Learning and Individual Differences 113 (2024) 102484

Contents lists available at ScienceDirect

Learning and Individual Differences

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

How does expectancy-value-cost motivation vary during a semester? An intensive longitudinal study to explore individual and situational sources of variation in statistics motivation

Claudia C. Sutter [a,b,*], Delaram A. Totonchi [b], Jamie DeCoster [b], Kenneth E. Barron [c], Chris S. Hulleman [b]

[a] Department of Psychology, University of California-Los Angeles, USA
[b] Center for Advanced Study of Teaching and Learning, University of Virginia, Charlottesville, USA
[c] James Madison University, Harrisonburg, VA, USA

ARTICLE INFO

Keywords:
Situated motivation
Expectancy-value-cost theory
Short-term motivational changes
Intensive longitudinal design
Gender and race

ABSTRACT

We measured expectancy, value, and cost 10 times over a 10-week introductory statistics course ($N = 219$) to examine their overall trajectory as well as individual (*between*-student) differences and situational (*within*-student) variability. First, our findings revealed an initial decline in expectancy and value and an initial increase in cost. Second, expectancy, utility value, and cost demonstrated individual and situational variability of comparable size, while intrinsic value had higher individual variability. Third, individual and situational variability in expectancy and value predicted variability in performance. Lastly, the relation of situational variability in expectancy and utility value with performance was stronger for Black, Latinx, and other racially marginalized students than for White/Asian students. Our findings provide empirical evidence for the situational nature of motivational beliefs and have implications for practitioners, course curriculum designers, and policymakers who aim to create more supportive and motivation-enhancing environments, particularly for statistics courses and students from racially marginalized and underserved backgrounds.

Educational relevance and implications statement: The aim of this research was to better understand the dynamic and situational nature of motivational beliefs (expectancy, value, and cost) in a college statistics course by measuring them 10 times over a 10-week term in an introductory statistics course. We found an initial decline in expectancy for success and values for statistics and an initial increase in perceived cost. We also found these beliefs fluctuated depending on the learning situation, which in turn, predicted their performance in that situation. Lastly, for students from racially marginalized and underserved groups (e.g., Black, Latinx, and Native-American students), we found that the learning situation played a key role in influencing their motivational beliefs and performance, highlighting the importance of taking the learning context into account when designing motivation-enhancing environments for students in statistics courses. These findings have implications for practice in that they (a) allow curriculum developers to redesign certain chapters based on motivational declines, and (b) help us identify the student groups whose motivational beliefs varies the most with contextual factors, and as such, any context-relevant interventions for creating more equitable learning contexts that support students of all backgrounds, particularly those who are historically marginalized by our education systems.

1. Introduction

Despite the fundamental role of introductory statistics courses as a gateway for many undergraduate degree programs (e.g., Biology, Psychology, Sociology), students often experience negative attitudes, lack motivation, and underperform in statistics courses (Najmi et al., 2018;

* Corresponding author at: 1285 Psychology Building, Box 156304, Los Angeles, CA 90095.
E-mail address: claudiasutter@ucla.edu (C.C. Sutter).

https://doi.org/10.1016/j.lindif.2024.102484
Received 26 September 2023; Received in revised form 6 May 2024; Accepted 31 May 2024
Available online 17 June 2024
1041-6080/

Primi et al., 2018; Sutter et al., 2022). As a result, introductory statistics courses can quickly become a barrier to students' academic success and progression in a given major (Schau & Emmioğlu, 2012). One way to guide recommendations on what can be done to improve learning in (introductory) statistics is to better understand individual (*between*-student) differences and situational (*within*-student) variability[1] and how they may contribute to differential learning outcomes. Because of its connection to learning outcomes and sensitivity to the learning situation, we centered the current investigation on student motivation.

Motivation is a dynamic process (Brown & Ryan, 2007) that changes in response to the learning environment (Kaplan & Patrick, 2016). Situated approaches to motivation (Nolen et al., 2015; Turner & Nolen, 2015) emphasize the situational nature of motivation and motivation-related constructs that are sensitive to the context and depend on momentary, dynamic factors such as learning materials, instructional practices, and tasks (Rosenberg et al., 2020). For example, learning materials that emphasize that making mistakes is part of the learning process can increase students' confidence in their own abilities, while instructional activities that incorporate real-world examples of course topics and provide students with opportunities to connect course topics to their personal interests can increase students' perceptions of the usefulness, practical relevance, and value of the content (Hulleman & Harackiewicz, 2021; Totonchi, Francis, et al., 2023; Totonchi, Tibbetts, et al., 2023). Thus, situated approaches to motivation (Nolen et al., 2015; Turner & Nolen, 2015) consider how motivation varies *within* students (i.e., situational variability) and is influenced by situational characteristics rather than varying solely *between* students (i.e., individual differences) due to inherent differences among individuals.

The learning context can further have a profound impact on the motivation of students from historically marginalized and underserved backgrounds (e.g., female students, Black, Latinx, Native-American students, first-generation college students), particularly within scientific disciplines. For example, female students and students from racially-marginalized backgrounds are frequently exposed to a variety of situational cues (e.g., in the context of scientific disciplines, a lack of diverse representation in learning materials, curriculum, and role models) that may question and undermine their abilities, signal that they do not belong in science-related fields, and contribute to lower motivation and motivation-related constructs (Canning et al., 2019; Muenks et al., 2020; Murphy et al., 2007; Murphy & Taylor, 2012; Steele & Aronson, 1995). Situational cues are thus important aspects of how individuals interact within their context and signal to individuals what and who is valued in a particular environment (Muenks et al., 2020). However, more research is needed to examine how motivation dynamically changes from one situation to another and whether the malleability of motivation to situational forces could be different for students of different demographic groups.

Although situational approaches have gained momentum among education researchers in recent years (Beymer et al., 2022; Eccles & Wigfield, 2020; Moeller et al., 2020), limited empirical research has examined the degree to which individual (between-student, e.g., who students are) versus situational levels (within-student, i.e., the situations students are in) contribute to students' overall motivational experience. This gap in research may be partially due to the limitations of the research designs that are commonly used in education (e.g., cross-sectional methods or longitudinal designs with only a few measurements). In turn, application of intensive longitudinal designs (e.g., Bolger & Laurenceau, 2013), which require the constructs to be measured repeatedly across time, would enable examination of constructs across individual levels (i.e., from one student to another) and situational levels (i.e., from one situation to another). Accordingly, in this study, we used an intensive longitudinal design and measured motivational beliefs 10 times over the course of a semester to explore the individual (*between*-student) and situational (*within*-student) sources of variability in students' motivation-related beliefs, their relations with performance, and differential associations based on students' gender, race, and generation status.

2. Theory and literature review

Frameworks that shed light on the contextual variability of motivation in the educational context are situated expectancy-value theory (Eccles & Wigfield, 2020) and expectancy-value-cost theory (Barron & Hulleman, 2015). These theories posit that students' choices, persistence, and performance on a given academic task are most proximally determined by students' expectancy, value, and cost beliefs. Expectancy beliefs refer to students' ability perceptions or their confidence in being able to do a given task, while value beliefs refer to students' reasons for wanting to do the task. Value beliefs are further differentiated into three major types, which are linked to positive reasons for wanting to do a task, including interest from engaging in a task (intrinsic value), perceived usefulness and relevance of engaging in a task for current or future goals (utility value), or being able to affirm an important aspect of one's identity by engaging in the task (attainment value). Within the larger context of this study - the online introductory statistics textbook - we focused on intrinsic and utility value for the following reasons. The mission of the textbook is to make learning statistics more interesting, useful, and relevant to students' lives and to promote future interest in statistics. The textbook focuses on transferable knowledge and making real-life connections using real-world examples and datasets. Given this vision of applicability, usefulness, and the relevance of the material and content, we are particularly interested in understanding students' experiences of intrinsic and utility value. Second, Coursekata is committed to the continuous improvement of the textbook based on students' experiences. In order to identify barriers or challenges in the textbook (e.g., chapters where students are experiencing dips in their perceived utility value) and as a result potential intervention opportunities, we focus on intrinsic and utility value as they seems more "amenable to a classroom intervention" compared to attainment value (Hulleman et al., 2010, p. 891).

Finally, cost beliefs refer to not wanting to do a task because of the perceived negative consequences of engaging in that task (e.g., Eccles et al., 1983; Flake et al., 2015), including effort cost (i.e., task requires too much time, energy, and resources to do it), psychological cost (i.e., task creates negative emotional states), or opportunity cost (i.e., the task prevents one from being able to engage in other desired activities).

2.1. The situational nature of expectancy, value, and cost

In the educational psychology literature there is growing attention on understanding variability in motivational beliefs (e.g., Berweger et al., 2022; Beymer et al., 2022; Moeller et al., 2020; Rutherford et al., 2023), emotions (e.g., Berweger et al., 2022; Bieg et al., 2013; Goetz et al., 2020), and engagement (Rosenberg et al., 2020; Lu et al., 2023; Xie et al., 2023) utilizing a variety of theoretical frameworks (e.g., the Dynamics of Achievement Motivation in Concrete Situations (DYNAMICS) framework, Moeller et al., 2020; control-value theory of emotions, Pekrun, 2006; Berweger et al., 2022, and situated-expectancy value theory, Eccles & Wigfield, 2020) and across a variety of learning environments including traditional classroom settings (e.g., Dietrich et al., 2017; Rosenberg et al., 2020) and online learning environments (e.g., Berweger et al., 2022). In this paper, we utilize the situated expectancy-value framework. Similar to Nolen et al.' (2015) situative approach to motivation in contexts, situated expectancy-value theory (Eccles & Wigfield, 2020) suggests that students' expectancy and value

[1] In multilevel literature, between-person differences are often also referred to as inter-individual differences, whereas within-person variability is often referred to as intra-individual variability. In the present paper, we will use the terms "individual (between-student) differences" to refer to differences in motivation between students and use the term "situational (within-student) variability" to refer to variation in motivation from one situation to the other within students.

can change based on the situation. For example, when the learning situation provides clear expectations and objectives, students are more likely to have a clearer understanding of what is expected of them, leading to higher expectancy (Getty et al., 2021; Hulleman et al., 2016). Or, when the learning situation emphasizes the relevance and real-world application of the subject matter, students are more likely to perceive the value of the material they are learning (Getty et al., 2021; Hulleman et al., 2016). On the other hand, an unsupportive learning environment can increase perceptions of cost. For example, a high volume of content or reading material can contribute to higher perceptions of effort cost. Thus, a student's perception of expectancy, value, and cost might change dynamically within the same week (or from one week to the next) depending on course material and how it is being taught (Dietrich et al., 2017).

A growing body of research conducted in introductory college courses is providing important insights into the “malleability” (Corpus et al., 2020, p. 2) of motivation and motivation-related constructs by assessing motivation over multiple timepoints within a course (Dai & Cromley, 2014; Flanigan et al., 2017; Kosovich et al., 2017; Robinson et al., 2019; Sutter et al., 2022; Young et al., 2018). For example, Sutter et al. (2022) measured perceived usefulness of course material (i.e., utility value) at three different time points in an introductory statistics course and found that utility value declined from the beginning to the middle of the course and then remained relatively stable. Similarly, examining three measurement points over a single semester in introductory psychology, Kosovich et al. (2017) found that both expectancy and utility value declined. Research on short-term motivational change at the postsecondary level has consistently found declining levels of motivational beliefs in introductory STEM courses including chemistry (Young et al., 2018; Zusho et al., 2003), biology (Gibbens, 2019; Rybczynski & Schussler, 2013; Young et al., 2018), engineering (Robinson et al., 2019), as well as physics and mathematics (Benden & Lauermann, 2022; Musu-Gillette et al., 2015). While this research reflects the dynamic nature of motivation and motivation-related constructs to some degree (Corpus et al., 2020), the small number of measurements across a relatively long span of time limits opportunities to model nuanced fluctuations in motivation and motivation-related constructs that might occur as a function of short-term situational influences.

2.2. Intensive longitudinal designs in examining situational constructs

To better understand the situational nature of motivation and its important role in boldening or discounting the effects of motivation on academic performance, recent research has called for motivation to be measured more intensively over a series of time points and to explore more regular (e.g., week by week) situation-specific motivational fluctuations that shape students' decision making (e.g., Benden & Lauermann, 2022). As such, employment of intensive longitudinal designs (Bolger & Laurenceau, 2013) is growing in motivation research. Intensive longitudinal designs have a myriad of advantages when employed to study situational constructs such as motivation (Zirkel et al., 2015). For instance, these methods enable us to examine factors that impact motivation within each student. Using this method, students will be asked to indicate their motivation at different times and in different situations. As such, this method is well-suited for research that aims to understand variation in motivation at the situational level. In addition, because of the large number of measurements, hence the close proximity of the experience to when it is measured, students are more likely to provide a valid response, because they remember the experience with more clarity (Schwarz, 2012). Therefore, using intensive longitudinal designs would provide assessments that are sensitive to variability within students, from one situation to another, as well as, to differences between students (Zirkel et al., 2015).

In conjunction with the situative perspective on motivation shaped by Nolen and colleagues and later Eccles and colleagues, empirical research within this situational focus has gained increasing prominence in the field of motivation. For instance, Dietrich et al. (2017) used an intensive longitudinal multi-level design among pre-service teachers, assessing expectancy, value, and cost three times per lesson across ten lessons with varying topics. They found that expectancy, value, and cost were topic specific, showing variability in assessments only 30 min apart. Additionally, Parrisius et al. (2022) examined the situational nature of expectancy and value beliefs among ninth graders across five consecutive math lessons, revealing that motivation not only varies substantially between students, but is also highly situational (i.e., influenced by contextual factors such as teaching behaviors). Finally, Benden and Lauermann (2022) investigated motivational changes among first-semester students in math-intensive study programs using weekly surveys. They identified a “motivational shock” (i.e., a rapid decline in intrinsic and utility value and an increase in cost) in the very first weeks of the semester (weeks 2 and 3), a change which served as a significant predictor of students' performance. This research, however, did not compare expectancy, value, and cost in their malleability to the situation versus individual sources of variation. Further, it remained unclear whether the individual or situational levels of variability in these motivational beliefs are stronger predictors of performance. Exploring the individual (i.e., between-student) and situational (within-student) sources of variability in students' expectancy, value, and cost beliefs will shed light on the degree to which each of these motivational beliefs are differentially malleable to the learning context, thereby potentially lending empirical support to the recently renamed situated expectancy-value theory (Eccles & Wigfield, 2020). Further, examining whether it is the individual (between-student) or situational (within-student) sources of variation that is responsible for the significant relations of motivational beliefs with achievement outcomes is promising with regards to the development of targeted interventions and instructional strategies to enhance learning outcomes.

2.3. Situational variation for historically marginalized and underserved students

While some research is starting to take the dynamic nature of expectancy-value-cost-motivation into account, more research is needed to examine motivational beliefs at the situational (within-student) level as well as interactions of the situation with other predictors (e.g., students' gender, race, or college generation status) on academic performance. This interaction is critical when considering the experiences of students who have been historically marginalized and underserved in scientific disciplines (e.g., female, Black, Latinx, Native-American, and first-generation college students). Research guided by (situated) expectancy-value-cost frameworks suggests that women (Kosovich et al., 2017; Wang & Degol, 2013) and students from racially-marginalized backgrounds (Perez et al., 2019, 2023; Robinson et al., 2019) often experience lower expectancies for success, intrinsic value, and utility value in quantitative fields compared to men or students from majority groups respectively.

In fact, the situational cue hypothesis (Murphy et al., 2007; Murphy & Taylor, 2012) posits that cues in the learning environment (which can be communicated via learning materials, instructional practices, messaging, tasks, or policies) can trigger experiences of social identity threats (like stereotype threat) among students from traditionally stigmatized groups, suggesting an interaction between individuals and their environment. For example, an instructor's mindset beliefs about the fixedness or malleability of ability (Dweck, 1999) can reinforce gender and racial stereotypical beliefs and undermine the psychological experiences of students from marginalized and underserved groups (Canning et al., 2019). Because such situational cues in the learning context are particularly salient for students from marginalized backgrounds, the way a learning environment is constructed has an important impact for students from groups who may be vulnerable to identity threat (Murphy et al., 2007). Therefore, it can be hypothesized that, for these students, the situation (e.g., seeing fixed versus growth-mindset language in instructional materials or having limited versus diverse perspectives and cultural backgrounds represented in examples/datasets) may play a more important role in determining how their motivational beliefs change and relate to achievement outcomes.

3. The present investigation

The purpose of the present study is to contribute to prior literature and research in four ways by exploring: (1) short-term trajectories in students' motivational beliefs during an introductory statistics course (2) individual (between-student) and situational (within-student) variability in students' expectancy, value, and cost beliefs, (3) situational (within-student) variability in motivational beliefs and its relation to achievement outcomes, addressing a gap in intensive longitudinal research, (4) the impact of contextual influences on the relationship between motivational beliefs and academic performance, specifically focusing on traditionally underrepresented student groups. Guided by the following four research questions, we employed an intensive longitudinal design by measuring expectancy-value-cost motivation 10 times over a 10-week term (See Fig. 1 for a conceptual model that depicts the hypothesized associations among variables at the individual (between-student) and situational (within-student) levels):

3.1. Research question 1: how do expectancy, value, and cost change over the course of the term?

In line with prior research (Benden & Lauermann, 2022; Gibbens, 2019; Kosovich et al., 2017; Musu-Gillette et al., 2015; Sutter et al., 2022; Young et al., 2018; Zusho et al., 2003), we expected expectancy and value to decline and cost to increase (on average) over the course of the term.

3.2. Research question 2: how much of the variability in expectancy, value, and cost can be attributed to individual (between-student) and situational (within-student) sources?

Based on the theoretical arguments outlined earlier (i.e., Nolen and colleagues' situative approach to motivation and Eccles and Wigfield's situated expectancy-value theory) and recent empirical findings (e.g. Benden & Lauermann, 2022; Dietrich et al., 2017; Parrisius et al., 2022), we expected variability on both levels, the individual (between-student) and situational (within-student) level.

3.3. Research question 3: how does individual (between-student) and situational (within-student) variability in expectancy, value, and cost predict variability in performance?

While we have no clear hypothesis as to whether the individual (between-student) or situational (within-student) levels of variability in expectancy, value and cost are stronger predictors of performance, we expected expectancy to be more predictive of performance than value beliefs given that expectancy-value theory (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000) and research (e.g., Sutter et al., 2023) generally suggest that expectancy is more strongly linked to performance whereas value beliefs are more strongly related to choice-related behaviors or future interest.

3.4. Research question 4: to what extent do student demographic characteristics (gender, racially marginalized status, and generation status) moderate the relationship between motivational beliefs and performance at the individual (between-student) and situational (within-student) levels?

Examining whether the impact of motivational beliefs on students' academic performance is more dependent on the situation for certain groups of students (e.g., students who have traditionally been underrepresented in science-related fields, like female students, Black and Latinx students, and first-generation college students) will help identify the student groups whose motivational beliefs vary the most with contextual factors. Based on the situational cue hypothesis (Murphy et al., 2007; Murphy & Taylor, 2012) which suggests that situational cues in the learning environment may be particularly salient for students from marginalized backgrounds (including female, racially marginalized, and first generation college students), we expected stronger relations in motivational beliefs and performance at the situational level

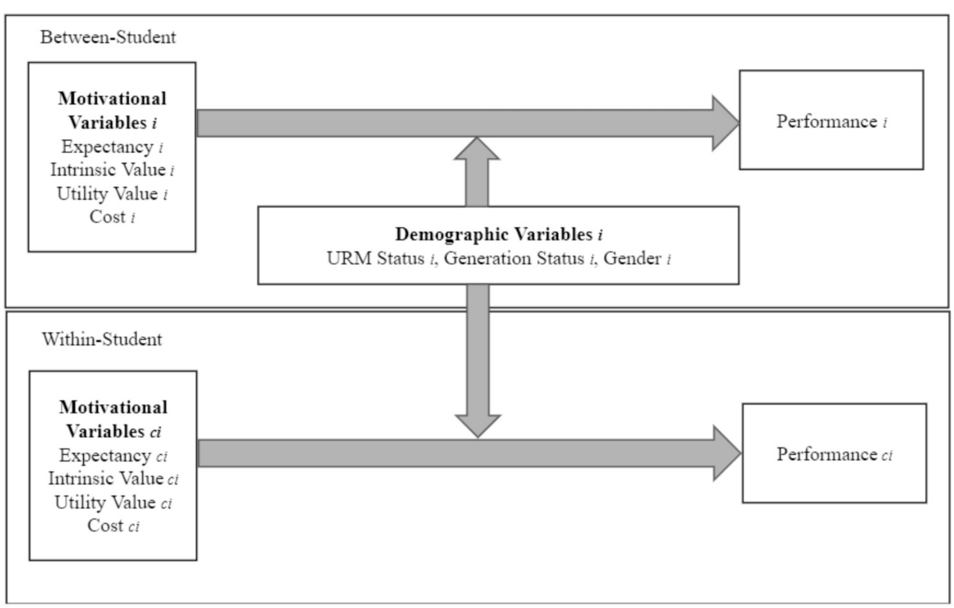

Fig. 1. Conceptual model examining the differential relations of motivation variables with performance at the within- and between-student levels for students of different demographic groups. Note. The subscript i denotes individual and the subscript c denotes chapter. We tested the direct associations of motivation variables with performance at the between-student and within-student levels and then examined whether these relations are moderated by racially marginalized status (URM), generation status, and gender.

for students who are marginalized.

4. Methods

4.1. Participants

Data were collected from 219 undergraduate students who were enrolled in an introductory statistics course during the Winter 2021 academic term. The course was offered by the psychology department at a large public research university in the western United States that runs off a quarter system (i.e., 10-week terms). The sample was 80.1 % female ($n = 173$), representative of the typical gender imbalance seen in psychology undergraduate courses (Cope et al., 2016). Of the students who indicated their race/ethnicity ($n = 214$; see Table 1), 37.9 % identified as belonging to a racially marginalized group, whereas 62.1 % students identified as either White or Asian. Lastly, 41.6 % identified as first-generation college students, indicating neither of their parents or guardians had a bachelor's degree.

4.2. Context and procedure

This study is part of a larger ongoing project to continuously improve an online interactive textbook for teaching introductory statistics, CourseKata Statistics and Data Science (available for preview at www.coursekata.org; Son & Stigler, 2017-2022). The online book consists of 12 chapters organized into three sections (i.e., exploring variation, modeling variation, and evaluating models; see Supplemental Fig. 1 for an overview of the chapter contents) and includes over 1200 embedded formative assessments, including R programming exercises. Most of the content of the course is conveyed in the online interactive textbook, whereas the lectures focused on deepening the understanding of concepts and the connections between them with new examples.

The design of the introductory statistics textbook is also unique in that all assessments of expectancy, value, and cost are embedded directly into the textbook at the beginning of each chapter (starting at chapter 2) and the review questions assessing statistics performance are embedded at the end of each chapter (see Supplemental Fig. 2 for an overview of the study design).

This study was approved by the Institutional Review Board at the [anonymized for peer-review] (IRB No: anonymized).

4.3. Measures

4.3.1. Expectancy, value, and cost

At the beginning of each chapter (beginning at chapter 2), students were asked to reflect on their learning experiences in the course so far ("You're about to start a new chapter! Before you do, reflect on how it's going so far and rate your level of agreement with each of the following statements"). They rated their ability perceptions as a component of expectancy ("I am confident in what I have learned so far in this course"), intrinsic value ("I think this class is interesting"), utility value ("I think what I have learned so far in this course is useful"), and cost ("I am unable to put in the time needed to do well in this course") on a six-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). These items assessed students' cumulative expectancy, value, and cost beliefs at that point in the course; thus, any changes in one's beliefs from one chapter to the next would highlight their most recent beliefs.

Supplementary Table S1 provides evidence for construct validity for our weekly, single-item measures with their longer, multi-item measures collected three times during the academic term (moderate to high correlations).

Table 1
Race/ethnicity and racially marginalized status of students.

	N	%
Race/ethnicity		
Asian/Asian American	84	39.3
Black/African American	8	3.7
Latinx/Hispanic	40	18.7
White	47	22.0
Other/Prefer to self-describe	35	16.4
Racially Marginalized Status		
Racially Marginalized	81	37.9
Non-Racially Marginalized	133	62.1

Note. For our analyses by race/ethnicity, Hispanic or Latinx, Black or African American, Indian Subcontinent, Native American, and Greater Middle Eastern students were considered belonging to a racially marginalized and underserved group, whereas White and Asian students were considered majority students. Students of mixed race were included in the racially marginalized and underserved group, unless their race was a mix of White and Asian.

4.3.2. Performance

At the end of each chapter, students were required to complete a set of review activities to assess students' knowledge and skills. The review activities comprised multiple choice questions, open-ended response items, and interactive R coding exercises that provided students with practice analyzing a new dataset. The end of chapter review questions[2] included between 17 and 29 items per chapter (with Cronbach's Alphas ranging between 0.713 and 0.900). Students' performance scores for each chapter were calculated as the number of points earned divided by the number of points possible, providing 10 separate performance scores that we used in the analyses below.

4.4. Analyses

Motivational beliefs and performance scores were collected at 10 different time points (corresponding to chapters 2 through 11) during the course. Due to the nested nature of the data (chapter-level motivational beliefs and performance were nested within students), we analyzed our data using multilevel models to address each of the four research questions (Level 1: chapter; Level 2: student). Multilevel models are used when responses are dependent on a higher-level factor (e.g., there is dependency among the responses of students who are in the same class because they have the same teacher). In the case of our study, the data includes "situational dependencies", which requires the use of multilevel models (Rosenberg et al., 2020). That is, there is dependency among the motivational responses in each situation/chapter within each student. Further, we chose to work with multilevel models (MLMs) rather than latent growth curves because of our ultimate interest in the relations of motivational beliefs (rather than time) with performance. To assess situational (within-student) variability in motivational beliefs, we examined within-person variation using repeated measures over chapters 2–11. To assess individual differences, we examined between-person variation using average scores in motivational beliefs for each student. To separately examine the effects of individual and situational variability, we used group-mean centering of our predictor variables at the within-person level and grand-mean centering of our predictor variables at the between-person level. Analyses were performed using Mplus 8.6. Coefficients were estimated using full information maximum likelihood estimation (FIML).

We had relatively low missingness in our study due to the surveys being directly embedded in the online textbook and being a course requirement to complete. Missingness on the chapter assessments ranged from 0.0 % to 4.1 % with a median of 1.8 %. Out of the 219 cases in our data set, 192 (87.7 %) had complete data on the chapter assessments. No other pattern of missingness accounted for >2 % of the cases. Our analyses do not provide us with any reason to suspect the presence of non-random missingness in our data.

[2] Review questions are available for preview under coursekata.org.

5. Results

5.1. Research question 1: how do expectancy, value, and cost change over the course of the term?

To address our study's first research question, we started with a graphical examination of the expectancy, value, and cost means for each chapter (see Fig. 2).

Based on this graph, we decided to test both the linear and quadratic trends of change in motivational variables using MLMs. In these models, measurements of motivational beliefs in each chapter (Level 1) were nested within students (Level 2). At Level 1, our MLM estimated a polynomial equation relating chapter number to motivational beliefs for each student. This method allowed us to investigate how motivational beliefs change as chapter numbers increase (i.e., as students progress through the chapters). This equation contained an intercept, a linear coefficient, and a quadratic coefficient. These coefficients were then included as random coefficients at Level 2, enabling us to determine the mean linear and quadratic effects (averaging over students) as well as the extent to which these effects varied between students (see Curran & Bauer, 2011). Thus, MLM is a suitable method for modeling change over time in our study because it allows us to not only calculate the overall mean-level linear and quadratic trends but also the degree to which these vary between students through the use of random coefficients. We chose to work with multilevel models (MLMs) rather than latent growth curves because of our ultimate interest in the relations of motivational beliefs (rather than time) with performance at the individual (between-student) and situational (within-student) levels.

These results of our analyses, presented in Table 2, indicated that - on average - expectancy, intrinsic value, and utility value declined linearly while cost increased linearly as students progressed through the chapters. The mean linear components indicate the average rate at which motivational beliefs changed over the course of chapters. Additionally, the linear change in all of these four motivational beliefs varied significantly between students. That is, different students experienced varying rates of decline in their expectancy, intrinsic value, and utility value, and varying rates of increase in their cost. Further results suggested that all four motivational beliefs also had significant quadratic trends. The mean quadratic components indicate the acceleration of change in motivational beliefs as students progress through the chapters (Biesanz et al., 2004). The positive signs for the quadratic means for expectancy, intrinsic value, and utility value indicated an upward curvature, suggesting that on average these beliefs initially declined and then somewhat increased. The negative sign for the quadratic mean for cost indicated a downward curvature suggesting that on average this belief initially increased and then slightly decreased. The quadratic trends in these motivational beliefs did not vary between students.

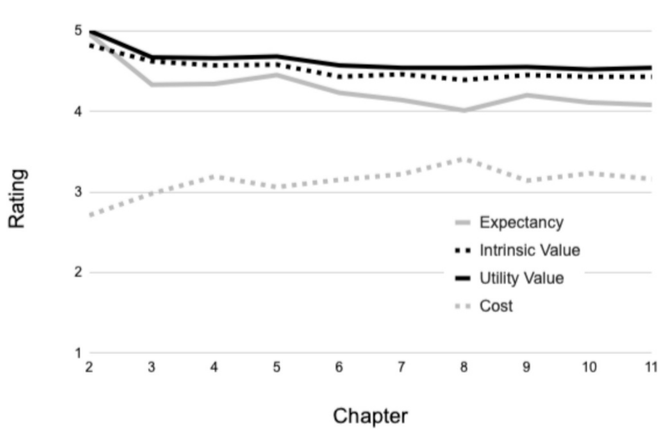

Fig. 2. Trends of change in averaged expectancy, intrinsic and utility value, and cost by chapter.

Table 2
Mean and variance of linear and quadratic trends in motivation across students.

	b (*SE*), *p*			
	Expectancy	Intrinsic Value	Utility Value	Cost
Linear mean	−0.263 (0.026), $p <$ .001	−0.137 (0.023), $p <$ .001	−0.141 (0.023), $p <$ .001	0.171 (0.026), $p <$ .001
Linear variance	0.092 (0.015), $p < .001$	0.072 (0.014), $p <$ .001	0.070 (0.015), $p <$ .001	0.067 (0.017), $p <$ .001
Quadratic mean	0.129 (0.020), $p < .001$	0.083 (0.019), $p <$ .001	0.083 (0.017), $p <$ .001	−0.135 (0.024), $p <$ .001
Quadratic variance	0.004 (0.011), $p = .68$	0.018 (0.008), $p =$ .02	0.003 (0.006), $p =$ .60	0.014 (0.013), $p =$ .28

Note. Estimates included in the table are unstandardized.

5.2. Research question 2: how much of the variability in expectancy, value, and cost can be attributed to individual (between-student) versus situational (individual-student) sources?

To address this research question, we explored individual (between-student) differences and situational (within-student) variability in each of the motivational variables. Individual (between-student) differences were calculated by examining variance at the student level and situational (within-student) variability was calculated by examining variance at the chapter level. We also provide the intra-class correlation (ICC), which represents the proportion of the variability in each motivational belief that can be attributed to individual differences (see Table 3). The ICC results indicated that roughly 50–65 % of the variance was due to individual (between-student) differences and the remainder was due to situational (within-student) variability. Therefore, contradicting the conventional approach that only focuses on individual (between-student) differences, the results indicated the presence of substantial situational (within-student) variability in all of the variables, highlighting the importance of examining motivational beliefs at both the individual and situational levels.

5.3. Research question 3: how does individual (between-student) and situational (within-student) variability in expectancy, value, and cost predict variability in performance?

To address this research question, we examined whether the individual (between-student) differences and situational (within-student) variability in motivational beliefs predict variability in performance. We determined that expectancy, value, and cost have substantial correlations at both the individual and situational levels (see Supplemental Table S2).

To understand any effects of multicollinearity on our results, we further estimated the relations of these variables with performance both separately and jointly. The goal was to explore which source of variation, individual (between-student) or situational (within-student) is

Table 3
Individual (Between-Person) and Situational (Within-Person) Variability in Study Variables.

Variable	Mean	Individual (between-person) variance	Situational (within-person) variance	Intra-class correlation
Expectancy	4.28	0.492	0.516	0.488
Intrinsic value	4.52	0.616	0.333	0.649
Utility value	4.62	0.474	0.359	0.569
Cost	3.12	0.799	0.653	0.550
Performance	0.73	0.029	0.025	0.540

more predictive of variability in performance.

Level 1 = Chapter c

$Y_{ic} = \beta_{0i} + \beta_{1i}motivation_{ic} + e_{ic}$

Level 2 = Individual i

$\beta_{0i} = \gamma_{00} + \gamma_{01}motivation_{i} + u_{0i}$

$\beta_{1i} = \gamma_{10} + u_{1i}$

At Level 1 (situational level, denoted by subscript c), Y is chapter-level performance while $motivation_{ic}$, represents a chapter-level motivational variable (e.g., expectancy). At Level 2 (individual level, denoted by subscript i), we predict the random intercept (representing overall performance) from $Xmotivation_{i}$, a student-level motivational aggregate. We do not have any Level 2 predictors of the random slope, but allow it to vary between students.

Table 4 presents the results of our models predicting performance from expectancy, intrinsic value, utility value, and cost. The models on the left side of the table examine the bivariate relations of expectancy, value, and cost with performance, while the model on the right examines their joint ability to predict performance.

These results show that when examined individually, expectancy and value were positively related to performances at both the individual (between-student) and situational (within-student) levels. The significant relations at the between-student level suggest that, averaging over the chapters, students with higher overall expectancy, intrinsic value, and utility value also had higher overall performance. The significant relations at the within-student level suggest that in chapters that students had higher expectancy, intrinsic value, and utility value, they also had higher performance. When examined individually, cost was negatively related to performance at the individual (between-student) level (i.e., averaging over chapters, students who had higher overall cost for the course had lower overall performance), but not at the situational (within-student) level (i.e., having higher cost in a chapter was not related to performance in that chapter). There was significant variability in the relations of all four motivational beliefs with performance (all p's < 0.05).

When expectancy, intrinsic value, utility value, and cost were examined simultaneously in the joint model, only the relationship between expectancy and performance was significant at both the individual and situational level, where higher expectancy ratings were associated with higher performance. The relationships of intrinsic value, utility value, and cost with performance were not uniquely significant at either the individual (between-student) or situational (within-student) levels when the predictors were examined in a single model simultaneously.

Table 4
Unstandardized coefficients from models predicting performance from expectancy, value, and cost.

	b (*SE*), *p*				
	Expectancy	Intrinsic Value	Utility Value	Cost	Joint
Within					
Expectancy	0.031 (0.006), *p* < .001				0.022 (0.006), *p* = .001
Intrinsic value		0.031 (0.008), *p* < .001			0.014 (0.009), *p* = .10
Utility value			0.030 (0.008), *p* < .001		0.010 (0.008), *p* = .23
Cost				−0.006 (0.005), *p* = .21	−0.001 (0.005), *p* = .88
Between					
Expectancy	0.112 (0.013), *p* < .001				0.093 (0.018), *p* < .001
Intrinsic value		0.055 (0.014), *p* < .001			−0.030 (0.022), *p* = .18
Utility value			0.083 (0.015), *p* < .001		0.048 (0.030), *p* = .11
Cost				−0.056 (0.012), *p* < .001	−0.013 (0.013), *p* = .33

5.4. Research question 4: to what extent do student demographic characteristics (gender, racially marginalized status, and generation status) moderate the relationship between motivational beliefs and performance at the individual (between-student) and situational (within-student) levels?

After estimating the individual (between-student) and situational (within-student) relationships of expectancy, intrinsic value, utility value, and cost with performance, we ran a final set of models attempting to predict these relationships from demographic characteristics. Specifically, we added gender, racially marginalized status, and first-generation college student status to the between-person level of the model as predictors of both individual performance as well as the situational (within-person) relations of motivational beliefs with performance.

Level 1 = Chapter c

$Y_{ic} = \beta_{0i} + \beta_{1i}motivation_{ic} + e_{ic}$

Level 2 = Individual i

$\beta_{0i} = \gamma_{00} + \gamma_{01}motivation_{ic} + \gamma_{02}female_{i} + \gamma_{03}urm_{i} + \gamma_{04}firstgen_{i} + \gamma_{05}motivation \times female_{i} + \gamma_{06}motivation \times urm_{i} + \gamma_{07}motivation \times firstgen_{i} + u_{0i}$

$\beta_{1i} = \gamma_{10} + \gamma_{11}female_{i} + \gamma_{12}urm_{i} + \gamma_{13}firstgen_{i} + u_{1i}$

At Level 1, Y is chapter-level performance while $motivation_{ic}$ represents a chapter-level motivational variable. At Level 2, we predict the random intercept (representing overall performance) by motivational beliefs, demographic variables (female gender, underrepresented marginalized status, and first-generation status), as well as the interactions of motivational beliefs with demographic variables. We also predict the Level 1 motivational beliefs random slope coefficient (i.e., the relation of expectancy with performance) from demographic variables. Including demographic predictors of the motivation coefficients allows us to assess whether the situation plays a different role for students of different demographic groups in the way it influences the relations of motivational beliefs with performance. We again estimated the relationships of expectancy, intrinsic value, utility value, and cost with performance both separately and jointly so that we would be able to understand any effects of multicollinearity on our results (See Supplemental Table S3 for the cross-level interactions of motivational beliefs with demographic variables predicting performance).

In the models examining expectancy, value, and cost separately, the relations of expectancy and utility value with performance at the situational (within-student) level were significantly predicted by racially marginalized status ($b = 0.001$, SE < 0.0005, $p = .03$ for expectancy; $b = 0.001$, SE < 0.001, $p = .05$ for utility value), such that expectancy and utility value beliefs in a chapter were more strongly related to performance in that chapter for racially marginalized students ($b = 0.034$, SE $= 0.009$, $p < .001$ for expectancy; $b = 0.037$, SE $= 0.016$, $p = .02$ for utility value) than for majority students ($b = 0.033$, SE $= 0.009$, $p < .001$ for expectancy; $b = 0.036$, SE $= 0.016$, $p = .02$ for utility value). These results could imply that for racially-marginalized students, situation (as measured by within-student variability) plays a more crucial role in determining the academic consequences of having strong or weak motivational beliefs, compared to majority students. Gender and first-generation status were not related to the relations of expectancy or utility value with performance at the situational (within-student) level, and no student demographics were related to the relations of intrinsic value or cost with performance at the situational (within-student) level (all *p*'s > 0.05). At the individual (between-student) level, only gender was significantly related to the relation of expectancy with performance ($b = -0.056$, SE $= 0.023$, $p = .01$), such that the relationship of expectancy with performance was stronger for males ($b = 0.120$, SE $= 0.015$, $p < .001$) than for females ($b = 0.064$, SE $= 0.015$, $p < .001$). This result suggests that overall and across all chapters, having strong expectancy beliefs would more positively and favorably predict performance for male students than for female students. No demographic characteristics were related to the relations of intrinsic value, utility value, or cost with performance at the between-student level (all p's > 0.05).

When expectancy, intrinsic value, utility value, and cost were examined simultaneously in the joint model, none of the demographics significantly predicted the relationships of any of the motivation variables with performance in the joint model at the situational (within-student) level (all p's > 0.05). At the individual (between-person) level, similar to the result of the separate models, the interaction of gender on the relation of expectancy with performance remained significant ($b = -0.101$, SE $= 0.038$, $p = .008$), indicating that the relationship of expectancy with performance was stronger for males ($b = 0.142$, SE $= 0.034$, $p < .001$) than for females ($b = 0.041$, SE $= 0.020$, $p = .04$). We also observed a new interaction of first-generation status on the relation of cost with performance ($b = 0.060$, SE $= 0.024$, $p = .02$), such that the relation of cost with performance was stronger for first-generation students ($b = 0.062$, SE $= 0.028$, $p = .03$) than for continuing generation students ($b = 0.002$, SE $= 0.019$, $p = .91$). This finding suggests that overall and across all chapters, perceptions of costs more strongly predicted performance for first-generation students than for continuing-generation students.

6. Discussion

In this study, we explored the situative nature of motivational beliefs by examining how expectancy, value, and cost vary both at the individual (between-student) and situational (within-student) levels over the course of an introductory statistics course using an intensive longitudinal design and multilevel modeling. We discuss our main findings in detail in the following sections.

6.1. Research question 1: how do expectancy, value, and cost change over the course of the term?

The findings of our study revealed that on average expectancy and value (intrinsic and utility) decreased and perceptions of cost increased as students from the beginning to the end of the course. These patterns are in line with prior findings at the college level showing that positive motivational beliefs tend to decline (Benden & Lauermann, 2022; Robinson et al., 2019), whereas perceptions of cost tend to increase (Kosovich et al., 2017). While prior studies have explored the trajectories of motivational beliefs in college introductory STEM courses such as physics and math (Dietrich et al., 2017; Musu-Gillette et al., 2015), biology (Gibbens, 2019; Rybczynski & Schussler, 2013), engineering (Robinson et al., 2019), and chemistry (Young et al., 2018; Zusho et al., 2003), the findings of our study provide evidence for similar trends using a more intensive longitudinal design (employing 10 time points compared to 2–4) within the context of introductory statistics – a field less studied despite its crucial role as a gateway course for students pursuing majors in scientific disciplines, including psychology, and beyond.

Similar to a recent study exploring students' short-term motivational trajectories in math-intensive study programs (Benden & Lauermann, 2022), we found indications of an initial motivational shift with declines in expectancy and value and increases in cost during the first weeks of the term. Although this initial motivational decline is rather small, these changes in expectancy, value, and cost may be explained by a "honeymoon phase" as students enter a new course with potentially high expectancy and value, which eventually settle down (Dietrich et al., 2017; Eccles & Midgley, 1989). In line with the argument of a "honeymoon phase", the nature of the first chapter of the textbook was an introductory chapter that differed from the subsequent chapters in terms of content and difficulty, which may have contributed to higher levels of expectancy and values.

While the initial change is consistent across expectancy, value, and cost (with declines in expectancy and value and an increase in cost), after the initial shift the trends differ with expectancy and cost changing more dynamically than values. These differences highlight the importance of exploring expectancy, value, and cost beliefs using more measurement timepoints across the term to capture more nuanced differences among specific motivational beliefs. Our findings suggest that interventions targeting different motivational constructs might be implemented at different times and might differ in treatment or assessment frequency. For example, interventions that target students' perceived usefulness of the course (i.e., utility value) within the context of introductory statistics may be particularly beneficial during these first few weeks, whereas interventions that aim to reduce students' perceptions of cost might be best implemented multiple times throughout the term.

6.2. Research question 2: how much of the variability in expectancy, value, and cost can be attributed to individual (between-student) and situational (within-student) sources?

The results of our study revealed that there was considerable variability in expectancy, value, and cost – both at the individual (between-student) and situational (within-student) level. Contradicting the conventional research approach that only examines motivational beliefs and their relations with relevant variables at the individual (between-student) level, our study revealed that for expectancy, utility value, and cost situational (within-student) variance was comparable in size or larger than individual (between-person) variance.

The findings at the individual (between-student) level are consistent with prior research showing that students experience different levels of motivational beliefs (e.g., Chow et al., 2012; Dietrich et al., 2017; Gaspard et al., 2017, 2018; Nagengast et al., 2013). At the situational, (within-student) level, our findings show that student motivational beliefs fluctuate as students progress through the course and start new chapters, indicating that motivational beliefs vary as the learning environment/content varies (e.g., topic, difficulty, length, task type, etc.). This speculation is consistent with research suggesting that expectancy and value vary across learning situations and fluctuate "from one topic and lesson to another and from one situation to another" (Dietrich et al., 2017, p. 60). Interestingly, however, the variances at the situational (within-student) level in our study are somewhat higher than in other studies (e.g., Berweger et al., 2022). This is particularly the case for expectancy (which demonstrate a situational variance of 0.516 compared to 0.301 in Berweger et al., 2022) and cost (with a variance of 0.653 compared to 0.292 in Berweger et al., 2022), whereas the variances of intrinsic value (0.359 compared to 0.329 in Berweger et al., 2022) and utility value (0.333 compared to 0.393 in Berweger et al., 2022) are similar. Although Berweger and colleagues' study was also conducted within an online learning environment, students were enrolled in a course in an Educational Science program. Perhaps the specific characteristics of the learning environment and content within the context of online introductory statistics and data science may have contributed to higher situational (within-student) variation. Factors such as diversity in concepts and topics, varying difficulty levels, or length of chapters might contribute to greater fluctuations in motivational beliefs. Although speculative, it's possible that the learning materials in this specific context (i.e., online introductory statistics and data science) triggers more pronounced shifts in expectancy and cost perceptions.

Comparing individual (between-student) differences and situational (within-student) variability among the motivational beliefs, we found that intrinsic value (followed by utility value) was the least dynamic, varying less from situation-to-situation than the other types of motivation. Intrinsic value is typically considered a more stable form of motivation because it derives from internal factors (Chung & Kim, 2022; Gottfried et al., 2001) and may perhaps be less susceptible to situational fluctuations. Intrinsic value varies *between* individuals, however, as students have different personal interests and preferences. Additionally, we found that utility value also did not vary as much between students as intrinsic value, expectancy, or cost. Although levels of utility value were more stable compared to expectancy and cost, they nevertheless declined, potentially indicating an opportunity for curriculum developers and designers to add supports throughout the book that guide students to reflect on the utility value of the course material (i.e., utility-value intervention; Hulleman & Harackiewicz, 2021).

Perceptions of cost showed the highest levels of both individual (between-student) and situational (within-student) variability. These results could imply that compared to other motivational beliefs, perceptions of cost are potentially more directly tied to the course content, difficulty, length, and topic (Getty et al., 2021). This aligns with how the course is set up in that the chapters within the online introductory textbook vary in length and difficulty. For example, chapter 7 is considerably longer than other chapters, which students might consider more time consuming (i.e., costly). Higher individual (between-student) differences in cost may also indicate that students have different responsibilities, interests, or commitments outside of the course, and that their ability to invest in the course varies over time. Compared to values, expectancy showed higher situational (within-student) variability. This greater variability could reflect expectancy's higher impressionability to task difficulty or its greater malleability as a function of receiving recurring performance evaluations within the term (Muenks et al., 2018). Expectancy also showed substantial individual (between-student) variation (though slightly smaller than situational (within-student) variation, which could be explained by variability in students' perceived preparedness for math-relevant courses.

6.3. Research question 3: how does individual (between-student) and situational (within-student) variability in expectancy, value, and cost predict variability in performance?

Our multilevel models revealed that when expectancy, value, and cost are examined separately, variation in expectancy and value ratings are associated with variation in performance both as a function of who students are (e.g., students who have more success expectancies and find the course to be more valuable on average have higher performance scores) and the context of the course (e.g., students perform better in chapters that they perceive higher success expectancies and value). The relation of cost with performance revealed differential patterns at the individual (between-student) and situational (within-student) level, with a significant association at the individual (between-student) level and a non-significant association at the situational (within-student) level. This suggests that averaging over chapters, students' overall performance is related to their overall perceptions of cost as students progress through the textbook. However, the variations in performance from chapter to chapter within each student are not related to variations in student's perceived costs This pattern may shed light on other things going on for certain students who are feeling cost pressures due to things beyond variations on how the course is structured (such as work or other curricular or extracurricular time commitments).

When examined simultaneously, only the relation between expectancy and performance is significant at both the individual (between-student) and situational (within-student) levels, indicating that variations in students' expectancy predict variations in performance both as a function of changes in the situation (i.e., as students progress through the different chapters) and as a function of differences between students (i.e., students having different overall expectancy), even when accounting for students' values (intrinsic and utility value) and perceptions of cost.

These findings align with expectancy-value research suggesting success expectancy are most strongly tied to performance whereas values are more related to choice-related behaviors or persistence (Eccles & Wigfield, 2002; Wigfield & Cambria, 2010), supporting the dominant role that students' success expectancy plays in predicting performance both at the individual and situational levels. Indeed, the presence of significant associations between values and performance in the separate models and the lack of those associations in the joint models suggests that values likely do not explain any unique variance in performance, over and beyond the variance explained by expectancies and costs.

6.4. Research question 4: to what extent do student demographic characteristics (gender, racially marginalized status, and generation status) moderate the relationship between motivational beliefs and performance at the individual (between-student) and situational (within-student) levels?

Finally, we examined how the relations of expectancy, value, cost with performance at the individual (between-student) and situational (within-student) levels varied between subgroups of students by adding gender, underrepresented marginalized status, and first-generation college student status to our models. We found that at the individual (between-student) level, the relation of expectancy with performance was stronger for male students. Although the effect size is relatively small, potential explanations are worth discussing. Perhaps female students, who typically have lower average expectancy scores in quantitative fields (e.g., Catsambis, 1994, 2005; Correll, 2001; Nagy et al., 2008), are more likely to receive messages or cues from the environment that they aren't competent, which disrupts the relationship between expectancies and outcomes (e.g., Murphy et al., 2007; Shapiro & Williams, 2012; Smith et al., 2015). These messages or cues, whether implicit or explicit, could potentially disrupt the otherwise positive relationship between expectancies and academic outcomes, contributing to a scenario where female students face challenges in realizing their full academic potential, despite possessing the capabilities. In contrast, men may be less likely to encounter messages that cast doubt on their capabilities in these fields. In fact, societal norms and expectations often reward men for their efforts to showcase competence in quantitative domains (e.g., through reinforcement and positive feedback). This favorable context for male students creates an environment wherein their positive expectations align with external cues and are, therefore, more predictive of their performance outcomes. The societal reinforcement of men's competence in quantitative fields might reinforce a virtuous cycle, where positive expectations are more likely to translate into successful academic achievements. Thus, the observed gender disparity in the predictiveness of expectancies for academic performance might be attributed to the differential contextual experiences between females and males in quantitative fields.

We also found that the relationships of expectancy and utility value with performance at the situational (within-student) level were stronger for students from racially marginalized backgrounds. These results highlight the importance of context particularly for student groups who are racially marginalized. For this student group, we found that the variation in motivational beliefs that occurs as a result of the situation more strongly predicted their performance. A number of theories suggest why racially marginalized students might be more sensitive to the fluctuations in the situation. For instance, the situational cue hypothesis (Murphy et al., 2007; Murphy & Taylor, 2012) posits that students look to the situational cues in their learning environments to determine what is expected of them and what is valued. For individuals who are marginalized (e.g., women and racially marginalized students in scientific disciplines), the threat of being stigmatized triggers a negative vigilance response, where students might pay an increased attention to any cues that might determine their value and identity. Therefore, for these students, the impact of the situation on their motivational beliefs and achievement may be more salient. Providing more frequent motivation boosts for expectancy and utility value might be particularly crucial from students for racially marginalized backgrounds. Because there is no evidence that such motivational boosts could harm students from non-racially marginalized backgrounds, it could be a best practice to implement them broadly with all students.

The finding that the relationships of expectancy and utility value with performance were stronger for students from racially marginalized backgrounds could also be explained through the lens of the stereotype threat theory (Shapiro, 2011; Steele & Aronson, 1995). According to this theory, in situations where the threat of being judged based on one's social identity is present, the anxiety associated with a poor performance and tainting the image of one's social group interferes with one's actual performance. Steele (1997) argued that for racially marginalized students in competitive learning environments, this threat is always present. Stereotypes about the competence and intellectual ability of racially marginalized students are so deeply woven into our policies, practices, and individuals' behaviors that there isn't a need for an individual to explicitly experience a racially-charged stereotype. Instead, individuals will automatically pick up stereotype-relevant cues in the environment. Therefore, students of racially marginalized groups may be more sensitive to situational cues that might impact their motivation and performance.

We also found that the relation of cost with performance at the individual (between-student) level was stronger for first-generation students compared to continuing-generation students. In the absence of access to family members who can guide and support them in their education journey, and enduring the identity threats (e.g., belonging uncertainty) that commonly face first-generation students in competitive academic environments, these students may experience increased cost in difficult quantitative courses (e.g., Totonchi, Francis, et al., 2023; Totonchi, Tibbetts, et al., 2023). Additionally, given that first-generation students are less likely to have completed less advanced math classes in high school (e.g., Cataldi et al., 2018), they may perceive the college statistics course as increasingly difficult, which could discourage them from placing effort in it, reducing their performance. These results highlight the importance of disaggregating the results by students' demographic characteristics.

7. Limitations

Despite the unique and intensive approach to measuring the situational nature of students' expectancy, value, and cost beliefs in introductory statistics using 10 measurement points, some limitations of the present study should be acknowledged.

First, the data used in this study came from one statistics course at one selective institution. The enrolled students also used a unique online interactive textbook. Thus, the generalizability of the results - particularly research questions 2–4 pertaining to situational (within-student) variability - to other introductory statistics courses, other course formats (e.g., other materials or in-person modality), students at other institutions, or other domains (e.g., introductory chemistry or biology etc.) remains unclear. However, the patterns and trends found in the current study align with prior findings regarding motivational trajectories in higher education settings (e.g., Corpus et al., 2020; Robinson et al., 2019; Sutter et al., 2022), providing some support for generalizability.

Second, we relied on single items for expectancy-value-cost constructs. Although this is a potential limitation with regards to the reliability and validity of our findings, we believe that using single items may be a necessary trade-off given our research design due to the repetitive, large number of assessments and the risk of participant fatigue (see e.g., Bolger & Laurenceau, 2013). Because intensive longitudinal studies are rare in the field of education, studies that help understand the situational (within-student) variance and the situational nature of achievement motivation contribute significantly to the field. The use of single-item measures allowed us to examine motivation more frequently throughout the course – a strategy typically employed to examine situational fluctuations by some of the most influential intensive longitudinal studies in the field of education, motivation, and engagement (e.g., Benden & Lauermann, 2022; Beymer & Robinson, 2022; Dietrich et al., 2017; London et al., 2011).

Third, we only assessed one form of cost (cost related to effort). Future research may want to look at other forms of cost, such as psychological or opportunity cost (Flake et al., 2015).

Finally, two limitations necessitate caution when interpreting and generalizing our results, particularly in terms of practical significance. Firstly, certain findings in our study, such as those related to gender and expectancy, revealed relatively small effect sizes. Secondly, the correlational nature of our study does not allow us to imply causation.

8. Implications for theory and practice

Our findings have implications for theory. Our study provides support for situated views of motivational beliefs (Nolen et al., 2015; Nolen, 2020) and extends expectancy-value-cost theory and situated expectancy-value theory in a number of ways. Our findings demonstrated that expectancy, value, and cost are all situational (Eccles & Wigfield, 2020), but to different degrees. Differences in the situational nature of motivational beliefs, in turn, have implications for their ability to predict performance. By failing to examine motivational beliefs at the situational level, we might have underestimated the strength of their influence on students' achievement. Further, although expectancy-value research emphasizes the importance of considering students' social groups when examining student motivation (Eccles & Wigfield, 2020), our findings suggest that for some groups of students (e.g., Black, Latinx and other racially marginalized students) the situational effects of motivation may be more salient than for other groups (e.g., White and Asian students). This highlights the importance of creating contexts that are supportive of student motivation, particularly for students from underrepresented groups.

Our findings also hold important implications for educational practice within the context of this specific online textbook. By exploring students' motivational beliefs throughout the term, we were able to identify specific "hot-spots" within the curriculum rather than just general motivational trends. One notable hot-spot we discovered was chapter 7 (topic: "Adding an Explanatory Variable to the Model"), where students reported particularly low levels of expectancy and high levels of cost. This pattern holds important implications for the curriculum designers who continuously seek to improve the textbook. As a result of these findings, chapter 7, which also happened to be the longest chapter, was completely redesigned and split into two chapters. Having repeated, motivational pulse check measures (Getty et al., 2021) throughout the course allowed the curriculum designers to not only identify but subsequently evaluate whether alterations to the textbook effectively changed situational motivations. More broadly, by tracking students' (situational) experiences throughout a course, researchers are able to provide feedback to instructors who are then able to evaluate their teaching materials and strategies after the course or school year has ended and perhaps think of topics that need motivational boosts such as adding real-life examples allowing students to see the connection between the discussed topic, material, or task and their own interests (see Moeller et al., 2020).

Our findings also have important implications for understanding and promoting equity in our educational practice. Disaggregating data by subgroups of students is crucial to understand their unique experiences and perspectives as they navigate a given course (McNair et al., 2020). This approach allows curriculum designers and instructors to recognize that students are not a homogenous group and that they may experience different motivational challenges, especially in difficult, gateway courses like statistics. The finding that students from racially marginalized backgrounds are more sensitive to the situational context suggests that infusing value-supportive practices into the learning context could improve racially marginalized students' motivation and success in statistics courses. As a result of this finding, the authors of the textbook have proposed adding more relevance and purpose messaging, the effects of which will be experimentally tested in an upcoming term. Making changes to the textbook that are informed by student data exemplifies the direct application of research findings to enhance the learning experience (see Getty et al., 2021). This approach not only benefits individual students but also contributes to the ongoing improvement of the curriculum and instructional materials, potentially creating a more equitable learning environment.

9. Conclusion

In line with recent research exploring the situational nature of motivational beliefs, our study demonstrated that expectancy, value, and cost beliefs were dynamic and situational, but to different degrees. We found that while expectancy and cost varied greatly as a function of the situation, intrinsic and utility value varied less across situations. Additionally, we found that variance in expectancy (individual and situational) was more strongly related to fluctuations in performance, compared to variance in other motivational beliefs. Lastly, it appeared that the impact of context was more salient for students from marginalized and underserved backgrounds, such that for these students the situational variance in expectancy and utility value was more strongly related to their performance than for racial majority students. Our results lend empirical support to the new situated expectancy-value theory, confirming that motivational beliefs are sensitive to the learning context. Our findings also highlight the "importance of the interaction between individual students and their learning contexts" (Dietrich et al., 2017, p. 62).

Author note

All data, materials, and analysis code pertaining to this study have been made publicly available on the Open Science Framework and can be accessed at https://osf.io/xa6fe/.

CRediT authorship contribution statement

Claudia C. Sutter: Writing – review & editing, Writing – original draft, Supervision, Project administration, Data curation. **Delaram A. Totonchi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Jamie DeCoster:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Kenneth E. Barron:** Writing – review & editing, Writing – original draft, Conceptualization. **Chris S. Hulleman:** Writing – review & editing, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

We have no conflicts of interest to disclose.

Acknowledgments

This project has been made possible in part by a grant from the Chan Zuckerberg Initiative DAF, an advised fund of Silicon Valley Community Foundation (DRL-1229004), a grant from the California Governor's Office of Planning and Research (OPR18115), and a grant from the Valhalla Foundation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2024.102484.

References

Barron, K. E., & Hulleman, C. S. (2015). Expectancy-value-cost model of motivation. In J. D. Wright (Ed.) (2nd ed.,, *Vol. 8. International encyclopedia of the social & behavioral sciences* (pp. 503–509). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.26099-6.

Benden, D. K., & Lauermann, F. (2022). Students' motivational trajectories and academic success in math-intensive study programs: Why short-term motivational assessments matter. *Journal of Educational Psychology, 114*(5), 1062–1085. https://doi.org/10.1037/edu0000708

Berweger, B., Born, S., & Dietrich, J. (2022). Expectancy-value appraisals and achievement emotions in an online learning environment: Within-and between-person relationships. *Learning and Instruction, 77*, Article 101546. https://doi.org/10.1016/j.learninstruc.2021.101546

Beymer, P. N., Benden, D. K., & Sachisthal, M. S. (2022). Exploring the dynamics of situated expectancy-value theory: A panel network analysis. *Learning and Individual Differences, 100*, Article 102233. https://doi.org/10.1016/j.lindif.2022.102233

Beymer, P. N., & Robinson, K. A. (2022). Motivating by measuring motivation? Examining reactivity in a diary study on student motivation. *Contemporary Educational Psychology, 70*, Article 102072. https://doi.org/10.1016/j.cedpsych.2022.102072

Bieg, M., Goetz, T., & Hubbard, K. (2013). Can I master it and does it matter? An intraindividual analysis on control–value antecedents of trait and state academic emotions. *Learning and Individual Differences, 28*, 102–108. https://doi.org/10.1016/j.lindif.2013.09.006

Biesanz, J. C., Deeb-Sossa, N., Papadakis, A. A., Bollen, K. A., & Curran, P. J. (2004). The role of coding time in estimating and interpreting growth curve models. *Psychological Methods, 9*(1), 30–52.

Bolger, N., & Laurenceau, J. P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research.* Guilford Press.

Brown, K. W., & Ryan, R. M. (2007). Multilevel modeling of motivation. In *Oxford handbook of methods in positive psychology* (pp. 530–541).

Canning, E. A., Muenks, K., Green, D. J., & Murphy, M. C. (2019). STEM faculty who believe ability is fixed have larger racial achievement gaps and inspire less student motivation in their classes. *Science Advances, 5*(2). eaau4734.

Cataldi, E. F., Bennett, C. T., & Chen, X. (2018). First-generation students: College access, persistence, and postbachelor's outcomes. In *Stats in Brief. NCES 2018–421*. National Center for Education Statistics.

Catsambis, S. (1994). The path to math: Gender and racial-ethnic differences in mathematics participation from middle school to high school. *Sociology of Education, 67*(3), 199–215. https://doi.org/10.2307/2112791

Catsambis, S. (2005). *The gender gap in mathematics: Merely a step function?* Cambridge University Press.

Chow, A., Eccles, J. S., & Salmela-Aro, K. (2012). Task value profiles across subjects and aspirations to physical and IT-related sciences in the United States and Finland. *Developmental Psychology, 48*(6), 1612–1628.

Chung, Y., & Kim, S. (2022). Expectancies, task values, and perceived costs: Reciprocal effects on math-related career intention and achievement among middle school girls. *Learning and Individual Differences, 96*, Article 102145. https://doi.org/10.1016/j.lindif.2022.102145

Cope, C., Michalski, D. S., & Fowler, G. A. (2016). Summary report, APA graduate study in psychology 2017: Student demographics. In *APA Office of Graduate and Postgraduate Education and Training.* Retrieved from www.apa.org/education/grad/survey-data/2017-student-demographics.

Corpus, J. H., Robinson, K. A., & Wormington, S. V. (2020). Trajectories of motivation and their academic correlates over the first year of college. *Contemporary Educational Psychology, 63*, Article 101907.

Correll, S. J. (2001). Gender and the career choice process: The role of biased self-assessments. *American Journal of Sociology, 106*(6), 1691–1730.

Curran, P. J., & Bauer, D. J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology, 62*, 583–619.

Dai, T., & Cromley, J. G. (2014). Changes in implicit theories of ability in biology and dropout from STEM majors: A latent growth curve approach. *Contemporary Educational Psychology, 39*(3), 233–247.

Dietrich, J., Viljaranta, J., Moeller, J., & Kracke, B. (2017). Situational expectancies and task values: Associations with students' effort. *Learning and Instruction, 47*, 53–64. https://doi.org/10.1016/j.learninstruc.2016.10.009

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development.* Philadelphia, PA: Psychology Press.

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives*. San Francisco, CA: Freeman (pp. 74e146).

Eccles, J. S., & Midgley, C. (1989). Stage/environment fit: Developmentally appropriate classrooms for early adolescence. In R. E. Ames, & C. Ames (Eds.), *Vol. 3. Research on motivation in education* (pp. 139–186). New York: Academic Press.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology, 53*(1), 109–132.

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*. https://doi.org/10.1016/j.cedpsych.2020.101859. Article 101859.

Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary*

Educational Psychology, 41, 232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002
Flanigan, A. E., Peteranetz, M. S., Shell, D. F., & Soh, L.-K. (2017). Implicit intelligence beliefs of computer science students: Exploring change across the semester. *Contemporary Educational Psychology, 48*, 179–196.
Gaspard, H., Häfner, I., Parrisius, C., Trautwein, U., & Nagengast, B. (2017). Assessing task values in five subjects during secondary school: Measurement structure and mean level differences across grade level, gender, and academic subject. *Contemporary Educational Psychology, 48*, 67–84. https://doi.org/10.1016/j.cedpsych.2016.09.003
Gaspard, H., Wigfield, A., Jiang, Y., Nagengast, B., Trautwein, U., & Marsh, H. W. (2018). Dimensional comparisons: How academic track students' achievements are related to their expectancy and value beliefs across multiple domains. *Contemporary Educational Psychology, 52*, 1–14. https://doi.org/10.1016/j.cedpsych.2017.10.003
Getty, S., Barron, K. E., & Hulleman, C. S. (2021). Five steps to improve student motivation in your college courses. *Journal on Excellence in College Teaching, 32*(4), 165–197.
Gibbens, B. (2019). Measuring student motivation in an introductory biology class. *The American Biology Teacher, 81*(1), 20–26. https://doi.org/10.1525/abt.2019.81.1.20
Goetz, T., Keller, M. M., Lüdtke, O., Nett, U. E., & Lipnevich, A. A. (2020). The dynamics of real-time classroom emotions: Appraisals mediate the relation between students' perceptions of teaching and their emotions. *Journal of Educational Psychology, 112*(6), 1243.
Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (2001). Continuity of academic intrinsic motivation from childhood through late adolescence: A longitudinal study. *Journal of Educational Psychology, 93*(1), 3–13. https://doi.org/10.1037/0022-0663.93.1.3
Hulleman, C. S., Barron, K. E., Kosovich, J. J., & Lazowski, R. A. (2016). Student motivation: Current theories, constructs, and interventions within an expectancy-value framework. In *Psychosocial skills and school systems in the 21st century: Theory, research, and practice* (pp. 241–278).
Hulleman, C. S., & Harackiewicz, J. M. (2021). The utility-value intervention. In G. W. Walton, & A. Crum (Eds.), *Handbook of wise interventions: How social psychology can help people change* (pp. 100–125). New York: Guilford Press.
Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology, 102*(4), 880–895.
Kaplan, A., & Patrick, H. (2016). Learning environments and motivation. In K. Wentzel, & D. Miele (Eds.), *Handbook of motivation at school* (2nd ed., pp. 251–274). New York: Routlege.
Kosovich, J. J., Flake, J. K., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology, 49*, 130–139. https://doi.org/10.1016/j.cedpsych.2017.01.004
London, B., Rosenthal, L., Levy, S. R., & Lobel, M. (2011). The influences of perceived identity compatibility and social support on women in nontraditional fields during the college transition. *Basic and Applied Social Psychology, 33*(4), 304–321.
Lu, G., Xie, K., & Liu, Q. (2023). An experience-sampling study of between-and within-individual predictors of emotional engagement in blended learning. *Learning and Individual Differences, 107*, Article 102348. https://doi.org/10.1016/j.lindif.2023.102348
McNair, T. B., Bensimon, E. M., & Malcom-Piqueux, L. (2020). *From equity talk to equity walk: Expanding practitioner knowledge for racial justice in higher education*. John Wiley & Sons.
Moeller, J., Viljaranta, J., Kracke, B., & Dietrich, J. (2020). Disentangling objective characteristics of learning situations from subjective perceptions thereof, using an experience sampling method design. *Frontline Learning Research, 8*(3), 63–84.
Muenks, K., Canning, E. A., LaCosse, J., Green, D. J., Zirkel, S., Garcia, J. A., & Murphy, M. C. (2020). Does my professor think my ability can change? Students' perceptions of their STEM professors' mindset beliefs predict their psychological vulnerability, engagement, and performance in class. *Journal of Experimental Psychology: General, 149*(11), 2119–2144. https://doi.org/10.1037/xge0000763
Muenks, K., Wigfield, A., & Eccles, J. S. (2018). I can do this! The development and calibration of children's expectations for success and competence beliefs. *Developmental Review, 48*, 24–39. https://doi.org/10.1016/j.dr.2018.04.001
Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science, 18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01
Murphy, M. C., & Taylor, V. J. (2012). The role of situational cues in signaling and maintaining stereotype threat. In M. Inzlicht, & T. Schmader (Eds.), *Stereotype threat: Theory, process, and application* (pp. 17–33). Oxford University Press.
Musu-Gillette, L. E., Wigfield, A., Harring, J. R., & Eccles, J. S. (2015). Trajectories of change in students' self-concepts of ability and values in math and college major choice. *Educational Research and Evaluation, 21*(4), 343–370. https://doi.org/10.1080/13803611.2015.1057161
Nagengast, B., Trautwein, U., Kelava, A., & Lüdtke, O. (2013). Synergistic effects of expectancy and value on homework engagement: The case for a within-person perspective. *Multivariate Behavioral Research, 48*(3), 428–460.
Nagy, G., Garrett, J., Trautwein, U., Cortina, K. S., Baumert, J., & Eccles, J. S. (2008). Gendered high school course selection as a precursor of gendered careers: The mediating role of self-concept and intrinsic value. In H. M. G. Watt, & J. S. Eccles (Eds.), *Gender and occupational outcomes: Longitudinal assessments of individual, social, and cultural influences* (pp. 115–143). American Psychological Association. https://doi.org/10.1037/11706-004.
Najmi, A., Raza, S. A., & Qazi, W. (2018). Does statistics anxiety affect students' performance in higher education? The role of students' commitment, self-concept and adaptability. *International Journal of Management in Education, 12*(2), 95–113.
Nolen, S. B. (2020). A situative turn in the conversation on motivation theories. *Contemporary Educational Psychology, 61*, Article 101866.
Nolen, S. B., Horn, I. S., & Ward, C. J. (2015). Situating motivation. *Educational Psychologist, 50*(3), 234–247. https://doi.org/10.1080/00461520.2015.1075399
Parrisius, C., Gaspard, H., Zitzmann, S., Trautwein, U., & Nagengast, B. (2022). The "situative nature" of competence and value beliefs and the predictive power of autonomy support: A multilevel investigation of repeated observations. *Journal of Educational Psychology, 114*(4), 791–814. https://doi.org/10.1037/edu0000680
Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*, 315–341.
Perez, T., Robinson, K. A., Priniski, S. J., Lee, Y. K., Totonchi, D. A., & Linnenbrink-Garcia, L. (2023). Patterns, predictors, and outcomes of situated expectancy-value profiles in an introductory chemistry course. *Annals of the New York Academy of Sciences, 1526*(1), 73–83. https://doi.org/10.1111/nyas.15031
Perez, T., Wormington, S. V., Barger, M. M., Schwartz-Bloom, R. D., Lee, Y. K., & Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education, 103*(2), 264–286. https://doi.org/10.1002/sce.21490
Primi, C., Donati, M. A., & Chiesi, F. (2018). The role of statistics anxiety in learning probability. In C. Batanero, & E. Chernoff (Eds.), *Teaching and learning stochastics. ICME-13 monographs* (pp. 145–157). Springer. https://doi.org/10.1007/978-3-319-72871-1_9.
Robinson, K. A., Lee, Y.-k., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*(6), 1081–1102. https://doi.org/10.1037/edu0000331
Rosenberg, J., Beymer, P. N., Phun, V., & Schmidt, J. (2020). *How does situational engagement vary between learners, situations, and classrooms? Findings from the use of intensive longitudinal methods and cross-classified, multi-level models*. https://doi.org/10.31219/osf.io/pj2v8 (2020).
Rutherford, T., Lee, H. R., & Duck, K. (2023). Dynamic relations between motivation and performance across content in a mathematics learning technology. *Learning and Individual Differences, 107*, Article 102346. https://doi.org/10.1016/j.lindif.2023.102346
Rybczynski, S. M., & Schussler, E. E. (2013). Effects of instructional model on student attitude in an introductory biology laboratory. *International Journal for the Scholarship of Teaching and Learning, 7*(2), Article n2.
Schau, C., & Emmioğlu, E. (2012). Do introductory statistics courses in the United States improve Students' attitudes? *Statistics Education Research Journal, 11*(2), 86–94.
Schwarz, N. (2012). Why researchers should think "real-time": A cognitive rationale. In *Handbook of research methods for studying daily life* (p. 22).
Shapiro, J. R. (2011). Different groups, different threats: A multi-threat approach to the experience of stereotype threats. *Personality and Social Psychology Bulletin, 37*(4), 464–480. https://doi.org/10.1177/0146167211398140
Shapiro, J. R., & Williams, A. M. (2012). The role of stereotype threats in undermining girls' and women's performance and interest in STEM fields. *Sex Roles, 66*, 175–183. https://doi.org/10.1007/s11199-011-0051-0
Smith, J. L., Brown, E. R., Thoman, D. B., & Deemer, E. D. (2015). Losing its expected communal value: How stereotype threat undermines women's identity as research scientists. *Social Psychology of Education, 18*, 443–466.
Son, J. Y., & Stigler, J. W. (2017-2022). *Statistics and data science: A modeling approach*. Los Angeles: CourseKata. https://coursekata.org/preview/default/program.
Steele, C. M. (1997). A threat in the air: How stereotypes shape intellectual identity and performance. *American Psychologist, 52*(6), 613–629. https://doi.org/10.1037/0003-066X.52.6.613
Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology, 69*(5), 797–811. https://doi.org/10.1037/0022-3514.69.5.797
Sutter, C. C., Givvin, K. B., & Hulleman, C. S. (2023). Concerns and challenges in introductory statistics and correlates with motivation and interest. *The Journal of Experimental Education*, 1–30. https://doi.org/10.1080/00220973.2023.2229777
Sutter, C. C., Hulleman, C. S., Givvin, K. B., & Tucker, M. (2022). Utility value trajectories and their relationship with behavioral engagement and performance in introductory statistics. *Learning and Individual Differences, 93*, Article 102095.
Totonchi, D. A., Francis, M. K., Tibbetts, Y., Huelskoetter, E., Davis, J., Smith, A., … Hulleman, C. S. (2023). Improving community college students' success in math: Findings from two utility-value studies. *The Journal of Experimental Education*, 1–24.
Totonchi, D. A., Tibbetts, Y., Williams, C. L., Francis, M. K., DeCoster, J., Lee, G. A., … Hulleman, C. S. (2023). The cost of being first: Belonging uncertainty predicts math motivation and achievement for first-generation, but not continuing-generation, students. *Learning and Individual Differences, 107*, Article 102365. https://doi.org/10.1016/j.lindif.2023.102365
Turner, J. C., & Nolen, S. B. (2015). Introduction: The relevance of the situative perspective in educational psychology. *Educational Psychologist, 50*(3), 167–172. https://doi.org/10.1080/00461520.2015.1075404
Wang, M. T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review, 33*(4), 304–340. https://doi.org/10.1016/j.dr.2013.08.001
Wigfield, A., & Cambria, J. (2010). Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. *Developmental Review, 30*(1), 1–35.
Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology, 25*(1), 68–81.

Xie, K., Vongkulluksn, V. W., Heddy, B. C., & Jiang, Z. (2023). Experience sampling methodology and technology: An approach for examining situational, longitudinal, and multi-dimensional characteristics of engagement. *Educational Technology Research and Development*, 1–31.

Young, A. M., Wendel, P. J., Esson, J. M., & Plank, K. M. (2018). Motivational decline and recovery in higher education STEM courses. *International Journal of Science Education, 40*(9), 1016–1033.

Zirkel, S., Garcia, J. A., & Murphy, M. C. (2015). Experience-sampling research methods and their potential for education research. *Educational Researcher, 44*(1), 7–16. https://doi.org/10.3102/0013189X14566879

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education, 25*(9), 1081–1094. https://doi.org/10.1080/0950069032000052207