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Concerns and Challenges in Introductory Statistics and Correlates with Motivation and Interest

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ABSTRACT

We explore how students' course concerns at the outset of their introductory statistics course predict their later perceived course challenges and future interest in statistics via a function of achievement motivation. Data were collected from undergraduate students ($N = 524$; 70% female; 37.8% students from racially marginalized groups) during the COVID-19 pandemic, using both open-ended (concerns and challenges) and closed-ended (achievement motivation and future interest) questions. Overall, incoming course concerns positively predicted perceived costs during the course and challenges at the end of the course and negatively predicted success expectancy and utility value during the course and future interest in statistics at the end of the course. Patterns varied by individual concerns/challenges, gender, and race/ethnicity. Cost played an important mediating role for female students and students from racially marginalized groups (e.g., Black, Latinx, or Native American/Indigenous students) between course concerns and future interest in statistics. Our findings (a) add to the increasing body of research reporting differences in how female and male students as well as students from racially marginalized backgrounds and racial majority students experience STEM courses and help explain different levels of interest in pursuing STEM careers, and (b) suggest that increasing future interest in statistics might require different interventions.

KEYWORDS

Qualitative and quantitative data; higher education; learning during the pandemic; expectancy-value-theory; gender and race

Introduction

Introductory statistics courses are required across a wide variety of college majors - from biology and psychology to sociology and political science. In the field of psychology, for example, statistical training is often considered an important component of the curriculum (Friedrich et al., 2000). Any concerns students might have about their performance in a statistics course, whether due to limited (or negative) experiences with math/statistics in the past or other factors are likely to shape students' achievement motivation - including success expectancy (i.e., appraisals of how well they will perform in a task), task values (i.e., motives for engaging in a task or behavior), and cost (i.e., perceived negative consequences of engaging in a task) as conceptualized within expectancy-value frameworks (EVT; Eccles, 1983). Students' concerns and achievement motivation are important in that they can determine whether students persist in their chosen major as well as whether they apply statistics in their everyday lives (Kosovich et al., 2017; Rosenzweig

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et al., 2019). Furthermore, low expectations of success and perceptions of value as well as high perceptions of course cost are likely to impact course outcomes (Gal et al., 1997).

Exploring the concerns with which students enter a course and whether those concerns are still present at the end of the course allows a deeper understanding of the dynamics of a course setting. If students find their initial concerns to be unfounded, it would be helpful to understand the factors that helped alleviate them. These conditions could be used by instructors with their future students. On the flipside, understanding the concerns that persist and are perceived by students as having been challenges that inhibited their success in the course would also be illuminating. This information would help identify particular pain points and guide instructional designers and curriculum developers as they develop interventions.

Understanding how concerns and challenges interrelate with students' motivation during the course will allow an even deeper understanding of the dynamics of the course. Specifically, understanding how motivational beliefs such as expectations of success, perceptions of utility value, and perceptions of cost (a) shape the relations between incoming concerns and later perceived challenges and (b) predict perceived challenges could help inform motivational interventions to improve the psychological experiences of students as they advance through the course. For example, if perceptions of utility value negatively predict perceived challenges or if perceptions of cost positively predict perceived challenges, designing interventions to enhance utility value or reduce cost might also lower students' perceived challenge(s).

Course concerns, challenges, and motivation might vary by students' background characteristics. For instance, perceived course cost may be especially high among students who face greater structural barriers in STEM or experience stereotype threat. Expectations of success and perceived course value may be lower for these students. In particular, college STEM learning contexts, including statistics, uniquely threaten motivation among students from racially marginalized backgrounds (e.g., Black, Latinx, or Native American/Indigenous students) and female students (Blackburn, 2017; Smith et al., 2015) for a number of reasons, including: the stereotypes about who can be successful favor individuals who are White, Asian, and/or male (e.g., Canning et al., 2019); the lack of diverse representation of students and faculty from different racial, ethnic, and socioeconomic backgrounds (e.g., Vazquez-Akim, 2014); a curriculum that emphasizes more masculine and Caucasian values, including both the number of White males and "the normative picture of a scientist" (Riegle-Crumb & King, 2010, p. 657); and the inability to support for students who enter the classroom with differing levels of academic preparation (Rosenzweig & Wigfield, 2016; van den Hurk et al., 2019). Beyond being confronted with structural and systemic barriers upon entering college, identity development becomes a critical process at this time, with students becoming particularly prone to ask themselves questions central to identity (Barron & Hulleman, 2015), including "Is this relevant to my life"? "Can I do this?", or "Am I free of barriers for doing this?".

Exploring how students' incoming course concerns interrelate with their perceptions of success, utility value, and cost as well as their intentions to pursue further study - especially among students from underrepresented groups - will generate practically relevant insights about how we can better support students in positively experiencing and successfully completing STEM courses. While opportunity gaps existed prior to the onset of the COVID-19 pandemic, they seem to have grown with the pandemic, exacerbating racial inequities and impacting students' motivation (Fong, 2022). Thus, gaining a deeper understanding of how course concerns might have shaped students' motivation and perceived challenges during the pandemic is critical.

Finally, beyond exploring individual concerns/challenges, we seek to explore the number of different concerns (i.e., diversity of concerns) expressed by students, how the quantity is related to motivation and course outcomes, and whether patterns vary by gender or race. Existing work (Meaders et al., 2020) suggests that (a) general levels of student concern (i.e., a summary score, per student, representing overall concern) are higher for female and first-generation students and (b) those students with higher levels of concern ultimately perform lower.

Concerns and perceived challenges in statistics classes

Identifying concerns students have about their introductory statistics course and the challenges they face in it may serve as a tool to (a) help instructors and curriculum developers to identify areas of struggle and potential barriers to success (Meaders et al., 2020); (b) guide curricular and pedagogical improvements in order to better aid students; and (c) inform interventions and identify the students needing them. All of these could serve to improve students' course experiences and increase their interest in taking more statistics classes in the future. Much of the undergraduate STEM literature has primarily focused on exploring "students' adverse experiences in course environments through the lens of anxiety" (Meaders et al., 2020, p. 196), highlighting, for example, gender differences in test anxiety or fear of failure with female students reporting overall higher levels of test anxiety than male students. However, concerns beyond anxiety or fear of failure are less frequently explored. In fact, to the best of our knowledge, there is only one study that explicitly explored undergraduate students' concerns in introductory STEM courses (Meaders et al., 2020) and no study that explored how students' incoming course concerns relate to students' perceptions and experiences (e.g., motivation) during the course and future interest as a course outcome. In this study, beyond highlighting course concerns and challenges voiced by undergraduate students enrolled in an introductory STEM course, we aim to gain a deeper understanding of the interplay between incoming course concerns, achievement motivation, perceived challenges, and future interest in statistics, and whether the interplay varies by subgroups of students, including by gender or race/ethnicity. This will enable us to better design learning contexts and opportunity structures to support students from underrepresented and traditionally marginalized backgrounds (e.g., Gray et al., 2018). Importantly, a unique contribution of this study lies in the distinction between students' individual concerns/challenges and the summed-up number of concerns/challenges (i.e., the diversity of concerns/challenges). We were interested in individual concerns and diversity of concerns because we believe that they have the potential to impact students in different ways. A concern about the need to memorize course material might, for instance, lead to different study behaviors. Students might engage in different levels of sense-making as they complete the materials and take different kinds of notes from which to study. That concern might be alleviated when the student recognizes that early assessments don't draw on memorized facts. Totaling the kinds of concerns held by a student paints a different picture of the student and their experience in the course. A student with a broad diversity of concerns about the course poses a bigger problem to intervention designers. Any single form of intervention might still leave important areas of concern unaddressed. A large number of concerns might also leave the student more likely to avoid course content altogether.

Expectancy, value, and cost

Expectancy-value theory (Eccles, 1983; Wigfield & Eccles, 2000) highlights the role of achievement motivation in educational environments, positing that students' achievement and achievement-related choices and behaviors are most proximally determined by an individual's success expectancy, perceptions of value for the task, and perceived costs to engaging in the task. Most recently, Eccles and Wigfield (2020) re-named their theory to *situated* expectancy-value theory to highlight the importance of individuals' perceptions of environmental factors and interpretation of their past experiences in influencing their decision making and subsequent learning process.

The success expectancy component addresses the "Can I do this?" (Barron & Hulleman, 2015) question and captures students' appraisals of how well they will perform in a given task or domain (Eccles, 1983; Eccles & Wigfield, 2002). The value component refers to the motives individuals have to engage in a task or behavior and comprises three components: Intrinsic value, utility value, and attainment value. When students hold the belief that they value something, they are more likely to engage in that behavior (Eccles & Wigfield, 2002). Intrinsic value refers to an individual's interest or enjoyment from engaging in a task or behavior; utility value (i.e.,"Is this relevant to my life"?), refers to the usefulness and value for one's current or future goals (i.e., short- or long-term goals); and attainment value refers to the extent to which an individual perceives a task to be personally meaningful or important. Thus, value refers to the enjoyment (intrinsic value), usefulness (utility value), and importance (attainment value) an individual associates with a task or behavior (Barron & Hulleman, 2015; Eccles, 1983; Rosenzweig et al., 2019).

Within the context of this study, we are particularly interested in *utility* value for two reasons. First, perceiving what they are learning as useful and relevant is a particularly important predictor of student learning outcomes in STEM - including statistics - such as motivation, future interest, and performance (Gaspard et al., 2015; Hulleman et al., 2008, 2010). Within the introductory statistics textbook on which this study is based, primary aims are to promote (a) deep learning, understanding, and engagement with the material, (b) transferable knowledge and making real-life connections, and (c) future interest in statistics. Thus, focusing on utility value is of high interest given the textbook's focus on the applicability, usefulness, and the relevance of the material and content. Second, in order to identify potential intervention opportunities within the context of introductory statistics, we focus on utility value "which seems the most amenable to a classroom intervention (…) given its more external nature" compared to intrinsic or attainment value (Hulleman et al., 2010, p. 891).

Part of understanding why students choose to pursue a given task or engage in a certain behavior requires that we consider students' reasons why they might *not* want to engage in a task or behavior. Finally, students may avoid, disengage, or withdraw from tasks they perceive as costly. Most broadly, cost captures the "negative appraisals of what is invested, required, or given up to engage in a task" (Flake et al., 2015, p. 237) and addresses the "Am I free of barriers for doing this? question (Barron & Hulleman, 2015). While cost has always been considered a subcomponent of the task value construct within the traditional expectancy-value theory, there is no clear consensus regarding its role within the framework, with the expectancy-value-cost framework considering cost a unique component that is distinct from the task value construct (Barron & Hulleman, 2015). While the construct of cost has been explored less extensively in educational research compared to expectancy and value, it has recently attracted growing attention as a unique, distinguished construct in understanding student motivation, particularly within the context of STEM education (Jiang et al., 2018; Perez et al., 2014; Robinson et al., 2019; Rosenzweig et al., 2020). In line with these recent studies and the expectancy-value-cost framework, cost will be considered a unique, distinct construct within this study.

Generally, research has provided evidence that expectancy-value-cost motivation is linked to choice-related behaviors in STEM as well as (future) interest, persistence, and performance (e.g., Durik et al., 2006; Hulleman et al., 2010; Kim et al., 2022). Specifically, a number of studies reveal that expectancy is more strongly associated with performance and achievement (e.g., grades), whereas values are more strongly linked to achievement-related choices and behaviors (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000). Further, there is a growing body of research providing evidence for the association between cost and and choice-related behaviors in STEM as well as interest, persistence, and performance outcomes (Flake et al., 2015; Gaspard et al., 2015; Kim et al., 2022; Perez et al., 2014). However, there are relatively few studies within the context of introductory statistics that explore achievement motivation from an expectancy-value-cost lens. The few studies that exist in statistics education at the postsecondary level point to success expectancy (e.g., Hood et al., 2012; Verhoeven, 2010) and perceived value (e.g., Hood et al., 2012; Schau et al., 1995; Sorge & Schau, 2002; Sutter et al., 2022) being positively related to effort, persistence, and performance, whereas cost has been found to negatively predict performance and continued interest (Beymer et al., 2022).

Student concerns, challenges, achievement motivation, and learning outcomes

In addition to expectancy-value-cost motivation, students' incoming course concerns are also likely to affect learning outcomes through several potential pathways, primarily *via* their perceptions of the course content with regard to expectancy, value, and cost.

In the following sections, we briefly outline the significance of exploring a) how perceived concerns predict motivational beliefs; b) how motivational beliefs predict perceived challenges; c) perceived interest as an outcome; d) why such relations might present as mediation effects as opposed to being other types of effects, and why that is important.

Concerns in the prediction of motivational beliefs

Exploring how students' concerns at the outset of a course shape their motivation during the course is particularly important from a practical perspective as it can help curriculum designers and developers respond to students' expected pain points and fears and guide interventions to alleviate potential concerns, thus enhancing students' experiences. For example, students' concerns are likely related to their perceptions of costs of taking and engaging in the course. Students' self-reported concerns may contain information about barriers that increase the perceived course costs. Consider a student who expresses concerns about balancing the workload of the course due to external obligations (such as having a job or family responsibilities). They might feel that they have to sacrifice valued time with family or friends (i.e., loss of valued alternatives), which in turn may lead to greater stress throughout the course (i.e., psychological cost).

Students' concerns may also reflect their past experiences with and expectations for academic success. For example, students who have struggled in prior courses may express concern about their abilities to succeed in future courses and hold lower expectations for success and be less likely to persist in the face of challenges. They may also be less motivated to succeed and engage less with course materials. In this case, instructors could emphasize that the course is designed for all students to succeed, regardless of their prior statistics background and knowledge.

Students' concerns may also influence their perceived usefulness (utility value) of a course. For example, a student may express concern that they don't see how what they will learn in the class would ever be useful to them and that they are concerned that the course content and material will be boring, leading to lower perceptions of intrinsic and utility value. This lack of value will likely undermine motivation to understand and engage with the course material, which in turn will undermine course outcomes (Gaspard et al., 2015; Hulleman et al., 2008, 2010). Thus, students who express concern at the start of a course about how relevant or valuable the course material is may be at a disadvantage compared to those students who do not. At the outset of the course, instructors could highlight the applicability and the relevance of the material and content either directly or *via* messaging in the textbook.

Motivational beliefs in the prediction of perceived challenges

Exploring how students' motivation during introductory statistics courses predicts their later perceived challenges is important from a practical and political/policy perspective. In the United States, policy experts have identified increasing interest, participation, and persistence in STEM domains as a national priority (Olson & Riordan, 2012). Often, students' experiences within a single introductory statistics course can be the determining factor in getting a degree or not and continuing to pursue a career in their chosen field (Goudas & Boylan, 2012). Introductory statistics courses are not only gateway courses for undergraduate students majoring in STEM, but also students majoring in other domains (e.g., Psychology, Biology, Sociology etc.). Whether students have positive psychological experiences, perceive what they are learning as useful and valuable, and complete such key courses with positive attitudes and in a confident manner plays a critical role with regards to their future interest, participation, and persistence (Kosovich et al., 2017; Rosenzweig et al., 2019). If students see value in the course, they may perceive certain components as less challenging, leading to more positive attitudes and higher interest in continuing to pursue statistics courses. Exploring how motivation interrelates with perceived challenges may shed light on "how undergraduate students develop a persevering and challenge-engaging disposition within STEM contexts", which is "a critical step in the path to successful STEM careers" (De & Arguello, 2020). From a practical perspective, exploring how students' motivation during introductory statistics courses predicts their later perceived challenges can help guide curriculum and instructional designers in developing interventions. For example, if perceptions of utility value negatively predict perceived challenges or if perceptions of cost positively predict perceived challenges, designing interventions to enhance utility value or reduce cost might help students in coping adaptively with challenges, thus lowering their perceptions of obstacles.

Future interest as a crucial outcome

Students' experiences in introductory statistics courses are likely to shape their attitudes toward this domain in the longer term. The major aim of the specific introductory statistics textbook on which this study is based is to (a) foster deep learning, understanding, and engagement with the material, (b) promote transferable knowledge and making real-life connections, and (c) trigger future interest in statistics. In particular, future interest in statistics is a key outcome metric of the course, thus, studying factors that hinder or foster students' future interest in engaging in statistics is critical.

In sum, students' self-reported concerns at the start of the course offer rich information that may be useful in predicting students' expectancy-value-cost motivation and learning outcomes. In addition, self-reported concerns may contain additional contextual information not easily captured by existing close-ended questions. In the current study, beyond examining the interrelations between students' course concerns, expectancy-value-cost motivation, perceived course challenges, and future interest, we are particularly interested in exploring whether students' expectancies for success, perceived utility value, and cost of the course, mediate the relationship between incoming concerns and (a) outgoing reports of course challenges, and (b) future interest in statistics. It's possible that students express concerns only to realize that their concerns are not warranted. For example, a student may be concerned that the course will require a lot of memorization, only to learn through experience that conceptual understanding is more important for successfully completing the course. Conversely, a student may express a concern which is reinforced by their course experience. For example, students may be concerned about the anticipated workload of the course and evidence from the course may, in fact, bear that out. Either way, while there might not be a direct link between incoming course concerns and later perceived challenges, it is possible that the incoming concerns that students experience will shape their motivation (i.e., through expectations of success, perceptions of course value and/or costs), which in turn shapes their perceptions of challenges or learning outcomes.

Overall - in particular from a practical perspective in terms of improving the course - it seems important to explore the effects of concerns on students' outcomes beyond direct relations and investigate how students' concerns shape their motivation in the course, which feeds into learning outcomes. Understanding the interrelations between students' concerns and their later perceived challenges and whether that relation is mediated by motivation will allow us to specifically target constructs or beliefs to increase students' experiences. Specifically, it will (1) allow us to identify which (if any) early concerns are consequential (i.e., signals early on of risk factors), (2) help designers inject messaging and interventions that would serve to reduce the impact of these early concerns on students' experiences and learning outcomes, and (3) help instructors build awareness of student experience, rationale behind curriculum design, and messaging to reinforce in their class.

Motivation, race, and gender

Learning environments in STEM continue to underserve female students and students from racially marginalized groups, including but not limited to Black, Latinx, and Native American/Indigenous students (Fong et al., 2021; Riegle-Crumb et al., 2019; Wang & Degol, 2013). Contextual factors contributing to barriers faced by female and racially marginalized students include messages of non-belonging and stereotype threat. For example, a curriculum that emphasizes more masculine and White/Caucasian values can contribute to female and racially marginalized students' experiences of belonging uncertainty and feelings of exclusion, which in turn can lead them to enter subsequent STEM learning situations with increased concerns and diminished motivation (Riegle-Crumb et al., 2019; Seo & Lee, 2021). Stereotype threat, defined as the "anxiety related to confirming the negative stereotypes about one's group (e.g., one's ethnic group or gender)" (Totonchi et al., 2021, p. 1), is also a common barrier faced by female students and students from traditionally marginalized and underserved groups STEM domains, where stereotypes that target their competence (e.g., women are not as good in math as men; or Black and Latinx students are underachievers) are more prevalent (Seo & Lee, 2021; Totonchi et al., 2021). Being confronted with such cultural stereotypes may lead to concerns (e.g., "I don't fit in here"), lower levels of motivation (e.g., diminished success expectations, increased levels of perceived costs), and lower performance (Eccles & Wigfield, 2002; Totonchi et al., 2021).

In line with these findings, a growing body of research provides evidence for lower levels of expectancy and intrinsic value, and higher levels of effort and psychological cost among female students (e.g., Eccles & Wigfield, 2002; Gaspard et al., 2015) and racially marginalized students in STEM settings. However, empirical evidence regarding gender and racial differences in motivation specifically in the domain of statistics is scarce. The limited number of studies conducted in introductory statistics suggest that female students tend to have lower success expectancies than their male counterparts (Van Es & Weaver, 2018), whereas value levels are similar (Ramirez et al., 2010; Sutter et al., 2022). A recent study provided evidence for similar levels of incoming utility value perceptions among students from racially marginalized groups (e.g., Black, Latinx, or Native American/Indigenous) and majority students in the context of introductory statistics, however racially marginalized students experienced greater declines in utility value across the school term than did majority students (Sutter et al., 2022).

In order to better grasp how we can support students from underrepresented and racially marginalized groups (e.g., female students, Black/African American, Latinx, or American Indian/Alaska Native students) in their intent to pursue more advanced work in statistics, we need to explore their concerns, perceived obstacles, and motivational experiences. Thus, this study will contribute to prior research by examining differential motivational experiences (expectancy, utility value, and cost) in statistics by gender and racial/ethnic background and how they relate to course concerns, perceived obstacles, and future interest in statistics. Importantly, while research on differential levels of motivation in STEM courses by gender and race exists, this is the first study to explore how motivation is linked to other motivational experiences and perceptions (specifically concerns and challenges) as well as course outcomes and how those interrelations and patterns differ by gender and race. While we have no specific hypotheses with regards to potential differential interrelations by gender and race, the pandemic has exacerbated students' concerns about their academic experiences and experiencing challenges as well as opportunity gaps to the disadvantage of female students and students from underrepresented racial backgrounds. This is evidenced, for example, by higher perceptions of cost (i.e., feeling of higher demands on their time) for students from racially minoritized groups (Barber et al., 2021). Thus, examining patterns by subgroups will allow us to gain a deeper understanding of how course concerns might have shaped students' motivation and perceived challenges during the pandemic.

The current study

We built on theory and research from expectancy-value-cost frameworks (Barron & Hulleman, 2015; Eccles & Wigfield, 2020) to explore how students' incoming course concerns in an introductory statistics course and expectancy-value-cost motivation predict their later perceived challenges related to the course and future interest in statistics. While previous research has shown that students' success expectancies, values, and cost are central drivers of achievement-related choices, engagement, and performance (e.g., Guo et al., 2015; Lauermann et al., 2015; Trautwein & Lüdtke, 2007), it remains unexplored how and to what extent course concerns and perceived course challenges interrelate with achievement motivation and future interest. Understanding these interrelations within the context of introductory statistics is critical as statistics take on an increasing role in satisfying quantitative reasoning requirements in higher education (Bateiha et al., 2020; Chiesi & Primi, 2010; Ramirez et al., 2010). Because female students and students from racially marginalized backgrounds (e.g., Black, Latinx, Indigenous) tend to face greater structural barriers in STEM learning environments, we are particularly interested in exploring the interrelations by gender and race. Combining quantitative and qualitative data, we investigate the following research questions based on the conceptual model presented in Figure 1:

1. How are the diversity of students' concerns[1], the diversity of perceived challenges, achievement motivation (i.e., expectancy, utility, cost), and future interest in statistics interrelated?
    a. To what extent does the diversity of students' concerns relate to the diversity of perceived challenges?
    b. To what extent does achievement motivation mediate the relationship between the diversity of incoming course concerns and the diversity of later perceived challenges and future interest in statistics?
    c. Are there differential interrelations by sex and race/ethnicity?
2. How are individual student concerns and challenges, achievement motivation (i.e., expectancy, utility value, cost), and future interest in statistics interrelated?
    a. To what extent do incoming individual course concerns predict later perceived course challenges?

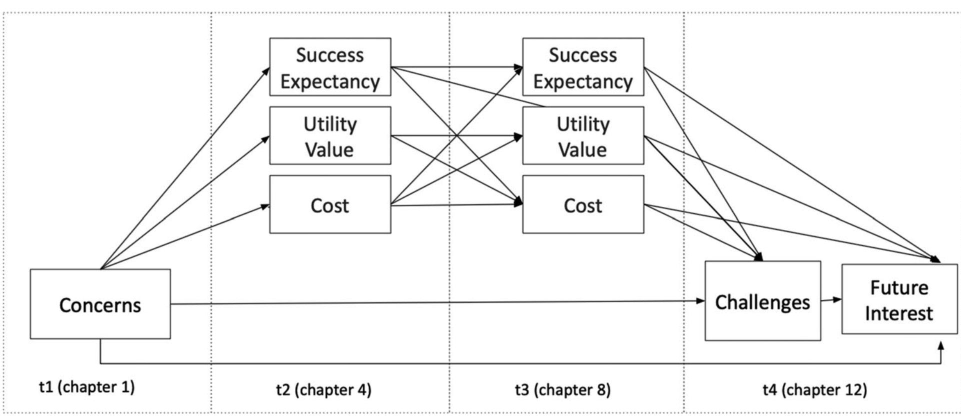

Figure 1. Conceptual model.
Note: Arrows indicating correlations are omitted in the figure for graphical simplicity.

b. To what extent does achievement motivation mediate the relationship between incoming course concerns and later perceived challenges and future interest in statistics?
c. Are there differential interrelations by sex and race/ethnicity?

Research questions regarding the kinds of concerns and challenges expressed by these students and how they differ by gender, race/ethnicity, and whether expressed before or during the COVID pandemic have been reported elsewhere (Sutter et al., 2022). Further, Sutter et al. (2022) outline how incoming concerns compared to later perceived challenges using a consistency indicator to capture emergent (i.e., something that was not mentioned as a concern at the start of the course but was brought up as a challenge at the end of the course), eliminated (i.e., something that was mentioned as a concern at the start of the course but not as a challenge at the end of the course) and consistent (something that was mentioned as an incoming course concern and a later perceived challenge) concerns. This present study extends this prior study by focusing on how concerns and challenges interrelate with motivational beliefs and future interest in statistics as a course outcome. Another unique contribution is the distinction between students' individual and summed up number of concerns/challenges.

Methods

Participants

The study included 524 undergraduate students who were enrolled in Introductory Statistics courses at the University of California, Los Angeles - a predominantly White/Asian institution - who agreed to have their data included for research purposes. The initial sample included 575 students, however, 51 opted out from having their data included. The sample was 70.3% female ($n = 364$), 27.8% male ($n = 144$), 1.9% non-binary ($n = 10$), 32.3% identified as Asian or Asian American ($n = 169$), 25.4% White ($n = 133$), 19.7% Hispanic or Latinx ($n = 103$), 4.8% as Black or African American ($n = 25$), and 12.4% as other races/ethnicities ($n = 65$). Twenty-nine (5.5%) did not indicate their race. For our analyses by race/ethnicity, White and Asian students were considered racial majority students and Hispanic or Latinx, Black or African American, Indian Subcontinent, Native American, and Greater Middle Eastern students were considered as students from racially marginalized backgrounds. Students of mixed race were included in the racially marginalized group, unless their race was a mix of White and Asian. Of those who indicated their race ($n = 495$), 62.2% ($n = 308$) students identified as either White or Asian and 37.8% ($n = 187$) identified as belonging to a racially marginalized group.

Course setting and procedure

Data were collected from four course sections held in Winter and Spring 2021 as part of an ongoing project, which was approved by the Institutional Review Board at the University of California, Los Angeles (IRB No: 20-001033). All four course sections used the same interactive statistics and data science textbook developed by CourseKata (https://coursekata.org; Son & Stigler 2017–2022), consisting of 12 chapters and including over 1200 embedded formative assessments, R programming exercises, and end of chapter review activities. The surveys were directly embedded into the online textbook. This study draws on the following measures: Student demographics and course concerns, which were collected prior to chapter 1, students' motivation, which were collected during the course after chapters 4 and 8, and students' future interest in statistics and perceived challenges, both collected at the end of the course, after chapter 12. Students were aware that their de-identified responses to questions throughout the book would be analyzed for the purpose of improving the materials themselves and at any time they were able to indicate that they wished for their data to be excluded.

Measures

Individual student concerns and challenges

In a required pre-course survey, students were asked the open-ended question, "When I think about this course, I'm concerned that … " and in a required post-course survey, they were asked "What, if anything, made it hard to succeed in this class?" allowing students to express a wide range of concerns and perceived challenges. The authors adopted the question asking about course concerns from Gal and Ginsburg (1994) and adapted it to form the post course question asking about perceived challenges. A preliminary coding scheme derived from the literature on student concerns/challenges (e.g., Meaders et al., 2020) as well as from students' responses was developed. Three of the authors coded sets of 20 responses, met to discuss the codes and their application, and modified the coding scheme as necessary. They did so five times before feeling satisfied that the scheme adequately represented the universe of likely responses and trusting that research assistants (RAs) could be trained to reliably apply the scheme. One of the authors trained the RAs, providing them with the final coding scheme, including the overarching concept, descriptors, definitions, and examples for each code. The original coding scheme consisted of 22 categories (see Supplemental Table 1 as well as Sutter et al., 2022. For the purpose of this study, we will focus on the struggles that were mentioned by at least 5% of the students - as identified in a previous study (Sutter et al., 2022) - either as an incoming course concern or a challenge (see Table 1). RAs practiced applying the codes independently and reconvened to discuss questions and discrepancies. When they felt confident, RAs were assigned a subset of responses to code independently. When inter-rater reliability (IRR) reached at least 90%, the remaining responses were divided among RAs. They reconvened to discuss responses they found difficult to code and discussed their coding until consensus was reached. To calculate the final IRR, we took the total number of items scored the same by all of the coders and divided it by the total number of items. This yielded an IRR of 0.98

Course concerns/challenges were coded as 0 if the concern/challenge was not mentioned and 1 if the concern/challenge was mentioned by students. A single student response could be coded for more than one concern or challenge. For example, "I'm concerned that I will not be able to do the R-Coding part of this course since I have no prior knowledge in programming" would be coded for R-Coding and lack of prior knowledge.

Diversity of concerns and challenges

We created a variable to reflect the number of concerns and challenges students voiced by summing up all concerns (and challenges) for each student. When students mentioned multiple concerns from the same category (e.g., they mentioned both workload and pace), this was counted as only one concern. Thus, the sums capture roughly the quantity of concerns/challenges mentioned and can also be thought of as reflecting the diversity of concerns/challenges.

Table 1. Frequency (in %) of mentioned concerns and perceived challenges overall ($n = 524$).

	Concerns overall	Challenges overall
R Coding	22.4	12.3
Understanding concepts	16.3	9.9
Workload	12.9	35.7
Lack of prior knowledge	11.5	1.9
Time management	8.3	4.1
Performance	8.5	0.5
Virtual course	6.7	12.8

Course expectancy, utility value, and cost

Students' success expectancies, utility value, and cost (Kosovich et al., 2015) were measured mid-course, after they completed chapters 4 and 8 of the course textbook. Students were asked to respond to two statements that measured their expectancies to succeed in the course (e.g., "I am confident I can learn the material in this course "$\alpha t_2 = .841$; $\alpha t_3 = .835$), three statements measuring utility value (e.g., "This class is useful", $\alpha t_2 = .844$; $\alpha t_3 = .851$ and two statements measuring perceived course costs (2 items, e.g., "I have to give up too much to do well in this class"; "This course is too stressful for me", $\alpha t_2 = .809$; $\alpha t_3 = .870$). Students responded on a six-point Likert scale from 1 (strongly disagree) to 6 (strongly agree).

Future interest in statistics

To assess future interest in statistics, a three-item scale based on Kosovich et al. (2015) was used: "I look forward to learning more about statistics," "I want to take more statistics classes in the future," and "I want to have a job that involves statistics someday" ($\alpha t_4 = .892$). Students responded on a six-point Likert scale from 1 (strongly disagree) to 6 (strongly agree).

Analysis

Preliminary analyses

Preliminary analyses included computing the frequencies of students' incoming course concerns and their later perceived challenges.

Measurement invariance

We conducted multi-group measurement invariance analyses (Cheung & Rensvold, 2002; Widaman & Reise, 1997) to ensure the key variables can be used for meaningful group comparisons. We computed four models for expectancy, utility value, and cost (see Supplemental Table 2) as well as four models for future interest (see Supplemental Table 3): Model 1 (configural invariance) included the same factor structure over time without constraints on factor loadings or intercepts. Model 2 (metric or weak invariance) constrained the factor loadings to be equal across groups. Model 3 (strong or scalar invariance) required the factor loadings and the item intercepts to be invariant across groups. We also estimated a model (Model 4, strict invariance) by additionally constraining the item residual variances to be equal across groups. Following the recommendations of Cheung and Rensvold (2002) and Chen (2007), the change in two fit indices—the comparative fit index (CFI) and the root mean square error of approximation (RMSEA)—between nested models was investigated in order to determine the plausibility of the assumption of invariance. If the change in CFI is not more than 0.01 (Cheung & Rensvold, 2002) and the change in RMSEA is less than 0.015 (Chen, 2007), the assumption of invariance is tenable (Little, 2013). Our analyses suggested that we established at least (partial) strong measurement invariance for all constructs, suggesting that these scales can be used to conduct meaningful comparisons between female and male students as well as between students from racially-minoritized groups and White/Asian students.

Missing data

Among the analytic sample, missing data increased by measurement time point. For incoming concerns at t_1 there were 3.8% missing, for achievement motivation at t_2 and t_3 and future interest at t_4 missings ranged between 11.5 and 14.3%, and for perceived challenges (also at t_4) there were 20.8% missing. It is important to note that we differentiated between students who did not answer or skipped the open-ended question and students who specifically indicated that they did not perceive any particular concerns/challenges. Thus, the high number of missings for students' responses regarding perceived challenges is likely due to students' skipping the question or not feeling the need to specifically state that they had no perceived challenges if they did not perceive any challenges.

We used the full information maximum likelihood (FIML) estimation option in Mplus for the analyses, allowing us to include participants with partially missing values (Muthén & Muthén, 1998-2012).

Path models exploring interrelations among course concerns, achievement motivation, perceived course challenges, and future interest in statistics

To explore the interrelations between students' concerns (diversity of concerns and individual concerns), challenges (diversity of challenges and individual challenges), achievement motivation (i.e., success expectancy, utility value, cost), and future interest, path models controlling for students' self-reported prior GPA (i.e., "What is your GPA at this school?") were specified in Mplus (see conceptual model in Figure 1) and multiple group path models were specified. Indirect effects were calculated via the model indirect statement in MPlus. Model fit was assessed using the following fit indices: the CFI, the Tucker-Lewis Index (TLI), the RMSEA, and the standardized Root Mean Squared Residual (SRMR). A good level of fit is indicated when RMSEA and SRMR are less than 0.06 and when CFI and TLI values exceed 0.95. The fit of a model is considered acceptable when RMSEA and SRMR are less than 0.08 and CFI and TLI fall between 0.90 and 0.95 (Hu & Bentler, 1999). All models yielded acceptable fit indices, with the exception of two models that were just above the acceptable value of 0.08 for RMSEA (e.g., Model fit for "Understanding": RMSEA = 0.082; Virtual format of the course: RMSEA = 0.081; see Table 3). Using equality constraints (Wald Test of Parameter Constraints) across the subgroups, we further tested for significant differences on each path between the groups (i.e., female vs. male; racially minoritized vs. racially non-minoritized) allowing us to compare a model with certain parameters constrained to be equal and a model with those same parameters freely estimated across the groups.

Results

Preliminary analyses: Frequencies of course concerns and perceived challenges

As previously reported in Sutter et al. (2022), the most frequently voiced incoming course concerns (see Table 1) by the overall sample ($N = 524$) include concerns related to the R coding component of the course (22.4%), understanding concepts (16.3%), workload (12.9%), lack of prior knowledge (11.5%), time management (8.3%), and performance (8.5%). In other words, 22.4% of students responded to the open-ended questions regarding course concerns that they were concerned about the R-Coding component of the course. The most frequently mentioned challenge at the end of the course was related to the workload of the course with over one-third (35.7%) of students mentioning challenges related to workload, difficulty, time required, and pace as factors inhibiting their success in the course. This perceived challenge was followed by virtual learning (12.8%), R coding (12.3%), and challenges with understanding concepts (9.9%). Three concerns that were among the six highest in frequency at the outset of the course, were mentioned less frequently as a perceived challenge at the end of the course: Time management (4.1%), lack of prior knowledge (1.9%), and performance (0.5%).

On average, students mentioned two distinct concerns and two distinct challenges (Concerns: $M = 1.75$; SD = 1.69; Challenges: $M = 1.81$, SD = 1.53). Descriptive statistics by sex and race/ethnicity are presented in Supplemental Table 4.

Interrelations between diversity of concerns, achievement motivation, diversity of challenges, and future interest in statistics (RQ1)

Correlations between the diversity of concerns, achievement motivation, diversity of challenges and future interest are reported in Table 2. In line with the expectancy- value-cost framework, success expectancy, utility value, and future interest were positively related, whereas they were negatively related with course costs. The diversity of students' incoming course concerns was negatively related with success expectancy (t_2 and t_3) and utility value (t_2) during the course as well as their future interest in statistics at the end of the course (t_4). In contrast, the diversity of concerns was positively related to perceptions of cost during the course (t_2 and t_3) as well as perceived challenges at the end of the course (t_4). Similarly, perceptions of course challenges were negatively related to students' success expectancy (t_2 and t_3) and positively related to perceptions of course costs (t_2 and t_3).

Relation between diversity of concerns and diversity of challenges (RQ1a)

Figure 2 depicts the results of the final path model. The final model fit was acceptable ($\chi2$ (10) = 34.089 $p < 0.001$, CFI = .985, TLI = .933, RMSEA = 0.068, SRMR = 0.021)[2]. Overall, the diversity of concerns directly predicted the diversity of challenges ($\beta = 0.18$, $p < .001$). In other words, the more diverse students' incoming course concerns, the more diverse their perceived challenges at the end of the course. There was a small negative path relating students' incoming course concerns with future interest in statistics ($\beta = -0.08$, $p = .049$). Furthermore, diversity of

Table 2. Descriptive statistics and sample correlations between diversity of concerns, achievement motivation, diversity of challenges, and future interest.

	n	*M*	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Concerns t_1	504	1.75	0.94	–								
(2) Expectancy t_2	462	4.41	1.00	−0.14**	–							
(3) Expectancy t_3	463	4.35	0.91	−0.10*	.64**	–						
(4) Utility value t_2	462	4.42	0.94	−0.12*	.45**	.34**	–					
(5) Utility value t_3	464	4.30	1.19	−0.06	.44**	.46**	.72**	–				
(6) Cost t_2	462	3.13	1.20	.15**	−0.49**	−0.46**	−0.28**	−0.28**	–			
(7) Cost t_3	464	2.89	1.53	.20**	−0.37**	−0.56**	−0.20**	−0.26**	.71**	–		
(8) Challenges t_4	415	1.81	1.18	.21**	−0.12*	−0.16**	−0.04	−0.06	.12*	.25**	–	
(9) Future interest t_4	460	3.62	0.94	−0.13**	.36**	.38**	.58**	.63**	−0.23**	−0.23**	−0.01	–

Note. **Correlation is significant at the 0.01 level (2-tailed); *Correlation is significant at the 0.05 level (2-tailed). The diversity of student concerns ranged from 0-11 concerns and the diversity of challenges ranged from 0-9.

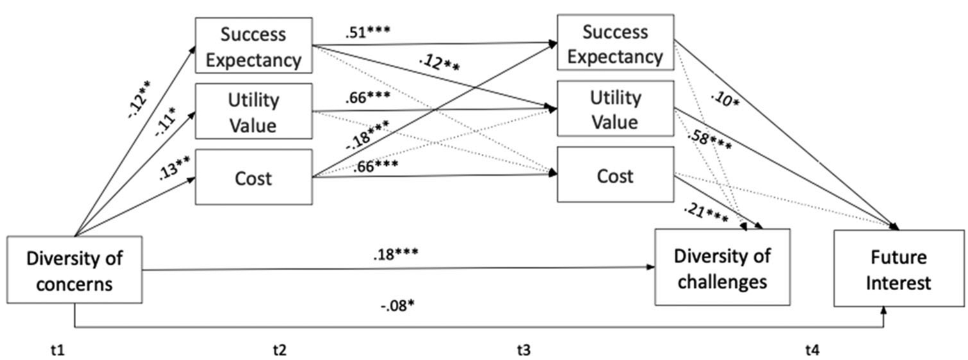

Figure 2. Final fitted model of the relationships between diversity of concerns, achievement motivation (success expectancy, utility value, cost), diversity of challenges and future interest in statistics (N = 524).
Notes. Depicted values are standardized coefficients that were statistically significant (***significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level). Dotted lines indicate non-significant paths.

concerns predicted achievement motivation during the course with a negative association between concerns and perceptions of success expectancy ($\beta = -0.12$, $p = .006$) and utility value ($\beta = -0.11$, $p = .019$) and a positive association between concerns and perceptions of cost ($\beta = .013$, $p = .004$). Success expectancy predicted subsequent success expectancy ($\beta = 0.51$, $p < .001$) and perceptions of utility value ($\beta = 0.12$, $p = .003$) during the course and cost predicted subsequent perceptions of cost ($\beta = 0.66$, $p < .001$) and success expectancy ($\beta = -0.18$, $p < .001$), whereas utility value solely predicted subsequent utility value ($\beta = 0.66$, $p < .001$). Perceptions of utility value ($\beta = 0.58$, $p < .001$) and success expectancy ($\beta = 0.10$, $p = .028$) predicted future interest in statistics, whereas perceptions of cost predicted diversity of challenges ($\beta = 0.21$, $p < .001$).

Achievement motivation as a mediator between the diversity concerns and (a) diversity of challenges and (b) future interest in statistics (RQ1b)

We tested for indirect effects between the diversity of students' incoming course concerns on perceptions of challenges and future interest at the end of the course (see Supplemental Table 5). The total indirect effect of the diversity of incoming student concerns on perceived challenges at the end of the course was significant ($\beta = 0.018$, $p = .043$) with one specific indirect effect *via* cost at t_2 and t_3 ($\beta = 0.019$, $p = .023$). The total indirect effect of diversity of concerns on future interest was significant ($\beta = -0.052$, $p = .024$) with specific indirect effects *via* utility value at t_2 and t_3 ($\beta = -0.041$, $p = .021$), and expectancy at t_2 and utility value at t_3 ($\beta = -0.008$, $p = .046$).

Differential interrelations by sex and race/ethnicity (RQ1c)

A multiple group path model by sex (see Figure 3) revealed differential interrelations. For female students, the incoming diversity of concerns predicted later perceived diversity of challenges ($\beta = 0.18$ $p = .002$), but not future interest ($\beta = 0.02$, $p = .584$), whereas it was the other way around for male students, with incoming diversity of course concerns directly predicting future interest in statistics ($\beta = -0.17$, $p = .015$), but not diversity of challenges ($\beta = -0.05$, $p = .605$). Further, while diversity of concerns predicted course expectancy ($\beta = -0.20$, $p = .012$) and utility value ($\beta = -0.32$, $p < .001$) of male students, incoming diversity of concerns predicted perceptions of cost for female students ($\beta = 0.13$, $p = .016$). Utility value at t_3 predicted future interest for both female ($\beta = 0.59$, $p < .001$) and male students ($\beta = 0.56$, $p < .001$), whereas success expectancy only predicted future interest for female students ($\beta = 0.12$, $p = .024$). Diversity of perceived

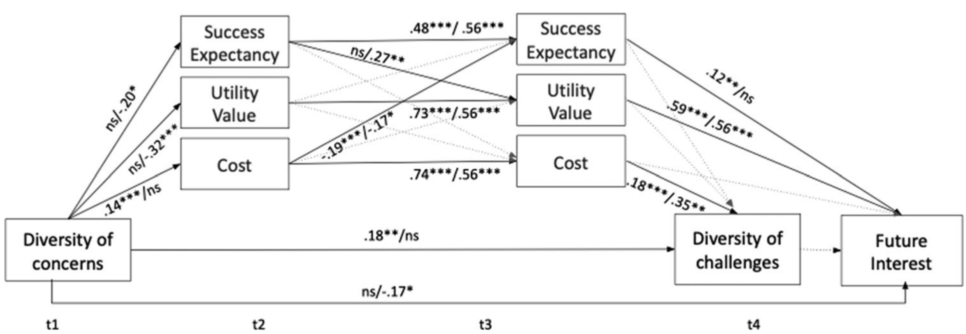

Figure 3. Final fitted model of the relationships between diversity of concerns, achievement motivation (success expectancy, utility value, cost), diversity of challenges and future interest in statistics (N = 524) for female/male students.

Notes. Model fit: ($\chi 2$ (20) = 49.485, p = 0.0003, CFI = .982, TLI = 918, RMSEA = 0.076, SRMR = 0.028). Depicted values are standardized coefficients (ns statistically not significant; ***significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level). Dotted lines indicate non-significant paths for both groups of students. Arrows representing residual correlations are omitted in the figure for graphical simplicity.

course challenges at the end of the course did not predict future interest in statistics for female ($\beta = 0.24$, $p = .584$) or male students ($\beta = 0.070$, $p = .391$).

When testing for indirect effects between the diversity of incoming course concerns and a) later perceived course challenges and b) future interest in statistics (see Supplemental Table 6), we found some significant indirect effects. For female students, there was a small significant total indirect effect between incoming course concerns and later perceived challenges ($\beta = 0.020$, $p = 0.004$) *via* cost at t_2 and t_3 ($\beta = 0.019$, $p = 0.067$). For male students, there was a significant total indirect effect between incoming course concerns and future interest ($\beta = -0.113$, $p = 0.001$) with a specific negative indirect effect *via* utility value at t_2 and t_3 ($\beta = -0.093$, $p = 0.002$).

A multiple group path model by race/ethnicity (see Figure 4) revealed differential interrelations between incoming diversity of course concerns, achievement motivation, diversity of perceived challenges, and future interest in statistics. For students from racially marginalized backgrounds, the incoming diversity of concerns did not predict later perceived diversity of challenges ($\beta = 0.09$, $p = .240$) or future interest in statistics ($\beta = -0.00$, $p = .962$), whereas it did for racial majority students (challenges: $\beta = 0.21$, $p = .001$; future interest: $\beta = -0.12$, $p = .014$). For students from racially marginalized backgrounds, however, incoming diversity of course concerns predicted perceptions of success expectancy ($\beta = -0.17$, $p = .028$), utility value ($\beta = -0.25$, $p = .001$), and cost ($\beta = 0.31$, $p < .001$) at t_2, whereas for racial majority students it only predicted success expectancy ($\beta = -0.12$, $p = .049$). For both students from racially marginalized backgrounds ($\beta = 0.25$, $p = .007$) and racial majority students ($\beta = 0.19$, $p = .010$), perceptions of course costs (at t_3) predicted the diversity of perceived course challenges, but costs only negatively predicted future interest for students from racially marginalized backgrounds ($\beta = -0.16$, $p = .036$). Utility value predicted future interest for both students from racially marginalized backgrounds ($\beta = 0.63$, $p < .001$) and racial majority students ($\beta = 0.55$, $p < .001$), whereas success expectancy only predicted future interest for racial majority students ($\beta = 0.18$, $p = .002$). Diversity of perceived course challenges at the end of the course did not predict future interest in statistics for students from racially marginalized backgrounds ($\beta = 0.12$, $p = .071$) or racial majority students ($\beta = 0.01$, $p = .862$).

When testing for indirect effects between the diversity of incoming course concerns and a) later perceived course challenges and b) future interest in statistics (see Supplemental Table 7), we found some significant indirect effects for students from racially marginalized backgrounds. The total indirect effect between the diversity of incoming course concerns and later perceived course challenges was not significant, however, there was one significant indirect effect *via* cost at t_2 and t_3 ($\beta = 0.049$, $p = .027$). While the total effect between diversity of incoming course

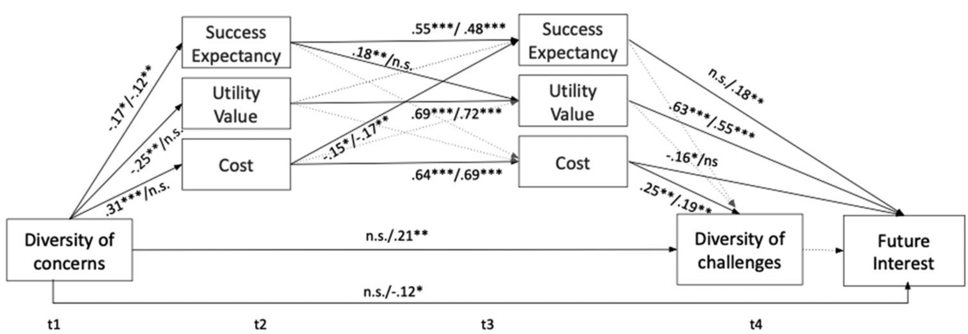

Figure 4. Final fitted model of the relationships between diversity of concerns, achievement motivation (success expectancy, utility value, cost), diversity of challenges and future interest in statistics (N = 524) for students from racially minoritized backgrounds (URM)/students from racially non-minoritized backgrounds (non-URM).

Notes. Model fit: ($\chi2$ (20) = 35.937, p = 0.0156, CFI = .990, TLI = .954, RMSEA = 0.057, SRMR = 0.023). Depicted values are standardized coefficients (ns statistically not significant; ***significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level). Dotted lines indicate non-significant paths for both groups of students. Arrows representing residual correlations are omitted in the figure for graphical simplicity.

concerns and future interest in statistics was not significant for students from racially marginalized backgrounds, the total indirect effect was significant ($\beta = -0.133$, $p = 0.002$) with a significant specific indirect effect *via* utility value at t_2 and t_3 ($\beta = -0.106$, $p = .002$) and *via* cost at t_2 and t_3 ($\beta = -0.034$, $p = .049$).

Finally, using equality constraints across the groups, we tested for significant differences on each path between the two groups (see Supplemental Tables 8 and 9). Across all paths, only one was significantly different between female and male students: The path from diversity of concerns on utility value ($\chi2 = 8.671$, $df = 1$, $p = 0.003$). Nested model comparison for the multi-group model by racially minoritized status revealed two significantly different paths: The path diversity of concerns on perceptions of cost ($\chi2 = 7.222$, $df = 1$, $p = 0.0072$) and the path from diversity of concerns on utility value ($\chi2 = 4.876$, $df = 1$, $p = 0.0272$).

Interrelations between individual concerns, achievement motivation, individual challenges, and future interest in statistics (RQ2)

Across all models (see standardized path coefficients for each model in Table 3), students' success expectancy and utility value at t_3 positively predicted their future interest in statistics, with the coefficient being larger for utility value. Further, perceptions of success expectancy, utility value, and cost were interrelated. Beyond success expectancy at t_2 predicting subsequent success

Table 3. Results of the final fitted models by concern/challenge category ($N = 524$).

	R coding	Understanding	Workload	Lack of prior knowledge	Time management	Performance	Virtual format
Future interest on							
Concern	−0.040	0.020	−0.011	−0.025	−0.004	−0.017	0.035
Challenge	−0.013	−0.035	0.032	−0.033	0.067	0.079	0.055
Expectancy t_3	**0.140****	**0.132****	**0.132****	**0.132****	**0.136****	**0.148****	**0.143****
Utility Value t_3	**0.542*****	**0.545*****	**0.546*****	**0.546*****	**0.542*****	**0.532*****	**0.539*****
Cost t_3	0.016	0.009	0.005	0.011	0.012	0.018	0.012
Challenge on							
Concern	−0.009	0.074	0.060	**0.122***	−0.018	−0.019	**0.221*****
Expectancy t_3	−0.013	−0.065	0.085	0.028	−0.011	**−0.157***	−0.035
Utility Value t_3	−0.079	−0.006	−0.004	−0.075	0.059	**0.146****	0.100
Cost t_3	0.073	−0.065	**0.218*****	0.040	−0.027	−0.031	−0.043
Expectancy t_3 on							
Expectancy t_2	**0.522*****	**0.522*****	**0.522*****	**0.521*****	**0.522*****	**0.522*****	**0.521*****
Utility value t_2	0.065	0.065	0.065	0.065	0.065	0.065	0.065
Cost t_2	**−0.198*****	**−0.198*****	**−0.198*****	**−0.199*****	**−0.198*****	**−0.198*****	**−0.199*****
Utility value t_3 on							
Expectancy t_2	**0.122****	**0.122****	**0.122****	**0.122****	**0.122****	**0.122****	**0.122****
Utility value t_2	**0.661*****	**0.661*****	**0.662*****	**0.661*****	**0.661*****	**0.661*****	**0.661*****
Cost t_2	−0.058	−0.057	−0.057	−0.058	−0.058	−0.057	−0.058
Cost t_3 on							
Expectancy t_2	−0.036	−0.036	−0.036	−0.036	−0.036	−0.036	−0.036
Utility value t_2	0.006	0.006	0.007	0.006	0.005	0.006	0.006
Cost t_2	**0.697*****	**0.697*****	**0.697*****	**0.697*****	**0.697*****	**0.697*****	**0.697*****
Expectancy t_2 on concern	−0.005	**−0.097***	0.002	0.018	−0.029	**−0.148****	**−0.131****
Utility value t_2 on concern	−0.040	−0.073	−0.064	0.067	0.011	**−0.137****	−0.048
Cost t_2 on concern	0.036	**0.102***	−0.041	−0.082	**0.125****	**0.161*****	0.051

Note. Depicted values are standardized coefficients (***significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level). Model fit indices: R coding ($\chi2$ (16) = 62.836, $p < 0.001$, CFI = .969, TLI = .916, RMSEA = 0.078, SRMR = 0.071); Understanding ($\chi2$ (16) = 68.618, $p < 0.001$, CFI = .966, TLI = .906, RMSEA = 0.082, SRMR = 0.070); Workload ($\chi2$ (16) = 61.076, $p < 0.001$, CFI = .971, TLI = .917, RMSEA = 0.076, SRMR = 0.070); Lack of prior knowledge ($\chi2$ (16) = 61.836, $p < 0.001$, CFI = .970, TLI = .918, RMSEA = 0.077, SRMR = 0.070); Time management ($\chi2$ (16) = 63.924, $p < 0.001$, CFI = .969, TLI = .914, RMSEA = 0.078, SRMR = 0.071); Performance ($\chi2$ (16) = 56.330, $p < 0.001$, CFI = .974, TLI = .927, RMSEA = 0.072, SRMR = 0.065); Virtual format ($\chi2$ (16) = 66.496, $p < 0.001$, CFI = .968, TLI = .911, RMSEA = 0.081, SRMR = 0.071).

expectancy at t_3, utility value at t_2 predicting subsequent utility value at t_3, and cost at t_2 predicting subsequent cost at t_3, cost at t_2 predicted success expectancy at t_3, and success expectancy at t_2 predicted utility value at t_3 across all models (see Table 3).

Relation between individual concerns and individual challenges (RQ2a)

Looking at the standardized path relating incoming course concerns with later perceived challenges, only two incoming course concerns predicted later perceived course challenges: Lack of prior knowledge as an incoming course concern predicted lack of prior knowledge as a perceived challenge ($\beta = 0.122$, $p = .012$) and virtual learning as an incoming course concern predicted virtual learning as a perceived challenge ($\beta = 0.221$, $p < .001$). Perceived course challenges related to the workload of the course were positively predicted by perceptions of cost at t_3 ($\beta = 0.218$, $p < .001$), whereas perceived course challenges related to performance were negatively predicted by success expectancy at t_3 ($\beta = -0.157$, $p = 0.016$). Surprisingly, perceived course challenges related to performance were positively predicted by utility value at t_3 ($\beta = 0.146$, $p = 0.010$). Finally, incoming course concerns related to understanding material/concepts ($\beta = -0.10$, $p = .037$), performance ($\beta = -0.15$, $p = .001$) and virtual learning ($\beta = -0.13$, $p = .006$) negatively predicted success expectancy at t_2. Concerns related to understanding material/concepts ($\beta = 0.10$, $p = .030$), time management ($\beta = 0.13$, $p = .009$), and performance ($\beta = 0.16$, $p < .001$) positively predicted course costs at t_2. Finally, concerns related to performance negatively predicted perceptions of utility value at t_2 ($\beta = -0.14$, $p = .003$).

Achievement motivation as a mediator between the individual concerns and (a) individual challenges and (b) future interest in statistics (RQ2b)

We tested for indirect effects between the individual incoming course concerns and a) later perceived course challenges and b) future interest in statistics (see Supplemental Table 8) and found some significant indirect effects. Across all models, only one small significant total indirect effect was found with incoming course concerns related to performance indirectly predicting later perceived course challenges related to performance ($\beta = -0.080$, $p < 0.001$). Specific indirect effects were found *via* expectancy at t_2 and utility value at t_3 ($\beta = -0.010$, $p = 0.028$), *via* expectancy at t_2 and expectancy at t_3 ($\beta = -0.011$, $p = 0.035$), *via* cost at t_2 and expectancy at t_3 ($\beta = -0.005$, $p = 0.044$), and *via* utility value at t_2 and t_3 ($\beta = -0.048$, $p = 0.004$). Further, while the total indirect effect between incoming course concerns related to virtual learning and future interest was not significant, one significant specific indirect effect was found *via* expectancy at t_2 and utility value at t_3 ($\beta = -0.009$, $p = 0.042$).

Differential interrelations by sex and race/ethnicity (RQ2c)

Results of multiple group path models by sex are presented in Table 4 and by race/ethnicity are presented in Table 5. One relation that was consistent across all subgroups of students and all models was that perceptions of the usefulness of the course (utility value) at t_3 positively predicted future interest in statistics at t_4.

We found differential interrelations by sex. For female students, success expectancy also positively predicted future interest across all concerns (see Table 4), whereas it did not for male students. For male students, incoming concerns related to R coding ($\beta = -0.147$, $p = 0.032$) and lack of prior knowledge ($\beta = -0.177$, $p = 0.012$) predicted future interest in statistics. For both female and male students, later perceived challenges did not predict future interest in statistics. For female students, concerns related to lack of prior knowledge ($\beta = 0.144$, $p = 0.010$) and virtual learning ($\beta = 0.280$, $p < 0.001$) predicted their subsequent concerns related to lack of prior

Table 4. Results of the multiple group models by female (n = 364) /male (n = 144) students.

	R Coding	Understanding concepts	Workload	Lack of prior knowledge	Time management	Performance	Virtual Learning
	female/male	female/male	female/male	female/male	female/male	female	female/male
Future interest on							
Concern	−0.013/**−0.147***	0.010/0.044	−0.030/0.024	0.044/−**0.177***	−0.016/0.057	−0.038	0.027/0.081
Challenge	−0.081/0.118	−0.025/−0.061	0.036/0.072	−0.034/0.024	0.084/0.027	0.057	0.014/0.164+
Expectancy t_3	**0.155****/0.048	**0.147****/0.013	**0.147****/0.013	**0.149****/−0.047	**0.149****/0.049	**0.159****	**0.154****/0.058
Utility Value t_3	**0.563*****/**0.523*****	**0.567*****/**0.508*****	**0.568*****/**0.495*****	**0.566*****/**0.553*****	**0.566*****/**0.497*****	**0.559*****	**0.565*****/**0.479*****
Cost t_3	−0.006/0.016	−0.014/0.004	−0.017/0.023	−0.007/−0.018	−0.012/0.023	−0.004	−0.018/0.040
Challenge on							
Concern	−0.046/0.009	0.063/0.074	0.092/−0.015	**0.144****/−0.013	−0.015/−0.053	−0.019	**0.280*****/0.025
Expectancy t_3	−0.060/**−0.239**$^{+}$	−0.036/−0.281+	−0.068/**0.267***	0.006/0.007	0.004/−0.098	**−0.189***	−0.033/−0.077
Utility Value t_3	−0.044/−0.186	−0.032/0.124	−0.061/−0.126	−0.052/0.158	0.033/0.155	**0.117+**	0.102/0.188
Cost t_3	0.094/−0.024	−0.013/**−0.241+**	0.099/**0.586*****	0.075/−0.96	−0.012/−0.062	−0.050	−0.039/−0.087
Expectancy t_3 on							
Expectancy t_2	**0.485*****/**0.605*****	**0.485*****/**0.603*****	**0.485*****/**0.603****	**0.485*****/**0.603*****	**0.485*****/**0.605*****	**0.485*****	**0.484*****/**0.604*****
Utility value t_2	0.076/0.079	0.076/0.080	0.077/0.079	0.077/0.079	0.077/0.080	0.077	0.077/0.080
Cost t_2	**−0.205*****/**−0.191*****	**−0.204*****/**−0.191*****	**−0.204*****/**−0.192*****	**−0.206*****/**−0.191*****	**−0.203*****/**−0.191*****	**−0.203*****	**−0.204*****/**−0.191****
Utility value t_3 on							
Expectancy t_2	0.024/**0.295*****	0.024/**0.293*****	0.024/**0.293*****	0.024/**0.291*****	0.024/**0.296*****	0.024	0.024/**0.293*****
Utility value t_2	**0.721*****/**0.573*****	**0.721*****/**0.575*****	**0.722*****/**0.576*****	**0.721*****/**0.563*****	**0.721*****/**0.573*****	**0.722*****	**0.721*****/**0.574*****
Cost t_2	−0.071/0.009	−0.070/0.009	−0.070/0.010	−0.071/0.006	−0.070/0.008	−0.069	−0.071/0.009
Cost t_3 on							
Expectancy t_2	0.013/−0.094	0.013/−0.094	0.013/−0.092	0.013/−0.094	0.013/−0.095	0.013/−0.094	0.012/−0.094
Utility value t_2	−0.008/0.013	−0.008/0.014	−0.008/0.016	−0.008/0.012	−0.009/0.013	−0.008/0.013	−0.008/0.014
Cost t_2	**0.758*****/**0.575*****	**0.757*****/**0.575*****	**0.758*****/**0.580*****	**0.758*****/**0.575*****	**0.757*****/**0.576*****	**0.757*****	**0.758*****/**0.575*****
Expectancy t_2 on concern							
	−0.013/0.030	−0.083/−0.148+	−0.027/0.018	0.051/−0.155*	0.024/**−0.195***	**−0.136****	**−0.145***/−0.122
Utility value t_2 on concern							
	0.018/**−0.162+**	−0.088/−0.065	−0.085/−0.067	0.050/0.068	0.044/−0.037	−0.104^{+}	−0.017/−0.134
Cost t_2 on concern							
	0.059/−0.055	**0.102**$^{+}$/0.087	−0.032/−0.048	−0.102/0.027	**0.114***/**0.172+**	**0.127***	0.061/0.047

Note. Depicted values are standardized coefficients. ***significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level.

Table 5. Results of the multiple group models by racial minoritized background (URM; $n = 308$) /racial non-minoritized background (Non-URM, $n = 187$).

	R Coding		Understanding concepts		Workload		Lack of prior knowledge		Time management		Performance	Virtual Learning	
	URM	Non-URM	URM	Non-URM	URM	Non-URM	URM	Non-URM	URM	Non- URM	URM	URM	Non- URM
Future interest on													
Concern	0.004	−0.050	0.097	−0.023	−0.017	−0.009	−0.016	−0.041	0.058	−0.034	−0.043	0.041	−0.020
Challenge	0.065	−0.082	−0.002	−0.045	0.088	0.005	0.089	−0.078	0.071	0.079	0.119^{+}	−0.030	0.115^{+}
Expectancy t_3	−0.027	**0.214****	−0.019	**0.201****	−0.040	0.205**	−0.037	0.196**	−0.029	0.208**	0.004	−0.022	**0.190****
Utility Value t_3	**0.614*****	**0.497*****	**0.601*****	**0.502*****	**0.607*****	**0.502*****	**0.608*****	**0.504*****	**0.600*****	**0.491*****	**0.570*****	**0.612*****	**0.495*****
Cost t_3	−0.119	0.091	−0.127	0.085	**−0.138**$^{+}$	0.083	−0.114	0.075	−0.113	0.085	−0.097	−0.107	0.079
Challenge on													
Concern	0.027	−0.029	0.052	0.082	−0.012	0.065	**0.281*****	0.102	−0.058	0.038	−0.035	−0.090	**0.398*****
Expectancy t_3	−0.063	0.032	−0.082	−0.061	0.178^{+}	0.034	0.094	−0.015	0.008	−0.050	**−0.280****	**−0.324****	0.120
Utility Value t_3	−0.093	−0.072	−0.002	0.009	−0.053	0.006	−0.027	−0.041	0.058	0.121^{+}	**0.238****	**0.243****	0.057
Cost t_3	0.085	0.104	−0.049	−0.016	**0.307****	0.122	0.024	0.024	−0.099	−0.035	−0.095	−0.123	0.006
Expectancy t_3 on													
Expectancy t_2	**0.551*****	**0.509*****	**0.551*****	0.508***	**0.552*****	**0.510*****	**0.552*****	**0.508*****	**0.553*****	**0.508*****	**0.551*****	**0.551*****	**0.508*****
Utility value t_2	**0.126***	0.049	**0.126***	0.048	**0.126***	0.049	**0.126***	0.049	**0.126***	0.048	**0.126***	**0.128***	0.049
Cost t_2	**−0.178****	**−0.177****	**−0.177****	**−0.178****	**−0.178****	**−0.176****	**−0.177****	**−0.178****	**−0.175****	**−0.178****	**−0.178****	**−0.178****	**−0.177****
Utility value t_3 on													
Expectancy t_2	**0.170****	0.015	**0.170****	0.015	**0.171****	0.016	**0.171****	0.015	**0.171****	0.015	**0.171****	**0.172****	0.015
Utility value t_2	**0.658*****	**0.729*****	**0.658*****	**0.729*****	**0.656*****	**0.730*****	**0.657*****	**0.729*****	**0.658*****	**0.728*****	**0.657*****	**0.657*****	**0.729*****
Cost t_2	−0.003	−0.080	0.000	−0.080	−0.002	−0.078	−0.002	−0.081	−0.001	−0.081	−0.001	−0.002	−0.080
Cost t_3 on													
Expectancy t_2	−0.066	0.018	−0.066	0.018	−0.066	0.018	−0.066	0.018	−0.067	0.018	−0.066	−0.067	0.017
Utility value t_2	0.017	−0.006	0.017	−0.005	0.019	−0.005	0.017	−0.006	0.016	−0.006	0.017	0.017	−0.005
Cost t_2	**0.659*****	**0.724*****	**0.658*****	**0.724*****	**0.658*****	**0.723*****	**0.658*****	**0.724*****	**0.657*****	**0.724*****	**0.658*****	**0.658*****	**0.723*****
Expectancy t_2 on concern													
	−0.076	0.046	−0.130	−0.092	0.050	−0.054	0.036	0.034	0.002	−0.049	−0.136^{+}	**−0.188***	**−0.104**$^{+}$
Utility value t_2 on concern													
	−0.171*	0.056	−0.081	−0.071	−0.135^{+}	−0.071	0.047	0.063	0.000	0.009	**−0.163***	−0.135	0.006
Cost t_2 on concern													
	0.181*	0.038	**0.198***	0.052	0.000	−0.044	0.006	**−0.118***	**0.143**$^{+}$	**0.110**$^{+}$	−0.119	0.022	0.069

Note. Depicted values are standardized coefficients. ****significant at the 0.001 level;* ***significant at the 0.01 level;* **significant at the 0.05 level.* Due to the small number of non-URM students voicing performance as a concern/challenge, the models were not performed for non-URM students.

knowledge and virtual learning, respectively. Further, success expectancy related to performance negatively predicted perceived challenges related to performance ($\beta = -0.189$, $p = 0.011$). For male students, perceptions of cost during the course negatively predicted their perceived challenges related to workload ($\beta = 0.586$, $p < 0.001$). There were also differential relations between incoming course concerns and perceptions of achievement motivation during the course: For female students, concerns related to performance ($\beta = -0.136$, $p = 0.012$) and virtual learning ($\beta = -0.145$, $p = 0.011$) negatively predicted success expectancies during the course and concerns related to time management negatively predicted success expectancy for male students ($\beta = -0.195$, $p = 0.046$). Finally, concerns related to performance predicted perceptions of cost for female students ($\beta = 0.127$ $p = 0.020$)

We further found differential interrelations by race/ethnicity. For racial majority students, in the models that include concerns/challenges related to R coding, understanding concepts, and virtual learning, perceptions of expectancies at t_3 also significantly predicted future interest in statistics.

For racial majority students, incoming concerns related to virtual learning predicted later perceived challenges related to virtual learning ($\beta = 0.398$, $p < 0.001$). For students from racially marginalized backgrounds, only one incoming course concern directly predicted students' later perceived course challenge, namely lack of prior knowledge ($\beta = 0.281$, $p < 0.001$). Further, perceived course costs of students from racially marginalized backgrounds positively predicted perceived challenges related to workload ($\beta = 0.307$, $p = 0.001$) and success expectancy negatively predicted challenges related to performance ($\beta = -0.280$, $p = 0.005$) and challenges related to virtual learning ($\beta = -0.324$, $p = 0.001$). Surprisingly, perceptions of utility value were positively related to perceived course challenges related to performance ($\beta = 0.238$, $p = 0.010$) and virtual learning ($\beta = 0.243$, $p = 0.008$). Incoming course concerns related to R coding ($\beta = 0.181$, $p = 0.021$) and understanding concepts ($\beta = 0.198$, $p = 0.013$) positively predicted perceptions of course costs for students from racially marginalized backgrounds. Interestingly, for racial majority students there was a negative path between lack of prior knowledge as a course concern and subsequent course costs ($\beta = -0.118$, $p = 0.041$).

Discussion

Using expectancy-value cost theory as a framework, the current study analyzed both qualitative and quantitative student data to explore incoming course concerns within the context of an introductory statistics course and how they interrelate with motivational experiences and perceptions (success expectancy, utility value, and cost), perceived course challenges, and future interest in statistics among undergraduate students during the pandemic. We discuss our main findings in detail in the following sections.

Interrelations between diversity of students' concerns, the diversity of perceived challenges, achievement motivation, and future interest in statistics (RQ1)

On average, the diversity of incoming course concerns positively predicted both diversity of challenges at the end of the course (RQ1a) and perceptions of cost experienced during the course (RQ1b), and negatively predicted both perceptions of success expectancy and utility value during the course and future interest in statistics at the end of the course (RQ1b). Thus, the number of different concerns students have as they start the course shapes their subsequent experiences. The more (different) concerns students have, the lower their expectations of success and perceived usefulness of the course, the higher their perceptions of course cost and perceived challenges, and the lower their future interest in statistics at the end of the course. This points to the difficulties faced not only by students during the pandemic, but also by their instructors. Were students hindered by a single (or small number) of concerns, resolving those concerns might have involved a more limited number of solutions. As it was, improving students' learning experiences during the course would have meant tackling a wide array of problems. We discuss these interrelations in more detail in the sections that follow.

Relation between diversity of concerns and diversity of challenges (RQ1a)

On average, the diversity of students' incoming course concerns positively predicted the diversity of challenges at the end of the course. In other words, the concerns with which students come into the course play a role in how they later perceive the course in terms of challenges. The finding that students who entered the course with diverse concerns were also likely to "exit" the course with diverse perceived challenges has important implications. If a main priority of policy and education is to increase participation and persistence in STEM, we need to ensure that students complete such gateway introductory courses with positive attitudes and perceptions. In order to effectively design interventions that address students' course-based concerns, it is crucial to identify and understand specific individual concerns that need to be targeted. By pinpointing the specific student concern that impacts their experiences and learning outcomes, specific interventions can be developed to directly address those areas. We will discuss individual concerns and how they relate to individual challenges under RQ2.

Achievement motivation as a mediator between the diversity concerns and (a) diversity of challenges and (b) future interest in statistics (RQ1b)

In our study, achievement motivation - on average - mediated the relationship between the diversity of concerns and the diversity of later perceived challenges as well as future interest in statistics. Thus, the relationship between the diversity of students' concerns at the outset of the course and the diversity of their perceived challenges at the end of the course was not only of direct nature, but also of indirect nature. Specifically, incoming course concerns predicted students' perceptions of course cost, which then fed into perceived course challenges. Cost was the most important predictor of perceived challenges. Importantly, while cost in traditional expectancy-value models has either been considered a subfacet of task values alongside with intrinsic, utility, and attainment value and thus combined with other components of task value to create a composite of task value score or excluded altogether, we explored cost as a separate construct in our models. Including cost as a separate factor seems to be useful in understanding the interplay with course concerns and challenges. Overall, reducing students' perceptions of course cost could reduce the diversity of their later perceived challenges. Research that aims to reduce perceptions of cost are rare and still in its infancy. However, a recent intervention study in introductory physics (Rosenzweig et al., 2020) demonstrated that having students reinterpret their attributions about their course challenges in physics reduced perceptions of cost and increased course grades for initially low-performing students.

The relationship between the diversity of students' incoming course concerns and their future interest in statistics was also both of direct and indirect nature. Students' concerns predicted students' success expectancies and utility value, which then shaped their future interest in taking more statistics classes. Utility value was a particularly strong predictor of students' future interest in statistics in all models. Thus, whether students perceive what they are learning as useful and relevant plays a crucial role in whether they are interested in statistics in the future (e.g., wanting to learn more about statistics, taking more statistics classes in the future, or having a job that involves statistics one day). This important finding aligns with the overall goal of the introductory online statistics textbook in which this study was embedded. That is, it seeks to promote transferable knowledge, applicability and relevance of the material and content, and making real-life connections. While statistics education has become an increasing area of interest "to educators and students given its applicability to understanding important real-world trends (…) in addition to the scholarly and professional opportunities it affords students" (Ober et al., 2022, p. 345) even prior to the pandemic, utility value may take a greater "future-oriented meaning" in the wake of the pandemic, as students are confronted with COVID-19 statistics (e.g., infection rate, effectiveness of vaccines etc.) on a daily basis. This exposure has the potential to make it easier for students to form connections between what they are learning in the statistics course and everyday life, as well as to possible careers in science (Fong, 2022). Because one key metric is students' future interest in statistics, this finding is particularly key in designing interventions. For example, implementing utility value interventions or activities (Hulleman & Harackiewicz, 2009) that encourage students to relate the course content to their everyday lives could help trigger future interest.

Differential interrelations by sex and race/ethnicity (RQ1c)

When exploring the interrelations between concerns, motivation, challenges, and future interest by sex, interesting patterns emerged, adding to the growing list of differences between how female and male students experience statistics courses and highlighting psychological barriers that potentially contribute to the underrepresentation of women in STEM. Incoming diversity of concerns positively predicted perceptions of cost for female students, which then fed into diversity of challenges. In other words, for female students, perceptions of cost mediate the relationship between incoming course concerns and later perceived challenges. Because perceptions of cost have been found to predict a number of student outcomes not measured in this study, such as students' college dropout intentions (Perez et al., 2014), students' adoption of avoidance goals, negative classroom affect, and exam scores (Jiang et al., 2018), perhaps this calls out an early point at which to intervene. Reducing the diversity of females' early course concerns might also reduce their perceived course cost and other outcomes that follow from it.

For male students, diversity of concerns negatively predicts utility value, which feeds into their future interest in statistics. Thus, experiencing a wide range of concerns lowers male students' perceptions of the usefulness and relevance of the course. This path significantly differed between female and male students. As with females, intervening to reduce diversity of incoming concerns might have a later benefit, though the outcome and mediating variables for males (utility value and interest, respectively) differ from those for females (cost and end-of-course challenges, respectively). Other gender differences help identify more proximal points at which to intervene. For female students, future interest was predicted by cost whereas for male students, future interest was predicted by success expectancy. If future interest in statistics is a goal, increasing it might require different interventions for female and male students. Future research is needed to explore potential interventions that reduce female students' concerns and cost perception in statistics.

We also found different interrelations by race/ethnicity. For students from racially marginalized backgrounds, incoming diversity of concerns does not directly predict later perceived diversity of challenges or future interest in statistics, whereas it does for racial majority students. Rather, for students from racially marginalized backgrounds diversity of course concerns play a more indirect role regarding challenges and future interest, *via* achievement motivation. Most strikingly, cost plays an important mediating role: Concerns predict perceptions of cost, which predict both course challenges and future interest in statistics - a pattern that was not found among racial majority students. In fact, the path relating concerns to cost significantly differed between the groups further highlighting that perceptions of costs seem to be a particular barrier for students from racially marginalized backgrounds. Perceptions of cost regarding their future interest in statistics, such as taking additional statistics courses. These findings have important implications for motivational interventions. While a large number of studies have demonstrated that brief motivational interventions targeting students' utility value can improve their interest in STEM subjects, intervention approaches that aim to reduce students' perceptions of costs have only recently gained increased attention (e.g., Rosenzweig et al., 2020, 2022). Helping students, and students from racially marginalized backgrounds in particular, reattribute their course concerns or challenges more adaptively, might potentially lower their perceived costs associated with their concerns or challenges (Rosenzweig et al., 2020). As outlined in Rosenzweig et al. (2020), an intervention could be designed in which students reflect on authentic student quotations gathered from the responses to the open-ended questions about the concerns they had and the challenges they had experienced. Although Rosenzweig et al. (2020) found that the cost reduction intervention helped college physics students perceive challenges related to their physics course as less costly, a more recent study (Rosenzweig et al., 2022) revealed that an intervention ultimately raised introductory biology students' (awareness of) effort and emotional cost. Although the increases in perceptions of cost were not harmful in terms of performance, these mixed findings "speak to the critical importance of continuing to replicate motivational interventions and understand their different effects across different types of learning contexts" (Rosenzweig et al., 2022, p. 9).

RQ2: Interrelations between individual concerns, individual challenges, achievement motivation, and future interest

Similar to the models exploring diversity of concerns/challenges, utility value was a particularly strong predictor of students' future interest in statistics across all models, highlighting the importance of students' perceptions of the usefulness of the course material for their continued interest in statistics.

Relation between individual course concern and later perceived course challenges (RQ2a)

In the overall model, only two incoming individual course concerns predicted later perceived course challenges: Lack of prior knowledge/experience and virtual learning, suggesting that these struggles are unique in their persistence across time. Thus, one enduring area of concern for students relates to their stress and struggles regarding succeeding in the online/remote learning environment (Clabaugh et al., 2021). Although enrollment in online/remote courses has grown over the past years - even prior to the COVID-19 pandemic - students may continue to remain unfamiliar and insecure with this new form of learning within the context of statistics. Indeed, learning statistics remotely seems to be a particular concern among students in our sample as evidenced by students' responses (e.g., "I'm concerned that it will be difficult for me to learn mathematical concepts in a virtual format. Math has always been my most challenging subject to learn, even during in-person instruction. I have not yet taken a math class over Zoom, so I am nervous that I will not succeed"). This lack of experience with remote learning within the context of math/statistics is likely to lead to significant academic stress and uncertainty. Of note is that the students were enrolled in the course in the Winter and Spring 2021 terms. Although they likely had experiences with remote learning in the previous terms, virtual learning remained a challenge.

While reports of challenges at the end of the course that were related to lack of prior knowledge and virtual learning did not predict future interest in statistics, the concerns about these things when expressed at the start of the course (mediated by achievement motivation) predicted future interest. Thus, for these two particular concerns, it may be crucial for instructors to provide additional support at the onset of the course. For example, instructors could ask students to fill out a technology survey, in which they are encouraged to voice any concerns and challenges they anticipate with remote learning during the class. If students mention concerns related to lack of internet access and connection, instructors could connect students directly to university technology services, provide support to ensure materials are accessible to all students, or directly connect with students to discuss their specific concerns related to the virtual format of the course and discuss solutions.

Instructors could alleviate other concerns by verbally emphasizing that although things like R coding and understanding concepts are common concerns among students taking the course, these concerns are later not perceived as actual challenges.

We also found that challenges related to the workload of the course are positively predicted by perceptions of cost, whereas challenges related to performance were negatively predicted by success expectancy. Similarly, students who are concerned about their performance, understanding course material, and the virtual/remote nature of the course show lower levels of success expectancy.

Interestingly, while concerns related to performance negatively predicted perceptions of utility value at t_2, utility value at t_3 positively predicted challenges related to performance. In other words, the higher students' perceptions of the usefulness of the course material, the more likely they were to perceive performance as a course challenge. It is possible that students attempt to alleviate their performance concerns at the beginning of the course by downplaying the value of the material, but by the end of the course recognizing the importance and usefulness of the course material triggers some anxiety around not doing well.

Achievement motivation as a mediator between incoming course concerns and (a) later perceived challenges and (b) future interest in statistics (RQ2b)

Across all individual concerns and challenges, we found two models in which achievement motivation functioned as a mediator. First, we found that success expectancy mediated the relation between students' individual concerns related to performance and their later perceived challenge related to performance. This finding aligns with expectancy-value research that suggests that expectancy is most strongly linked to performance (whereas, for example, value constructs are more strongly tied to choice related behaviors or persistence; Eccles & Wigfield, 2002; Wigfield & Cambria, 2010). This finding has practical significance. Students' concerns about performance directly shape their expectancy to succeed in the course, which then also feeds into their perceived challenges about performance. Although we did not include students' end of course performance in our study, we know from a large body of expectancy-value research that expectancy is closely tied to students' performance (Perez et al., 2019; Robinson et al., 2019). Hence, trying to alleviate students' incoming concerns related to performance may lead to higher levels of success expectancy, which then could increase course performance. Potentially, implementing messaging or brief activities in the textbook that encourage students to adopt a mastery goal orientation that emphasize understanding the material and content (versus a performance goal orientation) could enhance students' experiences (Martin et al., 2008; Yeager & Dweck, 2012).

Second, we found that the relation between concerns related to virtual learning and future interest in statistics were mediated *via* expectancy (t_2) and utility value (t_3). Course concerns about virtual learning shapes success expectancy, which feeds into their perceived usefulness of the course, which then predicts future interest in statistics. This finding has practical implications, particularly for instructors. One way of alleviating concerns related to the virtual nature of the course could be for instructors to ask students to fill out a technology survey at the outset of the course, in which they are encouraged to voice any concerns and challenges they anticipate with remote/virtual learning. For instance, if students are concerned about lack of internet access and connection or lack of quiet/private space to study, instructors could provide support to ensure materials are accessible to all students or connect students directly to university technology services. Alleviating such concerns can in turn increase students' expectations to succeed and perceptions of value. For example, if students feel more comfortable and supported with the virtual learning environment and have to worry less about issues related to the remote nature and online materials, they might feel more confident in their ability to successfully complete the class and are more likely to engage in the learning, which can lead to a deeper understanding of the material and a more positive perception of the value of the learning experience.

Differential interrelations by sex and race/ethnicity (RQ2c)

Exploring individual concerns and challenges, we found differential relations by sex and race/ethnicity. Specifically, female students' concerns regarding their lack of prior knowledge predicted their later perceived challenges regarding lack of prior knowledge. Female students could potentially benefit from interventions based on attribution theory (Weiner, 1985) that help them reattribute their concerns and challenges related to statistics as being less internally-caused (Rosenzweig et al., 2022). If students believe that their concerns or challenges are due to internal, stable causes (i.e., lack of prior knowledge or low ability), it can thwart their positive psychological experiences. Encouraging students - in particular female students - to perceive concerns and challenges as being due to external sources, it might help them "perceive the challenges as less effortful and/or emotionally threatening, and in turn that might make the challenges seem less costly" (Rosenzweig et al., 2022, p. 2). Thus, this shift in perception can ultimately make challenges appear less costly, reducing the psychological burden and potentially improving their overall engagement.

We also found some different patterns by race/ethnicity. There was one concern each that predicted subsequent perceived challenges. For students from racially minoritized backgrounds, concerns related to prior knowledge directly predicted their later perceived course challenge related to prior knowledge. Although neither this concern nor challenge predicted future interest in statistics, there may be other learning outcomes not assessed in this study that could be thwarted by students' concerns and challenges related to lack of prior knowledge. Not having enough prior knowledge or perceiving one's lack of prior knowledge as a barrier to succeeding in class should be addressed in order for students to maximally benefit from class. Although the textbook is designed for all students to succeed, regardless of their prior statistics background and knowledge, concerns about prior knowledge persisted for students from racially minoritized backgrounds and was later perceived as having been a challenge. This has important implications for the curriculum designers as well as instructors. Curriculum developers should investigate the perceptions of students from racially minoritized backgrounds further to identify what knowledge they felt they lacked and where in the course they felt their learning was impacted by it. Developers could address this particular concern/challenge by, for example, incorporating activities or tasks that activate prior knowledge. For example, at the start of each chapter, the textbook could embed either a brief summary or review of the content from the previous chapter or, alternatively, engage students in recalling the content of the prior chapter (e.g., write down what they remember from the prior chapter).

For White and Asian students, concerns related to virtual learning predicted later perceived challenges related to virtual learning. As previously stated, instructors could address this particular concern/challenge by circulating a technology survey at the outset of the course that encourages students to name any concerns and challenges they anticipate with remote/virtual learning and provide additional support.

While documenting differences across genders and racial/ethnic groups is a first step in recognizing disparities, they "should not be explored with the intention to highlight deficits in certain groups, but rather to focus on (…) the structural barriers that, when addressed, can provide more equitable opportunities for all students to become and stay motivated" (Lee et al., 2022, p. 3). In other words, we must identify (a) the underlying systemic and contextual causes of these disparities and (b) which psychological processes could be leveraged by intervening in order to better support students. Exploring gender and racial differences in concerns, challenges, and motivation is crucial for tailoring interventions and educational resources to meet the needs of each group's experiences, perceptions, and motivation (Lee et al., 2022). Thus, future research should explore how educational environments (i.e., instructional practices, learning material, teachers/instructors) can better support experiences and perceptions of students from underrepresented groups. Reducing perceptions of cost appears to have particular potential.

Overall, our findings with regards to both the diversity of concerns/challenges and individual concerns/challenges add to the increasing body of research reporting differences between how students from different groups experience STEM courses and they might help explain different levels of interest in pursuing STEM careers.

Strengths, limitations, and areas for future research

This study contributes to understanding students' expectations, experiences, and perceptions of learning statistics and how those experiences vary by sex and race/ethnicity. The strengths of our study are twofold. First, we collected data from real classrooms over the course of the full school term, lending to the ecological validity of the findings. Second, the study employed a Triangulation Design Approach: Data Transformation Model (Creswell & Clark, 2017). In this design, the qualitative data were collected, evaluated, and then transformed into quantitative data. Thus, we integrated quantitative and qualitative student data to explore interrelations among course concerns, achievement motivation, perceived course challenges, and future interest in statistics. Using open-ended survey questions to capture more nuanced aspects of students' incoming course concerns and their later perceived challenges allowed us to identify concerns and challenges that we would not expect a priori.

These strengths are balanced by three limitations, each of which direct researchers to areas for future work. First and foremost, the findings of our study might not generalize to other student populations. All participants were from one elite, predominantly White/Asian university in California. Student perceptions, expectations, and experiences are highly situational and may vary significantly from one institution to another. For example, the experiences of female students and students from underserved racially marginalized groups may depend on the proportion of female students or students from racially marginalized groups within their institution. It will be vital to explore concerns and challenges and their interrelations with achievement motivation and future interest of students at other institutions, characterized by different student body demographics and different types of institutions (e.g., community colleges). Similarly, future research should explore other student outcomes - such as course performance, dropout rates, etc.

Second, the findings are specific to the textbook used by all students. While we consider it a strength of our study that all students used the same textbook as it reduces variability in the content to which participants were exposed, we must acknowledge the likelihood that, for example, students' perceived challenges at the end of the course are highly specific to the content of said textbook. While this is of value for the developers of this book, as it helps in identifying appropriate interventions or instructional practices that can be embedded directly in the textbook, these interventions might not apply to other settings. Future work should also investigate the concerns and perceived challenges of students enrolled in introductory statistics courses that use different textbooks.

Finally, some of our constructs (e.g., expectancy and cost) were only measured using two items, which can undermine reliability and validity. Although other studies exist that only used two items to measure motivational constructs as conceptualized within expectancy-value frameworks (e.g., Kosovich et al., 2019), it is important to recognize and acknowledge this limitation.

Conclusions

The present study contributes to the growing literature exploring how female and male students as well as students from racially marginalized backgrounds and racial majority students experience STEM courses. Our findings revealed that - on average - incoming course concerns predicted achievement motivation, later perceived challenges, and future interest in statistics. Further, our study highlights differential patterns by gender and race. Importantly, for female students and students from racially marginalized groups including Black, Latinx, and Native American/Indigenous students a) perceptions of cost played an important mediating role between course concerns and future interest in statistics and b) incoming concerns related to lack of prior knowledge persisted throughout the course and were later perceived as having been barriers in succeeding in the course. The results emphasize the need for tailored interventions to address specific concerns and barriers faced by different student groups.

Notes

1. Diversity of concerns/challenges reflects the total number of concerns and challenges voiced per student. When students mentioned multiple concerns from the same category (e.g., they mentioned both workload and pace), this was counted as only one concern. Thus, the sums capture roughly the quantity of concerns/challenges mentioned and can also be thought of as reflecting the diversity of concerns/challenges.
2. Includes covariances between success expectancy, utility value, and opportunity cost within each time point (t2 and t3).

Disclosure statement

The authors report there are no competing interests to declare.

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