It is important to me to be the kind of person who is good at math.
- I believe that being good at math is an important part of who I am.
- It is important to me to be a person who can reason using math formulas and operations.

Cost

- I have to give up a lot to do well in math.
- I believe that success in math requires that I give up other activities that I enjoy.

Expectancy

Self-efficacy

- I believe I will receive an excellent grade in math.
- I'm certain I can understand the most difficult material presented in math.
- I'm confident I can learn the basic concepts taught in math.

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Table 1.
Descriptive statistics of the scales on learning strategies and motivational beliefs (n = 253)

		T1			T2				
Variable	# items	M	SD	ρ	M	SD	ρ	T2 – T1	p †
Motivation Variables									
Self-efficacy	3	3.44	0.97	.75	3.39	0.97	.71	- 0.05	ns
Value	9	3.24	0.91	.89	3.05	0.95	.90	- 0.19	< .001
Cost	2	2.37	1.10	.75	2.44	1.12	.78	+ 0.07	.04
Learning strategies									
Rehearsal	3	2.57	0.98	.63	2.56	0.90	.59	- 0.01	ns
Organization	3	2.10	0.94	.64	2.06	0.87	.57	- 0.04	ns
Elaboration	4	3.05	0.84	.58	2.94	0.79	.59	- 0.11	ns
Metacognition	12	3.03	0.74	.86	2.88	0.68	.84	- 0.15	< .001
Help seeking	3	3.77	0.89	.62	3.62	0.88	.55	- 0.15	.02
Time & Study	3	3.27	1.01	.78	3.12	0.99	.79	- 0.15	< .01

ρ = Raykov's rho internal consistency estimate
† Based on univariate ANOVAs

Table 2.
Correlations between motivation and learning strategy scales at T1 and T2.

		Time 1									Time 2							
		Value	Cost	Self-efficacy	Rehearsal	Organization	Elaboration	Metacognition	Help seeking	Time & Study	Value	Cost	Self-efficacy	Rehearsal	Organization	Elaboration	Metacognition	Help seeking
Time 1	Cost	.15																
	Self-efficacy	.60	-.33															
	Rehearsal	.14	.14	.08														
	Organization	.12	.08	.01	.51													
	Elaboration	.45	.01	.30	.19	.22												
	Metacognition	.42	.03	.27	.51	.49	.50											
	Help seeking	.28	-.02	.21	.28	.21	.22	.46										
	Time & Study	.42	.06	.19	.32	.26	.25	.46	.36									
Time 2	Value	.78	-.07	.44	.21	.11	.35	.40	.25	.40								
	Cost	-.09	.52	-.25	.12	.08	-.10	.05	-.01	.11	-.05							
	Self-efficacy	.58	-.20	.65	.11	.02	.31	.33	.14	.24	.66	-.23						
	Rehearsal	.22	.19	-.01	.57	.46	.28	.39	.22	.34	.30	.23	.10					
	Organization	.13	.13	-.08	.42	.56	.22	.41	.12	.25	.23	.20	.01	.55				
	Elaboration	.38	.00	.29	.12	.19	.53	.34	.11	.18	.37	.01	.34	.26	.30			
	Metacognition	.39	-.02	.29	.42	.37	.40	.65	.27	.40	.45	.11	.33	.51	.46	.52		
	Help seeking	.19	-.06	.17	.31	.28	.21	.36	.59	.23	.22	-.01	.21	.31	.21	.28	.42	
	Time & Study	.35	.06	.19	.37	.32	.26	.41	.29	.56	.46	.14	.31	.41	.24	.26	.47	.31

n = 253.
Coefficients ≥ .13 are significant at p < .05; ≥ .17 are significant at p < .01; ≥ .21 are significant at p < .001.

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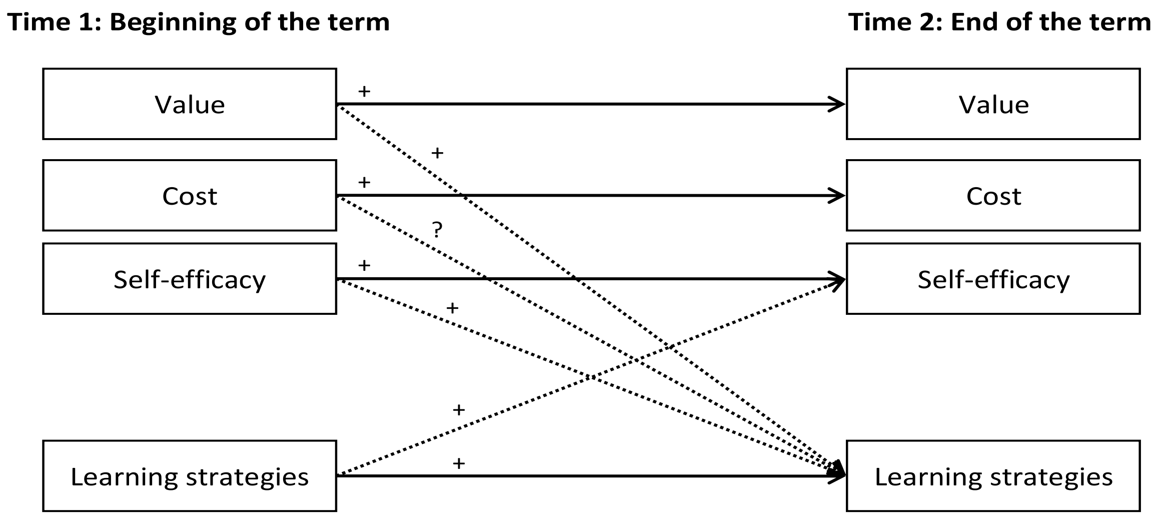

Fig. 1. Proposed cross-lagged correlation model linking expectancy-value constructs and learning strategies at Time 1 (T1) and Time 2 (T2).

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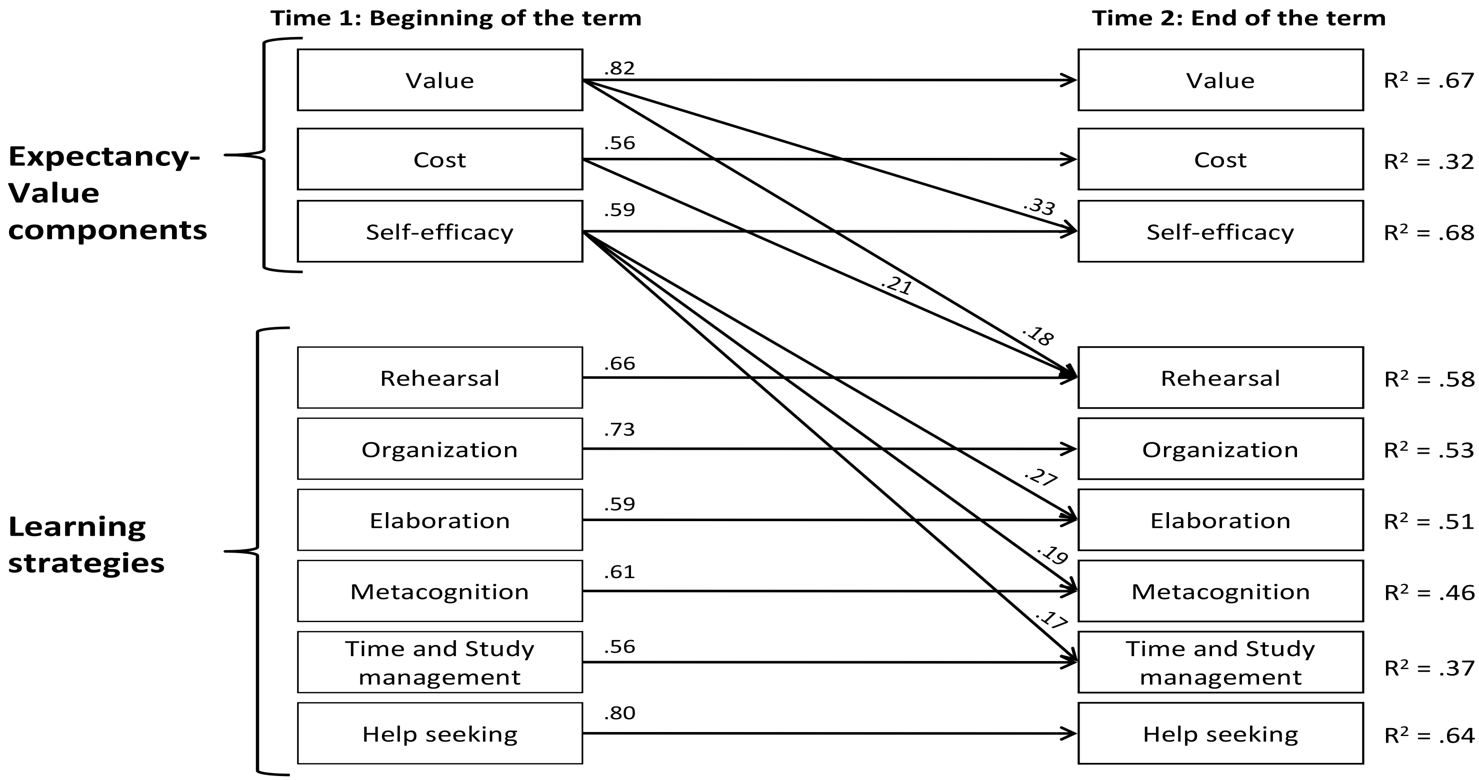

Fig. 2. Cross-lagged correlation model for task value, cost, self-efficacy, and learning strategies (n = 306). All paths shown are significant at $p < .05$.

Berger, J.-L., & Karabenick, S. A. (2011). Motivation and students' use of learning strategies: Evidence of unidirectional influences in mathematics classrooms. *Learning and Instruction, 21*, 416–428.