Kattoum and Baillie
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A more positive mindset context is associated with better student outcomes in STEM, particularly for traditional-age students

Ronia N. Kattoum[1,2*] and Mark T. Baillie[1,2]

Abstract

Background Students' beliefs about their ability to grow in STEM disciplines have been linked to better course outcomes. However, such mindset beliefs are subject to the environmental cues projected by the instructor in the classroom, which we refer to as the mindset context. Recent meta-analyses indicated heterogeneity in the benefits of student mindset interventions, which the classroom environment may shape. In this work, we use structural equation modeling (SEM) to investigate the mindset context and its impact on students' affect and performance in STEM courses, particularly for students from marginalized groups who may be disproportionately affected by these factors.

Results We collected student perceptions of their instructors' universality beliefs about student abilities (all people or only some people can reach excellence in STEM), students' growth beliefs, sense of belonging (as measured by peer support, faculty support, and classroom comfort) and course grades. The sample was collected from courses in a STEM college within a demographically diverse, moderately selective institution in the Southern United States ($N=625$). We found that student perceptions of the mindset context did not directly predict course grades, but ACT scores did (standardized exams used for college entry in the USA). However, SEM analysis revealed that when students perceived instructors to believe only some students can succeed in STEM (endorse more non-universal beliefs), they reported fewer growth beliefs about their abilities in STEM. This led to less classroom comfort in contributing to class discussions, ultimately lowering STEM grades. Multigroup moderation analysis showed no differences in paths based on race, gender, and generational status. However, the mindset context impacted traditional students' (age of 18–22) growth beliefs to a greater extent than non-traditional students (> 22 years old). Additionally, classroom comfort significantly predicted grades for traditional students but not for non-traditional students.

Conclusions Our finding suggests that when students perceive the mindset context more positively, their outcomes improve, especially for traditional students who may be more sensitive to classroom cues. Thus, mindset interventions for faculty (coupled with student interventions) may also be beneficial to supporting student success. Additionally, we recommend improving student content preparation to enhance foundational knowledge, considering that indicators of prior preparation (ACT scores) play a more direct role in predicting student grades.

Keywords Student perceptions, Lay theories, Universal and non-universal beliefs, ULTrA survey, Undergraduate STEM, Growth beliefs, Sense of belonging, Performance, Structural equation modeling, Multigroup moderation, Social cognitive theory

*Correspondence:
Ronia N. Kattoum
rkattoum@roosevelt.edu
Full list of author information is available at the end of the article

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Introduction

In an era of rapid technological advancements and shifting economic landscapes, the importance of Science, Technology, Engineering, and Mathematics (STEM) education cannot be overstated. STEM disciplines serve as the cornerstone of innovation, driving progress across various industries and shaping the future of our global workforce. However, despite the critical role STEM fields play in modern society, there is a pressing need to enhance STEM education to adequately prepare students for the demands of the contemporary workplace while fostering equity and inclusion within these domains.

One critical concern is the persistent shortage of skilled STEM professionals to meet the demands of emerging industries. With the "double disruption" of job automation and the COVID-19 recession, the risk of exacerbating inequities for lower-wage workers, women, and younger workers will continue to increase if left unchecked (The Future of Jobs Report, 2020). Research consistently highlights the underrepresentation of certain demographic groups in STEM fields (e.g., people of color, women, etc.), which is partly attributed to systemic barriers such as unequal access to resources, biased educational practices, and lack of representation in STEM-related careers (Malcom & Feder, 2016). Without a robust pipeline of STEM-literate individuals, the US risks falling behind in global innovation, hampering contributions to the development of the worldwide economy (The Future of Jobs Report, 2020).

Addressing these challenges requires a multifaceted approach that enhances the quality and accessibility of STEM education and promotes diversity, equity, and inclusion within STEM fields, including cultivating a growth mindset among students and educators. Conceptualized by psychologist Carol Dweck, a growth mindset is the belief that intelligence and abilities can be developed through effort, persistence, and learning from failure (Dweck & Yeager, 2019). Research indicates that individuals who lean toward a growth mindset are more likely to embrace challenges, persevere in the face of setbacks, and ultimately achieve greater success in academic and professional pursuits (Yeager & Dweck, 2012). By fostering a growth mindset within STEM education, educators can create a supportive learning environment where students feel empowered to take intellectual risks, explore diverse perspectives, and collaborate effectively with peers from diverse backgrounds, building skillsets for the workforce.

Moreover, integrating a growth mindset framework into STEM pedagogy can help mitigate the impact of stereotype threat and implicit biases that hinder the participation and achievement of students from marginalized groups in STEM fields (Aronson et al., 2002). Students from marginalized populations include Black, Indigenous, People of Color (BIPOC, Black, Native American, Native Hawaiian, Alaskan Native, Asian, Pacific Islander, Hispanic/Latino/a/e, other, multiracial), women, non-traditional students (> age of 22), and first-generation college students (parents did not earn college degree). By emphasizing the malleability of intelligence and the value of resilience, educators can counteract negative stereotypes and instill confidence in students who may face systemic barriers or feel marginalized within STEM disciplines (Canning et al., 2019, 2021).

However, recent meta-analyses on how students' mindset influences their course outcomes have revealed mixed findings, with some suggesting weak to no effects even when mindset interventions are utilized (Macnamara & Burgoyne, 2023; Sisk et al., 2018). In rebuttal, researchers using more fine-tuned meta-analytic techniques that account for different contexts showed that student mindset interventions have positive effects, especially for at-risk student populations (Burnette et al., 2023; Tipton et al., 2023). Hence, recent recommendations in the literature encourage researchers to move beyond students' mindset beliefs by studying the broader context that may influence those beliefs, which can be shaped by the environment (Canning & Limeri, 2023).

While we do not utilize mindset interventions in this study, we use Social Cognitive Theory (SCT) as a theoretical framework to guide our investigation of the interplay of cognitive, affective, and behavioral factors in determining student success. SCT builds on BF Skinner's behaviorism (Dilshad, 2017), which posits that learning/conditioning occurs based on external reward/punishment stimuli. SCT still acknowledges the role of external factors in learning but also incorporates how people think, feel, and interpret their experiences (affect). Bandura expanded on Skinner's ideas by arguing that people are not passive responders to stimuli (reward/punishment) but active participants in their learning. He proposed reciprocal determinism, which suggests that behavior is influenced by external reinforcement and the interaction between the individual, their cognitive processes, and their environment (Dilshad, 2017). The theory suggests that people learn through direct experiences and by observing others. Therefore, the mindset context (the classroom environment set by the instructor) may influence student proximal affective factors that, in turn, influence more distal outcomes (student performance in STEM). Thus, we assess how students' perceptions of the instructor's mindset influence their own mindset and how that leads to downward effects on their sense of belonging and course performance. In addition, we also examine how student demographic factors moderate these relationships to inform faculty professional development and increase success for all students, especially for at-risk groups in STEM.

Student perceptions of instructors' universality beliefs

The alignment between instructor and student mindsets has the potential to cultivate a learning environment conducive to risk-taking and exploration, where students feel empowered to tackle complex problems and seek out growth opportunities. For example, when their instructor's self-reported mindset beliefs support students' beliefs, mindset interventions are more effective in improving student math grades (Yeager et al., 2022). The environmental context can reinforce or refute students' beliefs about their STEM abilities (Walton & Yeager, 2020). This is especially impactful for marginalized students. When STEM faculty endorse a more fixed mindset (ability is an innate characteristic that cannot be developed), student achievement gaps are nearly doubled compared to those taught by faculty who endorse a growth mindset (ability can be developed) (Canning et al., 2019). These studies suggest that students pick up on contextual cues that shape their perceptions of the learning environment. This is supported by previous studies that found that when students perceived instructors to endorse a fixed mindset, they exhibited greater psychological vulnerability (less belonging, more evaluative concerns, etc.). This led to less engagement and lower grades in STEM courses (Muenks et al., 2020) and undermined women's performance (Canning et al., 2021). Additionally, when students perceived instructors to have more of a fixed mindset, this was correlated with increased academic misfit, which led to lower grades in chemistry courses (Kattoum et al., 2024).

To measure universality beliefs, we use a recently developed and validated tool that provides more nuances into the lay theory of human ability, the Undergraduate Lay Theories of Abilities (ULTrA) survey (Limeri et al., 2023). The ULTrA measures mindset (whether ability can be developed), universality beliefs (who has the potential to become excellent in a field, everyone or some people), and brilliance beliefs (raw talent is required for success in specific fields). We focus on the student perceptions of the instructors' universality beliefs that assess an individual's alignment with the idea that everyone can reach their highest potential of ability (universal beliefs) or that only some people can achieve their highest levels of abilities (non-universal beliefs) (Limeri et al., 2023; Rattan et al., 2018), that we refer to as the mindset context. Although student perceptions of the instructor's mindset and brilliance beliefs may also be a factor in determining students' outcomes, universality beliefs align more with the goal of this study. We hypothesize that students who perceive their instructor to believe that anyone can master complex subjects with the right resources and hard work (universal beliefs for conciseness) may lead to better outcomes. This may be particularly important for students from marginalized populations, who may question belonging in that space (Canning et al., 2021; Murphy & Zirkel, 2015). Perhaps if they perceive the instructor to believe all students can reach their highest level of achievement, this may increase their sense of belonging and achievement. On the other hand, if students perceive their instructor to believe that no matter how many resources and effort a person puts in, some people will be unable to master certain subjects (non-universal beliefs for conciseness), we hypothesize this may adversely affect their outcomes. They may internalize that to mean that STEM is exclusive, which can impact marginalized student populations' outcomes to a greater extent, as outlined in previous literature (Murphy & Zirkel, 2015). Additionally, student perceptions about the universality of their instructors' beliefs (universal and non-universal) can be critical in shaping their views about their abilities (growth beliefs), which we will discuss next.

Students' growth beliefs

While universality beliefs probe for an individual's beliefs about the distribution of abilities among people, growth beliefs measure the individuals' view that ability can be improved and developed (versus innate and unchangeable) (Limeri et al., 2023). Students with less growth beliefs may be more prone to giving up when faced with difficulties, as they interpret setbacks as evidence of their lack of ability to grow. This can lead to lower academic performance and reduced engagement with STEM subjects (Blackwell et al., 2007), which require resilience in the face of challenges. Conversely, students who endorse a growth mindset believe their abilities can be developed through effort, perseverance, and learning from mistakes. They view challenges as opportunities for growth and are more likely to persist in the face of setbacks (Yeager & Dweck, 2012). Additionally, students who endorse more growth beliefs tend to use more error-prone study strategies, which are more effective in student learning (Chouvalova et al., 2024). Instead of focusing on what they are comfortable with, students with a growth mindset focus on studying what they don't know, even though they may make more mistakes. While growth mindset interventions may enhance student outcomes, their benefits may depend on the specific context, namely the learning environment set by the instructors (Muenks et al., 2021; Yeager et al., 2022).

Thus, from the lens of SCT, we hypothesize that students' perceptions that their instructors endorse more universal and less non-universal beliefs may enhance their own growth beliefs about their abilities (growth beliefs for conciseness). Additionally, we assess whether students from marginalized groups who may already experience stereotype threat and question their ability to grow in STEM (Cohen & Garcia, 2005) are impacted more significantly by their perceptions of the mindset context. Additionally, because previous work indicates a connection between student perceptions of their learning environment and their sense of belonging in STEM (Rattan et al., 2018), we explore belonging as a potential mediating variable between the mindset context and course grade.

Student sense of belonging

Belonging refers to feeling accepted, valued, and connected within a group, community, or environment (Strayhorn, 2018). It encompasses a sense of inclusion, attachment, and identification with others who share common characteristics, interests, or experiences, but not necessarily assimilation within a community (Deil-Amen, 2011). Previous research has indicated that a sense of belonging in the academic setting can enhance student motivation, achievement, and well-being (Trujillo & Tanner, 2014). In this work, we build on the literature by investigating how the mindset context influences students' sense of belonging. We hypothesize that more negative perceptions of the mindset context (students believing that the instructor endorses more non-universal beliefs and less universal beliefs) may trigger a lack of belonging among students, which leads to downstream effects on their performance in STEM. Based on the previous literature outlined below, we believe the impact of the mindset context on students' sense of belonging may be more pronounced for students with marginalized identities.

When students perceive their instructors as leaning toward a fixed mindset, they experience increased psychological vulnerability and a decreased sense of belonging (Muenks et al., 2020), which is associated with lower performance, especially for women. When women get the message that ability can be developed, this mitigates their stereotype threat and increases their sense of belonging in math courses (Good et al., 2012). Additionally, underrepresented students' perceptions about their instructor's universality beliefs drive their sense of belonging to STEM (Rattan et al., 2018). Thus, it is essential to investigate how the mindset context impacts students' belonging and the downstream effects on course outcomes, particularly for students with marginalized identities.

With that being said, belonging may be elusive to measure (Kattoum et al., 2024). For example, when students are asked to rate their agreement with the statement "I belong in STEM", this comprehensive statement may not encompass the various dimensions of belonging. Belonging can be social ("I do not see others who look like me in class, so I don't belong here") and/or academic ("I am not good at math, and so I do not belong here") (Walton & Cohen, 2011).

Thus, we used a validated instrument to capture the essence of belonging within a college setting. The researchers identified five belonging factors: peer support, faculty support/comfort, classroom comfort, isolation, and empathetic understanding (Hoffman et al., 2002). While student isolation and instructor empathy may be essential elements in student retention and performance, for this study, we hone in on the aspects more relevant to students' academic belonging: perceived peer support, faculty support, and classroom comfort. Peer support probes students' sense of academic support from their peers, such as forming study groups outside of class. Faculty support probes for the student's comfort level in seeking help from the instructor, such as attending office hours. Lastly, classroom comfort measures a student's propensity to share ideas and thoughts within the classroom.

We hypothesize that when students perceive the instructor to endorse more universal and less non-universal beliefs, this may create an inclusive environment that encourages students to believe they can grow their abilities. This will, in turn, improve their sense of belonging (perceived peer and faculty support and classroom comfort), leading to better course grades in STEM.

Course grade and ACT scores

Course grades are an important (but not the only) determinant of whether students proceed in the STEM disciplines and, thus, are the primary outcome variable in this study. To determine how the independent variables (universality beliefs) and mediating variables (growth beliefs and belonging) influence the primary dependent variable (course grade), we controlled for ACT composite scores (American College Testing, indicator of prior preparation) on the course grade. Thus, any direct and indirect effects of the independent and mediating variables on the outcome variables can be isolated rather than confounded with the possibility that incoming preparation shapes those relationships.

ACT is a standardized test historically used for college admission in the USA. While ACT scores may reflect foundational knowledge in math and science (and, to some extent, cognitive ability), they are limited in assessing broader cognitive abilities, such as critical thinking or creativity, which are crucial for success in STEM. Additionally, systemic inequities—such as unequal access to test prep materials and resources—can skew results, particularly for marginalized students. These disparities limit our understanding of these students' true cognitive potential and can perpetuate gaps in educational outcomes, as their performance may not fully reflect their capabilities or learning experiences (Brunn-Bevel & Byrd, 2015). Thus, we use ACT scores as indicators of prior preparation rather than reflecting students' cognitive abilities.

Current study

In this work, we build on previous studies by focusing on new directions for exploring the mindset context guided by Social Cognitive Theory (SCT). SCT posits that the learning environment influences student affect (attitudes and feelings), influencing student behavior and engagement (Schaller et al., 2012). Previous work has uncovered that student perceptions of the instructors' mindset beliefs are related to student affective factors, which then impact course outcomes while controlling for the student's own mindset beliefs in chemistry courses (Kattoum et al., 2024) and the broader STEM context (Canning et al., 2021; Muenks et al., 2020). This work assesses how student growth beliefs mediate (rather than used as a control variable) between the learning environment and student outcomes in STEM courses. Recent work examined self-incremental beliefs (growth beliefs) as mediating variables between the instructors' beliefs and proximal affective factors (STEM interest, efficacy, sense of belonging, and grit) (Lytle & Shin, 2023). However, they did not connect those to more distal outcomes (i.e., course performance). While affective factors are indicators of student engagement and retention in STEM, course grades are the first determinants of whether students proceed in a course sequence or a STEM major. Hence, it is essential to understand how the mindset context influences both proximal and distal outcomes to give more insight into student retention. Structural equation modeling (SEM) was selected as the method of analysis to help provide a more holistic overview of student success by testing the direct effects of the mindset context on student performance and through indirect effects using mediating affective factors.

In addition, we use more developed and validated instrument items to assess the dimensions of mindset (Limeri et al., 2023) and student sense of belonging (Hoffman et al., 2002), contributing to more accuracy in conclusions. Because we adapted those instruments to our setting, we conduct validity and reliability checks and treat variables as latent (rather than manifest) variables in our statistical models to account for errors and biases in instrumentation, providing more robust conclusions to our analyses.

Lastly, we studied the mindset context in a native learning environment rather than a controlled laboratory setting. To help broaden our knowledge base, we conduct this research within a metropolitan, moderately selective research institution serving a diverse student body rather than selective and more demographically homogenous institutions (Canning et al., 2021), where marginalized students are less likely to attend (Reardon et al., 2012). Thus, this work will contribute to the narrative of student success in different settings, providing more tailored approaches for reform.

With these gaps in mind, we center our investigation on these guiding research questions to broaden the narrative of mindset research:

RQ1) How do student perceptions of the instructors' beliefs about their abilities impact their own beliefs, and how does that, in turn, influence their sense of belonging and, ultimately, their performance in STEM courses (Fig. 1)?

RQ2) How are those pathways moderated by demographic factors (race, gender, age group, and generational status) in a metropolitan research institution serving a diverse student population?

Methods

The research team recruited faculty members from a STEM college at a metropolitan research institution in the southern United States (~7000 undergraduate students) with Institutional Review Board (IRB) approval. Overall, the student population is approximately 54% White, 22% Black/African American, 11% multiracial, 7% non-resident immigrant, 3% Asian, 2% Asian, and <1% Native American/Alaska Native. The institution has approximately 370 faculty members, of which 110 belong to the STEM college. All STEM faculty members were invited to participate in the study, and 24 consented to allow the collection of data from consenting students in their classes (34 courses, student $N=625$). Student data were collected by the research team during the first or last ten minutes of classes or lab time in the 12th or 13th week of a 14-week semester (as part of a more extensive study). A QR code was provided to guide students to a Qualtrics survey administered during class time that collected student consent, questionnaires, self-identified demographics, and ACT scores. Regardless of their decision to participate, those who completed the consent form were entered into a raffle to win one of thirty $20 gift cards.

When an instructor taught multiple courses or sections of the same course, student data were aggregated since the primary focus of the study was to assess student perceptions of the instructor's mindset. However, if a student was enrolled in more than one of the courses

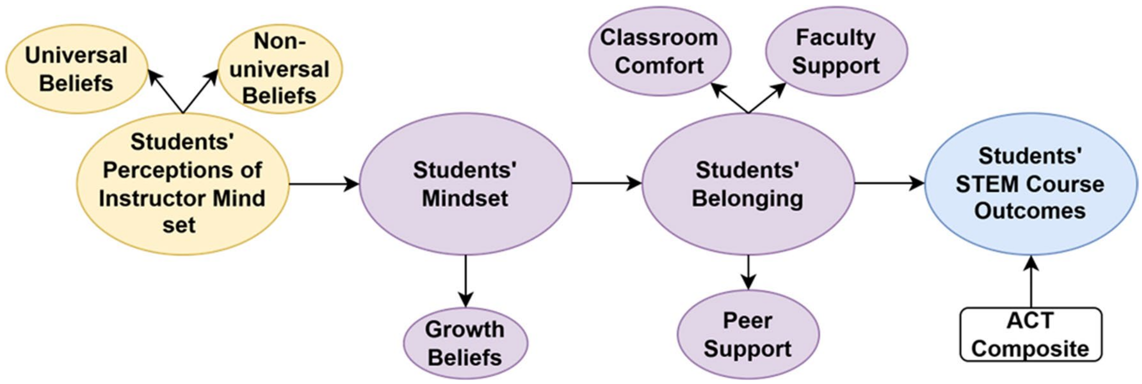

Fig. 1 Proposed model: we hypothesize that student perceptions of their instructors' beliefs about student abilities (universal and non-universal beliefs) impact their own mindset beliefs (growth beliefs), which, in turn, influences their sense of belonging (classroom comfort, peer support, faculty support) and, ultimately, their outcomes (course grade) in STEM courses. To isolate the impact of the variables of interest on course grade, we control for prior preparation as determined through ACT scores. Additionally, we assess how these pathways may differ based on demographic factors (race, gender, age group, and generational status)

surveyed with different instructors, they were treated as distinct data points for each instructor and retained for analysis.

Study participants

Student response rates from the 24 instructors across eight departments ranged from 45 to 85%, resulting in 625 student participants (ranging from 7 to 91 students per instructor). Table 1 presents the demographic details of the final sample population.

Students who identified as Black, Native American, Native Hawaiian, Alaskan Native, Asian, Pacific Islander, Hispanic/Latino/a/e, other, or multiracial were grouped under the category of Black, Indigenous, People of Color (BIPOC). Any combination of races/ethnicities resulting in multiple identifications was also categorized as BIPOC (e.g., African American and White). Individuals who opted not to disclose demographic characteristics were considered missing data (2 students). Overall, students identified as 51% BIPOC and 49% White. The sample consisted of 16% African American/Black students (102 students), 12% Asian (77 students), 12% Hispanic/Latino/a/e (77 students), < 2% other (10 students), and 8% multiracial (52 students).

Less than 2% of the total sample consisted of students identifying as non-binary/third gender, and approximately 1% chose not to identify their gender. Thus, both were treated as missing data because it is difficult to draw meaningful conclusions by comparing small samples. Overall, the sample consisted of 60% women and 37% men. It must be noted that there is an overrepresentation of women in STEM at this institution (~ 62%) compared to national representation (~ 31%) (McGee, 2023).

Table 1 Summary of student sample demographics. (N = 625)

Demographic category	Sample size	% of population
Race		
BIPOC[a]	316	51
White	307	49
Missing	2	< 1
Gender		
Man		
Woman	230	37
Non-binary/third gender/missing	378	60
Man	17	3
Age		
Traditional (18–22 years old)	386	62
Non-traditional (> 22 years old)	239	38
Generational status[b]		
First generation (FG)	280	45
Continuing generation (CG)	343	55
Missing	2	< 1
Classification		
First year	187	30
Second year	150	24
Third year	119	19
Fourth year	69	11
Post-baccalaureate	94	15
Missing	6	1

[a] Black, Indigenous People of Color: Black, Native American, Native Hawaiian, Alaskan Native, Asian, Pacific Islander, Hispanic/Latino/a/e, other, multiracial.
[b] First-generation (FG): parents/caretakers do not have a college degree; continuing generation (CG): at least one parent/caretaker has earned a college degree

Students 18–22 years old were categorized as traditional students, and students greater than 22 years old were categorized as non-traditional students. The sample consisted of 62% traditional students and 38%

non-traditional students. Specifically, non-traditional students consisted of 128 students (21%) between 23 and 28 years old, 65 students (10%) between 29 and 35 years old (65 students), and 46 students (7%) above 35 years old.

First-generation college students were defined as students whose parent(s)/caregiver(s) have not completed a college degree. In contrast, continuing-generation students had at least one parent/caregiver complete a college degree. Overall, 45% of students identified as first-generation and 55% as continuing-generation college students.

Lastly, students varied in terms of their academic year with 30% of students being first-year students, 24% second-year, 19% third-year, 11% fourth year, 15% post-baccalaureate, with 1% missing data.

Measures

The student questionnaires (26 items, SI Table S1) measured six latent variables that surveyed student perceptions of the instructors': (1) universal beliefs (5 items) and (2) non-universal beliefs (5 items), (3) students' growth beliefs (5 items), and students' perceptions of (4) peer support (4 items), (5) faculty support (3 items), and 6) classroom comfort (4 items), students self-identified demographics (race, age, gender, and first-generation status) and ACT composite scores. Students agreed with each statement on a scale of 1–6 (1—strongly disagree, 2—disagree, 3—somewhat disagree, 4—somewhat agree, 5—agree, 6—strongly agree, and prefer not to answer).

Perceptions of the instructor's universality beliefs

Universality beliefs items (universal and non-universal beliefs) were modified from the ULTrA survey (Limeri et al., 2023) to focus the student's attention on what they perceived their instructors to believe about student abilities rather than the broader perceptions of people's abilities. For example, the non-universal belief item "Even if they try, some <u>people</u> could never become as effective at analyzing information as their peers" was modified to "<u>The professor in this course seems to believe that</u> even if they try, some <u>students</u> could never become as effective at analyzing information as their peers." The remaining four items were modified similarly (see SI Table S1), with a higher scoring indicating that students perceived the instructor to endorse more non-universal beliefs about student abilities (i.e., only certain students can succeed in STEM).

Similarly, the ULTrA items measuring the student perceptions of the instructor's universal beliefs were modified from their source to focus the student's attention on the instructor and course. For example, an item such as "<u>Anyone</u> who tries could become as good at applying knowledge as STEM experts" was modified to "<u>The professor in this course seems to believe that any student</u> who tries could become as good at applying knowledge as STEM experts." A higher score on the universal beliefs scale would indicate that students perceived the instructor to align more universal beliefs about student abilities (i.e., all students have the ability to succeed in STEM).

The student growth belief items from the ULTrA surveys were used in their original form since they already assessed student beliefs about their ability to grow in STEM, with items such as "I could improve my intellectual abilities in this class to the same level as successful STEM professionals". A higher score would indicate that students align more with the belief that they can improve their STEM ability.

Sense of belonging

Sense of belonging was measured by students' perceived classroom comfort, faculty support, and peer support. All items were used in their original forms from the source (Hoffman et al., 2002; Limeri et al., 2023). When answering the questionnaire, students were asked to focus on the instructor/course. For example, classroom comfort was measured with items like "I feel comfortable volunteering ideas or opinions in class." Faculty support (was measured with items like "I feel comfortable asking the instructor/professor for help if I do not understand course-related material." Lastly, peer support was measured with items such as "I could call another student from class if I had a question about an assignment."

Course grades and ACT scores

Students were asked to report their ACT scores, which were used as control variables for course grades, the primary outcome variables. At the end of the semester, the instructors were asked to report students' overall averages in the course as percentages (only for consenting students).

Data analysis method

We assessed the validity and reliability of the instruments to our settings, including testing for measurement invariance before building the structural equation model path analysis based on our proposed model (Fig. 1). All analyses were conducted with Rstudio (version 4.2.5) *lavaan*, *psych*, and *statix* packages. Plots were constructed with RStudio packages (*ggplot2, ggpubr*) and *draw.io* in *G Suite*.

Instrument validity and reliability

Because all instruments utilized underwent thorough validation processes by their original authors, there was no need for an Exploratory Factor Analysis (EFA). However, since we modified some of the questions slightly and this work was conducted in a different context than the original surveys, we conducted a Confirmatory Factor Analysis (CFA) based on the factor structure established by previous literature for all latent variables (i.e., factor loadings for a group of items under a latent variable, also known as the "measurement part"). The CFA was conducted using complete information maximum likelihood approximations (FIML) for missing data and the robust maximum likelihood (MLR) estimator for all latent variables under investigation (data were not normally distributed, with details in the SI section, Table S2). Goodness of fit indices were used to assess model fit including the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The thresholds for acceptability are CFI/TLI > 0.95, RMSEA < 0.08, and SRMR < 0.06 (Hu & Bentler, 1999).

All four model fit parameters exceeded the thresholds of acceptability, indicating excellent model fit (Robust CFI/TLI = 0.98/0.97, Robust RMSEA = 0.044 (90% CI 0.038-0.050), SRMR = 0.046) based on the factor structure from the original source. Factor loading ranged from 0.64 to 0.97 with one exception on the non-universal scale: "The professor in this course seems to believe that students with a natural talent can become excellent at analyzing information" ($\lambda = 0.28$). Further inspection revealed an inconsistency in wording that may explain the poor loading of the item. The original item read, "Only people with a natural talent can become excellent at analyzing information." Leaving out "only" (most likely due to a transcription error) changed the statement's meaning. Instructors who are perceived to believe that talented students excel in information analysis don't necessarily indicate an endorsement of non-universal beliefs, whereas believing *only* talented students will excel in analyzing information suggests a partiality towards non-universal beliefs. Due to the potential for varied interpretations of this item, as evidenced by its factor loadings in the CFA, it was excluded from subsequent analysis that resulted in excellent model fit (Robust CFI/TLI = 0.98/0.98, Robust RMSEA = 0.041 (90% CI 0.034-0.047), SRMR = 0.029) and factor loadings that ranged from 0.64-0.97). In addition to validity measures with CFA, reliability measures for each factor were conducted using Cronbach's Alpha, which ranged from 0.87 to 0.96, indicating internal consistency of items with each factor (see SI section, Table S2 for details).

Measurement invariance testing

Given that this study aimed to examine how demographic factors moderate student perceptions and course grades, we conducted measurement invariance testing first to help determine whether various groups of students interpret questionnaires similarly (Rocabado et al., 2020). If measurement invariance is established, different groups (such as men and women) interpret questions similarly. Thus, when we conduct multigroup moderation analysis on the SEM path analysis, any disparities observed between groups could be attributed to genuine differences in the regression pathways in the simplest SEM path model (Kattoum et al., 2024) rather than a difference in how various groups are interpreting the questionnaires. It must be noted that measurement invariance was performed on the measurement part of the most parsimonious model in the SEM path analysis, which was also used for mediation analysis (direct and indirect effects). We assessed measurement invariance on the latent variables in the final SEM model to assess that all demographic groups (race, gender, age group, and generational status) interpret questions similarly. We found that factor loadings were similar across all demographic groups (see SI section, Table S3), establishing measurement invariance.

Structural equation modeling (SEM) path analysis

Once we established validity, reliability, and measurement invariance, we used structural equation modeling (SEM) path analysis to determine how latent variables were related to one another, which is grounded in previous work and SCT (also known as the "structural part"). We refined the path model so that the most parsimonious model was used for reporting based on model fit indices and the significance of regressions pathways (more details in Results and Discussion) to answer our first research question. We then conducted a multigroup moderation analysis to answer our second research question to assess whether regression pathways diverged based on race, gender, age group, and generational status (more details in Results and Discussion).

Results

Table 2 presents a comprehensive overview of the descriptive statistics concerning the variables under examination within the final dataset and an initial assessment of demographic differences. This equips readers with an initial understanding of the dataset, aiding them in interpreting subsequent statistical analyses and justifying the analytical approaches utilized. It's important to highlight that the median (Mdn) and interquartile range (IQR) presented here, after excluding missing data, serve as descriptive statistics intended for identifying broad trends rather than drawing definitive conclusions. Additionally, we assess if there are initial group differences (using the Wilcoxon test and effect size to compare the data distribution) for each variable of interest based on demographic factors. Later in the study, we

Table 2 Descriptive statistics of variables and preliminary comparison based on demographics

Variable	N	*Mdn*[a] (*IQR*)	Skew	Kurtosis	Demographics[b]	*Mdn* (*IQR*)	*W*[c]	Effect size
[d]Universal beliefs	552	5.6 (1.0)	− 1.51	2.81	BIPOC (*n* = 271) White (*n* = 279)	5.6 (1.0) 5.6 (1.0)	38,100	–
					Man (*n* = 201) Woman (*n* = 334)	5.6 (1.0) 5.6 (1.0)	34,100	–
					Non-Trad (*n* = 211) Trad (*n* = 341)	5.8 (1.0) 5.6 (1.0)	37,300	–
					CG (*n* = 302) FG (*n* = 248)	5.6 (1.0) 5.8 (1.0)	36,800	–
[e]Non-universal beliefs	594	1.8 (1.3)	1.55	2.14	BIPOC (*n* = 290) White (*n* = 302)	1.8 (1.5) 1.8 (1.3)	46,000	–
					Man (*n* = 219) Woman (*n* = 358)	1.8 (1.5) 1.8 (1.3)	40,000	–
					Non-Trad (*n* = 226) Trad(*n* = 368)	2.0 (1.5) 1.8 (1.3)	37,300	–
					CG (*n* = 322) FG (*n* = 270)	1.8 (1.3) 1.8 (1.5)	45,100	–
Growth beliefs	623	5.0 (1.4)	− 0.83	0.49	BIPOC (*n* = 315) White (*n* = 306)	5.0 (1.2) 5.0 (1.6)	46,000	–
					Man (*n* = 229) Woman (*n* = 377)	**5.2 (1.6) 5.0 (1.4)**	**49,700****	**0.13 small**
					Non-Trad (*n* = 237) Trad (*n* = 386)	**5.2 (1.6) 5.0 (1.4)**	**51,100***	**0.10 small**
					CG (*n* = 343) FG (*n* = 278)	5.0 (1.6) 5.0 (1.2)	50,500	–
Classroom comfort	568	4.8 (1.8)	− 0.90	0.22	BIPOC (*n* = 291) White (*n* = 295)	4.8 (1.3) 5.0 (2.0)	39,400	–
					Man (*n* = 213) Woman (*n* = 358)	**5.0 (2.0) 4.8 (1.5)**	**46,000********	**0.18 small**
					Non-Trad (*n* = 225) Trad (*n* = 363)	**5.0 (2.0) 4.5 (1.7)**	**51,500********	**0.22 small**
					CG (*n* = 321) FG (*n* = 265)	5.0 (1.8) 4.8 (2.0)	45,600	–
Peer support	588	4.8 (1.8)	− 0.79	− 0.15	BIPOC (*n* = 290) White (*n* = 290)	4.8 (1.8) 4.8 (2.2)	43,000	–
					Man (*n* = 213) Woman (*n* = 352)	4.5 (2.0) 5.0 (1.8)	34,000	–
					Non-Trad (*n* = 221) Trad (*n* = 361)	**4.8 (2.3) 4.8 (1.8)**	**35,500***	**0.09 small**
					CG (*n* = 319) FG (*n* = 261)	4.8 (2.0) 4.8 (2.0)	44,700	–
Faculty support	582	5.7 (1.0)	− 1.59	2.41	**BIPOC (*n* = 281) White (*n* = 285)**	**5.3 (1.3) 6.0 (1.0)**	**36,000***	**0.09 small**
					Man (*n* = 209) Woman (*n* = 342)	5.7 (1.0) 5.7 (1.3)	36,600	–
					Non-Trad (*n* = 214) Trad (*n* = 354)	**6.0 (1.0) 5.3 (1.3)**	**43,000****	**0.12 small**
					CG (*n* = 311) FG (*n* = 255)	5.7 (1.0) 5.7 (1.3)	41,300	–
Course grade	577	87.4 (16.5)	− 1.09	1.39	**BIPOC (*n* = 289) White (*n* = 286)**	**84.9 (17) 88.2 (16)**	**36,800****	**0.12 small**
					Man (*n* = 214) Woman (*n* = 346)	87.7 (15) 87.4 (18)	38,500	–
					Non-Trad (*n* = 213) Trad (*n* = 354)	88.5 (15) 86.8 (18)	41,900	–
					CG (*n* = 312) FG (*n* = 263)	**89.1 (17) 84.2 (17)**	**46,700****	**0.12 small**

Table 2 (continued)

Variable	N	*Mdn*[a] (*IQR*)	Skew	Kurtosis	Demographics[b]	*Mdn* (*IQR*)	*W*[c]	Effect size
ACT score	378	25.0 (7.0)	0.09	-0.84	**BIPOC ($n=183$)** **White ($n=193$)**	**23.0 (6.0)** **26.0 (7.0)**	**12,700******	**0.24 small**
					Man ($n=140$) **Woman ($n=225$)**	**25.0 (7.3)** **24.0 (7.0)**	**18,000***	**0.12 small**
					Non-Trad ($n=98$) Trad ($n=280$)	25.0 (8.5) 25.0 (7.0)	14,390	–
					CG ($n=208$) **FG ($n=168$)**	**26.5 (7.0)** **23.0 (6.0)**	**23,400******	**0.30 small**

[a] *Mdn* and *IQR* reported here (with missing data removed) do not account for the errors associated with latent variables. They are meant as descriptive statistics for general trends rather than conclusions. [b]Black, Native American, Native Hawaiian, Alaskan Native, Asian, Pacific Islander, Hispanic/Latino/a/e, other, multiracial (BIPOC), Non-Trad (non-traditional student over the age of 22), Trad (traditional student 18–22 years old); CG (continuing generation: at least one parent/caretaker has a college degree), FG: first-generation (neither parent/caretaker has a college degree). [c]Significance levels for the Wilcoxon test are represented: ****$p < 0.0001$, ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$ and bolded for clarity. [d,e]Students' perceptions of the instructor's universal and non-universal beliefs

will offer deeper insights into whether there is a difference in the regression pathways between variables based on demographic differences using multigroup moderation analysis.

General trends revealed that students perceived instructors as endorsing more universal beliefs ($Mdn=5.6$, $IQR=1.0$) and less non-universal beliefs ($Mdn=1.8$, $IQR=1.3$). Student perceptions of the instructors' universality beliefs did not differ based on any of the demographic groups assessed in this study (race, gender, age, generational status).

Students generally leaned toward endorsing growth beliefs about their abilities ($Mdn=5.0$, $IQR=1.4$), with no differences observed based on race and generational status. However, men endorsed growth beliefs significantly more than women ($Mdn_{men}=5.2$, $IQR=1.6$; $Mdn_{women}=5.0$, $IQR=1.4$, $W=49{,}700^{**}$, small Wilcoxon effect size) with a similar pattern uncovered for non-traditional students ($\mathrm{Mdn}_{\mathrm{Non\text{-}Trad}}=5.2$, $IQR=1.6$, $\mathrm{M}_{\mathrm{Trad}}=5.0$, $IQR=1.4$, $W=51{,}100^{**}$, small Wilcoxon effect size) as compared to their traditional peers.

Overall, students showed relatively high levels of classroom comfort (Mdn = 4.8, $IQR=1.8$), peer support ($Mdn=4.8$, $IQR=1.8$), and faculty support (Mdn = 5.7, $IQR=1.0$). However, men showed significantly greater classroom comfort than women ($\mathrm{Mdn}_{\mathrm{men}}=5.0$, $IQR=2.0$, $\mathrm{Mdn}_{\mathrm{women}}=4.8$, $IQR=1.5$, $W=46{,}000^{**}$, small Wilcoxon effect size). Non-traditional students showed significantly greater classroom comfort and support than their traditional peers ($\mathrm{Mdn}_{\mathrm{non\text{-}trad}}=5.2$, $IQR=1.6$, $\mathrm{Mdn}_{\mathrm{traditional}}=5.00$, $IQR=1.4$, $W=51{,}100^{*}$, small Wilcoxon effect size). Students showed similar levels of classroom comfort based on race and generational status.

Students showed similar perceptions of peer support based on race, gender, and generational status. However, non-traditional students showed greater distribution in their perceptions of peer support as compared to traditional students ($\mathrm{Mdn}_{\mathrm{non\text{-}trad}}=4.8$, $IQR=2.3$; $\mathrm{Mdn}_{\mathrm{women}}=4.8$, $IQR=1.8$, $W=35{,}500^{**}$, small Wilcoxon effect size).

While students had similar perceptions of faculty support based on gender and generational status, White students perceived faculty to be more supportive than BIPOC students (PFS, $\mathrm{Mdn}_{\mathrm{White}}=6.0$, $IQR=1.0$; $\mathrm{Mdn}_{\mathrm{BIPOC}}=5.3$, $IQR=1.0$, $W=36{,}000^{*}$, small Wilcoxon effect size). Additionally, non-traditional students perceived faculty to be more supportive than traditional students ($\mathrm{Mdn}_{\mathrm{non\text{-}trad}}=6.0$, $IQR=1.0$; $\mathrm{Mdn}_{\mathrm{trad}}=5.33$, $IQR=1.3$, $W=43{,}000^{**}$, small Wilcoxon effect size).

Overall, students had a median course grade of 87.4 ($IQR=16.5$) and a median ACT score of 25.0 ($IQR=7.0$). While course grades were similar for students based on gender and generational status, White students showed significantly higher grades in their STEM course grades ($\mathrm{Mdn}_{\mathrm{White}}=88.2$, $IQR=16.0$; $\mathrm{Mdn}_{\mathrm{BIPOC}}=84.9$, $IQR=17$, $W=36{,}800^{**}$, small Wilcoxon effect size). Additionally, continuing-generation students showed higher course grades than first-generation college students ($\mathrm{Mdn}_{\mathrm{CG}}=89.1$, $IQR=17$; $\mathrm{Mdn}_{\mathrm{FG}}=84.2$, $IQR=17.0$, $W=46{,}700^{**}$, small Wilcoxon effect size).

ACT scores were similar based on age group. However, they differed significantly based on race, gender, and generational status. White students had significantly greater ACT scores than their BIPOC peers ($\mathrm{Mdn}_{\mathrm{White}}=26.0$, $IQR=7.0$; $\mathrm{Mdn}_{\mathrm{BIPOC}}=23.0$, $IQR=6.0$, $W=12{,}700^{****}$, small Wilcoxon effect size). Men had significantly greater ACT scores than women ($\mathrm{Mdn}_{\mathrm{Men}}=25$, $IQR=7.3$; $\mathrm{Mdn}_{\mathrm{Women}}=24.0$, $IQR=7.0$, $W=18{,}000^{*}$, small Wilcoxon effect size). Lastly, continuing-generation students had greater ACT scores than first-generation students ($\mathrm{Mdn}_{\mathrm{CG}}=26.5$, $IQR=7.0$; $\mathrm{Mdn}_{\mathrm{FG}}=23.0$, $IQR=6.0$, $W=23{,}400^{****}$, small Wilcoxon effect size).

Thus, based on these trends in prior preparation and STEM course grades, BIPOC students, women, and first-generation college students may be more at risk for attrition and underperformance. Descriptive statistics in our data set do not indicate vulnerability in the affective or performance domains for non-traditional students compared to traditional students. A moderation analysis conducted later in this work will provide a more thorough understanding of how demographics shape the relationship between the environment and the student's affective and performance in STEM.

Before we built the structural path, we presented bivariate correlations of all variables under investigation to provide additional descriptive data sets and assess for multicollinearity. Although we expected variables to be correlated, they should not be redundant. Otherwise, this will result in less precision and faulty conclusions in the path analysis. The Spearman correlation matrix (used for non-normal distributions instead of the Pearson method) revealed correlations ranged from 0.10 to 0.67 (Fig. 2). The Variance Inflation Factor (VIF) ranged between 1.15 and 2.30, well below the threshold value of 10, indicating no multicollinearity among variables (Lavery et al., 2017).

In general, ACT scores do not seem to be significantly correlated with any affective variables or environmental aspects (aside from classroom comfort and non-universal beliefs) under investigation but were associated with course grades (0.33). This pattern justifies using ACT scores as a control variable on course grades in the SEM path analysis to distill the impact of the learning environment and student affective on their performance in STEM courses without confounding it with the impact of prior preparation. Course grades were significantly correlated with all variables in the study except for peer support and non-universal beliefs.

While bivariate correlations offer some initial insights into patterns, they must be interpreted cautiously as they do not account for other factors in the model or control variables. The SEM path analysis described below, however, will provide a more comprehensive understanding of how the latent variables are correlated with each other and the outcome variables. This analysis will not only provide more depth, but also more inferential conclusions. Moreover, SEM models offer directionality in the relationship of latent variables, a feature grounded in previous studies that assessed causality.

RQ1: How does the mindset context influence student affect and STEM course grades?

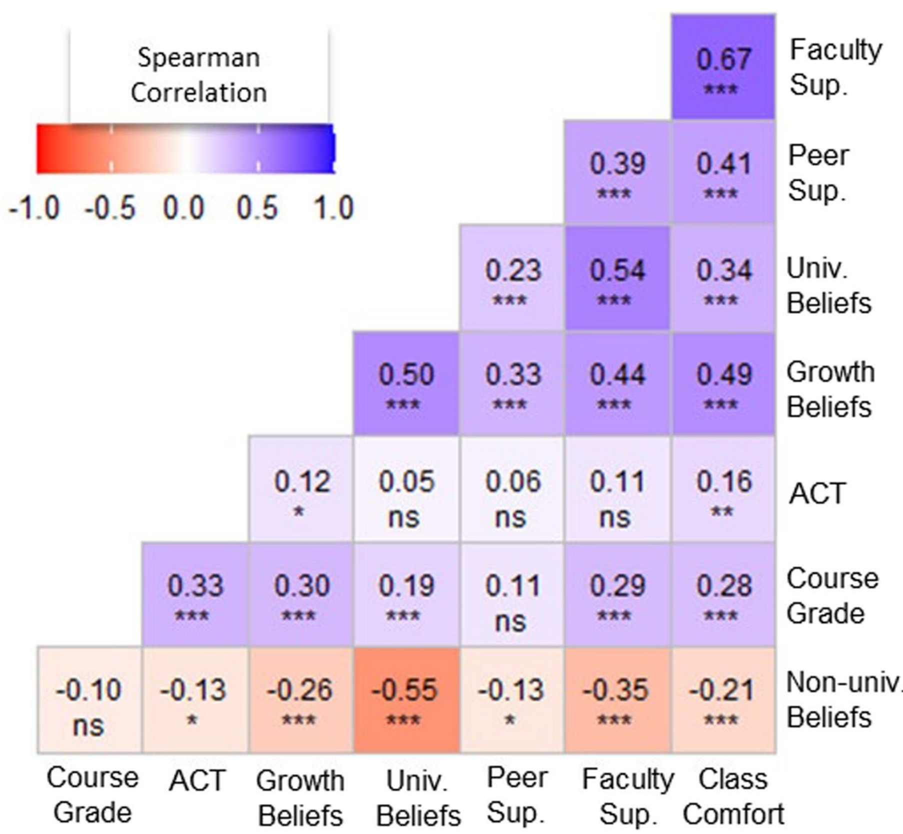

Fig. 2 Shows the Spearman bivariate correlation matrix, which shows the correlation of each pair of variables without considering control variables. This matrix shows descriptive patterns between variables and assesses for multicollinearity. ***$p<0.001$, **$p<0.01$, *$p<0.05$, ns = nonsignificant

We built a structural equation path analysis based on the proposed model in Fig. 1 to answer our first research question. Three out of four model fit indices met the threshold of acceptability (Robust CFI/TLI = 0.96/0.95, Robust RMSEA = 0.057 (90% CI 0.051-0.062), SRMR = 0.089). Modification indices indicated that classroom comfort and faculty support covariation would improve model fit. This was also theoretically justified because it would make sense that when students feel supported by the faculty, this increases their classroom comfort. This resulted in better model fit (CFI/TLI = 0.97/0.97, Robust RMSEA = 0.045 (90% CI 0.039-0.050), SRMR = 0.062), although the SRMR was slightly larger than the threshold of acceptability; Fig. 3.

To simplify the mediation analysis model, faculty and peer support were removed because they did not significantly predict course grades. However, universality beliefs were retained because they were the primary exogenous variables of interest, and we wanted to simplify the model systematically. This resulted in excellent model fit on all four parameters (CFI/TLI = 0.98/0.98, Robust RMSEA = 0.041 (90% CI 0.033–0.049), SRMR = 0.040); Fig. 4.

Because non-universal beliefs did not significantly predict course grades or any of the mediating variables in Fig. 4, it was removed from further analysis. Universal beliefs did not predict course grades, but they significantly predicted both mediating variables (growth beliefs and classroom comfort) and were retained for analysis. The resulting model, Fig. 5, showed excellent model fit (CFI/TLI = 0.99/0.99, Robust RMSEA = 0.041 (90% CI 0.029-0.052), SRMR = 0.039), with factor loadings shown on each latent variable in addition to the path model.

Overall, this model explains 19% of the variance observed in course grades, which means other factors influence course grades in addition to the measured variables in the model. Nonetheless, the study reveals intriguing findings regarding how the learning environment may influence students' affective and how that, in turn, influences student performance in their STEM courses. Universal beliefs did not directly predict student grades in STEM courses ($\beta = 0.08$, $p = 0.182$). However, when students perceived the instructor to endorse more universal beliefs, this significantly contributed to greater growth beliefs about their own abilities in STEM ($\beta = 0.44$, $p < 0.001$) and was associated with more classroom comfort ($\beta = 0.15$, $p = 0.006$). Growth beliefs and classroom comfort positively and significantly predicted student course grades ($\beta = 0.17$, $p = 0.001$; $\beta = 0.19$, $p < 0.001$), respectively). Unsurprisingly, ACT scores were also significant predictors of student course grades ($\beta = 0.26$, $p < 0.001$).

Just because universal beliefs significantly predict growth beliefs and growth beliefs predict course grades does not necessarily mean that the entire pathway is significant. Therefore, we conducted a mediation analysis on the SEM model to assess the significance of direct and indirect pathways using a resampling method (bootstrapping). Random data cohorts are repeatedly tested with the model and replaced to generate numerous samples

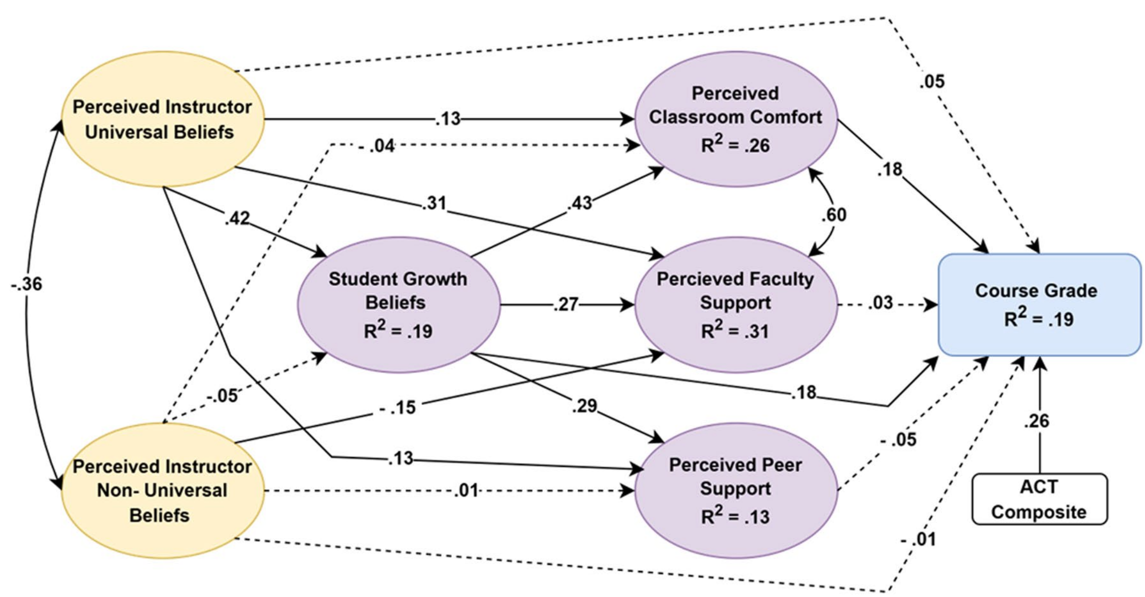

Fig. 3 Proposed SEM path analysis. All latent variables are represented as ovals, although the items compromising each latent variable were not included in the diagram for simplicity. Robust CFI/TLI = 0.97/0.97, Robust RMSEA = 0.045 (90% CI 0.039–0.050), and SRMR = 0.062. Solid lines represent significant pathways, while dashed lines represent non-significant pathways

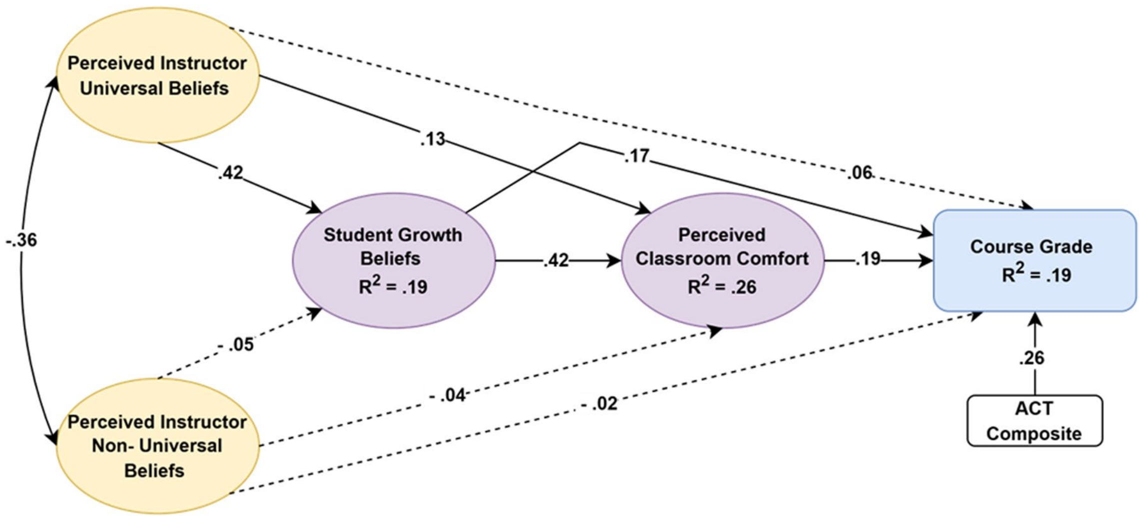

Fig. 4 Simplified SEM path analysis. The simplified model in which mediating variables (faculty support and peer support) that were not significantly correlated with course grades were removed. All latent variables are represented as ovals, although the items compromising each latent variable were not included in the diagram for simplicity. Robust CFI/TLI = 0.98/0.98, Robust RMSEA = 0.041 (90% CI 0.033–0.049), and SRMR = 0.040. Solid lines represent significant pathways, while dashed lines represent non-significant pathways

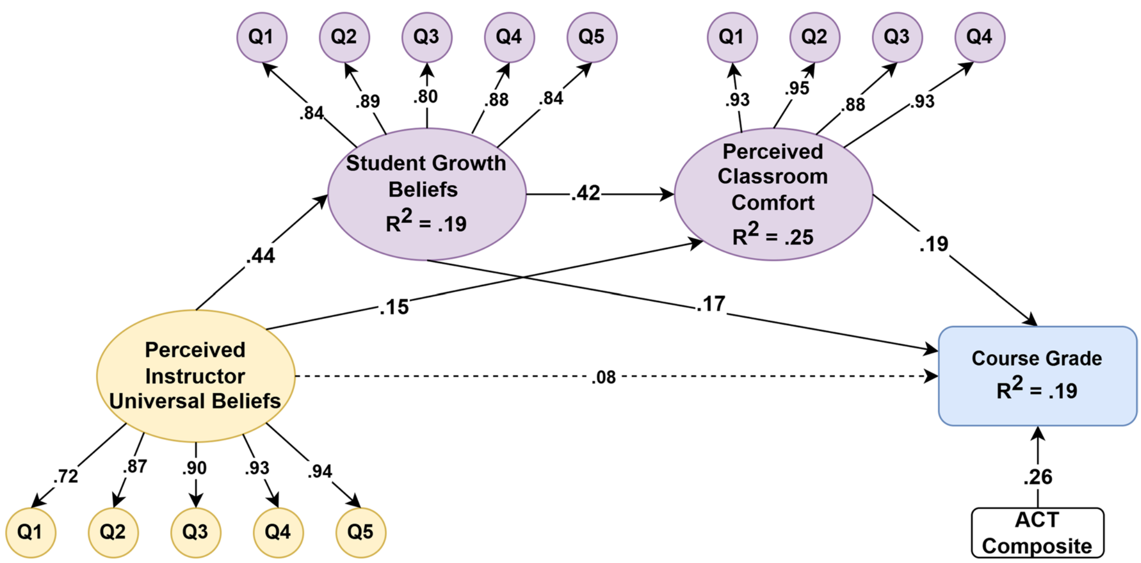

Fig. 5 Final SEM path analysis. The final SEM model after systematic simplification. All latent variables are represented as ovals with the items that compromise each latent variable (Q1, Q2, etc.) and their factor loadings. CFI/TLI = 0.99/0.99, Robust RMSEA = 0.041 (90% CI 0.029–0.052), SRMR = 0.039. Solid lines represent significant pathways, while dashed lines represent non-significant pathways

(10,000 iterations). Confidence intervals for assessing the significance of the direct and indirect effects are presented in Table 3.

When students perceive the instructor to endorse more universal beliefs about their abilities, they report greater growth beliefs about their own abilities, leading to more classroom comfort and higher grades in STEM courses (Path 1, Table 3). Students who report greater universal beliefs also report greater growth in their beliefs about their abilities, leading to higher grades in STEM courses (Path 2, Table 3). However, classroom comfort does not significantly mediate between universal beliefs and course grades in STEM (Path 3, Table 3). Overall, total indirect effects and total effects (direct and indirect) are also significant pathways. Thus, there is evidence from this work to indicate that students' growth beliefs are affected by their perception of the instructors' universal beliefs, ultimately impacting

Table 3 Direct and indirect effects of student perceptions of the instructors' universal beliefs on student affect and STEM course performance

Pathway	Understand. Estimate	Boot SE[a]	Boot LLCI[b]	Boot ULCI[c]
Direct universal belief → course grade	0.97	0.93	– 0.80	2.82
Path 1) universal beliefs → growth belief → classroom comfort → course grade	**0.38**	**0.20**	**0.02**	**0.82**
Path 2) universal beliefs→ growth beliefs → course grade	**1.11**	**0.46**	**0.26**	**2.10**
Path 3) universal beliefs → classroom comfort → course grade	0.15	0.15	– 0.07	0.51
Total indirect	**1.64**	**0.51**	**0.69**	**2.72**
Total effects	**2.62**	**0.79**	**1.13**	**4.23**

their grades in STEM courses. In addition, student growth beliefs may also influence their classroom comfort, leading to downstream effects on course grades. This corroborates the findings of the literature that the mindset context (albeit indirectly in our sample) plays a role in student outcomes by possibly shaping students' mindset beliefs about their abilities, which influence course grades. Hence, focusing on student interventions that change students' theories about their abilities may be beneficial but limited if instructors continue to teach in ways that do not project universal beliefs about their students' abilities in STEM.

While these findings are insightful, the question remains whether these pathways are similar for all demographic groups, information that can help us tailor our classroom environment and teaching approaches to a diverse student population. The results are presented next.

RQ2: Do pathways diverge based on student demographics?

To assess if there are divergent pathways in the SEM path analysis, we constrained all loadings, intercepts, and regressions in one model. We compared it to a model in which only the loadings and intercepts are constrained, and the regressions are freely estimated. If constraining regression coefficients result in a significantly worse model fit (as determined by a Chi-squared difference test (Kattoum et al., 2024)), this would suggest that regression pathways are indeed different for those groups (e.g., between men and women). Results indicated that regression coefficients did not differ based on race ($\Delta\chi^2=9.52$, $df=7$, $p=0.222$), gender ($\Delta\chi^2=6.03$, $df=7$, $p=0.541$) or generational status ($\Delta\chi^2=12.01$, $df=7$, $p=0.101$), but did differ significantly based on age ($\Delta\chi^2=15.73$, $df=7$, $p=0.033$). We systematically constrained each of the seven regression paths (one at a time, along with loading and intercepts) to determine which particular paths differed based on age group. We compared it to the model with no constrained regressions (only constrained loadings and intercepts). We then used a Chi-squared difference test to determine if there was a significant difference between the models. If the model fit were worse for the constrained model (in terms of individual regressions) as compared to the free model (in terms of regressions), this would indicate that those paths are indeed different for each group (i.e., traditional and non-traditional age students) and need to be freely estimated. Results are presented in Table 4 for each of the regression paths.

Because universal beliefs → growth beliefs (path 2, Table 4) and classroom comfort → course grade (path 6, Table 4) regression paths significantly differed based on age group, we built a model in which we constrained all other regression coefficients for paths 1, 3–5, and 7 and freely estimated path 2 and 6. The resulting model showed excellent model fit (CFI/TLI = 0.98/0.98, Robust RMSEA = 0.045 (90% CI 0.033-0.057), SRMR = 0.053), revealing how the regressions coefficients for Path 2 and 6 varied based on age group. The influence of student perceptions of the instructors' universality beliefs on their own growth beliefs was more pronounced for traditional students ($\beta=0.51$, $p<0.001$) than non-traditional students ($\beta=0.35$, $p<0.001$). That is, the learning environment seems to have a slightly greater impact on

Table 4 Serial Chi-squared moderation test

Regression path	$\Delta\chi^2$	*p*-value
1) Universal beliefs→ course grade	2.42	0.12
2) Universal beliefs → growth beliefs	**11.16**	**< 0.001**
3) Universal beliefs → classroom comfort	0.17	0.68
4) Growth beliefs → classroom comfort	0.22	0.64
5) Growth beliefs → course grade	0.41	0.52
6) classroom comfort → course grade	**5.26**	**0.022**
7) ACT → course grade	1.23	0.27

The bolded regression paths differed based on age ($\Delta\chi^2$ test was significant when the constrained and free models were compared) and were allowed to be freely estimated for traditional and non-traditional students traditional students' own growth beliefs than their non-traditional peers. Additionally, classroom comfort significantly influenced STEM course grades for traditional students ($\beta = 0.25$, $p < 0.001$) but was insignificant for non-traditional students ($\beta = 0.06$, $p = 0.413$). Therefore, students' affective (in the case of classroom comfort) influences student behavior (overall performance) for traditional students but not for non-traditional students.

Discussion and implications

In this study, we investigated (1) how the mindset context influenced student affective (students' own growth beliefs and belonging), and in turn, how that influenced their STEM course grades, and (2) how those pathways differed based on demographic factors (race, gender, age group, generational status). While some of this work has been conducted in previous studies, we contribute to the broader discourse by focusing on the mindset context with respect to the domains of (1) a demographically diverse, moderately selective metropolitan research institution and (2) within the native environment of STEM courses. We also specifically link student grades to a particular instructor (rather than the broader STEM context) to hone in on how student perceptions of their instructors' mindset influence their outcomes within that course.

Additionally, we use a more recently developed and validated instrument to measure mindset (Limeri et al., 2023) and an instrument that uncovers more nuances of belonging (Hoffman et al., 2002) in the college setting that contribute to more robust findings. Next, we used advanced structural equation modeling (SEM) techniques to build models that test for mediation and account for errors in latent variables to provide a more holistic and accurate view of how mindset context influences student affective that, in turn, influences their performance. Lastly, we conducted a moderation analysis to assess how that pathway may differ based on demographics to provide more insight that allows us to tailor techniques to increase the retention and participation of marginalized students in STEM disciplines.

Because course grades are the primary determinant of student retention, it is essential to understand how the context of mindset and students' affects shape them. Regarding our first research question, we found that the mindset context played a more secondary and indirect role in student performance. However, prior preparation played a more primary and direct role in predicting student grades in STEM. Using bivariate correlation matrices (Fig. 2) only provides a surface-level understanding of how the variables of interest are related. We used Social Cognitive Theory as the guiding framework along with Structural Equation Modeling to provide more nuances of understanding of the relationship between the mindset context, student affect, and performance. We also accounted for prior preparation and errors in latent variables while modeling the directionality of the relationship. For example, the bivariate correlation matrix revealed that course grade and student perceptions of the instructor's universal beliefs are significantly correlated (Fig. 2). However, we did not find a significant direct relationship between students' perception of their instructor's universal beliefs and course grades after controlling for students' ACT scores and affective factors. We detected an indirect effect in which student perceptions of their instructors' universal beliefs significantly impacted their own growth beliefs and perceptions of classroom comfort, which had downstream effects on their course grades. In other words, when students perceived instructors as endorsing more universal beliefs (e.g., believing that everyone can master STEM concepts with time and effort), this led to a greater growth belief about their own abilities, which was associated with greater classroom comfort and ultimately better grades. This may explain why mindset interventions that focus only on developing student mindset beliefs reveal mixed findings in terms of benefits to students (Burnette et al., 2023; Yeager et al., 2022). Our findings suggest that mindset interventions that focus on helping faculty project universal beliefs about student ability may be essential for supporting student success.

Additionally, our work revealed a particular mechanism of action to improve student outcomes that may be tied to instructional practices. While we found that student perceptions of their instructor's universality beliefs predicted their perceptions of peer support (collaborating with other students) and faculty support (feeling comfortable enough to ask questions and visit office hours), these factors were unrelated to course grades. However, perceived classroom comfort (contributing to class discussion) significantly predicted student grades. Thus, an active and engaging classroom environment may be connected to more positive cues that the instructor believes in their ability to grow, which leads to better performance (Kroeper et al., 2022; Muenks et al., 2021a, 2021b). Thus, "mindset + instructional practices" may work in tandem to improve student performance and retention in STEM.

While these findings are insightful, one cannot ignore that prior preparation (and, to some extent, student cognitive ability as determined by ACT scores) is also an essential part of the student success equation, directly impacting course grades in STEM. Gaps in student preparation are not the students' fault but may be attributed to disparities deeply rooted in societal systems and out of their control. However, when students are admitted to college, it falls upon the college to adequately set them up for success and should not solely fall on the instructor's shoulders. While providing a positive and engaging classroom environment is beneficial to student performance, this must be coupled with institutional support to alleviate some disparities in foundational knowledge. This can be accomplished with remediation courses, summer bridge programs, and in-class recitation with peer mentors, to name a few.

Since students with historically marginalized identities (BIPOC students, women, first-generation, non-traditional students) are particularly prone to systematic inequities, we explored if these pathways diverged based on demographic groups in our second research questions. We found some preliminary differences regarding student affect and performance based on gender, race, age group, and generational status (Table 2). However, this did not necessarily result in differences in pathways (mindset context → student affective → course grades) based on race, gender, or generational status in our study sample. For example, men and women viewed their instructors' universality beliefs similarly, but men were found to endorse more of a growth mindset about their abilities than women. This was consistent with the previous literature showing a gap between men and women in how they viewed their abilities in a physics class across the semester that impacted their course grades (Malespina et al., 2022). However, we did not find that the difference in growth beliefs between men and women affected their course grades differently in our sample. This was also contrary to another study, in which the mindset context triggered a stereotype threat that impacted women's performance only (Canning et al., 2021). We believe this to be more attributed to the setting in which this data was collected, where there was more representation of marginalized students and women at a moderately selective institution rather than a homogenous, more selective institution. Our results indicate that prior preparation may be more salient in predicting student performance in STEM courses at such institutions, regardless of demographics.

Thus, with regard to our second research question, we found that the mindset context predicted student outcomes similarly across race, gender, and generational status. However, we found interesting path divergences based on student age groups only. Generally, student perceptions of the instructors' universal beliefs (similar for both age groups, Table 2) predicted their own growth beliefs. However, the impact was greater for traditional students than for non-traditional students. How traditional students perceived their instructor's universal beliefs played a more prominent role in shaping their beliefs than their non-traditional peers. Additionally, student perceptions of classroom comfort were significantly greater for non-traditional students than for traditional students (Table 2). This also translated into different course outcomes; classroom comfort significantly impacted STEM grades for traditional students but was insignificant for non-traditional students. This suggests that traditional students are more sensitive to classroom cues about the mindset context than non-traditional students.

In exploring possible explanations for our observation, we found that even though non-traditional students tend to experience more obstacles (i.e., caretaking and job responsibilities), those obstacles may increase their resilience and motivation regardless of contextual cues (Chung et al., 2017). Although there is still a significant association between student perceptions of the instructors' universality beliefs and their own growth beliefs, the association is stronger for traditional students who may not have as many life experiences that shape their perspective and may be more susceptible to classroom cues. Additionally, enhancing the mindset context can lead to a stronger sense of belonging, particularly an increased perception of classroom comfort for all students. While we found no significant associations between classroom comfort and STEM course grades for non-traditional students (possibly due to more resilience and life experience), classroom comfort was a significant predictor of student performance for traditional students. Additionally, Social Cognitive Theory also highlights key concepts such as self-efficacy (belief in one's ability to succeed) and outcome expectations (beliefs about the consequences of actions) (Schaller et al., 2012) that may pertain to our observation. Perhaps non-traditional students have greater self-efficacy, contributing to improved outcomes and more experience that allows them to focus more on their studies due to more ample experience of behaviors that lead to success.

Conclusions

This study found that the mindset context played a more secondary and indirect role in student performance. However, prior preparation played a more primary and direct role in predicting student grades in STEM. While the mindset context contributes to the student success equation, a more salient barrier may be overlooked when serving a demographically heterogeneous student population with varied prior preparation. It cannot be understated that student incoming preparation (in the form of ACT scores) is a significant and direct predictor of student grades.

Thus, when institutions admit students, the onus falls not just on the instructor and student but on the institutional structure and culture supporting the mindset context. Therefore, we suggest future work should focus on the "*mindset-plus-supportive-classroom-and-institutional*" context (Yeager et al., 2022). Admitting students to college is not enough without additional academic support to make up for systemic inequities that disadvantage students at the start of their careers. These supports may be in the form of:

- In-course or pre-course remediation and skills-building specific to STEM
- A mastery-based curriculum that focuses on the process and learning rather than performance
- Faculty teaching reform in active learning and evidence-based instructional practices
- Implementation of near-peer learning models to enhance student learning in the classroom.

Collectively, these efforts may contribute more holistically to improving student outcomes. If an institution endorses universal beliefs about students' abilities, they may structure the system to support students learning through "failure" on their path to success and enable faculty to support their students.

Additionally, the mindset context did not impact non-traditional student performance in STEM courses as much as their traditional peers. Thus, a positive classroom environment may be particularly beneficial for the success of incoming students who may have fewer life experiences and are more reliant on classroom experiences to shape their growth beliefs and classroom comfort in STEM courses.

Aside from age groups, we did not find a substantial divergence in our path analysis for the variables under investigation in this study sample based on race, gender, or generational status. The collective human experience of facing obstacles and adversity as students progress through their academic journey spans demographic delineation. As researchers, we should focus on collecting student experiences (e.g., physical and mental health, external familial and job responsibilities, socioeconomic status) that may impede or enhance their success in STEM, irrespective of demographics. Developing more robust instrumentation to examine students' holistic experiences may provide more insight into how to support students. Some of these barriers result from systemic inequities engrained in societal structures that disadvantage students. While some students begin at the starting line in college, others may be a few steps behind, requiring excessive exertion at the start line. However, the nature of STEM courses relies on building knowledge and skills in a stepwise fashion. A sprained ankle is a legitimate risk in students falling behind in their progression toward success that is not a fault of their own.

Limitations

This study has limitations that may limit the generalizations of these findings. Faculty and student involvement in these studies was voluntary, potentially introducing selection bias. Moreover, student questionnaires were administered after the drop date, compounding selection bias as students who dropped or disengaged from the course were not represented. Although previous work has established causal patterns between the mindset context and student outcomes (Muenks et al., 2020), other factors may have shaped student perceptions in our field study.

Unlike prior research conducted in controlled environments, this study occurred in the native STEM classroom environment, potentially influenced by end-of-semester stressors that could have contributed to student perceptions of the instructors' mindset. Future studies should assess how the instructor's demographic characteristics and teaching practices affect student perceptions of the learning environment. Additionally, student perceptions may have been influenced by the course rather than the instructors, and future studies with larger sample sizes should consider the course type. The student sample also varied across academic years, which may have resulted in different perceptions based on their academic level (first-year students may have different perceptions than fourth-year college students).

Abbreviations

ACT	American College Testing
BIPOC	Black, Indigenous, and People of Color
CFI	Comparative fit index
IQR	Interquartile range
Mdn	Median
MLR	Robust maximum likelihood
RMSEA	Root mean squared error of approximation
SD	Standard deviation
SEM	Structural equation model
SRMR	Standardized root mean squared residual
STEM	Science, technology, engineering, and mathematics
TLI	Tucker–Lewis index
VIF	Variance inflation factor
ULTrA	Undergraduate lay theories of abilities survey

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40594-025-00535-5.

Supplementary Material 1. Table S1 Adaptation of the universality beliefs scales from the ULTrA survey (Limeri et al., 2023). Table S2 Descriptive data for items on each factor. Table S3 Measurement invariance testing.

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Author contributions
RNK was the primary author of this manuscript. RNK designed the research study, collected participant data, conducted all statistical analyses, and wrote the manuscript. MTB provided multiple rounds of reviews and revisions for the manuscript. All authors approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
All protocols in this study were reviewed and approved by the Institutional Review Board (IRB); participants were invited to participate in this study and were given a choice to opt-out at any time after granting their consent to participate with no consequences.

Consent for publication
All participants were notified that consenting to participate includes consent for authors to publish aggregated results without divulging the individual identity or personal information.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]School of Physical Sciences: Chemistry Program, University of Arkansas at Little Rock, 2801 S. University Ave., Little Rock, AR 72204, USA. [2]STEM Education Center, University of Arkansas at Little Rock, 2801 S. University Ave., Little Rock, AR 72204, USA.

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