

Searching for Short-Term Motivational Alignment and Spillover Effects:
A Random Intercept Cross-Lagged Analysis of Students' Expectancies and Task Values in
Math-Intensive Study Programs

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Abstract

Students' expectancy and value beliefs about math influence their academic choices and success in math-intensive study programs. Short-term declines in these motivational beliefs can serve as early warning signs of academic difficulties and dropout. However, such short-term motivational changes are underresearched. Based on Eccles et al.'s (2020) situated expectancy-value theory, this study analyzed *within-person* changes in the associations among students' course-specific (summative) or week-specific (situated) expectancies and task values in gateway math courses for students in physics, math, or math teacher education majors ($N = 773$). Random intercept cross-lagged panel models showed increasing within-person alignment between students' course-specific expected success and intrinsic/utility values (but not costs) over one semester. This alignment was linked to unidirectional spillover (i.e., cross-lagged) effects from expectancy to intrinsic/utility values. Students' week-specific expectancy-value beliefs, reported at the beginning of the semester, showed no significant alignment and spillover effects. Differences in students' course- or week-specific expectancy-value beliefs favored male and higher-achieving students and were largely time-invariant. Alignment between course-specific expectancy and value beliefs was higher for students who failed or dropped out of their math courses compared to those who succeeded. Greater motivational alignment can thus indicate greater disengagement from (math) coursework in challenging academic contexts. These findings highlight the importance of differentiating between-person and within-person motivational processes, suggest that summative versus situation-specific assessments of motivational beliefs may show different developmental patterns, and demonstrate that motivational alignment and spillover effects can be a sign of maladaptive motivational processes concerning students' persistence in challenging STEM contexts.

Keywords: situated expectancy-value theory, situation-specific assessments, summative assessments, random intercept cross-lagged panel model, motivation, STEM

Searching for Short-Term Motivational Alignment and Spillover Effects: A Random Intercept Cross-Lagged Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs

Eccles and colleagues' situated expectancy-value theory (SEVT; Eccles et al., 1983; Eccles & Wigfield, 2020) is one of the most prominent theoretical frameworks used to explain students' achievement-related choices and behaviors, such as their educational and career decisions. According to SEVT, students engage in tasks or domains in which they expect to succeed (i.e., high subjective expectancy) and that have a high value to them (i.e., high subjective task values). Students' expectancies and task values are powerful predictors of their career aspirations, academic achievement, persistence, retention, and career attainment in academic fields such as science, technology, engineering, and mathematics (STEM; e.g., Lauermann et al., 2017; Nagengast et al., 2011; Perez et al., 2014; Robinson et al., 2019). Declines in students' expectancy-value beliefs over short periods, such as a semester in college (Benden & Lauermann, 2022; Zusho et al., 2003), or long periods, such as multiple years (Gaspard et al., 2020; Jacobs et al., 2002), are a precursor to academic difficulties such as low achievement, dropout, and disengagement from school, college, or STEM in general.

It is therefore important to understand *how* students' expectancy-value beliefs develop and potentially influence each other over time, in particular in challenging STEM contexts. According to SEVT, two key developmental processes are likely to shape students' expectancy-value beliefs and academic choices: motivational alignment processes and cross-lagged effects, also known as "spill-over" effects (Mulder & Hamaker, 2021, p. 640). Eccles and colleagues proposed that students' expectancy-value beliefs are positively linked, that the emergence of this positive expectancy-value association is an important developmental process, and that these motivational beliefs should become increasingly well-aligned as students specialize in selected academic fields and disengage from others (Eccles, 2009; Wigfield & Eccles, 1992; Wigfield et al., 1997). Furthermore, the authors proposed that high

levels of expectancy-value beliefs that are well aligned should be linked to sustained engagement, positive learning experiences, long-term educational choices, and well-being (Eccles, 2009; Wigfield & Eccles, 1992; see also Harter, 1990). Increased alignment of students' expectancy-value beliefs may result from their cross-lagged associations (e.g., Marsh, Trautwein, et al., 2005). If students' expectancy and value beliefs influence each other over time, increases or declines in one type of belief (e.g., expectancy) should trigger corresponding increases or declines in the other (e.g., task values), resulting in an increasing alignment between them as students adjust to new educational contexts and tasks.

However, research on these motivational alignment processes and cross-lagged associations is limited in several ways. First, few studies have analyzed such expectancy-value alignment processes empirically (Denissen et al., 2007; Wigfield et al., 1997), and none have focused on higher education contexts after students have selected an academic domain in which to specialize (e.g., STEM). Thus, it is unknown if motivational alignment processes, as conceptualized by Eccles and colleagues (Eccles, 2009; Wigfield & Eccles, 1992), may play a role in students' engagement or disengagement from STEM fields, which often have high dropout rates (Chen, 2013; Heublein et al., 2022). Second, most studies to date have examined the longitudinal relations between students' expectancy-value beliefs over many years, typically using annual measurement points and rather general and stable, albeit subject-specific, motivational assessments (e.g., Arens et al., 2019; Denissen et al., 2007; Marsh, Trautwein, et al., 2005; Wigfield et al., 1997). Yet, important developmental processes often unfold over shorter periods and may thus be overlooked. For instance, postsecondary students' expectancy-value beliefs can decline dramatically over just one semester, which is a precursor to later academic difficulties and dropout intentions (Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017). Third, previous studies have failed to distinguish *between-* and *within-person* variability in students' expectancy-value beliefs over time (e.g., Arens et al., 2019; Marsh, Trautwein, et al., 2005), which can result in severely

biased estimates of cross-lagged associations (Berry & Willoughby, 2017; Hamaker et al., 2015). Finally, although many studies have examined interindividual differences in students' domain-specific motivational beliefs (e.g., for gender or prior achievement), less is known about analogous differences in situation-specific expectancies and task values (e.g., whether gender differences vary across situations or are relatively time-invariant; Eccles & Wigfield, 2020).

Accordingly, the present study had four main objectives. First, we examined the degree of within-person alignment of students' expectancy-value beliefs at different time points during their first semester in math-intensive study programs and whether it changes over time. Second, we examined so-called "spill-over" effects (Mulder & Hamaker, 2021, p. 640) between different expectancy-value constructs (i.e., within-person cross-lagged associations) as potential drivers of motivational alignment processes. We used a random intercept cross-lagged panel approach to separate within-person motivational changes over time from relatively stable between-person differences (Hamaker et al., 2015). We focused on three different time points spanning the entire semester (beginning, midpoint, and end-of-term) using *course-specific and summative expectancy-value assessments* that asked students to evaluate their experiences in their math course up until that point. In addition, over three consecutive weeks at the beginning of the semester, we used *weekly and situation-specific expectancy-value assessments* to capture students' situated beliefs about the content taught each week. We focused on consecutive weeks at the beginning of the semester because this is often a sensitive period of adaptation (Coertjens et al., 2017; Gale & Parker, 2014). This study design allowed us to examine the development of motivational alignment and spillover effects using different types of motivational assessments (i.e., course-specific/summative across the entire semester vs. week-specific/situated across the first weeks of the semester). Third, we examined group differences in students' summative or situated expectancy-value beliefs (i.e., mean-level differences and differences in the degree of within-person alignment) for students'

gender and prior achievement. Finally, fourth, we examined whether the degree of expectancy-value alignment is linked to students' academic success in gateway math courses for STEM majors (course dropout and pass/fail rates).

Students' Situated Expectancy and Task Value Beliefs and Their Short-Term Development

Eccles and colleagues' (Eccles et al., 1983; Eccles & Wigfield, 2020) SEVT posits that students' domain- and task-specific expectancy of success and their subjective task values are proximal predictors of their achievement-related choices and behaviors, such as effort and persistence in STEM. Students' expectancy reflects their subjective probability of success on a given task or domain (e.g., solving a math worksheet, succeeding in a math course, or generally succeeding in the math domain; Eccles et al., 1983; Eccles & Wigfield, 2020). Students' subjective task values reflect possible reasons for engaging in a given task or domain, as well as the perceived relative cost, which refers to what the individual has to give up or suffer if they were to engage in the task or domain (Eccles et al., 1983; Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Important task value components include, for instance, students' interest in or enjoyment of the task or domain at hand (*intrinsic value*), as well as its perceived usefulness for current or future goals (*utility value*). In addition, several cost components have been proposed in the literature (Eccles et al., 1983; Flake et al., 2015; Perez et al., 2014; Wigfield et al., 2017). The most frequently studied cost components are the perceived amount of effort required to be successful (*effort cost*) and the anticipated or experienced stress and negative emotions in achievement situations (*psychological cost*).

Recently, Eccles and Wigfield (2020) renamed their theory as *situated* expectancy-value theory and thus underscored the importance of studying not only developmental but also situational influences shaping students' expectancies and subjective task values. Such influences are comparatively underresearched, even though the number of studies using (a) short-term repeated-measures designs and (b) situation-specific motivational assessments is

growing. This research shows that the developmental trajectories of students' generalized versus situation-specific motivational beliefs can differ. Research focusing on domain-specific but relatively general expectancies and task values (e.g., "How much do you like math?"; Eccles & Wigfield, 1995) suggests that adolescents' expectancy-value beliefs are quite stable, both over long (e.g., years; Rieger et al., 2017) and short periods (e.g., weeks or months; Spinath & Steinmayr, 2008). Studies using situation-specific assessments (e.g., "I like these contents"; Dietrich et al., 2017) reveal substantial variability in these beliefs across different lessons and topics (Dietrich et al., 2017; Tanaka & Murayama, 2014). Furthermore, as noted previously, not only long-term but also short-term changes in students' (situated) motivational beliefs can predict important educational outcomes and therefore warrant attention. For instance, several studies identified significant declines in students' expectancy-value beliefs shortly after the transition to higher education, which predicted later academic difficulties such as poor achievement, low study program satisfaction, and dropout tendencies in college (Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017).

Motivational alignment and spillover effects are two important developmental processes that likely shape students' (situated) expectancy-value beliefs. We discuss these processes in the following sections.

Within-Person Alignment Between Students' Competence-Related Beliefs and Subjective Task Values

A key assumption in SEVT is that students' expectancies for success and subjective task values are positively related—students value tasks and domains for which they have high expectancies for success and vice versa (Eccles et al., 1983; Eccles & Wigfield, 2020). Eccles and Wigfield proposed that the emergence of this positive association is an important developmental process in elementary school (Eccles, 2009; Wigfield & Eccles, 1992; Wigfield et al., 1997). Elementary-school students tend to be optimistic about their abilities across various domains, but their competence-related beliefs become more realistic and their

valuing of different academic domains more differentiated over time, as students' experience successes and failures in different fields (Eccles, 2009; Wan et al., 2021; Wigfield & Cambria, 2010). Moreover, students' expectancy and task value beliefs become better aligned within a given domain over the school years, as they specialize in some domains and lose interest in others (Denissen et al., 2007; Fredricks & Eccles, 2002; Wigfield et al., 1997).

For instance, Denissen et al. (2007) observed an increase in the within-person alignment of students' domain-specific self-concepts of ability and their interests in math, science, and English across Grades 1 through 12, which is a likely sign of specialization (Denissen et al., 2007; Eccles, 2009). The authors proposed that students may align their expectancy and value beliefs at a high level in domains in which they have done well, and at a lower level in domains in which they have done comparatively worse. Motivational beliefs that are well-aligned at a high level should foster sustained engagement, well-developed interest, and well-being (Eccles, 2009; Harter, 1990; Hidi & Renninger, 2006; Wigfield & Eccles, 1992). Motivational alignment at a low level should lead to disengagement from relevant tasks and domains (Eccles, 2009; Wigfield & Eccles, 1992).

However, these theorized links between students' motivational alignment and their academic success have not been systematically studied, and there has been no examination of such motivational alignment processes in demanding postsecondary contexts, after students have specialized in a chosen field of study. Higher education contexts, especially in STEM fields, are of interest because STEM students often experience motivational declines, academic difficulties, and high dropout rates (Chen, 2013; Heublein et al., 2022; Seymour & Hewitt, 1997). Students in STEM fields need to adapt to the high demands and workload of their study programs, to the nature of math as a scientific discipline, and to an academic environment with many high-achieving peers (Gueudet, 2008; Seymour & Hewitt, 1997). Research further suggests that many students have unrealistic expectations about the content and workload in STEM fields, which necessitates an adjustment period (e.g., Gueudet, 2008).

A motivational (re)alignment process may thus occur, as students adapt to the high demands in their new educational context or disengage and drop out.

Within-Person Cross-Lagged Links Among Students' Expectancy and Task Value Beliefs

As noted previously, the cross-lagged associations between students' expectancy for success and their task value beliefs are one mechanism through which motivational alignment processes may occur. Eccles and colleagues do not preclude the possibility that these cross-lagged associations are unidirectional but noted that bidirectional links are also possible (Eccles, 2005, 2009; Wigfield et al., 1997). Students likely come to value tasks and domains in which they have done well because the experience of competence is intrinsically rewarding. In addition, students tend to devalue tasks and domains in which they have a low expectancy of success as a means to protect their self-worth in case of failure (Eccles, 2009; Harter, 1990; Wigfield & Eccles, 2020). Reverse associations from values to expectancy are also possible because students' valuing of a given task or domain increases the likelihood of task engagement, which in turn supports students' skill improvement, task mastery, and thus expectancies of future success (Eccles, 2005, 2009). Cross-lagged expectancy-value associations have garnered attention from education researchers as a way to determine which motivational constructs have the greatest potential to alter other motivational beliefs and should thus be targeted in interventions designed to prevent declines in academic motivation (Marsh, Trautwein, et al., 2005; Rosenzweig et al., 2022).

Importantly, more than 15 years ago Eccles (2005) pointed out that analyses of the cross-lagged links between students' expectancy and task values must carefully consider (a) which time lags and (b) which types of assessments are best suited to capture such links (see also Dormann & Griffin, 2015). Eccles (2005) proposed that the optimal time lag likely depends on the underlying developmental processes of the respective constructs. Some processes may unfold over many years (e.g., a long-term motivational decline across school years; Gaspard et al., 2020), others over a short period (e.g., short-term motivational declines

after the transition to higher education; Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017). However, most of the available evidence has focused on long-term cross-lagged associations using annual assessments (e.g., Arens et al., 2019; Lee & Seo, 2021; Viljaranta et al., 2014). With some exceptions (e.g., Lee & Seo, 2021; Marsh, Trautwein, et al., 2005; Pinxten et al., 2014), these studies point to significant cross-lagged effects of students' expectancy (or other competence-related beliefs) on their subjective task values but do not support reciprocal links (Arens et al., 2019; Du et al., 2021; Lauermann et al., 2017; Lent et al., 2008; Sewasew et al., 2018; Viljaranta et al., 2014). Thus, changes in students' expectancy beliefs, rather than values, could be a key mechanism driving motivational alignment processes.

Only a few studies have examined cross-lagged associations over shorter periods (Beymer et al., 2022; Moeller et al., 2022; Perez et al., 2019; Spinath & Steinmayr, 2008). These studies show mixed results, potentially due to different time lags between measurement points (ranging from 30 minutes to three months) and different types of motivational assessments (e.g., situation-/task-specific, Beymer et al., 2022; Moeller et al., 2022; vs. course-/domain-specific, Perez et al., 2019; Spinath & Steinmayr, 2008). For instance, Spinath and Steinmayr (2008) found little evidence of cross-lagged associations between students' competence beliefs and intrinsic motivation in math, German, and school in general across four time points about three months apart. However, they used relatively general motivational assessments that may not have been sufficiently sensitive to context-specific motivational changes (e.g., "How good are you at math?"; autoregressive coefficients up to .87). By comparison, Perez et al. (2019) used context-specific expectancy-value measures with a similar time lag of about three months (e.g., "How well do you think you will do in this biology course this semester?") and found significant cross-lagged effects of students' expectancy beliefs on their intrinsic and attainment values. Therefore, analyses of cross-lagged associations between students' motivational beliefs should consider not only the

appropriate time lag between measurement points but also the appropriate level of specificity of their measures (Eccles, 2005).

In postsecondary settings, either domain-specific or course-specific assessments have been used to examine motivational changes and cross-lagged associations (e.g., "I expect to do well in this class"; Kosovich et al., 2017). We believe that most of these assessments can be described as *summative* because students are likely to aggregate their self-evaluations across multiple situations and tasks to rate their motivational beliefs in a given "class" or "domain" (e.g., for self-concept measures, see Marsh et al., 2019). In contrast, situation-specific items explicitly reference a particular task and situation, such as a specific lesson (e.g., "I understand these contents."; Moeller et al., 2022). Situation-specific measures are sensitive to contextual influences in a given situation but may not represent students' overall experiences (e.g., lack of interest in one particular topic rather than the entire course). Summative measures represent overall experiences by asking students to aggregate information across situations (e.g., level of interest across topics covered in the course) but may miss significant events, such as students' reactions to particularly challenging tasks. A recent experience sampling study found no moment-to-moment cross-lagged associations using situation-specific expectancy-value measures (Moeller et al., 2022) but it is unclear if this is due to the specific context, measures, or time lags (see discussion in Eccles, 2022). No study to date has examined within-person motivational alignment processes or cross-lagged links using both summative and situation-specific assessments of students' expectancy-value beliefs in the same sample.

Interindividual Differences in Students' Expectancy-Value Beliefs: The Role of Gender and Prior Achievement, and Links to Academic Success

A substantial amount of research based on SEVT has examined interindividual differences in students' expectancies and subjective task values, including the effects of students' gender and prior achievement (e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015;

Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015; Perez et al., 2014; Robinson et al., 2019; Watt, 2004). However, much of this research has focused on students' relatively general expectancy (or competence-related) beliefs and valuing of academic domains such as math or science. For the math domain, this research suggests that gender differences in students' expectancy-value beliefs—when such differences exist—tend to favor male over female students (e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015; Guo, Marsh, et al., 2015; Watt, 2004). For both genders, students' prior achievement has emerged as a consistent positive predictor of students' expectancy-value beliefs (e.g., Guo, Parker, et al., 2015; Perez et al., 2014; Robinson et al., 2019).

However, comparatively less is known about interindividual differences in students' situation-specific motivations (see also Eccles & Wigfield, 2020). On the one hand, male and high-achieving students may be comparatively better equipped to handle situational challenges successfully so that similar results should emerge for domain-specific and situation- or task-specific motivational assessments. On the other hand, evidence suggests that situation-specific (state-like) and generalized (trait-like) assessments of psychological constructs such as human emotions (Robinson & Clore, 2002), and possibly motivations, can elicit different cognitive processes and thus reveal different group effects. For instance, Goetz et al. (2013) found that situation-specific measures of high school students' math anxiety (i.e., the anxiety experienced in a specific situation in math class) revealed smaller gender differences compared to a more global assessment of math anxiety. Similarly, Tsai and colleagues (Tsai, Kunter, Lüdtke, & Trautwein, 2008; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008) found no gender differences in students' perceived competence and interest in math using lesson-specific measures, whereas more general assessments of these constructs in similar samples typically reveal mean level differences favoring male over female students (e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015; Guo, Marsh, et al., 2015).

These measurement-specific effects have been attributed to different cognitive processes. State-like measures capture an individual's momentary experiences, such as anxiety, whereas trait-like measures also capture more general beliefs and attitudes, such as stereotypes (e.g., female students being viewed as more emotional than male students; Goetz et al., 2013; Robinson & Clore, 2002; see also Eccles et al., 1983 and Frieze et al., 1978). Accordingly, group-specific differences in students' motivational beliefs, for instance, by gender, might depend on the type of motivational assessment used and whether this assessment is situation-specific or generalized across different situations.

Finally, several studies examined the links between students' expectancy-value beliefs and their academic achievement and educational choices in STEM fields (e.g., Lauermann et al., 2017; Perez et al., 2014; Robinson et al., 2019). These studies show that interindividual differences in students' math- or science-related expectancy-value beliefs contribute to interindividual differences in students' educational choices and behaviors in STEM. Students who report higher expectancies and values and lower costs are comparatively more likely to enter STEM programs in higher education, achieve better grades, and are less likely to drop out of their STEM programs (e.g., Fleischer et al., 2019; Perez et al., 2014; Perez et al., 2019; Robinson et al., 2019). These studies further show that students' expectancies for success are generally the strongest motivational predictor of students' academic achievement, whereas students' subjective task values are more predictive of their persistence or dropout intentions in STEM fields. However, no study to date has examined the links between students' motivational alignment and their (dis)engagement in STEM fields.

The Present Study

Drawing on SEVT (Eccles & Wigfield, 2020), we specified random intercept cross-lagged panel models to examine the level of alignment and cross-lagged links between students' expectancy-value beliefs in gateway math courses at the beginning of higher education in math-intensive study programs. We used two types of assessments spanning

different time frames. First, similar to prior research (Kosovich et al., 2017; Perez et al., 2019), course-specific, summative assessments of students' expectancy of success and task values at the beginning, midpoint, and end of the semester captured students' experiences in the course up until that point. This time lag is typically sufficient to capture motivational changes (e.g., Kosovich et al., 2017; Zusho et al., 2003) and allows for an adaptation period at the beginning of the semester. Second, week- and situation-specific assessments during three consecutive weeks at the beginning of the semester measured students' expectancy-value beliefs about the content taught that particular week, which was assessed on mandatory math worksheets. We focused on the beginning of the semester because it is a sensitive period of adaptation after the transition to higher education (Coertjens et al., 2017; Gale & Parker, 2014; Kosovich et al., 2017; Zusho et al., 2003). These situation-specific motivational assessments focused on consecutive weeks to capture potential motivational alignment and spillover effects from one class (i.e., "situation") to the next.

The following research questions guided our analyses: First, *does the within-person alignment of students' expectancy-value beliefs increase over time for different types of assessments and at different time points during the semester?* Based on Eccles and colleagues' (Eccles, 2009; Wigfield & Eccles, 1992) theoretical assumptions and the few prior studies in the school context (Denissen et al., 2007; Wigfield et al., 1997), we expected to find an increasing alignment of students' course-specific, summative expectancy-value beliefs. We did not formulate specific predictions about the alignment of students' week-specific, situated expectancies and task values because it is unclear to what extent these experiences may be contained within a given situation or become increasingly consistent from week to week due to students' cumulative experiences. In both cases, we controlled for stable between-person differences in our analyses of within-person associations.

Second, *are there significant within-person cross-lagged associations between students' expectancy-value beliefs over time (i.e., so-called motivational spillover effects)?*

These cross-lagged associations were examined for students' course-specific/summative and week-specific/situated expectancy-value beliefs and controlled for stable between-person differences. Consistent with prior research and predictions by Eccles and colleagues (Eccles, 2005, 2009; Moeller et al., 2022; Perez et al., 2019; Sewasew et al., 2018), we expected to find some evidence for students' expectancy beliefs as driving force behind changes in their subjective task values. However, we did not pose specific hypotheses about cross-lagged associations due to the scarcity of prior research on short-term motivational changes, and because no study to date has used a RI-CLPM that controls for stable between-person differences in analyses of within-person motivational spillover effects.

Third, *are there significant interindividual differences in students' expectancy-value beliefs and their degree of alignment depending on students' gender and prior achievement, and are these differences consistent across different types of assessments and time points?*¹ If motivational differences exist, we expected them to favor male and high-achieving students. In a set of exploratory analyses, we examined whether the predictive effects of students' gender and prior achievement on their motivational experiences were invariant across time, as well as group differences in the degree of motivational alignment within a given time point.

Fourth, *are there significant interindividual differences in the degree of alignment of students' expectancy-value beliefs between students who were successful versus unsuccessful in their math course (i.e., course dropout vs. retention and final exam passed vs. failed)?*

These analyses were exploratory because motivational alignment processes have only been studied in the school context (Denissen et al., 2007; Fredricks & Eccles, 2002; Wigfield et al., 1997). An increasing alignment of students' competence-related beliefs and valuing of academic domains has been interpreted as a specialization process as students mature

¹ We also examined potential interindividual differences depending on students' socioeconomic status and their participation in math preparatory courses before enrollment. We found no significant differences between these groups, with one exception: Students with high compared to low socioeconomic status perceived the content of their math worksheets as more useful in Weeks 3 to 5 of the semester (i.e., higher levels of utility value at T1w–T3w, $\beta_s = .08/.09$, $p_s = .016$). These variables are not discussed further for the sake of brevity.

(Denissen et al., 2007; Eccles, 2009) but it is unclear how these alignment processes operate once students have specialized in a given domain.

In a previous study using the same data [masked for blind review], we found significant declines in first-semester students' expectancy-value beliefs in challenging gateway math courses in STEM fields. Controlling for differences in students' prior achievement, socioeconomic status, and gender, students who experienced greater motivational declines, particularly at the beginning of the semester, had lower end-of-term exam performance, lower study program satisfaction, and a higher likelihood of course dropout. Thus, motivational declines can be an important warning sign of later academic difficulties, but we know little about the within-person developmental processes that may contribute to such changes over time. The present study expands upon these findings by conducting theory-driven analyses of within-person motivational alignment and spillover effects among different facets of students' math-related expectancy-value beliefs shortly after the transition to higher education. These alignment processes have been proposed in SEVT (Eccles, 2009; Wigfield et al., 1997) but have not yet been empirically tested on the within-person level, controlling for stable, between-person motivational differences.

Method

Participants and Procedure

The sample of the study included five cohorts of students enrolled in demanding math courses for beginning students in their respective study programs at a German university ($N = 773$, 36% female). The students were enrolled in physics ($n = 366$; two cohorts), math ($n = 214$; one cohort), or math teacher education study programs ($n = 193$; two cohorts). As is typical in Germany, students in this study had declared their major before enrollment and were admitted only for this major. The data were collected in the winter terms of 2017 and 2018. Most students were in the first year of their respective study program (90%), were born in Germany (92%), and had at least one parent with a university degree (60%). The majority

of all students had a high socioeconomic status (i.e., at least one parent with a university degree; 60%) and had participated in math preparatory courses before enrollment (63%).

The students completed paper-and-pencil questionnaires in math lectures that were required for their respective study programs and functioned as gateway math courses. There were six data collections during the semester. Three data collections were scheduled at the beginning (Week 2, T1c), midpoint (Week 8, T2c), and end of the semester (Week 15, T3c) and focused on students' motivational beliefs about their math course.² Three additional data collections in Weeks 3 to 5 of the semester (T1w–T3w) focused on students' week-specific experiences with their current coursework. The students were required to submit weekly math worksheets to qualify for their final exam. Solutions to the worksheets were discussed in separate tutoring sections but new content was covered solely in the lectures. All data collections took place during the lecture in which students had to submit their weekly worksheets. Nearly all students who were present in the lecture participated in the study (98%–100% at each time point).

Measures

The students answered questions about their expectancy-value beliefs at each of the six data collections during the semester (i.e., expectancy of success, intrinsic and utility values, and psychological and effort costs, see **Figure 1**).

Course-Specific Expectancies and Task Values (Summative Judgments)

Students' course-specific, summative expectancy-value beliefs were assessed at the beginning (T1c), midpoint (T2c), and end of the semester (T3c). All items are reported in the online supplemental materials (Supplement S1). Students' summative *expectancy beliefs* were assessed with three items adapted from Eccles and Wigfield (1995) and Tanaka and Murayama (2014), for instance: “Based on my experiences in this class so far, I think I will do

² Lectures in Week 1 were mostly used for organizational purposes. The students received their first mandatory worksheet in Week 2 and their first feedback regarding the solutions in Week 3.

well on the exam” ($\alpha = .90$ to $.92$ across time points). Subjective task values were assessed using scales adapted from Gaspard, Dicke, Flunger, Schreier, et al. (2015). Two-item scales were used for students’ *intrinsic value* (e.g., “Doing the coursework and the assignments for this class is something I enjoy,” $\alpha = .79$ to $.85$), *utility value* (e.g., “Doing the coursework and the assignments for this class is useful for my future,” $\alpha = .66$ to $.76$), *psychological cost* (e.g., “Doing the coursework and the assignments for this class is stressful for me,” $\alpha = .80$ to $.83$), and *effort cost* (e.g., “Doing the coursework and the assignments for this class drains a lot of my energy,” $\alpha = .88$ to $.91$). All items were assessed on a 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. Note that the items referenced students’ overall experiences in the course and did not refer to a specific situation or content.

Week-Specific Expectancies and Task Values (Situated Judgments)

Week-specific motivational assessments were used in Weeks 3 to 5 of the semester (T1w–T3w). These assessments referenced students’ experiences with the content that was covered each week and that was assessed on their mandatory weekly worksheets. Single items were used to reduce survey fatigue due to repeated exposure to the same items. The items were preceded by the statement: “Think about the current worksheet you turned in this week.” As noted previously, the students had to turn in their worksheets in the same lecture in which the data were collected. Students’ expectancy was measured with the item “If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?” (1 = *very poorly* to 6 = *very well*). Intrinsic and utility values and perceived psychological and effort costs were assessed with the following items: “Doing this week’s assignments is something I enjoyed/...was generally useful/...was stressful for me/...drained a lot of my energy.” (1 = *completely disagree* to 6 = *completely agree*).

Students’ Academic Success

Students’ nonattendance at the end of the semester was recorded by a research assistant and used as an indicator of course dropout (43% course dropout). Students provided

written consent at T2c or T3c to obtain their course performance from the instructor (i.e., whether they passed vs. failed their math course). In total, 82% of the students who were present at these data collections gave consent. In all courses, students had to pass the final exam to pass their math course, and students who failed their first attempt could participate in a second exam a few weeks later. Overall, 67% of the students who gave consent to access their performance data passed their math course (59% passed the first exam, 8% the second).

Students' Personal Characteristics

The students reported their gender (36% female; 0 = *male*, 1 = *female*) and high school grade point average (GPA) in the first data collection. In Germany, lower scores indicate higher achievement. We recoded students' high school GPA so that higher scores indicate higher achievement to facilitate the interpretation ($M = 3.1$, $SD = 0.65$, range from 1 = *sufficient* to 4 = *very good*).

Statistical Analyses

We examined bivariate correlations and missing data patterns in a set of preliminary analyses. Confirmatory factor analyses (CFA) tested the assumption of measurement invariance across time points and study programs for all multi-item scales (i.e., for students' course-specific expectancy and task value beliefs). We specified random intercept cross-lagged panel models to test our main research questions (RI-CLPM; Hamaker et al., 2015; Mulder & Hamaker, 2021; **Figure 2**), using Mplus 8.6. The RI-CLPM, introduced by Hamaker et al. (2015), expands upon the traditional cross-lagged panel model (CLPM) by including random intercepts that capture trait-like between-person differences across the observation period (e.g., students' average levels of expectancy and task values across all time points) and estimating within-person deviations from an individual's personal baseline at each time point (e.g., a student may report generally high expected success over time, but a lower-than-usual expectancy in a given week). This model thus differentiates between- and within-person associations for all constructs of interest. The RI-CLPM is therefore better suited than

the CLPM for research questions concerning within-person developmental processes, such as motivational alignment and spillover effects.

In this study, the RI-CLPMs estimated (a) relatively stable and thus “trait-like” between-person associations of students’ expectancies and task values, which are captured by the random intercepts (e.g., Do students who on average have higher expectancies than their peers also have higher task values?), (b) “state-like” within-person associations within a given time point (e.g., Are higher-than-usual levels of expectancy for a given individual related to higher-than-usual levels of task value within a given time point for the same individual?), and (c) within-person autoregressive (i.e., carryover) and cross-lagged (i.e., spillover) effects over time (e.g., Are higher-than-usual levels of expectancy at one time point linked to higher-than-usual levels of task values at the next time point for the same individual?).

We tested four RI-CLPMs including students’ expectancy in combination with intrinsic value, utility value, psychological cost, or effort cost, respectively. One set of RI-CLPMs focused on students’ course-specific, summative expectancy and task values across the entire semester (T1c–T3c). The second set of RI-CLPMs focused on students’ week-specific expectancy-value beliefs (T1w–T3w). Dummy variables representing the different math courses were included as predictors of students’ motivational beliefs to control for mean-level differences between these courses (Mulder & Hamaker, 2021). The same instructor taught both courses in the physics program so only one dummy variable was included in this case. Students’ gender and high school GPA were included in the final models to test possible group-specific differences.

For our first research question regarding within-person motivational alignment over time, we specified a correlational model within the RI-CLPM framework. That is, we modeled bivariate associations instead of autoregressive and cross-lagged associations between students’ expectancy and task values. This allowed us to examine whether the within-person correlations increased over time (i.e., the degree of motivational alignment). To

address our second research question regarding motivational spillover effects, we examined within-person cross-lagged effects between students' expectancy and value beliefs with a set of RI-CLPMs and using either course- or week-specific assessments (**Figure 2**).

For our third research question regarding interindividual differences, we included students' gender and prior achievement as predictors of students' motivational beliefs in the RI-CLPMs (Mulder & Hamaker, 2021). There are two possibilities for these analyses. One can test group differences either for students' random intercepts or students' motivational beliefs at each time point. We chose the second option because it allowed us to test whether these interindividual differences are time-invariant. Time invariance would suggest that mean-level differences in students' expectancy-value beliefs are constant over time and thus "trait-like" (Mulder & Hamaker, 2021). Multigroup models in the RI-CLPM framework (Mulder & Hamaker, 2021) tested interindividual differences in the degree of alignment of students' expectancy-value beliefs across gender and prior achievement. For prior achievement, we split the sample into high-achieving (GPA greater than 3.3, which is the cut-off for "very good" grades in Germany) and low-achieving students (GPA smaller or equal to 3.3, corresponding to "sufficient" to "good" grades). This split resulted in two groups of roughly equal size (43% of the students had "very good" grades).

Finally, for our fourth research question, we specified multigroup multilevel models to examine within-person correlations (Bland & Altman, 1995) between students' expectancy and task values (i.e., the degree of alignment) separately for students who dropped out of their math course versus persisted until the end of the semester and those who passed versus failed their final exam. These analyses allowed us to examine whether the degree of alignment of students' expectancy-value beliefs differed between successful and unsuccessful students.³

³ We were unable to test multigroup RI-CLPMs for this research question because students who dropped out did not have data at the end of the semester, and thus RI-CLPMs could not be estimated for this subgroup of students. As noted in the Results section, we report RI-CLPMs for students who passed vs. failed their course in supplemental materials.

Full information maximum likelihood estimation (FIML) was used to account for missing data. Multiple indicator RI-CLPMs (Mulder & Hamaker, 2021) were modeled for students' course-specific, summative expectancy-value beliefs. Students' motivational beliefs were modeled as latent constructs, which were then decomposed into a time-invariant between-person part and time-specific within-person factors. Analogous models were tested for students' week-specific, situated motivational beliefs, but these analyses relied on single-item scales for each week. Across all models, we used maximum likelihood estimation with robust standard errors (MLR) and evaluated model fit based on the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Good model fit is generally indicated by a CFI value of .95 or higher and RMSEA and SRMR values of .06 or lower (Marsh, Hau, et al., 2005). For model comparisons, a CFI difference between two models of less than .01 and an RMSEA difference of less than .015 generally indicate a negligible change in overall model fit and support the more parsimonious model (Chen, 2007; Cheung & Rensvold, 2002). We compared nested models using Satorra-Bentler scaling-corrected chi-square difference tests, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC).

Results

Preliminary Analyses

Descriptive statistics and bivariate correlations are shown in **Table 1** for all variables and time points. All correlations were consistent with our expectations, confirming positive associations among expectancy, intrinsic value, and utility value, and negative associations among expectancy and psychological and effort costs, as well as among intrinsic and utility values and perceived costs. The only exception was a nonsignificant correlation between utility value and effort cost.

Mean values of students' expectancies and task values (**Table 1**) suggest that the students experienced a motivational decline in the first half of the semester and perceived

relatively high levels of psychological and effort costs. This pattern likely results from the high workload students were expecting and experiencing in their respective math courses.

Table 1 further shows the number of students with available data for each variable and time point. Missing data were generally due to course dropout, as almost all students who were present in a given week to turn in their mandatory worksheets participated in our surveys. The course dropout rate of 43% by the end of the semester is comparable to prior research in demanding math courses (36% in Geisler, 2021; 38% in Rach & Heinze, 2017). Missing data were linked to lower socioeconomic status ($r = -.10, p = .011$), lower high school GPA ($r = -.35, p < .001$), and a lower likelihood of participation in preparatory math courses before enrollment ($r = -.23, p < .001$). These student characteristics were included as auxiliary variables or as covariates in all analyses (Graham, 2003; Schafer & Graham, 2002). Importantly, our findings concerning motivational alignment and cross-lagged effects were consistent when we limited our analyses to students who did not drop out.

For students' course-specific motivational beliefs, multigroup CFAs including expectancy and the four task value facets confirmed the same factor structure across the different study programs (i.e., physics, math, and math teacher education) at the beginning, midpoint, and end of the semester (T1c, T2c, and T3c). The CFA supported strong measurement invariance, which is a prerequisite for our subsequent analyses (Mulder & Hamaker, 2021). We specified correlated residuals between repeated assessments of the same indicator at different time points to account for indicator-specific covariances (Little, 2013). The invariance analyses are reported in the online supplemental materials (Supplement S2).

Within-Person Alignment of Students' Course-Specific and Week-Specific Expectancies and Task Values Over Time

To answer our first research question about motivational alignment, we decomposed the observed scores into between- and within-person factors using the RI-CLPM framework but specified bivariate associations instead of autoregressive and cross-lagged effects for all

within-person factors. The resulting within-person correlations between students' expectancy and the different task value facets are reported in **Table 2**. As expected, the correlation between students' course-specific expectancy and their intrinsic and utility values increased significantly from the beginning to the midpoint of the semester (T1c: $r_s = .18/.13$, T2c: $r_s = .71/.42$, $p_s < .001$) suggesting an increased alignment of these motivational beliefs. This alignment remained at a moderate-to-high level towards the end of the semester (T3c: $r_s = .69/.47$, $p_s \geq .288$). In contrast, the analogous correlations between students' expectancy and psychological and effort costs were somewhat weaker and not statistically different across the three time points (T1c: $r_s = -.26/-.12$, T2c: $r_s = -.43/-.25$, T3c: $r_s = -.38/-.24$; $p_s \geq .063$). Thus, the alignment of students' positively valenced motivational beliefs increased towards the midpoint of the semester and then stabilized at a moderate-to-high level, whereas no significant increase occurred in the alignment of students' expectancy and perceived costs.

Analogous analyses were conducted for students' week-specific, situated motivational beliefs. However, we found no statistically significant differences in the correlations between students' week-specific expectancy beliefs and their intrinsic and utility values ($p_s \geq .184$; **Table 2**). The estimated coefficients were generally lower than those for summative assessments. The correlations between students' week-specific expectancy and their psychological and effort costs were greater at T2w compared to the remaining two time points (T2w: $r_s = -.49/-.36$, T1w: $r_s = -.24/-.18$, T3w: $r_s = -.26/-.18$; $p_s < .027$). Overall, in contrast to our findings for summative assessments, we found no evidence of an increasing alignment of students' week-specific expectancy-value beliefs during the first weeks of the semester (Weeks 3–5).

Associations of Students' Expectancies and Task Values and Within-Person Motivational Spillover Effects

To address our second research question regarding motivational spillover effects, we specified RI-CLPMs for students' expectancies and the different task value facets. Controlling

for stable between-person motivational differences, we tested whether there are significant within-person autoregressive and cross-lagged effects and whether these effects were invariant over time. We report the results separately for students' course- and week-specific motivational beliefs.

Course-Specific Expectancies and Task Values Across the Entire Semester

The RI-CLPMs showed a satisfactory model fit for all expectancy and task value facets (i.e., expectancy in combination with intrinsic value, utility value, psychological cost, or effort cost). The random intercepts for intrinsic value and utility value did not have significant variance, indicating that, after controlling for mean-level differences between students' math courses, very little of the observed variance was due to stable between-person motivational differences. As recommended by Mulder and Hamaker (2021), we fixed the variance of these random intercepts and their covariances with the random intercept of students' expectancy to zero.⁴ All other random intercepts had significant variances. Next, we tested if the autoregressive and cross-lagged parameters were invariant across time or differed at the beginning versus towards the end of the semester. Chi-square difference tests and changes in overall model fit, reported in online supplemental materials (Supplements S3 and S4), supported time-invariant autoregressive and cross-lagged effects for models including expectancy and intrinsic and utility values but not for expectancy and perceived costs.⁵ All time-variant effects were freely estimated in subsequent models and are reported below.

⁴ These constrained models had comparable fit to the unconstrained models and were therefore retained. The loglikelihood difference of the two models does not follow a regular chi-square distribution because two (co)variances are fixed to zero (Hamaker et al., 2015; Mulder & Hamaker, 2021). Therefore, a nonsignificant test does not necessarily imply that the variance of the random intercept is indeed not statistically different from zero. However, the model with constrained variance and covariance showed better model fit in terms of lower AIC and BIC values and was retained. We additionally repeated our main analyses with models including a random intercept for intrinsic/utility values. The results are consistent with the results presented below and are reported in the online supplemental materials (Supplement S10).

⁵ The constrained models showed similar model fit in terms of RMSEA, CFI, and TLI values and had lower BIC values compared to the unconstrained models. The results are consistent for both models. We report the autoregressive and cross-lagged parameter estimates for the constrained models in the online supplemental materials (Supplement S10).

The random intercepts of students' course-specific expectancy and psychological and effort costs were significantly negatively correlated ($r_s = -.65$ and $-.63$, $p_s \leq .001$; **Table 3**). Students who had higher expectancies about being successful in their math course relative to their peers reported lower levels of psychological and effort costs across time points. Furthermore, significant contemporaneous within-person associations emerged between students' expectancies and task values. These associations were positive for students' expectancy and intrinsic and utility values ($r_s = .30$ to $.67$, $p_s \leq .005$) and negative for students' expectancy and perceived costs ($r_s = -.56$ to $-.20$, $p_s \leq .030$; **Table 3**). Within a given time point, students who reported higher-than-usual expectancy beliefs also reported higher-than-usual intrinsic and utility values, as well as lower-than-usual psychological and effort costs. Students' course-specific motivational beliefs thus seemed to shift "in synchrony" within a given time point.

As shown in **Table 3**, analyses of within-person autoregressive and cross-lagged effects across the semester revealed significant autoregressive (i.e., carryover) effects for students' course-specific expectancy, intrinsic value, and utility value ($\beta_s = .47$ to $.77$, $p_s \leq .001$; **Table 3**), whereas the autoregressive (i.e., carryover) effects in models including perceived costs were significant only from the midpoint towards the end of the semester and only marginally significant for psychological cost (expectancy: $\beta = .77$, effort cost: $\beta = .46$, $p_s \leq .002$; psychological cost: $\beta = .27$, $p = .062$). Accordingly, higher-than-usual expectancy, intrinsic value, and utility value for a given individual at one time point were linked to higher-than-usual values of the same construct and for the same individual at the next time point. Furthermore, we found significant within-person cross-lagged (i.e., spillover) effects for students' expectancy beliefs on later intrinsic and utility values, indicating that higher-than-usual expected success at one time point predicted higher-than-usual intrinsic and utility values at the next time point ($\beta_s = .15$ to $.30$, $p_s \leq .014$). In contrast, no significant within-person spillover effects emerged for students' expectancy and subsequent intraindividual

changes in perceived costs, nor for task values and subsequent changes in expectancy (β s = $-.23$ to $.18$, $ps \geq .115$). The observed within-person motivational spillover effects were thus unidirectional, from expectancy to intrinsic/utility values, and they were limited to the positively valenced task values.

Week-Specific Expectancies and Task Values at the Beginning of the Semester

Similar to the models including students' course-specific motivational beliefs, we tested RI-CLPMs for students' week-specific expectancy and different task value facets (**Table 3**). The overall model fit was satisfactory across all analyses, and model fit comparisons supported time-invariant autoregressive and cross-lagged effects (see online Supplements S3 and S4 for model fit and model comparisons). The random intercepts of students' week-specific expectancy and task values were moderately-to-highly correlated (r s = $.63$ and $.39$ for intrinsic/utility values, r s = $-.58$ for psychological/effort costs, $ps \leq .001$; **Table 3**). Thus, students who felt more confident about mastering their weekly worksheet, relative to their peers, also experienced working on the current worksheet as more interesting, more useful, less stressful, and less effortful. Furthermore, significant concurrent within-person associations indicated that, within a given time point, a student's higher-than-usual expected success for a given worksheet was associated with higher-than-usual interest and perceived utility, as well as lower-than-usual perceived costs (r s = $.24$ to $.48$ for intrinsic/utility values, r s = $-.44$ to $-.14$ for psychological/effort costs, $ps \leq .049$; **Table 3**). Finally, and in contrast to the results for students' course-specific assessments, we did not find significant within-person autoregressive (i.e., carryover) or cross-lagged (i.e., spillover) effects from one week to the next (β s = $-.06$ to $.17$, $ps \geq .059$; **Table 3**). The only exception were significant negative within-person autoregressive effects for students' intrinsic value across time, suggesting that, higher-than-usual interest in a given worksheet/week predicted lower-than-usual interest the following week (β s = $-.16$ to $-.13$, $ps \leq .027$).

Interindividual Differences Related to Gender and Prior Achievement

To address our third research question regarding group-specific effects, we added students' gender and high school GPA as predictors of their expectancies and task values in the RI-CLPMs. We examined potential group-level effects for (a) students' expectancy-value beliefs at each time point and (b) the within-person motivational alignment of students' course- and week-specific expectancy-value assessments. The inclusion of these covariates in the RI-CLPMs did not affect the results of the first two research questions presented above. The overall model fit for these RI-CLPMs was good (see online Supplements S6 and S7).

Interindividual Differences in Students' Course-Specific Expectancies and Task Values

Gender. Across all three time points, female students reported significantly lower course-specific expectancies for success than did male students (β s = $-.24$ to $-.16$, $ps \leq .001$; **Table 4**). The predictive effects of students' gender on their subjective task values were less consistent. Female students reported lower levels of utility value at the midpoint of the semester (T2c: $\beta = -.14$, $p = .002$) and higher levels of psychological cost at the beginning and midpoint of the semester (T1c/T2c: β s = $.16$, $ps \leq .001$). No significant gender differences emerged for students' intrinsic value and effort cost (β s = $-.03$ to $.05$; $ps \geq .153$). As shown in **Table 4**, the time-invariance analyses for the effects of gender on students' motivational beliefs revealed that only four of the overall 24 estimated parameters were significantly different. Thus, the observed gender differences were largely time-invariant.

Prior achievement. Students' high school GPA significantly predicted all course-specific expectancy-value beliefs across all time points. Students with comparatively higher high school GPAs reported higher levels of expectancy, intrinsic value, and utility value and lower levels of perceived psychological and effort costs (expectancy and intrinsic/utility values: β s = $.14$ to $.36$, $ps \leq .001$; costs: β s = $-.23$ to $-.11$, $ps \leq .002$). These predictive effects were mostly time-invariant, with only six exceptions out of 24 predictive effects, four of which concerned the same constructs (**Table 4**). Specifically, the predictive effect of students'

high school GPA on their expectancy at the beginning of the semester (T1c) was significantly lower than the analogous effects at the midpoint and end of the semester (T2c and T3c) in all four tested models, accounting for four of the six predictive effects that were not time-invariant. Time invariance was thus supported for most constructs and comparisons.

Interindividual Differences in Students' Week-Specific Expectancies and Task Values

Gender. Female compared to male students reported lower week-specific expectancies, intrinsic and utility values, and higher psychological costs associated with working on their weekly math worksheets (expectancy and positively valenced task values: β s = $-.16$ to $-.07$, $ps \leq .026$; psychological cost: β s = $.06/.07$, $ps \leq .038$; **Table 4**). All of these effects were time-invariant and thus stable, although the effect sizes were relatively small.

Prior achievement. In addition, students with lower high school GPAs reported significantly lower levels of expectancy, intrinsic value, and utility value, as well as higher levels of psychological cost compared to students with higher GPAs (expectancy and positively valenced task values: β s = $.16$ to $.26$, $ps \leq .001$; psychological cost: β s = $-.08/-.09$, $ps \leq .018$). These effects were time-invariant, except for the predictive effect of students' high school GPA on their perceived psychological cost, which was smaller and nonsignificant at T1w (Week 3) compared to the other two time points.

In summary, female relative to male students and students with comparatively lower achievement in high school perceived the content of the weekly worksheets as less interesting and useful, were more stressed, and less confident that they would do well on the final exam if these contents were to be tested.⁶ These differences were largely time-invariant.

⁶ In the model including students' psychological cost, constraining the predictive effects of students' gender to be time-invariant resulted in an increase of RMSEA that was larger than .015, even though the chi-square difference test was nonsignificant and BIC favored the constrained models (AIC was almost identical). We describe this case in the online Supplement S7.

Interindividual Differences in Students' Within-Person Motivational Alignment

Finally, we specified multigroup RI-CLPMs to test group-specific differences in the degree of alignment of students' expectancies and task values as a function of students' gender and high school GPA (Mulder & Hamaker, 2021). These analyses are shown in Table S7.3 in the online supplemental materials. Overall, there was little evidence of interindividual differences in the alignment of students' expectancies and task values, which suggests that the developmental process of increasing within-person alignment of students' course-specific expectancies and intrinsic and utility values is fairly universal (see chi-square difference tests in the online Supplement S7). The only exception was the association between students' course-specific expectancy and utility value at the midpoint and at the end of the semester, which was significantly higher for students with lower than those with higher high school GPAs (T2c: $r_{\text{lowGPA}} = .64$ vs. $r_{\text{highGPA}} = .28$, $p = .013$; T3c: $r_{\text{lowGPA}} = .69$ vs. $r_{\text{highGPA}} = .22$, $p = .003$).⁷

Links Between Students' Within-Person Expectancy-Value Alignment and Academic Success

Finally, to address our fourth research question, we examined within-person correlations between students' expectancies and task values separately for students who were successful versus unsuccessful in their math course.

For students' *course-specific* expectancy-value beliefs, we found that the degree of alignment of students' expectancies and intrinsic/utility values was significantly higher for students who dropped out of their math course than students who persisted ($r_{\text{SDropout}} = .66/.44$ vs. $r_{\text{SnoDropout}} = .46/.27$, $ps \leq .021$; **Table 5**). Similarly, the within-person correlation between students' expectancy and intrinsic/utility values was significantly higher for students who failed their math course compared to students who passed it ($r_{\text{Sfail}} = .57/.38$ vs. $r_{\text{Spass}} = .39/.22$,

⁷ In two cases, constraining the covariances to be equal across groups resulted in an increase in RMSEA that was larger than .015, even though the chi-square difference tests were nonsignificant and BIC values favored the constrained models (AIC values were almost identical). We describe these cases in the online Supplement S7.

$ps \leq .015$). In contrast, no significant differences emerged in the within-person alignment of students' course-specific expectancies and perceived costs ($ps \geq .108$; **Table 5**). The only exception was that the alignment of students' expectancy and their psychological costs was significantly higher for students who failed their math course compared to students who passed it ($r_{\text{fail}} = -.43$ vs. $r_{\text{pass}} = -.36$, $p = .031$). Higher within-person motivational alignment was consistently associated with dropout and failing the course.⁸

For students' *week-specific* expectancy-value beliefs, we found significant differences in the within-person alignment of students' expectancies and task values for only three out of eight estimated parameters: Students who failed their math course had a significantly higher within-person alignment of their expectancies and intrinsic values compared to students who passed their math course ($r_{\text{fail}} = .53$ vs. $r_{\text{pass}} = .43$, $p = .031$; **Table 5**). In addition, students' week-specific expectancies and perceived psychological and effort costs were more closely aligned for students who did not drop out of their math course compared to students who did ($r_{\text{Sdropout}} = -.24/- .17$ vs. $r_{\text{SnoDropout}} = -.41/- .34$, $ps \leq .022$; **Table 5**). Overall, no consistent pattern emerged for the degree of motivational alignment in week-specific motivations at the beginning of the semester and its links to students' academic success.

We conducted follow-up analyses to examine mean-level motivational changes for students who dropped out versus persisted or failed versus succeeded in their math course. As mentioned above, students' expectancy, intrinsic value, and utility value declined in the first half of the semester, whereas their psychological and effort costs increased. We conducted a set of repeated measures analyses of variance for each motivational construct to test differences in how students' expectancy-value beliefs changed over time for successful versus

⁸ For students' course performance (i.e., whether students failed or passed their final exam), we also conducted analyses of within-person correlations in multigroup RI-CLPMs to examine whether there are group-differences in the observed motivational alignment process between successful and unsuccessful students. These analyses show that students' course-specific expectancies and intrinsic/utility values became more closely aligned across the semester for all students, but this increased motivational alignment was more pronounced for students who failed their final exam (online Supplement S8). We were not able to conduct the same analysis for students' dropout because these models require at least three measurement points; students who dropped out of their math course had no end-of-term motivation data.

unsuccessful students (time was the repeated-measures factor and dropout or exam failure served as a between-subjects factor). We report these analyses in the online supplemental materials (Supplement S9).

For students' *course-specific* expectancy-value beliefs, we found that students who dropped out or failed their math course reported significantly lower expectancies for success and values and higher levels of perceived costs at all three time points than students who succeeded. Significant Time \times Group interactions further indicated that students who dropped out or failed their math course experienced greater declines in their expectancy and intrinsic value across the semester than students who succeeded ($ps \leq .047$). No significant interactions emerged for students' utility value and perceived costs, even though all differences were in the expected direction ($ps \geq .243$). For students' *week-specific* expectancy-value beliefs, mean-level differences were somewhat smaller than for course-specific motivational beliefs and most pronounced for students' expectancy and intrinsic value. If significant mean-level differences emerged, these favored students who persisted or succeeded in their math course compared to students who dropped out or failed. No significant Time \times Group interactions emerged for students' *week-specific* expectancy-value beliefs ($ps \geq .051$).

In summary, interindividual differences in the within-person motivational alignment were mostly limited to students' course-specific and summative motivational beliefs and were most pronounced for the alignment of students' expectancies and positively valenced task values. Students who dropped out or failed their math course had a higher degree of within-person alignment of their course-specific expectancies and intrinsic/utility values than students who persisted. Importantly, students who failed or dropped out of their math course experienced greater declines in their course-specific expectancy and intrinsic values across the semester than successful students, suggesting that these students aligned their course-specific expectancies and values at a comparatively lower level. Thus, a higher degree of motivational

alignment (at a low level) was associated with greater disengagement and lower academic achievement in our sample.

Discussion

Short-term declines in students' domain-specific expectancy-value beliefs shortly after the transition to higher education predict poor academic performance and course dropout, especially in demanding academic contexts such as STEM (Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Zusho et al., 2003). Understanding how and why students' motivations change over short periods and at critical educational stages such as the transition to higher education is therefore important. Accordingly, the present study examined developmental changes in the degree of alignment of students' expectancy-value beliefs in gateway math courses, whether these motivational beliefs are reciprocally related, and whether the observed motivational (mis)alignment differs depending on students' gender, prior achievement, and later academic success. Our study is the first to examine these developmental processes and cross-lagged effects on the *within-person* level, controlling for stable, between-person motivational differences. Different types of motivational assessments captured either students' expectancy-value beliefs about their math course in general (i.e., course-specific, summative assessments) or the specific content taught in a given week at the beginning of the semester (i.e., week-specific, situated assessments).

Significant motivational alignment and spillover (i.e., cross-lagged) effects were found for students' course-specific (summative) but not their week-specific (situated) expectancy-value beliefs. Our analyses revealed an increasing within-person alignment of students' course-specific success expectancy and intrinsic and utility values across the semester, whereas the degree of alignment between students' expectancy and perceived costs remained stable and only low to moderate over time. This increasing alignment was linked to significant unidirectional motivational spillover effects: Students' expectancy for success predicted subsequent intraindividual changes in their intrinsic and utility values. Interindividual

differences in students' course- or week-specific expectancy-value beliefs favored male and comparatively higher-achieving students and were mostly time-invariant. We found little evidence of interindividual differences in the degree of alignment of students' expectancy-value beliefs depending on their gender and prior achievement, which may suggest that the observed alignment process was fairly universal. However, the alignment of students' course-specific expectancy and intrinsic/utility values was significantly higher for students who failed or dropped out of their math courses compared to those who succeeded. We discuss these findings in greater detail in the following sections.

Changes in the Within-Person Alignment of Students' Course- and Week-Specific Expectancy-Value Beliefs Over Time

In line with the associations theorized by Eccles and Wigfield (Eccles, 2009; Wigfield, 1994) and previous research from the school context (Denissen et al., 2007; Wigfield et al., 1997), our analyses show that students' *course-specific* expectancies of success and their intrinsic and utility values become better aligned over time. Our results expand upon previous evidence by showing that motivational alignment processes also occur over shorter periods (i.e., one semester in STEM) and in the context of higher education. After the transition to higher education, students need to adapt to the context of math-intensive STEM programs and calibrate their expectancy-value beliefs to the new demands, workload, and content in their study program (Coertjens et al., 2017; Seymour & Hewitt, 1997). Accordingly, the developmental process of motivational alignment observed in the elementary and secondary school context may become restarted as students adjust to this new and challenging educational environment.

Notably, this developmental process of increasing motivational alignment was limited to students' course-specific expectancy and positively valenced task values (intrinsic/utility values), and similar alignment did not occur for students' expectancy and perceived costs (psychological/effort costs). Contextual factors may have influenced this pattern. The math

courses in the present study were highly demanding and most students likely expected a substantial time and effort investment. Indeed, students reported relatively high levels of effort costs already at the beginning of the semester, which may have reduced the association of cost and expectancy (see within-person correlations in **Table 2**).

Furthermore, in contrast to our findings for *course-specific* expectancy-value beliefs, the degree of alignment of students' *situated, week-specific* beliefs remained relatively stable across the three weeks of observation at the beginning of the semester. These measure-specific differences in the alignment of students' expectancy-value beliefs indicate that situated (week-specific) and summative (course-specific) assessments of students' expectancy-value beliefs may evoke different cognitive processes (Robinson & Clore, 2002). The summative assessments asked students to reflect on their overall experiences in their math course so that students needed to aggregate their experiences up until that point. Thus, students are prompted to think about how well they adapted to the high demands and workload in their math course and may update potentially unrealistic initial expectations (Gueudet, 2008). In contrast, the situated assessments asked about students' experiences with the content assessed on each math worksheet in a given week so that situational and week-specific influences may play a comparatively greater role in this case (e.g., the difficulty and length of the current worksheet). In addition, when students are asked to form summative evaluations, they may selectively focus on situations that are representative of their overall course experiences and disregard events that they consider unimportant. Situation-specific assessments, on the other hand, also capture unusual experiences such as students' interactions with an unusually challenging/easy or interesting/boring topic. Situated assessments may thus be better suited to capture within-person fluctuations from one situation to the next, whereas summative assessments may be better suited to capture students' overall experiences such as students' adaptation to a new educational context.

Within-Person Motivational Spillover Effects: Cross-Lagged Associations Between Students' Course- and Week-Specific Expectancy-Value Beliefs

Consistent with the assumptions of SEVT (Eccles, 2009; Eccles & Wigfield, 2020), our findings suggest that students who expect to do well (vs. poorly) in their math courses come to value (vs. devalue) their coursework throughout the semester. Our analyses supported unidirectional expectancy-to-values spillover effects but no bidirectional effects. Furthermore, motivational spillover effects of students' expectancy beliefs emerged for students' positively valenced task values but not their perceived costs. This may be because the perceived costs were quite salient and relatively high in the context of our study.

The observed unidirectional spillover effects from expectancy to task values are consistent with prior research over longer time periods, which has mostly used domain-specific but relatively general motivational assessments and traditional CLPM approaches (e.g., Arens et al., 2019; Sewasew et al., 2018; Viljaranta et al., 2014). Our results expand upon this previous work by focusing on within-person motivational shifts over time and controlling for stable between-person motivational differences. These analyses highlight the role of students' expectancies as a likely driving force behind declines in students' valuing of their math courses at the beginning of their postsecondary education. Accordingly, SEVT interventions, which have thus far mostly targeted students' utility value or perceived costs (Gaspard, Dicke, Flunger, Brisson, et al., 2015; Rosenzweig et al., 2022), should also target students' expectancy for success to buffer students from short-term motivational declines and support their retention in STEM.

However, our analyses also demonstrated that motivational spillover effects between students' expectancies and task values depend on whether we focus on course-specific (summative) expectancy-value assessments over one semester versus week-specific (situated) assessments at the beginning of the semester. Motivational spillover effects emerged only for course-specific and summative assessments, whereas students' expectancy-value beliefs about

their weekly worksheets were relatively self-contained within a given week. These different assessments and the chosen time lags likely capture different developmental processes—a period of adaptation after the transition to higher education versus situation-specific experiences with a given worksheet and within a given week. A better understanding of the interplay of students' situated versus more generalized expectancy-value beliefs is important to inform the timing, dosage, and target of interventions based on SEVT. Our results suggest that motivationally-supportive interventions aiming to spark positive spillover effects and buffer negative ones, may need to target students' situated expectancy-value beliefs across multiple weeks so positive course experiences can accumulate and affect students' more generalized motivational beliefs (see dynamic, synergistic, and situated interventions; Rosenzweig et al., 2022).

Several factors have been theorized as possible influences on whether students revise their more generalized expectancy-value beliefs based on situational experiences. First, according to SEVT (Eccles & Wigfield, 2020), students' attributions of success and failure likely play a role. For instance, attributing a poor performance on a math worksheet to unstable causes (e.g., lack of effort) may not affect students' expectancy to be successful in their math course, whereas attributing it to relatively stable causes (e.g., lack of talent or aptitude) may do so. Second, individuals strive to maintain coherent self-views (Swann & Schroeder, 1995). Therefore, a few situated experiences that are not consistent with students' identity are unlikely to prompt a revision of their more generalized beliefs (e.g., "I still like math, even if this worksheet was boring."). Similarly, high levels of generalized expectancies and task values may serve as a buffer against negative situation-specific experiences (e.g., a boring worksheet or poor achievement on a worksheet). Accordingly, after the transition to higher education, students' situated, week-to-week experiences may need time to accumulate to form their more generalized beliefs about a course or their study program in general (see also Dietrich et al., 2019). More research on the interplay of students' situated and more

generalized (summative) expectancy-value beliefs is therefore needed to understand when and how students' situational experiences shape their generalized motivational beliefs, which, in turn, influence students' long-term engagement and educational choices (Eccles, 2022).

Gender and Achievement Differences in Within-Person Motivational Alignment, Mean-Level Differences, and Links to Academic Success

We examined mean-level and alignment differences across gender and prior achievement to test the generalizability of the observed alignment processes across relevant student characteristics. Gender differences in students' *course-specific* motivational beliefs were limited to students' expectancy and psychological cost. By comparison, gender differences in students' *week-specific* motivational beliefs emerged consistently for their expectancies, intrinsic and utility values, and perceived psychological cost. These differences appear to capture "trait-like," and likely preexisting, gender differences in favor of male students (Mulder & Hamaker, 2021). This finding is at odds with our expectations that more generalized (i.e., summative and retrospective) assessments of students' motivations and emotions may reveal greater gender differences than situation-specific assessments, which tend to be less affected by broad stereotypes (e.g., beliefs about gender and math; Eccles et al., 1983; Frieze et al., 1978; Robinson & Clore, 2002). However, situated assessments can also be affected by gender stereotypes. For instance, Frieze et al. (1978) argued that in novel achievement situations, students have little experience to draw from and may therefore rely on stereotypes about gender and math to form their expectancy beliefs. The math worksheets in the present study represented novel tasks for students, and thus their week-specific ratings may also be affected by generalized beliefs and stereotypes.

Consistent with our expectations and prior evidence (e.g., Guo, Parker, et al., 2015; Perez et al., 2014), students with lower high school GPAs reported lower levels of expectancy and intrinsic and utility values and higher levels of perceived costs than did higher-achieving students. Similar to gender, these differences were mostly time-invariant and thus "trait-like"

(Mulder & Hamaker, 2021). Thus, across all analyses, we found little evidence of gender or prior achievement-related differences in the degree of alignment of students' expectancies and task values. Accordingly, the increased motivational (re)alignment across the semester likely reflects a relatively universal process of adjustment to the new educational context in STEM, at least across gender and prior achievement.

However, our analyses revealed a stronger alignment between students' course-specific expectancies and intrinsic/utility values for students who dropped out or failed their math course compared to those who succeeded. Analyses of mean-level differences further suggested that students who dropped out or failed their class experienced greater declines in their course-specific expectancy-value beliefs across the semester, which implies that they aligned their motivations at a comparatively lower level. Consistent with Eccles' (2009) theoretical assumptions, we found that a greater within-person motivational alignment at a relatively *low* level was linked to disengagement and a lower likelihood of success in gateway math courses. To our knowledge, this is the first study to demonstrate an empirical link between within-person motivational alignment processes and disengagement in challenging educational contexts. Students who struggled with course demands and lacked confidence in their ability to succeed may have lowered their course-specific task values as a means to protect their self-worth in the event of failure (Eccles, 2009; Harter, 1990). Although we can only speculate about the underlying causal effects, this interpretation is consistent with the identified unidirectional spillover effects of students' success expectancy on their values.

In addition, in contrast to prior research in the school context (Denissen et al., 2007; Wigfield et al., 1997), our analyses suggest that motivational alignment can signify maladaptive motivational processes that affect students' persistence and academic success in STEM after they have specialized in their field of study. Motivational alignment can be adaptive in elementary and secondary school because students' expectancy-value beliefs become more realistic and differentiated over time, allowing students to specialize in chosen

domains and develop their identities (Eccles, 2009; Wan et al., 2021). In challenging postsecondary contexts, however, motivational alignment seems to reflect motivational declines “in synchrony” as many students struggle to sustain their academic motivation across different constructs. The extent to which these maladaptive alignment processes may be limited to challenging postsecondary contexts and the potential for positive re-alignment at a later time remain open questions for future research. In addition, it may be that well-aligned motivations are more resistant to change due to mutual reinforcement. Early interventions may be necessary to support students during the transition to higher education, buffer students from experiencing motivational declines, and thus prevent motivational alignment at relatively low levels of academic motivation.

Limitations and Directions for Future Research

Several limitations must be considered in the interpretation of our results and suggest possible directions for future research. First, the sample of our study was comparatively high-achieving and homogeneous in terms of students’ family backgrounds. Group differences in students’ expectancy-value beliefs and the degree of alignment of these beliefs might emerge in more diverse samples. In addition, even if there are mean-level differences between groups, individual differences within groups are often quite substantial as well (Wigfield & Eccles, 2002). Thus, it may be interesting to examine if there are groups of students with different degrees of alignment of their motivational beliefs as a function of individual or context characteristics such as current experiences with worksheets and course content.

Second, we focused on the developmental relations of two constructs within the SEVT framework at a time (i.e., students’ expectancy and different task value facets). These analyses allowed us to identify if the alignment processes and cross-lagged expectancy-value links varied for different task value facets. However, given that students’ expectancy and subjective task value beliefs are posited to be a dynamic and complex system (Wigfield & Eccles, 2020), alternative modeling approaches, such as psychometric network models

(Beymer et al., 2022; Epskamp, 2020), may reveal a more complete picture of the links between multiple expectancy-value constructs at the same time.

Third, our analyses of cross-lagged links and the alignment of students' expectancy-value beliefs were limited to students' intrinsic and utility values and two facets of perceived costs. Further task value components can be included in future research (Wigfield et al., 2017). For instance, Eccles (2009) argued that the importance of attainment value, i.e., the importance of a task or domain for one's identity, should increase over time as students incorporate the task or domain into their identity. However, such studies should also consider appropriate time lags for their analyses because attainment value has been shown to change relatively little over short periods such as a single semester (Robinson et al., 2022).

Finally, it remains an open question whether the alignment of students' situated expectancies and task values increases later in the semester as students gain more experience with their math assignments. The situated assessments in our study focused on the first weeks of the semester because motivational changes are particularly likely during this time and declines in students' expectancies and task values shortly after the transition to higher education can be a warning sign of later academic difficulties (Benden & Lauermann, 2022; Zusho et al., 2003). Our results suggest that students' summative (course-specific) expectancy-value beliefs converge and stabilize toward the midterm. Thus, it may be that students' situated expectancy-value beliefs also become better aligned and stabilize after this initial adaptation process. However, it may become increasingly difficult for students to separate their generalized beliefs about the course from their situation-specific beliefs about weekly worksheets and topics, once their motivational beliefs have become well-aligned. That is, situation-specific experiences may become overshadowed by generalized beliefs. Additional assessments of students' situated expectancy-value beliefs after this initial adaptation process (e.g., across multiple weeks toward the end of the semester) would have been necessary to answer this question.

Conclusion

Based on Eccles and colleagues' situated expectancy-value theory (Eccles & Wigfield, 2020), we examined the degree of within-person motivational alignment of students' math-related expectancy-value beliefs in gateway math courses for STEM majors, as well as possible within-person motivational spillover effects across different time frames and measures. Controlling for stable between-person motivational differences, our analyses revealed an increasing within-person alignment between students' course-specific (summative) expectancy and intrinsic/utility values across the semester. In addition, the analyses showed unidirectional expectancy-to-intrinsic/utility value motivational spillover effects, suggesting that expectancy, rather than values, may be a key driving force behind motivational alignment processes in our sample. In contrast, students' week-specific (situated) motivational beliefs were relatively self-contained in a given week at the beginning of the semester; their degree of alignment did not change from week to week during the observation period, and no spillover effects emerged. Differences in students' expectancies and task values favored male and higher-achieving students and were mostly time-invariant, suggesting "trait-like" and likely preexisting interindividual differences. Finally, the degree of alignment between students' course-specific expectancy and intrinsic/utility values was significantly higher for students who dropped out or failed their math courses compared to those who succeeded. Such students struggled to sustain their academic motivation, and different motivational facets aligned at a relatively low level, potentially leading to disengagement and dropout. All in all, these findings highlight the importance of differentiating between-person and within-person motivational processes, suggest that summative versus situation-specific assessments of motivational beliefs may show different developmental patterns, and demonstrate that motivational alignment and spillover effects can be maladaptive for students' persistence in challenging STEM contexts.

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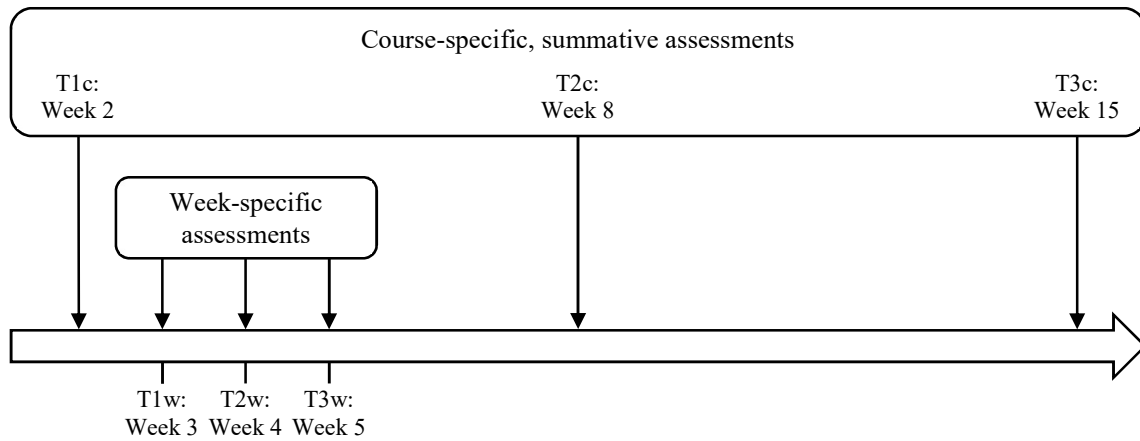
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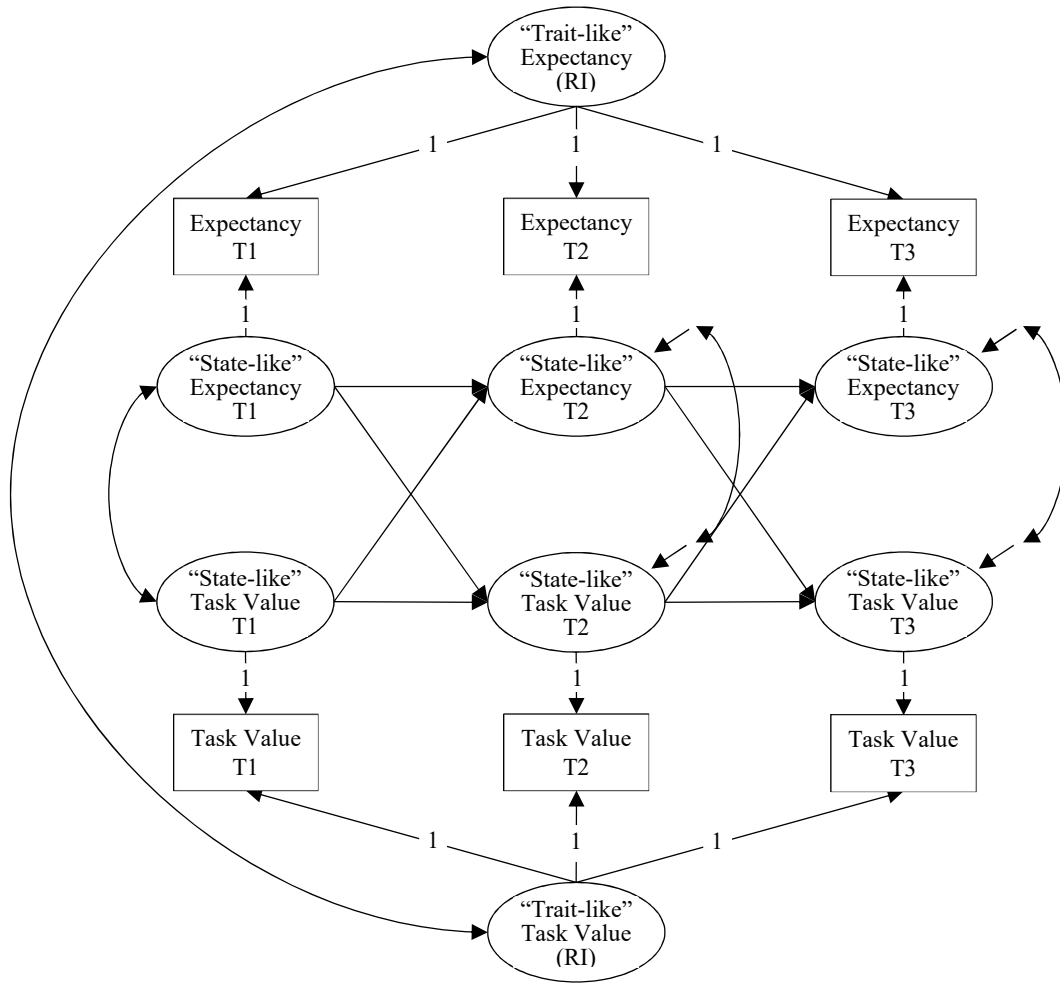
Figures

Figure 1

Time Points and Types of Assessments of Students' Expectancy and Subjective Task Values in the Present Study



Note. T = time point, T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.

Figure 2*Random Intercept Cross-Lagged Panel Model for Students' Expectancy and Subjective Task Values*

Note. Analogous models were specified for each task value construct (intrinsic value, utility value, psychological cost, effort cost). Two sets of models were specified focusing on students' course-specific, summative expectancies and task values across the entire semester (T1c/Week 2, T2c/Week 8, T3c/Week 15) and week-specific expectancy-value beliefs across three weeks at the beginning of the semester (T1w/Week 3, T2w/Week 4, T3w/Week 5). RI = random intercept (i.e., trait-like between-person differences in students' expectancy and task values), T1 = time point 1, T2 = time point 2, T3 = time point 3. For course-specific assessments, expectancy and task values were modeled as latent variables (see multiple-indicator RI-CLPM in Mulder & Hamaker, 2021).

Tables

Table 1

Descriptive Statistics and Observed Bivariate Correlations for Course-Specific (Above the Diagonal) and Week-Specific (Below the Diagonal) Expectancy-Value Beliefs

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Female	—	.06	-.17**	-.03	-.03	.18**	.04	-.20**	-.03	-.08	.13**	.05	-.17**	-.01	-.07	.08	.02	-.03	-.05
2. High school GPA	.06	—	.15**	.15**	.06	-.07	-.03	.22**	.20**	.09*	-.17**	-.10**	.16**	.11*	.14**	-.10	-.06	.36**	-.38**
3. Expectancy Time T1c/T1w	-.15**	.20**	—	.44**	.30**	-.51**	-.44**	.65**	.36**	.27**	-.33**	-.31**	.61**	.28**	.24**	-.38**	-.35**	.15**	-.14**
4. Intrinsic value T1c/T1w	-.07	.21**	.48**	—	.39**	-.37**	-.22**	.30**	.47**	.29**	-.21**	-.10*	.24**	.39**	.26**	-.26**	-.12*	.10	-.17**
5. Utility value T1c/T1w	-.06	.14**	.31**	.53**	—	-.21**	-.12**	.16**	.20**	.54**	-.08	-.02	.23**	.21**	.49**	-.17**	-.07	.06	-.02
6. Psychological cost T1c/T1w	.02	-.02	-.43**	-.30**	-.12**	—	.63**	-.40**	-.24**	-.20**	.57**	.40**	-.39**	-.27**	-.25**	.58**	.42**	-.18**	.13**
7. Effort cost T1c/T1w	.02	-.01	-.42**	-.21**	-.03	.74**	—	-.39**	-.15**	-.16**	.43**	.52**	-.38**	-.17**	-.16**	.39**	.52**	-.17**	.07
8. Expectancy T2c/T2w	-.11*	.25**	.55**	.24**	.13**	-.28**	-.27**	—	.56**	.35**	-.50**	-.44**	.79**	.46**	.35**	-.49**	-.47**	.31**	-.22**
9. Intrinsic value T2c/T2w	-.10*	.19**	.33**	.40**	.28**	-.18**	-.11*	.54**	—	.49**	-.33**	-.18**	.40**	.65**	.39**	-.34**	-.18**	.24**	-.23**
10. Utility value T2c/T2w	-.08	.15**	.19**	.22**	.42**	-.08	.01	.34**	.58**	—	-.15**	-.05	.32**	.34**	.65**	-.17**	-.09	.12*	-.10*
11. Psychological cost T2c/T2w	.10*	-.09*	-.34**	-.16**	-.08	.47**	.38**	-.53**	-.38**	-.22**	—	.72**	-.45**	-.33**	-.26**	.70**	.55**	-.25**	.15**
12. Effort cost T2c/T2w	.08	-.07	-.31**	-.09*	.02	.40**	.46**	-.45**	-.25**	-.07	.77**	—	-.40**	-.23**	-.11*	.54**	.73**	-.17**	.07
13. Expectancy T3c/T3w	-.13*	.21**	.52**	.27**	.19**	-.27**	-.25**	.57**	.35**	.26**	-.36**	-.31**	—	.55**	.35**	-.49**	-.41**	.25**	a
14. Intrinsic value T3c/T3w	-.08	.22**	.34**	.48**	.34**	-.14**	-.06	.30**	.45**	.29**	-.14**	.00	.56**	—	.48**	-.36**	-.23**	.16*	a
15. Utility value T3c/T3w	-.05	.13**	.23**	.29**	.47**	-.03	.05	.29**	.38**	.52**	-.12**	-.01	.39**	.56**	—	-.23**	-.08	.12*	a
16. Psychological cost T3c/T3w	.05	-.05	-.28**	-.15**	-.10*	.46**	.34**	-.27**	-.19**	-.12**	.48**	.40**	-.43**	-.34**	-.16**	—	.64**	-.22**	a
17. Effort cost T3c/T3w	.00	.01	-.26**	-.06	.00	.39**	.40**	-.25**	-.14**	-.04	.43**	.46**	-.36**	-.13**	.01	.73**	—	-.20**	a
18. Course passed	-.03	.36**	.21**	.17**	.09	-.11*	-.12*	.28**	.25**	.16**	-.17**	-.11*	.16**	.15**	.12*	-.14**	-.14**	—	-.44**
19. Course dropout	-.05	-.38**	-.14**	-.15**	-.03	.07	.02	-.22**	-.20**	-.02	.08	.05	-.19**	-.22**	-.11*	.06	.00	-.44**	—
<i>Course-specific assessments</i>			T1c					T2c					T3c						
<i>M</i>	.36	3.06	3.71	4.74	4.55	3.15	4.27	3.36	4.32	4.26	3.55	4.53	3.44	4.42	4.28	3.46	4.46	.67	.43
<i>SD</i>	.48	.65	.85	.80	1.01	1.25	1.08	.94	.91	1.06	1.22	1.05	1.02	.91	1.01	1.24	1.02	.47	.50
<i>N</i>	715	688	686	693	688	693	693	523	524	522	523	524	366	368	366	368	368	431	773
Skewness		-.33	-.04	-.68	-.83	.31	-.34	-.12	-.66	-.61	.06	-.69	-.12	-.83	-.54	.26	-.46		
Kurtosis		-.75	.52	.97	.71	-.62	-.25	.26	.76	.30	-.56	.20	.12	.73	.12	-.42	-.11		
Cronbach's α			.90	.79	.66	.81	.88	.92	.82	.76	.80	.91	.92	.85	.69	.83	.91		
<i>Week-specific assessments</i>			T1w					T2w					T3w						
<i>M</i>			3.56	3.70	4.17	4.13	4.62	3.60	3.72	4.13	3.92	4.25	3.55	3.71	4.09	4.11	4.34		
<i>SD</i>			1.08	1.20	1.07	1.33	1.24	1.10	1.10	1.03	1.39	1.25	1.03	1.14	1.03	1.25	1.18		
<i>N</i>			617	619	615	621	620	582	585	583	584	585	557	557	554	553	555		
Skewness			-.11	-.38	-.70	-.43	-.80	-.39	-.56	-.57	-.20	-.36	-.30	-.47	-.71	-.27	-.52		
Kurtosis			-.19	-.34	.42	-.61	.00	.05	.02	.34	-.85	-.54	-.05	-.16	.61	-.64	-.24		

Note. $N = 773$. GPA = grade point average. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.^a Course dropout implies that the students were not present at the end-of-semester data collection (T3c) so that no motivation data were available to compute correlations.* $p < .05$. ** $p < .01$.

Table 2*Within-Person Correlations Between Students' Expectancy and Task Values in the Correlational Models*

	Intrinsic value model	Utility value model	Psychological cost model	Effort cost model
	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>
<i>Course-specific assessments</i>				
Expectancy T1c ↔ Task value T1c	.18	.13	-.26	-.12
Expectancy T2c ↔ Task value T2c	.71***	.42***	-.43***	-.25*
Expectancy T3c ↔ Task value T3c	.69***	.47***	-.38***	-.24*
<i>Week-specific assessments</i>				
Expectancy T1w ↔ Task value T1w	.16***	.23**	-.24***	-.18**
Expectancy T2w ↔ Task value T2w	.25***	.26**	-.49***	-.36***
Expectancy T3w ↔ Task value T3w	.27***	.36***	-.26***	-.18*

Note. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 3

Standardized Parameters Estimates of RI-CLPMs for Students' Course-Specific Expectancy-Value Beliefs Across the Entire Semester and Week-Specific Expectancy-Value Beliefs Across Three Weeks at the Beginning of the Semester

	Intrinsic value model	Utility value model	Psychological cost model	Effort cost model
<i>Course-specific assessments</i>				
<i>Between-person associations</i>				
Random intercept Expectancy ↔	a	a	-.65***	-.63***
Random intercept Task value				
<i>Within-person associations</i>				
(Residual) Correlations				
Expectancy T1c ↔ Task value T1c	.67***	.49***	-.36	-.21
Expectancy T2c ↔ Task value T2c	.62***	.39***	-.56**	-.31*
Expectancy T3c ↔ Task value T3c	.53***	.30**	-.28**	-.20*
Autoregressive effects				
Expectancy T1c → Expectancy T2c	.56*** ^b [.38; .75]	.63*** ^b [.46; .80]	.25 [-.93; 1.43]	.25 [-.81; 1.31]
Expectancy T2c → Expectancy T3c	.77*** ^b [.48; .91]	.77*** ^b [.65; .92]	.77*** [.47; 1.06]	.73*** [.48; .99]
Task value T1c → Task value T2c	.47*** ^c [.33; .61]	.57*** ^c [.44; .70]	-.18 [-.86; .49]	.13 [-.27; .53]
Task value T2c → Task value T3c	.56*** ^c [.39; .73]	.72*** ^c [.58; .85]	.27 [-.03; .56]	.46** [.17; .75]
Cross-lagged effects				
Expectancy T1c → Task value T2c	.24** ^d [.10; .39]	.15* ^d [.05; .25]	.07 [-1.03; 1.16]	.12 [-.50; .73]
Expectancy T2c → Task value T3c	.30** ^d [.12; .48]	.21* ^d [.06; .36]	-.23 [-.54; .07]	-.13 [-.35; .10]
Task value T1c → Expectancy T2c	.12 ^e [-.04; .28]	.01 ^e [-.09; .10]	-.05 [-.41; .31]	-.11 [-.39; .17]
Task value T2c → Expectancy T3c	.14 ^e [-.05; .33]	.02 ^e [-.10; .11]	.13 [-.04; .30]	.12 [-.03; .27]
<i>Week-specific assessments</i>				
<i>Between-person associations</i>				
Random intercept Expectancy ↔	.63***	.39***	-.58***	-.58***
Random intercept Task value				
<i>Within-person associations</i>				
(Residual) Correlations				
Expectancy T1w ↔ Task value T1w	.28***	.27***	-.21**	-.14*
Expectancy T2w ↔ Task value T2w	.42***	.24*	-.44***	-.31***
Expectancy T3w ↔ Task value T3w	.48***	.31***	-.27***	-.21**
Autoregressive effects				
Expectancy T1w → Expectancy T2w	.14 ^b [-.01; .28]	.11 ^b [-.04; .25]	.11 ^b [-.04; .25]	.09 ^b [-.05; .24]
Expectancy T2w → Expectancy T3w	.17 ^b [-.01; .31]	.12 ^b [-.05; .30]	.13 ^b [-.05; .30]	.10 ^b [-.07; .28]
Task value T1w → Task value T2w	-.16* ^c [-.30; -.02]	-.06 ^c [-.24; .11]	.01 ^c [-.12; .14]	.10 ^c [-.04; .13]
Task value T2w → Task value T3w	-.13* ^c [-.23; -.02]	-.06 ^c [-.21; .10]	.01 ^c [-.14; .17]	.11 ^c [-.05; .15]
Cross-lagged effects				
Expectancy T1w → Task value T2w	.07 ^d [-.07; .21]	.07 ^d [-.07; .21]	-.04 ^d [-.16; .09]	.01 ^d [-.11; .13]
Expectancy T2w → Task value T3w	.07 ^d [-.07; .20]	.08 ^d [-.08; .22]	-.05 ^d [-.19; .10]	.01 ^d [-.13; .15]
Task value T1w → Expectancy T2w	-.07 ^e [-.18; .05]	-.04 ^e [-.16; .08]	-.01 ^e [-.11; .09]	.00 ^e [-.10; .10]
Task value T2w → Expectancy T3w	-.06 ^e [-.17; .05]	-.04 ^e [-.15; .08]	-.02 ^e [-.13; .10]	.00 ^e [-.12; .12]

Note. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts (^b, ^c, ^d, ^e) within a model indicate that unstandardized coefficients were fixed to be the same. Unstandardized parameter estimates are reported in the online supplemental materials (see Supplement S5). For autoregressive and cross-lagged effects, 95% confidence intervals are shown in parentheses.

^a The variance of the random intercept for intrinsic/utility value was nonsignificant; it was fixed at zero in subsequent analyses to obtain a more parsimonious model (Mulder & Hamaker, 2021).

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 4*Standardized Path Coefficients for Predictors of Students' Expectancy-Value Beliefs*

	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	Expectancy	Intrinsic value	Expectancy	Utility value	Expectancy	Psych. cost	Expectancy	Effort cost
	β	β	β	β	β	β	β	β
<i>Course-specific assessments</i>								
Female → T1c	-.22*** ^a	-.02 ^b	-.20*** ^a	-.06 ^b	-.20*** ^a	.16*** ^b	-.22*** ^a	.05 ^b
Female → T2c	-.19*** ^a	-.02 ^b	-.24***	-.14**	-.24***	.16*** ^b	-.19*** ^a	.05 ^b
Female → T3c	-.17*** ^a	-.02 ^b	-.16*** ^a	-.06 ^b	-.16*** ^a	.07	-.18*** ^a	.05 ^b
GPA → T1c	.22***	.21***	.22***	.16*** ^f	.22***	-.13** ^f	.22***	-.11** ^f
GPA → T2c	.36*** ^c	.29*** ^f	.35*** ^e	.14*** ^f	.35*** ^c	-.23***	.35*** ^e	-.11** ^f
GPA → T3c	.33*** ^c	.28*** ^f	.32*** ^e	.15*** ^f	.32*** ^c	-.12** ^f	.32*** ^e	-.12** ^f
Teacher1 → T1c	-.08	-.20***	-.08*	-.26***	-.08*	.19***	-.08	.11**
Teacher1 → T2c	.06	-.01	.06	-.19***	.06	-.03	.06	-.13**
Teacher1 → T3c	.04	.04	.04	-.22**	.03	-.02	.04	-.16**
Teacher2 → T1c	-.04	-.11*	-.04	-.36***	-.04	.15***	-.04	.13**
Teacher2 → T2c	.11**	.13**	.12**	-.04	.12**	-.07	.11**	-.13**
Teacher2 → T3c	.03	.03	.03	-.26***	.02	-.02	.03	-.12*
Math → T1c	-.14**	-.17***	-.15**	-.41***	-.15**	.28***	-.15**	.27***
Math → T2c	-.14**	-.07	-.15**	-.28***	-.15**	.08	-.14**	-.03
Math → T3c	-.21***	-.18**	-.20***	-.40***	-.20***	.06	-.20***	-.05
<i>Week-specific assessments</i>								
Female → T1w	-.16*** ^a	-.09** ^b	-.16*** ^a	-.07* ^b	-.15*** ^a	.07* ^b	-.15*** ^a	.04 ^b
Female → T2w	-.15*** ^a	-.10** ^b	-.15*** ^a	-.07* ^b	-.15*** ^a	.06* ^b	-.15*** ^a	.04 ^b
Female → T3w	-.16*** ^a	-.10** ^b	-.16*** ^a	-.08* ^b	-.16*** ^a	.07* ^b	-.16*** ^a	.04 ^b
GPA → T1w	.24*** ^c	.21*** ^f	.24*** ^e	.16*** ^f	.25*** ^c	.00	.25*** ^e	.02 ^f
GPA → T2w	.24*** ^c	.22*** ^f	.24*** ^e	.17*** ^f	.25*** ^c	-.08* ^f	.25*** ^e	-.07
GPA → T3w	.26*** ^c	.22*** ^f	.26*** ^e	.17*** ^f	.26*** ^c	-.09* ^f	.26*** ^e	.02 ^f
Teacher1 → T1w	.10*	.14***	.10*	.02	.09*	-.06	.09*	-.11**
Teacher1 → T2w	.02	-.04	.02	-.08	.02	-.03	.02	-.05
Teacher1 → T3w	.04	.01	.04	-.05	.04	-.04	.04	-.04
Teacher2 → T1w	.21***	.18***	.21***	.06	.20***	-.17***	.21***	-.25***
Teacher2 → T2w	-.12*	-.17***	-.12*	-.18***	-.12*	.15***	-.12*	.10*
Teacher2 → T3w	-.02	.02	-.03	-.08	-.03	-.02	-.03	-.05
Math → T1w	.13**	.21***	.13**	.04	.13**	-.20***	.13**	-.30***
Math → T2w	-.12**	-.08	-.12**	-.19***	-.12**	.09*	-.12**	.05
Math → T3w	-.13**	-.03	-.13**	-.20***	-.13**	.08	-.13**	.02

Note. Psych. cost = psychological cost. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. GPA = high school grade point average. Teacher1, Teacher2, Math = dummy variables for the math courses (physics was used as the reference category). Equal superscripts within a model indicate that unstandardized coefficients were fixed to be the same. Unstandardized parameter estimates are reported in the online supplemental materials (see Supplement S5).

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5*Within-Person Correlations of Students' Expectancy and Task Values in Multigroup Multilevel Models*

	<i>Course Dropout</i>					
	<i>r</i> Dropout	<i>r</i> NoDropout	Δr	Δcov	Wald test	<i>p</i>
<i>Course-specific assessments</i>						
Expectancy ↔ Intrinsic value	.66***	.46***	.19	.19	3.48**	< .001
Expectancy ↔ Utility value	.44***	.27***	.17	.14	2.31*	.021
Expectancy ↔ Psychological cost	-.44***	-.39***	-.05	-.11	-1.61	.108
Expectancy ↔ Effort cost	-.29**	-.25***	-.04	-.05	-1.00	.316
<i>Week-specific assessments</i>						
Expectancy ↔ Intrinsic value	.45***	.44***	.01	.02	0.31	.760
Expectancy ↔ Utility value	.32***	.31***	.01	.01	0.19	.852
Expectancy ↔ Psychological cost	-.24***	-.41***	.17	.11	2.29*	.022
Expectancy ↔ Effort cost	-.17**	-.34***	.17	.12	2.56*	.011
	<i>Course Performance</i>					
	<i>r</i> Fail	<i>r</i> Pass	Δr	Δcov	Wald test	<i>p</i>
<i>Course-specific assessments</i>						
Expectancy ↔ Intrinsic value	.57***	.39***	.19	.19	3.52***	< .001
Expectancy ↔ Utility value	.38***	.22***	.16	.13	2.44*	.015
Expectancy ↔ Psychological cost	-.43***	-.36***	-.07	-.13	-2.15*	.031
Expectancy ↔ Effort cost	-.28***	-.25***	-.02	-.05	-1.12	.264
<i>Week-specific assessments</i>						
Expectancy ↔ Intrinsic value	.53***	.43***	.10	.15	2.15*	.031
Expectancy ↔ Utility value	.34***	.31***	.03	.04	0.75	.453
Expectancy ↔ Psychological cost	-.38***	-.45***	.08	.00	-0.03	.975
Expectancy ↔ Effort cost	-.32***	-.37***	.05	.01	0.13	.895

Note. Dropout = students who dropped out of their math course (i.e., did not attend the end-of-term class). NoDropout = students who attended the end-of-term class. Fail = students who failed the exam at the end of the semester, Pass = students who passed the exam at the end of the semester. Cov = covariance.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Supplemental Materials:

Searching for Short-Term Motivational Alignment and Spillover Effects: A Random Intercept Cross-Lagged Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs

Supplement S1. Full List of Self-Report Items

Supplement S2. Tests of Measurement Invariance Across Study Programs and Time

Supplement S3. Model Fit of Final Random Intercept Cross-Lagged Panel Models

Supplement S4. Model Fit of Correlational Models with Constrained or Freely Estimated Covariances

Supplement S5. Standardized and Unstandardized Parameter Estimates for the Analyses Reported in the Manuscript

Supplement S6. RI-CLPMs Including Students' Personal Characteristics (Gender & Prior Achievement)

Supplement S7. Multigroup Correlational Models for Students' Personal Characteristics

Supplement S8. Multigroup Correlational Models for Students Who Failed Versus Passed Their Math Course

Supplement S9. Results of Repeated Measures Analysis of Variance

Supplement S10. Results of Alternative Models for Students' Course-Specific Expectancy-Value Beliefs

Supplement S1. Full List of Self-Report Items Used in Study 1a and Study 1b**Table S1***List of Self-Report Items*

Construct	Instruction and items (translated from German)
<i>Course-specific (summative) expectancy-value beliefs (Weeks 2, 8, and 15)</i>	
Expectancy	Based on my experiences in this class so far, I think I will do well on the exam. ^a Based on my experiences in this class so far, I think I am good at my major. ^a Based on my experiences in this class so far, I think I will perform at a high level. ^a
Intrinsic value	Doing the coursework and the assignments for this class is something I enjoy. ^a Doing the coursework and the assignments for this class is interesting. ^a
Utility value	Doing the coursework and the assignments for this class is useful for my future. ^a Doing the coursework and the assignments for this class is important because one just needs the content. ^a
Psychological cost	Doing the coursework and the assignments for this class is stressful for me. ^a Doing the coursework and the assignments for this class makes me really nervous. ^a
Effort cost	Doing the coursework and the assignments for this class is exhausting for me. ^a Doing the coursework and the assignments for this class drains a lot of my energy. ^a
<i>Week-specific (situated) expectancy-value beliefs (Weeks 3–5)</i>	
Expectancy	Think about the current worksheet you turned in this week: If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam? ^b
Intrinsic value	Doing this week's assignments is something I enjoyed. ^a
Utility value	Doing this week's assignments was generally useful. ^a
Psychological cost	Doing this week's assignments was stressful for me. ^a
Effort cost	Doing this week's assignments drained a lot of my energy. ^a

Note. ^a 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. ^b 6-point scale ranging from 1 = *very poorly* to 6 = *very well*.

Supplement S2. Tests of Measurement Invariance Across Study Programs and Time

In the following tables, tests of measurement invariance across students' study programs and time are reported for students' course-specific expectancy-value beliefs (T1c–T3c). In the configural model, the factor structure was constrained to be equal across groups or time. The model testing weak invariance was specified by additionally constraining the factor loadings to be equal across groups or time. Finally, in the model testing strong measurement invariance, item intercepts were additionally constrained to be the same across groups or time.

Table S2.1*Multigroup Analyses by Study Program*

Models and Time Points	χ^2	<i>df</i>	CFI	TLI	RMSEA	SRMR	Δ CFI	Δ RMSEA
T1c								
Configural	177.40	102	.977	.963	.055	.042	—	—
Weak	184.87	114	.978	.969	.051	.052	-.001	.004
Strong partial ^a	218.21	124	.971	.962	.056	.058	.007	-.005
T2c								
Configural	147.77	102	.987	.978	.043	.036	—	—
Weak	163.73	114	.985	.979	.042	.048	.002	.001
Strong	211.70	126	.975	.967	.053	.057	.010	-.009
T3c								
Configural	139.68	102	.984	.974	.039	.040	—	—
Weak	159.14	114	.981	.972	.040	.062	.003	-.001
Strong partial ^b	190.38	125	.972	.963	.046	.069	.009	-.006

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1c = beginning of the semester (Week 2), T2c = midpoint of the semester (Week 8), T3c = end of the semester (Week 15).

^a The intercept of one item assessing psychological cost was freely estimated across groups.

^b The intercept of one item assessing expectancy was freely estimated in the math teacher education group.

Table S2.2*Tests of Measurement Invariance Across Time*

Models	χ^2	<i>df</i>	CFI	TLI	RMSEA	SRMR	Δ CFI	Δ RMSEA
Freely estimated parameters (configural) ^a	512.58	359	.986	.980	.024	.035	—	—
Fixed factor loadings (weak) ^a	526.33	371	.986	.980	.024	.035	.000	.000
Fixed factor loadings and item intercepts (strong) ^a	554.66	383	.985	.979	.025	.036	.001	-.001

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

^a The residual variances for one item assessing utility value and one item assessing psychological cost at time points T2c and T3c were estimated to be very close to zero and nonsignificant. Therefore, we removed the correlated residual for these items between time points T2c and T3c from the model.

Supplement S3. Model Fit of Final Random Intercept Cross-Lagged Panel Models**Table S3.1***Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Course-Specific or Week-Specific Expectancy and Different Task Value Facets*

	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	p
<i>Models Including Course-Specific Assessments</i>											
<i>Expectancy and intrinsic value</i>											
M1a: RI-CLPM	207.700 (100)	.037	.981	.971	.030	21836.080	22649.879	—	—	—	—
M1b: RI-CLPM – only RI for expectancy	208.852 (102)	.037	.981	.972	.030	21832.478	22636.976	.000	.000	0.476 (2)	.788
M1c: M1b with constrained AR & CL paths	217.231 (106)	.037	.981	.972	.033	21833.225	22630.422	.000	.000	8.374 (4)	.079
<i>Expectancy and utility value</i>											
M2a: RI-CLPM	186.069 (100)	.033	.983	.974	.035	23651.888	24465.686	—	—	—	—
M2b: RI-CLPM – only RI for expectancy	186.972 (102)	.033	.983	.974	.035	23649.062	24453.561	.000	.000	1.05 (2)	.591
M2c: M2b with constrained AR & CL paths	192.404 (106)	.032	.983	.975	.040	23647.958	24433.855	.001	.000	5.659 (4)	.226
<i>Expectancy and psychological cost</i>											
M3a: RI-CLPM	210.987 (100)	.038	.980	.970	.034	23954.569	24768.368	—	—	—	—
M3b: M3a with constrained AR & CL paths	230.073 (104)	.040	.978	.967	.042	23960.417	24755.615	-.002	.002	40.699 (4)	< .001
<i>Expectancy and effort cost</i>											
M4a: RI-CLPM	155.535 (100)	.027	.991	.986	.028	22275.105	23088.904	—	—	—	—
M4b: M4a with constrained AR & CL paths	172.567 (104)	.029	.989	.984	.039	22283.282	23078.480	-.002	.002	18.860 (4)	< .001
<i>Models Including Week-Specific Assessments</i>											
<i>Expectancy and intrinsic value</i>											
M1a: RI-CLPM	1.872 (1)	.034	.999	.979	.007	15153.107	15632.086	—	—	—	—
M1b: M1a with constrained AR & CL paths	4.015 (5)	.000	1.000	1.000	.012	15147.693	15608.071	.034	-.001	2.375 (4)	.667
<i>Expectancy and utility value</i>											
M2a: RI-CLPM	2.464 (1)	.044	.999	.955	.008	15082.701	15561.679	—	—	—	—
M2c: M2a with constrained AR & CL paths	8.731 (5)	.031	.997	.977	.018	15081.656	15542.033	.013	.002	6.367 (4)	.173
<i>Expectancy and psychological cost</i>											
M3a: RI-CLPM	0.049 (1)	.000	1.000	1.000	.001	15768.280	16247.259	—	—	—	—
M3b: M3a with constrained AR & CL paths	6.854 (5)	.022	.999	.990	.020	15767.941	16228.319	-.022	.001	6.655 (4)	.155
<i>Expectancy and effort cost</i>											
M4a: RI-CLPM	0.045 (1)	.000	1.000	1.000	.001	15592.659	16071.638	—	—	—	—
M4b: M4a with constrained AR & CL paths	3.709 (5)	.000	1.000	1.000	.019	15588.712	16049.090	.000	.000	3.598 (4)	.463

Note. AR = autoregressive, CL = cross-lagged, χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. The final model is shown in bold.

Supplement S4. Model Fit of Correlational Models with Constrained or Freely Estimated Covariances**Table S4.1***Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Course-Specific Expectancy and Different Task Value Facets*

<i>Models Including Course-Specific Assessments</i>	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	<i>p</i>
<i>Expectancy and intrinsic value</i>											
M1a: Correlational model	208.048 (100)	.037	.981	.971	.030	21836.078	22649.876	—	—	—	—
M1b: M1a with correlations at T1c and T2c equal	238.868 (101)	.042	.976	.964	.071	21866.482	22675.631	-.005	.005	26.177 (1)	< .001
M1c: M1a with correlations at T2c and T3c equal	209.066 (101)	.037	.981	.972	.032	21835.386	22644.535	.000	-.001	1.128 (1)	.288
M1d: M1a with all correlations equal (T1c–T3c)	248.168 (102)	.043	.975	.962	.091	21874.494	22678.992	-.006	.006	34.939 (2)	< .001
<i>Expectancy and utility value</i>											
M2a: Correlational model	186.269 (100)	.033	.983	.973	.034	23651.808	24465.607	—	—	—	—
M2b: M2a with correlations at T1c and T2c equal	196.617 (101)	.035	.981	.971	.043	23660.748	24469.897	-.002	.002	10.511 (1)	.001
M2c: M2a with correlations at T2c and T3c equal	186.006 (101)	.033	.983	.974	.034	23649.869	24459.018	.000	.000	0.059 (1)	.808
M2d: M2a with all correlations equal (T1c–T3c)	198.941 (102)	.035	.981	.971	.047	23661.545	24466.043	-.002	.002	12.082 (2)	.002
<i>Expectancy and psychological cost</i>											
M3a: Correlational model	211.548 (100)	.038	.980	.970	.035	23955.599	24769.398	—	—	—	—
M3b: M3a with correlations at T1c and T2c equal	214.975 (101)	.038	.980	.970	.040	23957.188	24766.337	.000	.000	3.452 (1)	.063
M3c: M3a with correlations at T2c and T3c equal	211.880 (101)	.038	.981	.970	.036	23953.978	24763.127	.000	.000	0.347 (1)	.555
M3d: M3a with all correlations equal (T1c–T3c)	216.740 (102)	.038	.980	.970	.045	23957.083	24761.581	.000	.000	5.197 (2)	.074
<i>Expectancy and effort cost</i>											
M4a: Correlational model	157.062 (100)	.027	.991	.986	.030	22276.840	23090.639	—	—	—	—
M4b: M4a with correlations at T1c and T2c equal	158.868 (101)	.027	.991	.986	.032	22276.804	23085.952	.000	.000	1.875 (1)	.171
M4c: M4a with correlations at T2c and T3c equal	156.808 (101)	.027	.991	.986	.030	22274.857	23084.005	.000	.000	^a	
M4d: M4a with all correlations equal (T1c–T3c)	158.979 (102)	.027	.991	.986	.033	22275.268	23079.767	.000	.000	2.079 (2)	.354

Note. T1c–T3c = course-specific summative evaluation of experiences thus far (beginning, midpoint, and end-of-term assessments). χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion.

^a The chi-square difference had a negative value due to a negative difference in the scaling factors (see Asparouhov & Muthen, 2013). We did not compute a strictly positive chi-square difference because model indices suggest that the constrained model does not fit significantly worse than the unconstrained model.

Table S4.2*Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Week-Specific Expectancy and Different Task Value Facets*

<i>Models Including Week-Specific Assessments</i>	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	<i>p</i>
<i>Expectancy and intrinsic value</i>											
M1a: Correlational model	1.937 (1)	.035	.999	.977	.007	15153.255	15632.234	—	—	—	—
M1b: M1a with correlations at T1w and T2w equal	3.696 (2)	.033	.999	.980	.017	15152.995	15627.322	.002	.000	1.767 (1)	.184
M1c: M1a with correlations at T2w and T3w equal	1.862 (2)	.000	1.000	1.000	.008	15151.343	15625.671	.035	-.001	0.082 (1)	.774
M1d: M1a with all correlations equal (T1w–T3w)	4.757 (3)	.028	.999	.986	.021	15152.182	15621.860	.007	.000	2.862 (2)	.239
<i>Expectancy and utility value</i>											
M2a: Correlational model	3.095 (1)	.052	.998	.936	.010	15083.490	15562.469	—	—	—	—
M2b: M2a with correlations at T1w and T2w equal	2.852 (2)	.023	.999	.987	.011	15081.518	15555.846	.029	-.001	0.023 (1)	.878
M2c: M2a with correlations at T2w and T3w equal	3.014 (2)	.026	.999	.984	.012	15081.856	15556.184	.026	-.001	0.281 (1)	.560
M2d: M2a with all correlations equal (T1w–T3w)	3.357 (3)	.012	1.000	.996	.014	15080.156	15549.834	.040	-.002	0.563 (2)	.755
<i>Expectancy and psychological cost</i>											
M3a: Correlational model	0.003 (1)	.000	1.000	1.000	.000	15768.233	16247.212	—	—	—	—
M3b: M3a with correlations at T1w and T2w equal	10.730 (2)	.075	.993	.880	.031	15775.860	16250.189	-.075	.007	12.437 (1)	< .001
M3c: M3a with correlations at T2w and T3w equal	10.342 (2)	.073	.994	.885	.034	15775.415	16249.743	-.073	.006	12.155 (1)	< .001
M3d: M3a with all correlations equal (T1w–T3w)	14.251 (3)	.070	.991	.897	.036	15776.861	16246.539	-.070	.009	15.417 (2)	< .001
<i>Expectancy and effort cost</i>											
M4a: Correlational model	0.076 (1)	.000	1.000	1.000	.002	15592.688	16071.667	—	—	—	—
M4b: M4a with correlations at T1w and T2w equal	5.056 (2)	.044	.997	.953	.021	15595.635	16069.963	-.044	.003	4.910 (1)	.027
M4c: M4a with correlations at T2w and T3w equal	5.127 (2)	.045	.997	.952	.024	15595.616	16069.945	-.045	.003	5.066 (1)	.024
M4d: M4a with all correlations equal (T1w–T3w)	6.595 (3)	.039	.997	.963	.025	15595.274	16064.952	-.039	.003	6.422 (2)	.040

Note. χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion.

Supplement S5. Standardized and Unstandardized Parameter Estimates for the RI-CLPMs Reported in the Manuscript**Table S5.1***Autoregressive and Cross-Lagged Parameters for Students' Expectancy-Value Beliefs Over Time*

	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]
<i>Course-specific assessments</i>								
Autoregressive effects								
Expectancy T1c → Expectancy T2c	.73*** (.12) ^a	.56 [.38; .75]	.82*** (.08) ^a	.63 [.46; .80]	.39 (.80)	.25 [−.93; 1.43]	.38 (.73)	.25 [−.81; 1.31]
Expectancy T2c → Expectancy T3c	.73*** (.12) ^a	.77 [.48; .91]	.82*** (.08) ^a	.77 [.65; .92]	.90*** (.12)	.77 [.47; 1.06]	.85*** (.10)	.73 [.48; .99]
Task value T1c → Task value T2c	.58*** (.09) ^b	.47 [.33; .61]	.67*** (.07) ^b	.57 [.44; .70]	−.20 (.37)	−.18 [−.86; .49]	.13 (.22)	.13 [−.27; .53]
Task value T2c → Task value T3c	.58*** (.09) ^b	.56 [.39; .73]	.67*** (.07) ^b	.72 [.58; .85]	.32 (.17)	.27 [−.03; .56]	.43** (.13)	.46 [.17; .75]
Cross-lagged effects								
Expectancy T1c → Task value T2c	.34** (.12) ^c	.24 [.10; .39]	.23* (.09) ^c	.15 [.05; .25]	.09 (.77)	.07 [−1.03; 1.16]	.19 (.58)	.12 [−.50; .73]
Expectancy T2c → Task value T3c	.34** (.12) ^c	.30 [.12; .48]	.23* (.09) ^c	.21 [.06; .36]	−.24 (.09)	−.23 [−.54; .07]	−.12 (.11)	−.13 [−.35; .10]
Task value T1c → Expectancy T2c	.14 (.09) ^d	.12 [−.04; .28]	.01 (.05) ^d	.01 [−.09; .10]	−.06 (.23)	−.05 [−.41; .31]	−.12 (.14)	−.11 [−.39; .17]
Task value T2c → Expectancy T3c	.14 (.09) ^d	.14 [−.05; .33]	.01 (.05) ^d	.02 [−.10; .11]	.18 (.13)	.13 [−.04; .30]	.13 (.10)	.12 [−.03; .27]
<i>Week-specific assessments</i>								
Autoregressive effects								
Expectancy T1w → Expectancy T2w	.15 (.08) ^a	.14 [−.01; .28]	.12 (.08) ^a	.11 [−.04; .25]	.12 (.08) ^a	.11 [−.04; .25]	.10 (.08) ^a	.09 [−.05; .24]
Expectancy T2w → Expectancy T3w	.15 (.08) ^a	.17 [−.01; .31]	.12 (.08) ^a	.12 [−.05; .30]	.12 (.08) ^a	.13 [−.05; .30]	.10 (.08) ^a	.10 [−.07; .28]
Task value T1w → Task value T2w	−.14* (.06) ^b	−.16 [−.30; −.02]	−.06 (.08) ^b	−.06 [−.24; .11]	.01 (.07) ^b	.01 [−.12; .14]	.10 (.08) ^b	.10 [−.04; .13]
Task value T2w → Task value T3w	−.14* (.06) ^b	−.13 [−.23; −.02]	−.06 (.08) ^b	−.06 [−.21; .10]	.01 (.07) ^b	.01 [−.14; .17]	.10 (.08) ^b	.11 [−.05; .15]
Cross-lagged effects								
Expectancy T1w → Task value T2w	.07 (.07) ^c	.07 [−.07; .21]	.07 (.07) ^c	.07 [−.07; .21]	−.05 (.09) ^c	−.04 [−.16; .09]	.02 (.09) ^c	.01 [−.11; .13]
Expectancy T2w → Task value T3w	.07 (.07) ^c	.07 [−.07; .20]	.07 (.07) ^c	.08 [−.08; .22]	−.05 (.09) ^c	−.05 [−.19; .10]	.02 (.09) ^c	.01 [−.13; .15]
Task value T1w → Expectancy T2w	−.06 (.06) ^d	−.07 [−.18; .05]	−.04 (.06) ^d	−.04 [−.16; .08]	−.01 (.04) ^d	−.01 [−.11; .09]	.00 (.05) ^d	.00 [−.10; .10]
Task value T2w → Expectancy T3w	−.06 (.06) ^d	−.06 [−.17; .05]	−.04 (.06) ^d	−.04 [−.15; .08]	−.01 (.04) ^d	−.02 [−.13; .10]	.00 (.05) ^d	.00 [−.12; .12]

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts within a model indicate that unstandardized coefficients were fixed to be the same.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table S5.2*Unstandardized Path Coefficients for Predictors of Students' Expectancy-Value Beliefs*

Predictors	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	Expectancy	Intrinsic value	Expectancy	Utility value	Expectancy	Psych. cost	Expectancy	Effort cost
<i>Course-specific assessments</i>								
Female → T1c	-.37*** a	-.03 b	-.34*** a	-.11 b	-.34*** a	.33*** b	-.38*** a	.10 b
Female → T2c	-.37*** a	-.03 b	-.46***	-.29**	-.48***	.33*** b	-.38*** a	.10 b
Female → T3c	-.37*** a	-.03 b	-.34*** a	-.11 b	-.34*** a	.14	-.38*** a	.10 b
GPA → T1c	.28***	.23***	.28***	.22*** f	.28***	-.20** f	.28***	-.17** f
GPA → T2c	.52*** e	.40*** f	.50*** e	.22*** f	.52*** e	-.35***	.51*** e	-.17** f
GPA → T3c	.52*** e	.40*** f	.50*** e	.22*** f	.52*** e	-.20** f	.51*** e	-.17** f
Teacher1 → T1c	-.18	-.43***	-.18*	-.68***	-.18*	.55***	-.18	.31*
Teacher1 → T2c	.15	-.01	.16	-.56***	.17	-.08	.16	-.36*
Teacher1 → T3c	.11	.12	.11	-.59**	.09	-.06	.12	-.46**
Teacher2 → T1c	-.10	-.28*	-.11	-1.06***	-.12	.48***	-.11	.43**
Teacher2 → T2c	.34**	.37**	.36**	-.12	.36**	-.22	.35**	-.44**
Teacher2 → T3c	.11	.10	.10	-.81***	.06	-.05	.11	-.38**
Math → T1c	-.26**	-.28***	-.27**	-.83***	-.27**	.64***	-.27**	.61***
Math → T2c	-.30**	-.14	-.31**	-.64***	-.31**	.19	-.29**	-.07
Math → T3c	-.47***	-.38**	-.46***	-.85***	-.47***	.13	-.46***	-.11
<i>Week-specific assessments</i>								
Female → T1w	-.35*** a	-.23** b	-.35*** a	-.16* b	-.34*** a	.18* b	-.35*** a	.09 b
Female → T2w	-.35*** a	-.23** b	-.35*** a	-.16* b	-.34*** a	.18* b	-.35*** a	.09 b
Female → T3w	-.35*** a	-.23** b	-.35*** a	-.16* b	-.34*** a	.18* b	-.35*** a	.09 b
GPA → T1w	.41*** e	.38*** f	.41*** e	.27*** f	.42*** e	.01	.42*** e	.04 f
GPA → T2w	.41*** e	.38*** f	.41*** e	.27*** f	.42*** e	-.18* f	.42*** e	-.13
GPA → T3w	.41*** e	.38*** f	.41*** e	.27*** f	.42*** e	-.18* f	.42*** e	.04 f
Teacher1 → T1w	.30*	.49***	.30*	.07	.29*	-.23	.29*	-.38*
Teacher1 → T2w	.06	-.12	.06	-.22	.06	-.05	.05	-.17
Teacher1 → T3w	.12	.04	.12	-.14	.11	-.12	.11	-.12
Teacher2 → T1w	.74***	.72***	.73***	.21	.72***	-.74***	.73***	-1.01***
Teacher2 → T2w	-.43*	-.62***	-.43*	-.59***	-.43*	.67***	-.44*	.39*
Teacher2 → T3w	-.07	.06	-.08	-.27	-.09	-.09	-.09	-.17
Math → T1w	.32**	.57***	.32**	.09	.31**	-.60***	.31**	-.83***
Math → T2w	-.29**	-.19	-.29**	-.44***	-.30**	.29*	-.31**	.13
Math → T3w	-.29**	-.08	-.30**	-.45***	-.30**	.21	-.30**	.04

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. GPA = high school grade point average. Teacher1, Teacher2, Math = dummy variables for the math courses. Equal superscripts within a model indicate that unstandardized coefficients were fixed to be the same.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Supplement S6. RI-CLPMs Including Students' Personal Characteristics (Gender & Prior Achievement)**Table S6.1**

Model Comparisons for Random Intercept Cross-Lagged Panel Models Including Students' Personal Characteristics as Predictors of Their Course-Specific Expectancy-Value Beliefs

<i>Models Including Course-Specific Assessments</i>	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	<i>p</i>
<i>Expectancy and intrinsic value</i>											
M0: RI-CLPM including all covariates	234.391 (120)	.035	.980	.969	.029	21821.670	22542.463	—	—	—	—
M1a: M0 with time-invariant effects for gender	241.211 (124)	.035	.980	.969	.030	21820.606	22522.798	.000	.000	6.808 (4)	.146
M1b: M0 with time-invariant effects for GPA	258.127 (124)	.037	.977	.965	.041	21837.231	22539.423	-.002	.003	25.495 (4)	< .001
M2: All covariates time-invariant except for GPA on EXP T1c and INT T1c	241.970 (126)	.035	.980	.970	.035	21817.069	22509.961	.000	.000	7.437 (8)	.282
<i>Expectancy and utility value</i>											
M0: RI-CLPM including all covariates	224.805 (120)	.034	.980	.968	.032	23650.441	24371.234	—	—	—	—
M1a: M0 with time-invariant effects for gender	236.811 (124)	.034	.978	.966	.034	23654.663	24356.855	.000	.002	12.236 (4)	.016
M1b: M0 with time-invariant effects for GPA	245.715 (124)	.036	.976	.964	.042	23663.689	24365.881	-.002	.004	22.170 (4)	< .001
M2: All covariates time-invariant except for gender on EXP T2c, UTL T2c and GPA on EXP T1c	230.988 (125)	.033	.979	.969	.034	23646.227	24343.769	.001	-.001	5.940 (5)	.312
<i>Expectancy and psychological cost</i>											
M0: RI-CLPM including all covariates	236.236 (118)	.036	.980	.967	.031	23943.168	24673.261	—	—	—	—
M1a: M0 with time-invariant effects for gender	249.619 (122)	.037	.978	.966	.033	23948.589	24660.082	-.001	.002	13.791 (4)	.008
M1b: M0 with time-invariant effects for GPA	258.879 (122)	.038	.977	.964	.038	23958.087	24669.579	-.002	.003	24.046 (4)	< .001
M2: All covariates time-invariant except for gender on EXP T2c, CSTR T3c and GPA on EXP T1c, CSTR T2c	238.560 (122)	.032	.980	.969	.032	23937.356	24648.848	.004	.000	2.142 (4)	.710
<i>Expectancy and effort cost</i>											
M0: RI-CLPM including all covariates	182.952 (118)	.027	.990	.983	.026	22266.989	22997.082	—	—	—	—
M1a: M0 with time-invariant effects for gender	190.959 (122)	.027	.989	.983	.028	22266.772	22978.265	.000	.000	8.090 (4)	.088
M1b: M0 with time-invariant effects for GPA	204.141 (122)	.030	.987	.979	.036	22280.224	22991.717	-.003	.004	21.502 (4)	< .001
M2: All covariates time-invariant except for GPA on EXP T1c	192.142 (125)	.026	.989	.984	.028	22262.128	22959.670	.001	-.000	9.170 (7)	.241

Note. χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. GPA = high school grade point average.

Table S6.2*Model Comparisons for Random Intercept Cross-Lagged Panel Models Including Students' Personal Characteristics as Predictors of Their Week-Specific Expectancy-Value Beliefs*

Models Including Week-Specific Assessments	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	p
<i>Expectancy and intrinsic value</i>											
M0: RI-CLPM including all covariates	2.170 (1)	.039	.999	.960	.006	15153.368	15632.347	—	—	—	—
M1a: M0 with time-invariant effects for gender	3.127 (5)	.000	1.000	1.000	.007	15146.514	15606.892	.039	-.001	1.162 (4)	.884
M1b: M0 with time-invariant effects for GPA	7.849 (5)	.027	.998	.981	.010	15150.636	15611.014	.012	.001	5.721 (4)	.221
M2: All covariates time-invariant	16.283 (9)	.002	1.000	1.000	.011	15144.040	15585.817	.037	-.001	6.978 (8)	.539
<i>Expectancy and utility value</i>											
M0: RI-CLPM including all covariates	2.754 (1)	.048	.999	.926	.007	15082.945	15562.923	—	—	—	—
M1a: M0 with time-invariant effects for gender	4.224 (5)	.000	1.000	1.000	.008	15076.487	15536.865	.048	-.001	1.571 (4)	.814
M1b: M0 with time-invariant effects for GPA	7.762 (5)	.027	.998	.977	.012	15079.626	15540.004	.021	.001	5.013 (4)	.286
M2: All covariates time-invariant	9.390 (9)	.007	1.000	.998	.013	15073.350	15515.126	.041	-.001	6.687 (8)	.571
<i>Expectancy and psychological cost</i>											
M0: RI-CLPM including all covariates	0.145 (1)	.000	1.000	1.000	.002	15768.373	16247.352	—	—	—	—
M1a: M0 with time-invariant effects for gender	8.528 (5)	.030	.998	.973	.009	15768.711	16229.089	-.030	.002	8.358 (4)	.079
M1b: M0 with time-invariant effects for GPA	10.188 (5)	.037	.996	.961	.014	15770.178	16230.556	-.037	.004	10.056 (4)	.040
M2: All covariates time-invariant except for GPA on CSTR T1w	12.273 (8)	.026	.997	.980	.012	15766.318	16212.744	-.026	.003	12.123 (7)	.097
<i>Expectancy and effort cost</i>											
M0: RI-CLPM including all covariates	0.264 (1)	.000	1.000	1.000	.003	15592.781	16071.850	—	—	—	—
M1a: M0 with time-invariant effects for gender	5.744 (5)	.014	.999	.994	.009	15590.491	16050.868	-.014	.001	5.432 (4)	.248
M1b: M0 with time-invariant effects for GPA	11.354 (5)	.041	.995	.948	.014	15595.920	16056.298	-.041	.005	11.047 (4)	.026
M2: All covariates time-invariant except for GPA on CEFF T2w	10.655 (8)	.021	.998	.986	.013	15589.412	16035.839	-.021	.002	10.349 (7)	.170

Note. χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. GPA = high school grade point average.

Model comparisons in Table S6.2 show that in the models including students' expectancy and psychological cost, constraining the predictive effects of students' gender to be time-invariant, led to increases in RMSEA that was larger than .015 even though the chi-square difference tests were not significant (BIC favored the constrained model and AIC was similar for the constrained and unconstrained model). We therefore report the predictive effects of students' gender on their expectancy and perceived costs both for the constrained model as well as for an unconstrained model in Table S6.3. One small difference occurred for the predictive effect of students' gender on their perceived psychological cost, which was estimated to be significant at T2w in the unconstrained model and nonsignificant at the other two time points, whereas in the constrained model, the predictive effect of students' gender on psychological cost was small but significant. However, in terms of the effect size, these differences were comparatively small.

Table S6.3

Standardized Path Coefficients for Predictors of Students' Expectancy-Value Beliefs

	Unconstrained Model		Constrained Model	
	Expectancy	Psychological cost	Expectancy	Psychological cost
	β	β	β	β
<i>Week-specific assessments</i>				
Female → T1w	-.18***	.03	-.15*** ^a	.07* ^b
Female → T2w	-.14***	.09*	-.15*** ^a	.06* ^b
Female → T3w	-.15***	.01	-.16*** ^a	.07* ^b

Note. T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts indicate that unstandardized coefficients were fixed to be the same.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Supplement S7. Multigroup Correlational Models for Students' Personal Characteristics**Table S7.1***Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Course-Specific Expectancy and Different Task Value Facets*

<i>Models Including Course-Specific Assessments</i>	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	<i>p</i>
<i>Expectancy and intrinsic value</i>											
M1a: Multigroup correlational model for gender	542.482 (216)	.065	.942	.918	.077	20581.583	21898.401	—	—	—	—
M1b: M1a with constrained covariances across groups	544.217 (219)	.064	.942	.919	.083	20579.224	21882.324	.001	.000	2.862 (3)	.413
M1c: Multigroup correlational model for GPA	501.198 (216)	.062	.946	.924	.083	19622.535	20928.266	—	—	—	—
M1d: M1c with constrained covariances across groups	509.178 (219)	.062	.945	.923	.085	19626.321	20918.451	.000	.001	7.787 (3)	.051
<i>Expectancy and utility value</i>											
M2a: Multigroup correlational model for gender	500.495 (216)	.061	.943	.919	.077	22295.056	23611.873	—	—	—	—
M2b: M2a with constrained covariances across groups	504.446 (219)	.060	.943	.920	.078	22293.733	23596.834	.001	.000	4.202 (3)	.241
M2c: Multigroup correlational model for GPA	424.319 (216)	.053	.955	.937	.081	21297.733	22603.464	—	—	—	—
M2d: M2c with constrained covariances across groups	441.751 (219)	.054	.952	.933	.079	21310.482	22602.612	-.001	.003	16.346 (3)	< .001
<i>Expectancy and psychological cost</i>											
M3a: Multigroup correlational model for gender	532.221 (216)	.064	.943	.920	.087	22638.374	23955.192	—	—	—	—
M3b: M3a with constrained covariances across groups	535.238 (219)	.064	.943	.921	.087	22635.979	23939.079	.000	.000	3.275 (3)	.351
M3c: Multigroup correlational model for GPA	486.584 (216)	.060	.949	.928	.091	21674.781	22980.513	—	—	—	—
M3d: M3c with constrained covariances across groups	488.919 (219)	.060	.949	.929	.089	21671.447	22963.577	.000	.000	2.484 (3)	.478
<i>Expectancy and effort cost</i>											
M4a: Multigroup correlational model for gender	508.329 (216)	.062	.952	.933	.082	21000.373	22317.190	—	—	—	—
M4b: M4a with constrained covariances across groups	509.711 (219)	.061	.953	.934	.081	20995.891	22298.992	.001	-.001	1.504 (3)	.681
M4c: Multigroup correlational model for GPA	479.759 (216)	.060	.954	.935	.086	20037.577	21343.309	—	—	—	—
M4d: M4c with constrained covariances across groups	483.015 (219)	.059	.954	.936	.084	20035.472	21327.601	.001	-.001	3.591 (3)	.309

Note. χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. GPA = high school grade point average.

Table S7.2*Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Week-Specific Expectancy and Different Task Value Facets*

<i>Models Including Week-Specific Assessments</i>	χ^2 (df)	RMSEA	CFI	TLI	SRMR	AIC	BIC	Δ RMSEA	Δ CFI	$\Delta\chi^2$ (df)	<i>p</i>
<i>Expectancy and intrinsic value</i>											
M1a: Multigroup correlational model for gender	1.381 (2)	.000	1.000	1.000	.006	13484.505	14298.372	—	—	—	—
M1b: M1a with constrained covariances across groups	7.544 (5)	.038	.998	.975	.027	13484.956	14285.106	-.038	.002	5.955 (3)	.114
M1c: Multigroup correlational model for GPA	2.075 (2)	.010	1.000	.998	.007	12774.483	13581.497	—	—	—	—
M1d: M1c with constrained covariances across groups	10.144 (5)	.055	.996	.946	.025	12776.720	13570.133	-.045	.004	7.645 (3)	.054
<i>Expectancy and utility value</i>											
M2a: Multigroup correlational model for gender	5.358 (2)	.069	.997	.894	.012	13441.299	14255.165	—	—	—	—
M2b: M2a with constrained covariances across groups	7.943 (5)	.041	.997	.963	.021	13438.727	14238.876	.028	.000	2.981 (3)	.395
M2c: Multigroup correlational model for GPA	6.199 (2)	.078	.996	.860	.014	12726.457	13533.472	—	—	—	—
M2d: M2c with constrained covariances across groups	7.072 (5)	.035	.998	.972	.017	12722.168	13515.581	.043	-.002	1.460 (3)	.692
<i>Expectancy and psychological cost</i>											
M3a: Multigroup correlational model for gender	0.097 (2)	.000	1.000	1.000	.002	14091.608	14905.475	—	—	—	—
M3b: M3a with constrained covariances across groups	3.077 (5)	.000	1.000	1.000	.013	14088.641	14888.790	.000	.000	3.066 (3)	.382
M3c: Multigroup correlational model for GPA	0.177 (2)	.000	1.000	1.000	.003	13322.858	14129.872	—	—	—	—
M3d: M3c with constrained covariances across groups	2.274 (5)	.000	1.000	1.000	.016	13318.855	14112.268	.000	.000	2.174 (3)	.537
<i>Expectancy and effort cost</i>											
M4a: Multigroup correlational model for gender	0.160 (2)	.067	1.000	1.000	.003	13900.941	14714.807	—	—	—	—
M4b: M4a with constrained covariances across groups	2.928 (5)	.000	1.000	1.000	.016	13897.840	14697.990	.067	.000	2.748 (3)	.432
M4c: Multigroup correlational model for GPA	0.423 (2)	.000	1.000	1.000	.004	13189.238	13996.252	—	—	—	—
M4d: M4c with constrained covariances across groups	2.017 (5)	.000	1.000	1.000	.007	13184.852	13978.265	.000	.000	1.573 (3)	.666

Note. χ^2 = Satorra-Bentler χ^2 ; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. GPA = high school grade point average.

Table S7.3*Within-Person Correlations of Students' Expectancy and Task Values in the Multigroup Correlational Models*

	Intrinsic value model	Utility value model	Psych. cost model	Effort cost model	Intrinsic value model	Utility value model	Psych. cost model	Effort cost model
	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>
	<i>Female</i>				<i>Male</i>			
<i>Course-specific assessments</i>								
Expectancy T1c ↔ Task value T1c	.35*	.27*	-.39**	-.26*	.46**	.43*	-.51**	-.33*
Expectancy T2c ↔ Task value T2c	.74***	.41***	-.49***	-.40***	.77***	.51***	-.59***	-.37***
Expectancy T3c ↔ Task value T3c	.68***	.48***	-.54***	-.46***	.75***	.57***	-.47***	-.33***
<i>Week-specific assessments</i>								
Expectancy T1w ↔ Task value T1w	.31***	.30***	-.25***	-.17*	.32***	.28***	-.28***	-.20**
Expectancy T2w ↔ Task value T2w	.54***	.26**	-.45***	-.33***	.46***	.23*	-.48***	-.35***
Expectancy T3w ↔ Task value T3w	.49***	.34*	-.25**	-.19**	.50***	.32***	-.27**	-.24**
	<i>Low GPA</i>				<i>High GPA</i>			
<i>Course-specific assessments</i>								
Expectancy T1c ↔ Task value T1c	.42*	.45	-.46**	-.35*	.38*	.27	-.42**	-.32*
Expectancy T2c ↔ Task value T2c	.74***	.64*** a	-.45***	-.33***	.76***	.28 b	-.65***	-.43***
Expectancy T3c ↔ Task value T3c	.69***	.69*** a	-.42***	-.30**	.73***	.22 b	-.51***	-.40***
<i>Week-specific assessments</i>								
Expectancy T1w ↔ Task value T1w	.29***	.30***	-.22**	-.14*	.29***	.27***	-.27***	-.17*
Expectancy T2w ↔ Task value T2w	.48***	.20	-.43***	-.29***	.43***	.20	-.45***	-.34***
Expectancy T3w ↔ Task value T3w	.44***	.31***	-.21**	-.16*	.55***	.37***	-.31***	-.21**

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. GPA = high school grade point average. Psych. cost = psychological cost.

^{ab} Unequal superscripts within a row indicate significant differences between groups. If no superscripts are shown, there were no statistically significant differences between groups.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Model comparisons in Table S7.2 show that in the model including students' expectancy and intrinsic value, constraining the covariances to be equal for female and male students as well as for students with low and high GPA, the increases in RMSEA in the constrained model was larger than .015 even though the chi-square difference tests were not significant (BIC values favored the constrained models and AIC values were similar for the constrained and unconstrained models). We therefore report the within-person correlations for the constrained model as well as for an unconstrained model in Table S7.4. In the constrained models, the covariances are constrained to be equal across groups, whereas covariances were estimated separately for female and male students in the unconstrained models. Table S7.4 shows that the within-person correlations were mostly of similar size in the unconstrained and constrained models. There was a tendency that the within-person correlations between students' week-specific expectancy and intrinsic value were somewhat larger for students with low compared to high GPAs.

Table S7.4

Parameter Estimates for Within-Person Correlations of Students' Expectancy and Task Values in the Multigroup Correlational Models for Constrained and Unconstrained Models

	Unconstrained model		Constrained model	
	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>
	<i>Female</i>	<i>Male</i>	<i>Female</i>	<i>Male</i>
<i>Week-specific assessments</i>				
Expectancy T1w ↔ Intrinsic value T1w	.33***	.31***	.31***	.32***
Expectancy T2w ↔ Intrinsic value T2w	.36 [†]	.53***	.54***	.46***
Expectancy T3w ↔ Intrinsic value T3w	.32**	.57***	.49***	.50***
	<i>Low GPA</i>	<i>High GPA</i>	<i>Low GPA</i>	<i>High GPA</i>
<i>Week-specific assessments</i>				
Expectancy T1w ↔ Intrinsic value T1w	.44***	.14	.29***	.29***
Expectancy T2w ↔ Intrinsic value T2w	.60***	.31*	.48***	.43***
Expectancy T3w ↔ Intrinsic value T3w	.45**	.54***	.44***	.55***

Note. T1w–T3w = week-specific experiences on a given math worksheet. GPA = high school grade point average.

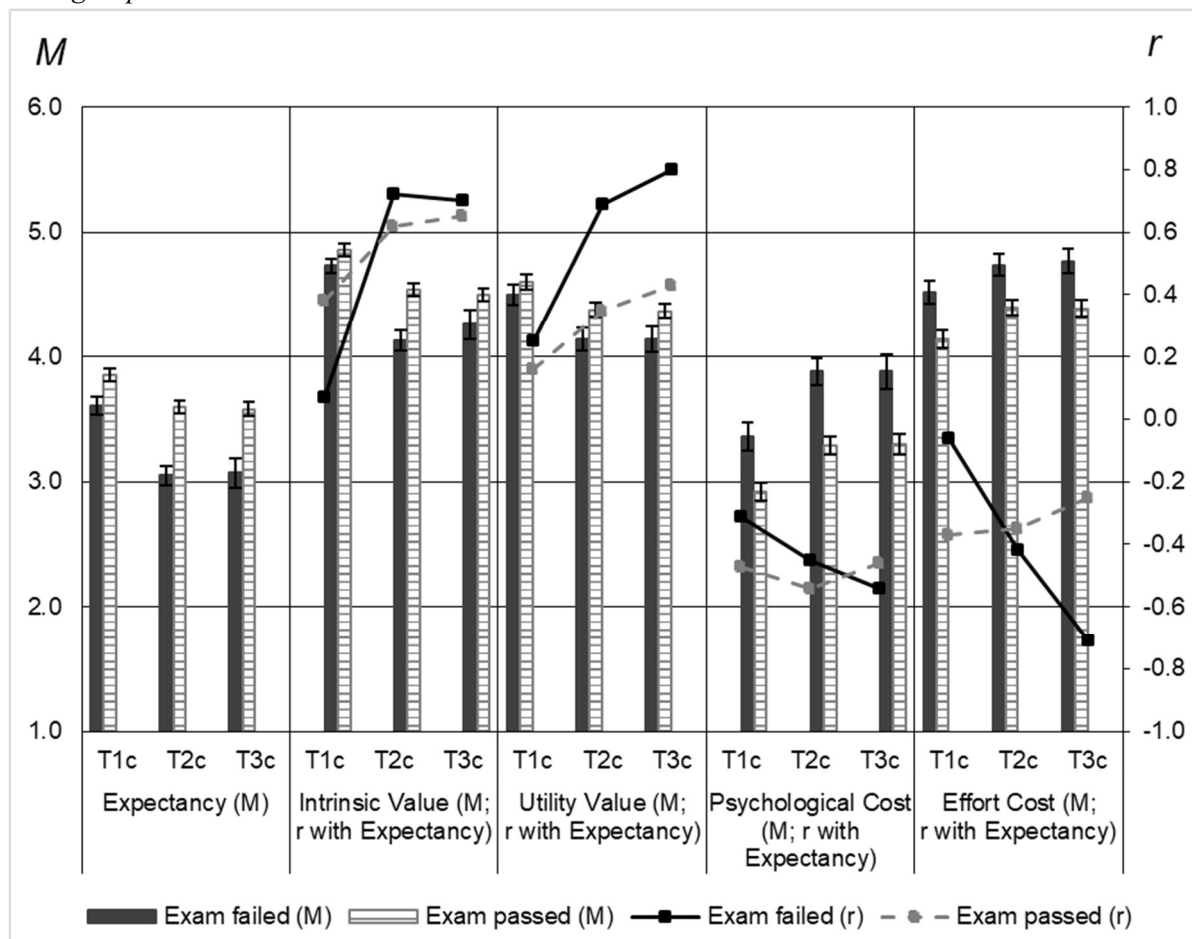
[†] $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Supplement S8. Multigroup Correlational Models for Students Who Failed Versus Passed Their Math Course

Figure S8 below shows mean-level differences (bar charts) and changes in the within-person correlations (lines) for students who passed vs. failed their final math exam. The corresponding within-person correlations are shown in Table S8. The Figure shows that the within-person correlations between students' *course-specific* expectancy and intrinsic and utility values increase over time for all students (T1c-T3c), but this increase is particularly strong for students who failed their final exam (see black vs. gray lines). Furthermore, the bar charts in Figure S8 show mean-level differences between the two groups and indicate that the motivations of students who failed their exam converge at a relatively low level, whereas the motivations of students who succeeded remain more misaligned.

Figure S8

Within-Person Correlations and Mean Levels of Students' Course-Specific Expectancy and Task Values in Multigroup Correlational Model



Note. T1c–T3c = course-specific summative evaluation of experiences thus far.

Table S8*Within-Person Correlations of Students' Expectancy and Task Values in Multigroup Multilevel Models*

	<i>Course Performance</i>					
	<i>r_{Fail}</i>	<i>r_{Pass}</i>	Δr	Δcov	Wald test	<i>p</i>
<i>Course-specific assessments</i>						
Expectancy T1c ↔ Intrinsic value T1c	.07	.38*	-.31	-.06	-0.76	.445
Expectancy T2c ↔ Intrinsic value T2c	.72***	.62*	.11	.33	2.64***	< .001
Expectancy T3c ↔ Intrinsic value T3c	.70***	.65**	.04	.35	2.44***	< .001
Expectancy T1c ↔ Utility value T1c	.25	.16	.09	.03	0.34	.736
Expectancy T2c ↔ Utility value T2c	.69***	.35*	.34	.40	2.80**	.005
Expectancy T3c ↔ Utility value T3c	.80***	.43**	.37	.38	2.44*	.015
Expectancy T1c ↔ Psychological cost T1c	-.31	-.47**	.16	.06	0.56	.578
Expectancy T2c ↔ Psychological cost T2c	-.45*	-.54***	.09	-.17	-1.05	.295
Expectancy T3c ↔ Psychological cost T3c	-.54***	-.46***	-.07	-.26	-1.73	.084
Expectancy T1c ↔ Effort cost T1c	-.06	-.37**	.32	.09	1.05	.295
Expectancy T2c ↔ Effort cost T2c	-.42**	-.35**	-.08	-.15	-1.37	.171
Expectancy T3c ↔ Effort cost T3c	-.71***	-.25*	-.46	-.38	-3.58***	< .001
<i>Week-specific assessments</i>						
Expectancy T1w ↔ Intrinsic value T1w	.40**	.25**	.15	.18	1.58	.115
Expectancy T2w ↔ Intrinsic value T2w	.56***	.39**	.18	.19	1.35	.179
Expectancy T3w ↔ Intrinsic value T3w	.57***	.43***	.14	.16	1.32	.187
Expectancy T1w ↔ Utility value T1w	.41**	.22*	.19	.16	1.44	.149
Expectancy T2w ↔ Utility value T2w	.31	.32*	-.02	.01	0.08	.939
Expectancy T3w ↔ Utility value T3w	.38**	.22*	.16	.12	1.35	.177
Expectancy T1w ↔ Psychological cost T1w	-.44***	-.23*	-.21	-.32	-2.23*	.026
Expectancy T2w ↔ Psychological cost T2w	-.47***	-.49***	.02	-.07	-0.39	.693
Expectancy T3w ↔ Psychological cost T3w	-.17	-.35***	.18	.06	0.41	.683
Expectancy T1w ↔ Effort cost T1w	-.38**	-.08	-.30	-.23	-2.00*	.045
Expectancy T2w ↔ Effort cost T2w	-.29*	-.39***	.10	.00	0.00	.999
Expectancy T3w ↔ Effort cost T3w	-.15	-.29***	.15	.05	0.36	.720

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Fail = students who failed the exam at the end of the semester, Pass = students who passed the exam at the end of the semester. Cov = covariance.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Supplement S9. Results of Repeated Measures Analysis of Variance**Table S9**

Mean-Level Differences in Students' Expectancy-Value Beliefs Over Time for Students Who Dropped out of or Failed Their Math Course Compared With Successful Students

	Course Dropout						Wilks' Λ	F	df_1, df_2	p
	M_{Dropout}			$M_{\text{noDropout}}$						
	T1	T2	T3	T1	T2	T3				
Course-specific assessments										
Expectancy	3.59	2.94	a	3.81	3.47	3.44	.971	14.479	1, 482	< .001
Intrinsic value	4.56	3.93	a	4.84	4.44	4.42	.989	5.355	1, 487	.021
Utility value	4.47	4.06	a	4.58	4.30	4.28	.997	1.368	1, 482	.243
Psychological cost	3.45	3.95	a	3.01	3.46	3.46	1.000	0.189	1, 487	.664
Effort cost	4.38	4.71	a	4.22	4.49	4.48	.999	0.285	1, 487	.594
Week-specific assessments										
Expectancy	3.34	3.40	3.27	3.67	3.78	3.70	.998	0.348	2, 447	.706
Intrinsic value	3.40	3.46	3.37	3.82	3.88	3.88	.998	0.354	2, 450	.702
Utility value	4.03	4.09	3.91	4.20	4.15	4.15	.993	1.551	2, 445	.213
Psychological cost	4.29	4.03	4.12	4.07	3.82	4.02	.998	0.533	2, 445	.587
Effort cost	4.67	4.23	4.29	4.63	4.22	4.34	.999	0.187	2, 449	.829
Course Performance										
	M_{Fail}			M_{Pass}			Wilks' Λ	F	df_1, df_2	p
	T1	T2	T3	T1	T2	T3				
Course-specific assessments										
Expectancy	3.65	3.09	3.00	3.88	3.62	3.59	.958	6.341	2, 288	.002
Intrinsic value	4.79	4.24	4.14	4.87	4.55	4.52	.979	3.093	2, 291	.047
Utility value	4.55	4.13	4.04	4.63	4.35	4.34	.989	1.567	2, 288	.210
Psychological cost	3.35	3.96	3.90	2.88	3.27	3.28	.992	1.130	2, 291	.324
Effort cost	4.56	4.88	4.83	4.13	4.39	4.35	.999	0.075	2, 291	.928
Week-specific assessments										
Expectancy	3.30	3.34	3.46	3.79	3.92	3.75	.982	3.006	2, 319	.051
Intrinsic value	3.50	3.51	3.65	3.88	3.97	3.91	.993	1.147	2, 326	.319
Utility value	4.07	3.94	4.01	4.23	4.23	4.18	.996	0.720	2, 322	.488
Psychological cost	4.36	4.20	4.32	4.04	3.69	4.00	.995	0.859	2, 319	.424
Effort cost	4.86	4.42	4.63	4.58	4.14	4.29	.999	0.137	2, 323	.872

Note. Dropout = students who dropped out of their math course (i.e., did not attend the end-of-term class). NoDropout = students who attended the end-of-term class. Fail = students who failed the exam at the end of the semester, Pass = students who passed the exam at the end of the semester.

^a Course dropout implies that the students were not present at the end-of-semester data collection (T3c) so that no motivation data were available to compute correlations.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Supplement S10. Results of Alternative Models for Students' Course-Specific Expectancy-Value Beliefs

As recommended by Mulder & Hamaker (2021), we fixed the variance of the random intercept for intrinsic/utility values and the covariance with the random intercept of expectancy to zero due to lower AIC and BIC values (see Table S3.1). However, we repeated our main analyses with a model including random intercepts for both expectancy and intrinsic/utility values. The estimated within-person autoregressive and cross-lagged effects are reported in Table S10. The results are consistent with the results reported in the manuscript; however, the standard errors for the task value effects are somewhat larger compared to the models reported in the paper. Thus, the within-person cross-lagged effect from expectancy on utility value is only marginally significant ($p = .058$), but the effect size is similar compared to the model reported in the manuscript ($\beta_s = .15/.21$ vs. $\beta_s = .17/.26$).

Furthermore, chi-square difference tests suggested that the within-person autoregressive and cross-lagged parameters in the models including psychological and effort cost were not invariant over time (see Table S3.1); yet, model fit indices (i.e., BIC, RMSEA, CFI) suggested that there were little differences between the unconstrained and constrained models. We thus report the estimated autoregressive and cross-lagged effects for a model with time-invariant effects in Table S10. The results are consistent with the unconstrained versions of the models reported in the manuscript.

Table S10

Autoregressive and Cross-Lagged Parameters for Students' Course-Specific Expectancy-Value Beliefs Across the Entire Semester

	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]
<i>Course-specific assessments</i>								
<i>Autoregressive effects</i>								
Expectancy T1c \rightarrow Expectancy T2c	.72*** (.12) ^a	.53 [.30; .76]	.82*** (.08) ^a	.59 [.37; .81]	.81*** (.10) ^a	.59 [.30; .88]	.81*** (.10) ^a	.61 [.33; .89]
Expectancy T2c \rightarrow Expectancy T3c	.72*** (.12) ^a	.68 [.47; .90]	.82*** (.08) ^a	.78 [.64; .92]	.81*** (.10) ^a	.77 [.58; .96]	.81*** (.10) ^a	.77 [.60; .94]
Task value T1c \rightarrow Task value T2c	.55** (.19) ^b	.42 [.09; .75]	.56** (.19) ^b	.42 [.03; .82]	.25 (.53) ^b	.22 [−.62; 1.06]	.45** (.16) ^b	.40 [.14; .66]
Task value T2c \rightarrow Task value T3c	.55** (.19) ^b	.52 [.16; .88]	.56** (.19) ^b	.62 [.25; .98]	.25 (.53) ^b	.26 [−.90; 1.42]	.45** (.16) ^b	.55 [.19; .90]
<i>Cross-lagged effects</i>								
Expectancy T1c \rightarrow Task value T2c	.34* (.17) ^c	.24 [−.04; .52]	.25 (.13) ^c	.17 [−.03; .37]	−.25 (.32) ^c	−.21 [−.82; .41]	−.07 (.11) ^c	−.05 [−.21; .11]
Expectancy T2c \rightarrow Task value T3c	.34* (.17) ^c	.31 [−.01; .64]	.25 (.13) ^c	.26 [−.04; .55]	−.25 (.32) ^c	−.30 [−1.16; .55]	−.07 (.11) ^c	−.09 [−.35; .18]
Task value T1c \rightarrow Expectancy T2c	.13 (.11) ^d	.11 [−.07; .28]	−.02 (.07) ^d	−.01 [−.12; .09]	.00 (.09) ^d	.00 [−.15; .14]	−.01 (.06) ^d	−.01 [−.12; .10]
Task value T2c \rightarrow Expectancy T3c	.13 (.11) ^d	.13 [−.08; .34]	−.02 (.07) ^d	−.02 [−.15; .11]	.00 (.09) ^d	.00 [−.15; .15]	−.01 (.06) ^d	−.01 [−.12; .11]

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts within a model indicate that unstandardized coefficients were fixed to be the same.

* $p < .05$, ** $p < .01$, *** $p < .001$

Supplemental References

- Asparouhov, T., & Muthén, B. (2013). Computing the strictly positive Satorra-Bentler chi-square test in Mplus. *Mplus Web Notes*, 12, 1–12.
<https://www.statmodel.com/examples/webnotes/SB5.pdf>