Racism, sexism, and classism: The uneven terrain of student belonging in introductory biology classrooms

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ABSTRACT

Sense of belonging supports student success in science, technology, engineering, and mathematics (STEM), yet prior research indicates that systemic inequities shape who feels included in college classrooms. Racism, sexism, and classism can shape students' belonging, which then can impact their outcomes. We studied students' sense of belonging in 56 large introductory biology courses that used active learning, reaching more than 4900 students. We used a QuantCrit methodological framework and hierarchical linear models to examine how the intersection of racism and sexism, and racism and classism, related to three components of students' belonging. Racism impacted groups differently, and its impact varied across intersecting identities and components of belonging. Sexism undermined women's comfort sharing ideas in class and seeking instructor help across racial/ethnic groups. Women in some racial/ethnic groups experienced greater connectedness to classmates than men. Classism diminished students' sense of belonging across most racial/ethnic groups. Disaggregating students into more racial/ethnic groups revealed important differences in the experiences of Native American, Latiné, Black/African, and two groups of Asian students. These findings demonstrate that within the same classroom, students can have profoundly different experiences and challenge us to recognize the influence of intersecting forms of oppression on our students.

INTRODUCTION

A strong sense of belonging is a powerful predictor of undergraduate student success, as it's linked to higher academic achievement, greater engagement, and increased retention (O'Keeffe, 2013; Strayhorn, 2013). Sense of belonging refers to a student's perception of being supported, connected, and valued in an academic setting (Goodenow, 1993), and it plays a critical role in shaping motivation and learning outcomes (Cox *et al.*, 2021; Edwards *et al.*, 2022). When students experience a low sense of belonging, it negatively impacts their attitudes, interests, and intentions to pursue STEM degrees and careers (Strayhorn, 2013; Thoman *et al.*, 2014; Xu and Fang, 2021). Despite growing attention to the importance of belonging in higher education, perpetual systemic inequities in STEM learning environments continue to erode the sense of belonging of women, students from racially and ethnically marginalized backgrounds, and first-generation college students (Hoffman *et al.*, 2002; Strayhorn, 2018; Cwik and Singh, 2022; Google *et al.*, 2023). Addressing these disparities is essential for creating more equitable learning in STEM.

Systems within higher education routinely undermine individuals' sense of belonging among racially and ethnically marginalized students. Research consistently finds that Black (Burt *et al.*, 2018; Ong *et al.*, 2018; Rainey *et al.*, 2018; McGee, 2020), Latiné (Nuñez, 2009; Camacho and Lord, 2011), Native American (Smith *et al.*, 2014; Strayhorn *et al.*, 2016), and Southeast Asian

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(Maramba and Museus, 2013; Museus, 2014) students experience a lower sense of belonging in US STEM higher education than their peers. Though isolated incidents can inflict lasting harm, the erosion of belonging among these students largely reflects patterned institutional culture and practices that normalize exclusion and routinely fail to affirm the identities and contributions of marginalized students (Denaro *et al.*, 2022; Wong *et al.*, 2024). Classroom experiences can leave students feeling overlooked in academic settings, such as during group work and classroom discussions, where their contributions are undervalued or dismissed (Ong *et al.*, 2018; Stanton *et al.*, 2022). Students also face racial microaggressions from peers and instructors in and out of the classroom, defined here as subtle or overt messages that question competence or belonging, which accumulate over time and can erode confidence (Solorzano *et al.*, 2000; McGee and Bentley, 2017; Harrison and Tanner, 2018; Lee *et al.*, 2020; Stanton *et al.*, 2022). In addition, limited access to culturally aware mentorship and institutional support structures makes it harder for students to find guidance that affirms their identities and experiences (Byars-Winston and Butz, 2021; Tuma and Dolan, 2024). Even initiatives designed to promote inclusion, such as university makerspaces, which aim to foster creativity and collaboration, often fall short by failing to address cultural disconnects and the everyday exclusion that marginalized students encounter in makerspaces (Barton *et al.*, 2017; Andrews and Boklage, 2024). At historically White institutions (HWI), these dynamics are intensified by low racial representation and a lack of role models, further isolating students and signaling that they do not fully belong (Rainey *et al.*, 2018; Dancy *et al.*, 2020). Taken together, these patterns reveal how systemic features within higher education can actively damage the sense of belonging that racially and ethnically marginalized students feel in STEM educational settings, despite surface-level commitments to diversity and inclusion.

STEM classrooms also foster a lower sense of belonging for women (Stout *et al.*, 2013; Thoman *et al.*, 2014; Cwik and Singh, 2022). Women leave STEM disciplines at a higher rate than men because they perceive less support from STEM versus non-STEM instructors, contributing to a lower sense of belonging (Seymour *et al.*, 2019). These experiences "push" women away from STEM, while non-STEM disciplines "pull" in women students with more accessible and welcoming classrooms. This push–pull that the systemic features of higher education exert on women is especially impactful early in students' academic careers, as this is when they are more susceptible to leaving STEM. For example, introductory math courses, such as Calculus I, have been repeatedly linked to a lower sense of belonging and women's decisions to leave STEM (Good *et al.*, 2012; Ellis *et al.*, 2016). Even in contexts where institutions assert commitments to diversity and inclusion, the entrenched structures and cultures of STEM still obscure the systemic barriers women face. Rather than interpreting women's departure from STEM as a matter of individual choice or fit, these patterns reveal how structural exclusion is responsible for failing to foster a sense of belonging among women students in STEM education. For first-generation students, a sense of belonging in higher education is often shaped by competition and unspoken assumptions about who college is for and what forms of knowledge are valued (Hausmann *et al.*, 2009; Stebleton *et al.*, 2014). STEM education frequently rewards individualism and unacknowledged cultural capital, making it difficult for students without generational college experience to feel supported (Stephens *et al.*, 2012). Rather than fostering inclusion, STEM classrooms frequently reproduce racialized and classed expectations that render first-generation students' strengths invisible, while framing their struggles as individual deficiencies (Yosso, 2005). For example, schools often assume that students arrive with an understanding of how to navigate academic systems, such as knowing how to approach professors and seek out research opportunities (Cooper *et al.*, 2021). At the same time, these systems undervalue the strengths first-generation students develop outside of traditional academic pathways, such as adaptiveness and resourcefulness (Yosso, 2005; Stephens *et al.*, 2012). As first-generation students move through academic environments, where norms and expectations are rarely made explicit, the combined weight of financial strain and unsupported cultural identities may lead them to internalize their marginalization as a personal failing, rather than recognize it as a product of systemic exclusion (Engle and Tinto, 2008; Jehangir, 2010). Without affirming mentorship and classroom practices that validate their lived experiences, students are left to persist in spaces that do not recognize them.

Within STEM classrooms, systemic disadvantages also compound, resulting in students with multiple marginalized identities experiencing additional and unique barriers to a strong sense of belonging. In her foundational work on intersectionality, Crenshaw argued that multiple forms of oppression do not act independently, but intersect to shape outcomes in ways that cannot be captured by examining each identity alone (Crenshaw, 1989). Within STEM departments at HWIs, Black and Hispanic women often navigate environments where microaggressions regarding their race and gender subtly signal their outsider status, and where the lack of meaningful representation and sustained support deepens feelings of exclusion (Strayhorn, 2013; Garriott *et al.*, 2019). Though White men experience a higher sense of belonging than White women in STEM, Latinas and Latinos both felt similar, lower levels of belonging, indicating that identities interact in complex ways to shape students' experiences (Rainey *et al.*, 2018). First-generation students from racially and ethnically marginalized backgrounds face layered forms of exclusion in STEM, where the intersection of race and class magnifies barriers to mentorship and preparation that are often less visible when identities are considered in isolation (Covarrubias and Fryberg, 2015; Garriott *et al.*, 2019). To fully understand and address these inequities, it is essential to examine how systems of power operate at the intersections of race, gender, class, and other identities. A singular lens obscures the complexity of students' experiences and risks reinforcing incomplete or harmful narratives. Educational equity efforts must move beyond additive models and instead adopt intersectional frameworks that center the lived realities of students with multiple marginalized identities (Museus and Griffin, 2011).

This paper builds upon prior research on students' sense of belonging in undergraduate STEM by examining the impact that structural injustices have in shaping classroom experiences. We focus on introductory biology courses across the United States because these courses serve as a gateway to the life sciences, and introductory courses often play a decisive role in whether students continue in STEM (Seymour *et al.*, 2019). The classroom is a critical site for intervention, as it lies within the sphere of faculty influence and can shape students' engagement, retention, and academic success (Cooper *et al.*, 2018; Krause-Levy *et al.*, 2021). Though earlier studies explored classroom belonging, most have been limited to single institutions (Ballen *et al.*, 2017; Wilton *et al.*, 2019; Canning *et al.*, 2020). We pursued a broader, more generalizable understanding by sampling across institutions. We also disaggregated belonging into its multiple dimensions, as evidence indicates that belonging is not unidimensional (Hoffman *et al.*, 2002; Wilton *et al.*, 2019). Finally, although prior work points to the damaging roles of racism, sexism, and classism in shaping belonging in STEM (Robnett, 2016; Rainey *et al.*, 2018), no studies have quantitatively examined how these systems intersect to influence students' belonging at the classroom level. This paper aims to start to fill these gaps by addressing the following research questions:

Research question 1: To what extent does the intersection of racism and sexism predict a student's sense of belonging in large introductory biology courses?

Research question 2: To what extent does the intersection of racism and classism predict a student's sense of belonging in large introductory biology courses?

QuantCrit as a Methodological Framework

This work is grounded in QuantCrit, a term coined by Gillborn *et al.* (2018) that refers to a methodological framework that uses the principles of Critical Race Theory (CRT) to guide scholars as they make explicit and direct connections to race and racism and its convergence with quantitative data (Tabron and Thomas, 2023). It aims to call attention to how systemic racism is perpetuated by using quantitative data. We briefly describe the history and scholarship that necessitated QuantCrit and then describe the specific tenets of QuantCrit that we centered in this study.

Scholars brought CRT into quantitative data analysis as a direct response to the racist origin, history, and current practices in statistical analyses across fields. As a discipline, statistics arose as scholars worked to formalize their eugenic beliefs into indisputable laws about human differences (Bonilla-Silva and Zuberi, 2008; Louçã, 2009; Clayton, 2021). Though some of this has been discarded, key assumptions on which their work rested remain central in our thinking today. STEM disciplines often treat statistical results as objective reflections of reality. However, these results are better understood as human-made estimates shaped by uncertainty and grounded in the logic, theories, norms, and agreements of the scientific community (Zuberi, 2001; Tabron and Thomas, 2023). These shared interpretations don't exist in a vacuum but rather are shaped by the culture of STEM and a broader societal context that continues to uphold systemic racism. Unfortunately, the role of quantitative analyses in oppression has not subsided in modern Western society. Quantitative data are often used to silence and disrupt equity work (Gillborn *et al.*, 2018). The heavy reliance on whether a difference is statistically significant is an important example of this. Because many marginalized groups are numerically underrepresented in STEM, collecting sufficiently large sample sizes to have the power to detect differences between groups that exceed typical significance thresholds (i.e., p value of >0.05) can be prohibitive or even impossible. This lack of data has led projects to find that racism's impacts are not statistically significant and to conclude that equity was present (Kauh *et al.*, 2021; Ricard *et al.*, 2023; Nissen *et al.*, 2025).

As a society, we continue to assume that numbers offer more objective and factual representations of the world compared with qualitative data, which is both inaccurate and dangerous. It is more accurate to assume that quantitative data are socially constructed in the same way as qualitative data and that the authoritative facade of numbers hides racist, sexist, and/or classist assumptions and practices. We respect racial scholars' suspicion of quantitative analyses and also see value in trying to use statistical analyses responsibly toward radical changes. We have therefore chosen to use QuantCrit as the methodological framework for this work, as one small act to challenge privilege in education research, while also acknowledging our own positioning as learners in this area. Within STEM, whiteness operates not only through racial overrepresentation but through the normalization of exclusion that is framed as merit-based, masking how racial, gendered, and classist structures systematically marginalize those not in power (Le and Matias, 2019). Drawing on prior work, we define the QuantCrit key tenets for *this* work as the following (Garcia *et al.*, 2018; Gillborn *et al.*, 2018; Jang, 2023):

1. **The centrality of oppression.** We make the assumption that racism, sexism, and classism are systemic, and social power structures create oppression for anyone who is not from the dominant group (i.e., White, continuing-generation, men) (Byng, 2013). This tenet empowers us as researchers to state *a priori* that the differences between groups in this study are due to racism, sexism, and/or classism. Rather than treating race/ethnicity, gender, or first-generation status as neutral demographic variables, we frame them as markers of students' structural location within systems of power. For example, first-generation status reflects classism, seen as academic norms that privilege inherited knowledge and render unfamiliarity with college systems as personal failure (Rice *et al.*, 2017). Racial differences are understood as manifestations of systemic racism, where institutional cultures prioritize whiteness and exclude people with other (non-white) racial identities (Banaji *et al.*, 2021; Southern, 2025). Similarly, gender-based disparities are framed as outcomes of sexism that diminish women's participation and voices (Cruz-Castro and Sanz-Menéndez, 2023; Takahashi, 2024). These interpretations are not added after the fact; they are central to our methodological stance.
2. **Groups/categories are neither natural nor inherent.** Identity is fluid and socially constructed (Crenshaw, 1991). In our work, we categorize students by race, gender, and first-generation college status, which are socially constructed categories that reflect and uphold existing power dynamics (Bonilla-Silva and Zuberi, 2008). The categories that society imposes on individuals should be interrogated for their role in promoting deficit analyses, and at the same time, racism, sexism, and classism experienced by individuals that society assigns to these categories remain tangible

and significant. We acknowledged this in our analysis by attempting to preserve our participants' self-reported identities by disaggregating into a greater number of racial and ethnic groups and transparently sharing the aggregations we have made.

3. **Data and methods are not neutral and cannot "speak for themselves"** (Gillborn *et al.*, 2018, page 168). Assumptions that mask inequities and uphold the status quo can influence every stage of data collection, analysis, and interpretation (Ladson-Billings, 1995; Benjamin, 2019). To counter this, we intentionally applied methods that highlight racism, sexism, and classism in student experiences, while acknowledging the inherent imperfections of the data and methods used. We used weighted effect coding to compare groups with the overall sample mean, rather than setting one identity as the reference point, as is common in regression analyses (Mayhew and Simonoff, 2015). This analytic approach better avoids positioning dominant groups as the implicit "norm." We also do not prioritize p-values as a marker of "significance," and instead display 95% confidence intervals and report trends across comparisons.

   When data are presented without critical interpretation, it is often read through dominant social lenses. We therefore operate from the assumption that all results must be understood within the contexts in which they arise, particularly racism, sexism, and classism, in order to call attention to systemic inequities rather than treating demographic variables as individual traits. A limitation of quantitative work is that we lack experiential accounts from participants to explain the patterns in the data. Therefore, we draw on prior research documenting the exclusionary experiences of marginalized groups to bring more meaning to observed patterns.
4. **Taking an intersectional approach** recognizes identity as multifaceted and shaped by societal power structures that influence students' experiences and outcomes (Crenshaw, 1991). Race, class, and gender operate relationally, as the structures of racism, classism, and sexism are deeply interconnected (Collins, 2015). These overlapping systems of power and oppression give rise to complex and persistent social inequalities that manifest as disparities in outcomes, representation, and experiences that vary across both time and disciplinary contexts (Museus and Griffin, 2011; Ong *et al.*, 2011). We explicitly attempt to quantitatively understand intersectional identities as they shape people's experiences of the world (López *et al.*, 2017). Additionally, we used the identity information provided directly by students, disaggregating racial and ethnic categories, and avoided the use of broad categories such as *underrepresented minorities*, which can obscure important disparities (Shafer *et al.*, 2021). We examined the intersection of racism with sexism and classism because QuantCrit centers racism as a primary structure of oppression and guides researchers to examine how it converges with other systemic forces. Future work should examine other intersectional systems of oppression, including the intersection of sexism and classism.

Equity has been conceptualized in various ways, providing different affordances and constraints for research and teaching decisions (Gutiérrez and Rogoff, 2003). We define equity for this work as the effort to recognize and confront systemic inequalities within higher education and quantitative data practices, particularly in how data are analyzed and interpreted, to prevent the reinforcement of racial, gendered, and class-based disparities. Our commitment lies in critically examining the assumptions underlying traditional quantitative methodologies and reimagining data as a powerful tool for social justice. Through this lens, we seek to foster a more inclusive, representative, and equitable system that challenges existing power structures and promotes fairness for all. This framing guided our approach to data analysis.

MATERIALS AND METHODS

This work was determined by the Institutional Review Board at the University of Georgia to be exempt (PROJECT00000297). In this study, we deliberately and critically situate our own positionalities, acknowledging that our identities, experiences, and values are integral to how we engage with data and interpret findings. By doing so, we contribute to the rigor of our analysis and also challenge the notion that quantitative methods are neutral or free from bias. This approach reflects the QuantCrit tenet that data and methods are not neutral and that by making our standpoint explicit, we resist deficit-based interpretations and challenge the assumption that quantitative research is free from bias.

Positionality Statements

CD: As a White, continuing-generation woman with multiple neurodivergent identities, my positionality is shaped by both privilege and the challenges of navigating systems that often overlook and misunderstand neurodiversity. My experiences have shaped how I understand belonging, both in moments where I felt included and those where I did not. These experiences have given me a heightened awareness of how power dynamics influence educational spaces and have underscored the importance of creating environments where all students feel valued and supported. I am a tenure-track teaching professor at an R1 institution in California, where I bring my background in immunology and my formative experiences as an undergraduate and graduate student at minority-serving institutions into my teaching and research. Throughout my academic journey, the sense of belonging I experienced, particularly through meaningful mentorship and inclusive learning spaces, played a crucial role in my ability to thrive. Over the past six years, I have focused on studying biology education to challenge and dismantle the barriers that marginalize students, particularly within STEM. In these efforts, I strive to remain mindful of how my positionality influences my interactions with students and collaborators. My commitment to fostering inclusive, accessible, and equitable educational environments is rooted in my belief that belonging is fundamental to student success.

TCA: I approach this work as a learner. As a white person who was a continuing-generation college student, I have had the privilege of not questioning whether I belong in STEM higher educational spaces. As a woman, my experiences of belonging have been more varied, and I can acutely recall the self-doubt and questioning that rose up regularly when I was the only woman on a large collaborative team of field

TABLE 1. Counts of student-reported identities, by race/ethnicity, gender, and generation status.

Race/ethnicity[a]	Women	Men	1st Gen	Cont. Gen
Middle Eastern	234	87	90	231
Native American	62	17	37	42
Latiné	591	270	541	320
Asian Group 1	270	122	139	253
Asian Group 2	490	258	168	580
Black/African	388	112	178	322
White	1820	764	496	2088
Total	3855	1630	1649	3836

NOTE: Latiné includes: Caribbean, LatinX Central American, Chicanx/Mexican, Guyanese, Hispanic, LatinX South American; Asian Group 1 includes: Bangladeshi, Bengali, Burmese, Cambodian, Hmong, Indonesian, Laotian, Mongolian, Nepalese, Pacific Islander, Pakistani, FilipinX, Sri Lankan, Taiwanese, Thai, Vietnamese; Asian Group 2 includes: Chinese, Indian, Japanese, Korean; Black/African includes: African American/Black, African
[a]Students are counted for every identity they selected.

biologists. I am grateful for the opportunities I have had to learn about the exclusionary experiences of students who have different identities than mine, and I make deliberate choices in my teaching as a result of what I've learned. However, I have often assumed that the instructional choices that I make will mean that most, if not all, students feel that they belong in my classroom, and I approached this work naive to the vast potential for students to have widely variable experiences in my courses. I was also positioned, at the start of this work, as someone who had not yet sufficiently questioned the role of quantitative analyses in creating and perpetuating sexist and racist norms in science. This work represents a journey of learning that we hope can help advance the methodological boundaries of our field and shed light on the pernicious effects of racism, sexism, and classism in our introductory biology courses.

MJM: I also approach this work as a learner. As a Black man, my positionality is shaped by the privilege of having two Black, educated parents, including one who was a college professor, and the challenges of navigating systemic educational inequities. As a quantitative methodologist, I have often been the only or one of very few Black individuals, and throughout my training and academic career, I have struggled with self-doubt and imposter syndrome. Only recently, with several professional accomplishments, have I felt more confident in my abilities and belonging. This work made me reflect on the ways my teaching practices can impact students with varying identities. It has also made me reflect on how my methodological decisions in data analyses have upheld or countered oppressive power structures. Throughout this work, I have learned about the QuantCrit framework, and plan to implement its tenets in my future work to more thoroughly and accurately highlight and honor the experiences of underserved and underrepresented students.

Participants

This study included 4911 students taught in 56 introductory biology courses at 44 institutions across 20 different US states (Table 1; Supplemental Table S1). This included 31 Historically White Institutions and 13 Minority Serving Institutions. Using the Carnegie classification of institutions of higher education, 24 had very high research activity (i.e., R1), and 20 were high research activity or master's-granting institutions (i.e., R2/M1). The sample included 38 public institutions and six private institutions.

Each instructor self-identified as using active-learning strategies and teaching an introductory biology course with 50 or more students and agreed to participate in a larger study of instructor thinking, practices, and student outcomes. Analysis of classroom videos indicated that all instructors had class time dedicated to students working on in-class assignments and/or answering questions. We recruited instructors via email, from a list of all introductory biology instructors teaching in a given term at a wide range of large institutions. We purposely oversampled instructors at minority-serving institutions to diversify the students included. Instructor appointments ranged from 20 to 100% teaching effort, with an average of 72.5% (SD = 22.6%) of their appointment dedicated to teaching. Most instructors reported extensive teaching-related professional development, with 45 who had completed 40+ h. Many participants also engaged in mentoring for teaching, leading professional development, or formal training in teaching. Participants had significant teaching experience, having taught an average of 26.8 (SD = 18.7) academic terms.

Instructors recruited student participants using emails, announcements in learning management systems, and verbal announcements. Participation was voluntary, and students earned a small amount of extra credit or course credit for completing surveys that produced the data for this study, independent of the inclusion of their data in the study. We informed students that their instructors did not have any access to their responses, except to know that they had completed the survey. Students reported about their sense of belonging in the latter half of the course to ensure they had time to experience the classroom environment. All courses included in this study had a student response rate of at least 25%.

Data Collection

Sense of Belonging. We measured students' sense of belonging using an established instrument, and we also confirmed the internal structure of the instrument for our dataset. The original instrument included 26 items in five factors, and aimed to advance understanding of why students persist in, or withdraw from college (Hoffman *et al.*, 2002). Given our narrower focus on classroom sense of belonging, we followed established methods (Solanki *et al.*, 2019) and used an abbreviated instrument with eight items (Table 2). These items reflected three key components of classroom belonging, which we have renamed to better communicate the nature of the items: classmate connections, climate for sharing ideas, and instructor support. Classmate connections encompass both social and academic support from peers, highlighting how forming friendships and academic networks fosters a sense of connection (Tinto, 1994). The climate for sharing captures students' comfort with asking questions and sharing answers in front of the class. Instructor support deals with how comfortable students feel seeking help from the instructor about academic and personal matters. Students rated how true each statement was for them using a 7-point Likert scale ranging from one (not at all true) to seven (very true).

TABLE 2. Sense of belonging survey items, by factor.

Item #	Please indicate how true each statement is for you[a]	Factor
1	If I miss a class, I know students who I could get the notes from	Classmate connections
2	I discuss events which happen outside of class with my classmates	
3	I have developed personal relationships with other students in the class	
4	I feel comfortable volunteering ideas or opinions in class	Climate for sharing
5	I feel comfortable asking a question in class	
6	I feel comfortable seeking help from my teacher before or after class	Instructor support
7	I feel comfortable asking my teacher for help if I do not understand course-related material	
8	I feel comfortable asking my teacher for help with a personal problem	

[a] A 7-point scale with only endpoints labeled "Not at all true" at one pole and "Very true" at the other pole.

We conducted confirmatory factor analysis (CFA) to determine whether the data adhered to the three-factor model that would be hypothesized based on Hoffman *et al.* (2002). The internal structure of the abbreviated eight-item instrument has not been previously established. We used robust maximum-likelihood estimation (MLR) to extract variances in the data, as this method better handles violations of the assumption of multivariate normality. The assumptions of a CFA were met by the data, except for multivariate normality, which we discuss below. We conducted all CFA analyses in R (R Core Team, 2020).

We first cleaned the data to remove nonserious responses and tested for outliers. We considered response patterns that could indicate that a student had not seriously considered each item. We queried the data for answer patterns that had the same value for all eight items and other predictable patterns (e.g., sequential). We removed 121 students who selected one (not at all true) or four (unlabeled midpoint) for all eight items. Some of these answers may represent authentic responses, but we opted to minimize measurement error by removing these cases. No students selected other answer choices (e.g., 2 and 7) for every item, and we did not identify any other suspicious answer patterns. We used the Mahalanobis distance test to identify multivariate outliers. This finds the distance of each observation (student) from the center (mean) of the data, taking into account the shape of the data cluster. Here, each student is represented by one vector point with eight dimensions. No students had statistically significant data, indicating that no responses could be justified as outliers. Therefore, we did not remove any responses as outliers.

We also considered the distribution of answers for each item. Mean values for the eight items ranged from 3.8 to 5.5 (Supplemental Table S2). Skewness describes the spread, or horizontal pull of the data, and kurtosis describes the height, or vertical pull of the data. All items had skewness less than $|1.1|$, and kurtosis below $|3.0|$, which meets the standards for factor analysis laid out by (Bandalos and Finney, 2018) (Supplemental Table S2). To determine whether the eight items were normally distributed as a group, we used Mardia's multivariate normality test, QuantPsyc package (Fletcher, 2010). This test showed significant multivariate skewness and kurtosis values, indicating that our dataset was not normally distributed. We therefore used robust MLR, which improves the interpretation of chi-squared analysis of factors.

CFAs assume factorability among the items. We tested factorability using an inter–item correlation matrix (IICM) and Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, using the EFAtools package (Steiner and Grieder, 2020). IICM examines the extent to which scores of one item are related to scores of another item, providing an assessment of item redundancy. In our IICM, the items that were hypothesized to factor together had correlations greater than or equal to 0.6, well above the suggested 0.3 cutoff value (Supplemental Tables S3 and S4) (Clark and Watson, 1995). The KMO measures the proportion of variance that might be caused by underlying factors, for each item and the complete model. The higher the KMO value, the more suited the data are for factor analysis. Our overall KMO value of 0.8 suggests the items in our data were interrelated and shared a large proportion of common variance (Supplemental Table S4), indicating good factorability (Kaiser, 1974). The individual KMO values help us understand which items might be contributing positively or negatively to the overall factorability. Our individual KMO values ranged from 0.8 to 1.0, again indicating good factorability. (Kaiser, 1974; Supplemental Tables S2 and S4).

Multicollinearity in CFAs indicates that the items are highly correlated with each other, potentially leading to issues with model estimation and interpretation. We looked at the Variance Inflation Factor (VIF) for all eight items, using the Olsrr package (Hebbali, 2024). If VIF for any of the items is above 10, or the value of tolerance is less than 0.1, it points toward multicollinearity (O'brien, 2007). None of our items exceeded these suggested cutoff values (Supplemental Table S4).

After establishing that the assumptions were met in our data, we used multiple measures to determine whether the three-factor model predicted by Hoffman *et al.* (2002) adequately fit our data. We examined absolute measures of model fit (χ^2, RMSEA, and SRMSR) and incremental measures (CFI and TLI) to evaluate the fit of the hypothesized three-factor model. Absolute measures evaluate how well the model fits the data in isolation, without comparison with any other model, whereas incremental measures assess how well the model fits the data compared with a baseline model that assumes no relationships between the variables. A holistic approach that examines multiple fit indices balances the shortcomings of any one fit index and ensures that we capture the various aspects of model fit (Kline, 2005). This holistic approach considers sample size and model complexity, resulting in a more robust and nuanced evaluation of the model's goodness of fit (Alavi *et al.*, 2020).

The Standardized Root Mean Square Residual (SRMSR) quantifies how well the hypothesized model reproduces the relationships observed in the data, with lower values, indicating better agreement between observed and predicted

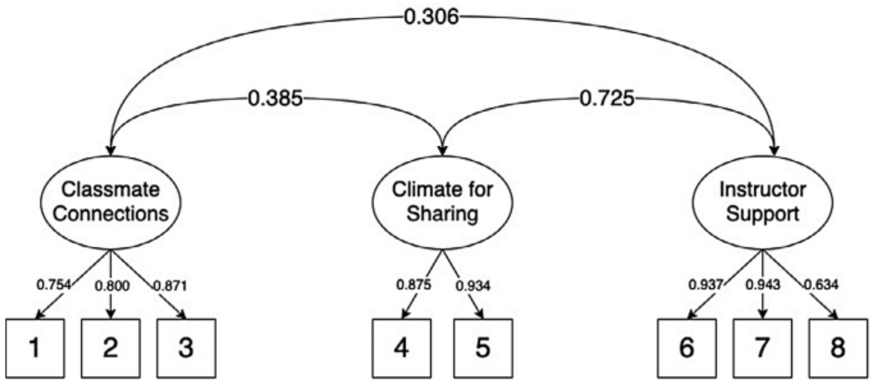

FIGURE 1. Final factor model for the sense of belonging survey. Squares represent items one to eight, and ovals represent factors. Standardized factor loadings are shown as numbers above the items, and the values connecting factors are the correlations between factors.

correlations and, thus, better overall model fit. The SRMR of the three-factor model was 0.04, which is considered an excellent fit (Hu and Bentler, 1999). The Root Mean Square Error of Approximation (RMSEA) measures how well a hypothesized model approximates the data. It provides an error measure that considers both the size of the discrepancies between observed and estimated values and the complexity of the model, giving a more balanced view of model fit. Our RMSEA = 0.09, indicating a mediocre fit. Values below 0.05 indicate a close fit, between 0.05 and 0.08 indicate a reasonable fit, between 0.08 and 0.10 indicate a mediocre fit, and anything above 0.10 is considered inadequate for analysis (Hu and Bentler, 1999). We used three absolute measures of model fit. A χ^2 test assesses the fit between the observed data and the model, but is highly sensitive to sample size. Thus, is it not surprising, given our sample of more than 5000 students, that this test indicated that we should reject the null hypothesis that our data fit the hypothesized three-factor model ($\chi^2 = 18{,}003$, df $= 28$, $p < 0.0001$).

We also used two incremental measures of fit. The Comparative Fit Index (CFI) assesses model fit by comparing the hypothesized model with a baseline model where no relationships exist among the variables. Its output can range from 0 to 1, with values closer to 1, indicating a better fit. Our robust CFI was 0.97, which indicates a very good fit (Hu and Bentler, 1999). The CFI is less affected by sample size compared with other indices, making it a more reliable indicator of model fit across studies with varying sample sizes. The Tucker–Lewis Index (TLI) evaluates model fit by comparing the χ^2 values with a baseline model, adjusting for model complexity. The robust TLI was 0.96 for the hypothesized three-factor model, indicating a very good fit (Hu and Bentler, 1999).

Based on these fit indices and guidance about cutoff values from the literature, we determined that the three-factor model adequately fits our data. We report the factor loadings and R^2 for each item and correlations between factors (Figure 1; Supplemental Table S5). Factor loadings, which represent the strength and direction of the relationship between items and factors, ranged from 0.634 to 0.943 (Figure 1). Higher factor loadings indicate stronger relationships between the factor and the item. R^2 values, which indicate the proportion of variance in each item accounted for by the factor, ranged from 0.402 to 0.889, where higher values indicate a larger proportion of variance in the item explained by the factor. We also report the correlations between factors, which is a standardized version of covariance that measures the strength and direction of the linear relationship between two factors but does not depend on the scales of the factors (Figure 1).

Finally, we determined reliability using Coefficient ω and Cronbach's α in the Psych package (Revelle, 2025). These assess the consistency and stability of a factor, and higher values increase the trustworthiness of the scores derived from the factors. Alpha is widely used to measure internal consistency reliability but assumes that the factors are unidimensional and have equal factor loadings, whereas omega does not. Coefficient ω is a more flexible and accurate estimate of reliability (McNeish, 2018). Supplemental Table S6 displays these reliability measurements, which meet the general rule of acceptability and are equal to or higher than those previously reported (Hoffman *et al.*, 2002; Lance *et al.*, 2006). We did not calculate the coefficient ω for the climate for sharing factor because it includes only two items, and ω requires at least three items to produce a stable and meaningful estimate of reliability.

The primary goal of our analysis was to analyze group differences in sense of belonging, which depends on the measurement instrument performing similarly across these groups (Vandenberg and Lance, 2000). We therefore examined measurement invariance across racial/ethnic groups, gender, and first-generation status. We lacked sufficient sample sizes to examine measurement invariance across intersectional groups (Vandenberg and Lance, 2000). Each analysis examined: 1) configural invariance, which determines whether the factor structure is the same across groups; 2) metric invariance, which examines whether the factor loadings are the same across groups; and 3) scalar invariance, which examines whether error variance is the same across groups. These analyses confirmed that the sample demonstrated configural, metric, and scalar measurement invariance across racial/ethnic groups, gender identity, and generation status (see full results in Appendix 1).

Student Identities. We asked students to provide information about their gender, race/ethnicity, and generation status.

We used these data to examine how students' experiences of belonging in the classroom varied by their intersectional racial/ethnic and gender identity and their intersectional racial/ethnic and generation status identity.

To ascertain students' gender identity, we asked "With which gender(s) do you most identify?" Students could select multiple options, self-identify, or decline to respond (Supplemental Table S7 lists all options). The analyses in this paper concentrate on men and women students because samples for other genders were too small to examine intersectionally. We opted to exclude students rather than grouping them with a gender identity that they did not select. This choice aligns with QuantCrit Tenet 2, which recognizes that social identity categories are socially constructed and cautions against collapsing identities in ways that erase or distort participants' self-reported identities. Beyond men and women, the next largest group in our sample was non-binary students, with 103 respondents. Our intersectional analyses would then divide these students into seven race/ethnicity groups, most of which had fewer than 15 respondents (Supplemental Table S9). Therefore, it was not feasible to maintain our focus on intersectional identities and examine additional gender identities in this study. To avoid completely erasing these students' experiences (Casper *et al.*, 2022), we report average scores for each gender identity for each component of belonging, allowing readers to compare groups with each other and with men and women (Supplemental Table S7).

We asked students to share their racial and ethnic identities by asking, "With which ethnicity do you most identify?" Students could select multiple options, self-describe, or decline to respond (Supplemental Table S8 lists all options). In alignment with a QuantCrit methodological framing, we disaggregated racial/ethnic data as much as possible (Table 1), recognizing that social groups are neither natural nor inherent. In addition to disaggregating groups often lumped together as underrepresented minorities into three groups: Black/African, Latiné, and Native Americans, we disaggregated Asian students into two groups with the goal of better reflecting variation in experiences among students from different Asian backgrounds. For all groups, we prioritized honoring the identities that students reported. In some cases, we were unsure of the most appropriate aggregation for a self-reported identity, and we therefore excluded these students to avoid misidentifying them. This includes seven students who identified as Armenian, Jewish, Mediterranean, Singaporean, and Slavic.

We relied on prior research, census data, and their own self-reported identities to disaggregate Asian students into two groups. Though disaggregation aligns with our QuantCrit methodological framework, we also recognize that any grouping of students from multiple backgrounds inevitably obscures important differences. Asian students experience wide disparities in educational outcomes (Vue *et al.*, 2023). For instance, though 50% of all Asian American and Pacific Islanders have earned a Bachelor's degree or higher, only 15% of Hmong, Laotian, and Cambodian students have, and 25% of Vietnamese students (Shah and Ramakrishnan, 2017). In this study, Asian Group 1 includes students from backgrounds that research and census data suggest face additional barriers to STEM participation (Bureau, 2025). The two largest contributors to Asian Group 1 were Filipino and Vietnamese students. Filipino students are less likely than their Asian peers to choose STEM majors upon college entry, despite earning Bachelor's degrees at comparable rates overall (Shah and Ramakrishnan, 2017; Kang and García Torres, 2021). Vietnamese students are awarded Bachelor's degrees at lower rates both in STEM and across all majors (Bureau, 2025). Following this, we also included all students who identified as having a Pacific Islander background, a group who remain significantly underrepresented in higher education both in and out of STEM. Asian Group 1 also includes students who identified as Laotian, Sri Lankan, Burmese, and other less-represented Asian ethnicities in the United States, many of which were submitted as write-in responses. Asian Group 2 includes students who identified as Chinese, Indian, Korean, or Japanese, some of the more well-represented racial/ethnic Asian backgrounds in STEM.

By grouping students in these ways, we aim to resist the flattening effects of racial categories and highlight how structural barriers affect students differently, even within groups that are often treated as monolithic. All students from these backgrounds contend with racialized assumptions, including those shaped by the Model Minority Myth (Museus and Kiang, 2009). Our decision to create a second group was guided by a desire to better capture how layered forms of marginalization shape educational experiences. To maintain transparency and avoid imposing inaccurate meaning through category names, we used the labels "Asian Group 1" and "Asian Group 2" to describe researcher-created aggregations. Alternative terms (e.g., "Southeast Asian and/or Pacific Islander," "Historically Underrepresented Asian Subgroups") either excluded some students or implied shared cultural or political identities that did not accurately reflect the diversity of participants included in each group.

Finally, we asked students to report their parents' levels of education, to determine whether they were a first- or continuing-generation college student. We asked "What is the highest level of education your parent(s)/guardian(s) completed?" and students could report this for one or two parents/guardians. We considered students first-generation if none of the reported parents/guardians had completed a four-year degree. This definition is consistent with common usage in education research and aligns with federal guidelines (Cataldi *et al.*, 2018; Toutkoushian *et al.*, 2018), enabling comparisons with prior studies on college access and retention.

Instructional Practices. Some scholars and empirical evidence suggest that students experience a greater sense of belonging in courses that use effective active-learning strategies (Ballen *et al.*, 2017; McDonald *et al.*, 2024). Therefore, our analyses controlled for class time spent in active learning. We gathered data about the use of active learning by video-recording three class sessions with a camera placed at the back of the room and a lapel microphone. Most class sessions ranged from 50 to 75 min. Due to filming technical difficulties, seven courses had fewer than three class recordings. To quantify active learning, we determined the average percentage of class time that students spent actively working. Working included any time students worked individually or in small groups, which could include writing, drawing, answering an audience response question, talking with peers, working on a computer, or responding to a nonrhetorical question or problem posed by the instructor, provided students were given at least 5 s to think or respond. We determined whether students were working in each 2-min segment of class, in the same style as other classroom observation protocols (Smith *et al.*, 2013; Alkhouri *et al.*, 2021).

Our coding team trained on practice videos, using a larger set of codes than is included in this study. We coded videos independently and then discussed disagreements, refining our approach until we consistently reached an average IRR above 0.8. Once confident in our shared understanding of the protocol, we transitioned to coding independently. To maintain reliability over time, we regularly returned to joint coding, analyzing one shared video periodically. We calculated IRR, discussed any discrepancies, and reached a consensus before continuing. In total, we coded 178 videos, with an average IRR of 0.944 (calculated for 20 videos).

Data Analysis

We used a multilevel linear regression model framework (Hox *et al.*, 2017) to answer our research questions. Multilevel models are appropriate when observations are nested within dependent units. In this study, students were nested in classrooms, where it is reasonable to assume that students might have some dependencies. Preliminary analyses indicated that this was indeed the case, with intraclass correlations ranging from 4 to 6%, and design effects ranging from 8 to 12, which indicate non-negligible intraclass dependence and necessitate a multilevel modeling framework (Muthén and Satorra, 1995). Additionally, multilevel models are appropriate when there are predictor variables at different levels. In this study, we included student-level variables (e.g., intersectional identity) and class-level variables (e.g., class size, semester, active-learning usage). In these analyses, we used a random intercept model, allowing different courses to have varying intercepts but fixed slopes. We used fixed slopes because the number of students with each intersectional identity per classroom was insufficient to model variation in slopes across classrooms without risking overfitting.

We fit separate models for each component of sense of belonging, resulting in three possible response variables. We also fit separate models to examine: 1) the intersection of race/ethnicity and gender, and 2) the intersection of race/ethnicity and generation status. We took this approach, rather than examining three-way intersectional identities, to increase the interpretability of the model output. For each model ($n = 6$), we included the predictor variable of interest, intersectional identity, which had 14 categories, and several control variables. We controlled for class size, percent class time in active learning, and semester of data collection to remove potential confounds. Data were coded and analyzed using R statistical software (R Core Team, 2020) and the lme4 R package (Bates *et al.*, 2015).

We used weighted effect coding for race/ethnicity, gender, and first-generation status (Mayhew and Simonoff, 2015; Ro and Bergom, 2020). Using effect coding, versus traditional reference or dummy coding, provides three notable benefits: First, it allows our analysis to align with the QuantCrit framework by not having one group (e.g., men, continuing-generation, or White) serve as the basis for comparison. Rather, all groups are compared with the grand mean. Second, this approach avoids collapsing all multiracial students into one category. Weighted effects distribute shared racial membership proportionally across participant-selected categories. With this strategy, for example, a biracial student contributes partially and equally to both racial categories with which they identify. Third, the weighted effect coding approach is more appropriate when groups are unbalanced (Nieuwenhuis *et al.*, 2017). Though weighted effect coding had clear benefits in our study, we also acknowledge that it is imperfect. Distributing shared racial membership across self-identified categories for multiracial students treats these students' experiences as additive (e.g., as the experience of being Black plus the experience of being Latiné). This approach overlooks ways in which these experiences may be distinct because they are Black *and* Latiné. In this way, the methodological choice to use weighted effects aligns with the QuantCrit framework by increasing racial/ethnic disaggregation, while still falling short of fully capturing the lived experiences of all students.

To demonstrate the multilevel modeling approach and interpretation of parameters for effect-coded variables, Eq. 1 displays a simplified multilevel regression equation that includes predictors for intersectional identity groups:

$$belonging_{ij} = b_{0j} + b_1(intersectional.identity) + e_{ij} + u_j \quad (1).$$

Equation 1 models the belonging (e.g., classmate connection) for Student i in Class j. The intercept, b_{0j}, represents the grand mean belonging across all students in an average-sized course with average active-learning use; b_1 represents the predicted difference in belonging for a given intersectional identity group relative to the grand mean belonging; finally, e_{ij} and u_j represent the residuals at the individual and course levels. In our analyses, the equations are cumbersome because of the number of intersectional identities and class-level variables (i.e., class size, active-learning time, and semester of data collection), but the interpretations are similar. The model parameter estimates of interest are weighted effects, and they represent the difference between the sense of belonging reported by students with a given intersectional identity and the belonging reported by the average student. In the results section, for ease of interpretation, we refer to these as differences rather than weighted effects. We plotted mean weighted effects with 95% confidence intervals.

RESULTS

QuantCrit emphasizes the need to move away from traditional null hypothesis testing but does not dictate any particular method for data analysis and interpretation. We chose to interpret our data using more than just traditional statistical significance cutoff values by looking at 95% confidence intervals and trends across comparisons. This is especially important for groups that have experienced greater structural inequities because the underrepresentation caused by these inequities can make it impossible to have enough statistical power to detect real differences in experiences. Whereas p values use binary thresholds, confidence intervals offer additional information, though they too require careful interpretation and do not eliminate the influence of underlying assumptions (Cumming and Finch, 2005). These intervals reflect the uncertainty of the estimate, with wider intervals indicating more uncertainty and narrower intervals indicating more precision. This approach can reveal patterns that may not meet conventional thresholds but still reflect systemic disadvantages worthy of attention. QuantCrit encourages researchers to resist reductive interpretations and focus on contextualizing data within broader structural patterns. For those interested in examining statistical significance and measures of model fit, we have included these values in the Supplementary Materials (Supplemental Tables S10–S12). However, we advise against focusing solely on statistical significance, as it can obscure systemic inequities and perpetuate deficit narratives that we are seeking to dismantle.

Classmate Connections

A sense of connection to classmates includes familiarity and relationships with other students in the course (Table 2). Though women in most racial and ethnic groups had a higher sense of connection to classmates than men, racism resulted in a lower-than-average sense of connection for Native American, Latiné, and Black/African women (Figure 2A). Men also experienced the toll of racism on their connections to classmates, with lower connectedness to peers for Native American, Latiné, Asian Group 1, and Black/African men (Figure 2A).

Classism consistently resulted in a lower sense of connection with classmates, which racism further exacerbated. Most racial/ethnic groups of first-generation students reported connections to peers that were much lower than that of the average student, including Native American, Latiné, Asian Group 1, Asian Group 2, and Black/African students (Figure 2D). Among continuing-generation students, racism lowered connectedness to classmates, with Native American, Asian Group 1, and Black/African students experiencing lower than average connections to peers.

Climate For Sharing

The climate for sharing reflects students' comfort asking questions and volunteering ideas in class (Table 2). Sexism considerably undermined women's comfort sharing in class, relative to men, across racial and ethnic groups (Figure 2B). Racism further reduced comfort sharing among Asian Group 1 women, and potentially among Native American women, though uncertainty was high (Figure 2). Among men, comfort sharing was above average for most groups, though racism erased this advantage for Asian Group 1 men. Classism also undermined students' comfort in sharing their ideas in class. First-generation students reported lower comfort sharing compared with continuing-generation peers across racial and ethnic groups (Figure 2E). Racism particularly reduced comfort sharing among Native American, Latiné, Asian Group 1, and Black/African first-generation students. Even among continuing-generation students, racism reduced comfort sharing in class for Asian Group 1 students, relative to the average student. (Figure 2E).

Instructor Support

A sense of instructor support involves comfort with seeking help from the instructor (Table 2). The impact of racism and sexism on students' comfort seeking instructor help was less clear than for other components of belonging. In general, sexism undermined comfort seeking help, with women reporting lower comfort than men for most racial and ethnic groups, though uncertainty was high for most groups (Figure 2C).

Classism tended to result in first-generation students experiencing somewhat lower comfort seeking instructor help than their continuing-generation peers, but many of these estimates were near zero (Figure 2F). First-generation Native American ($n = 37$) students faced the largest racist and classist systems of oppression, with especially low comfort seeking instructor help. Among continuing-generation students, racism reduced comfort seeking instructor help for Asian Group 1 students.

DISCUSSION

We undertook this study with the premise that racism, sexism, and classism are central structures that shape educational outcomes (i.e., Tenet 1, the centrality of oppression (Van Dusen and Nissen, 2020; Van Dusen *et al.*, 2021; Whitcomb and Singh, 2021). Using QuantCrit framing, the findings illuminate ways in which oppression results in differences in how students experience support and connection (or lack thereof) with classmates and their instructor in introductory biology classes across the United States. Quantitative results gain meaning only when interpreted alongside critical theory and the lived realities of the students whose experiences they reflect. Therefore, our findings should be read with the broader context of all critical work, positioning quantitative patterns within systemic structures.

Racism Impacted Students Differently, and Intersecting Identities Mattered

In general, racism compromised students' sense of belonging in biology classrooms, aligning with prior work demonstrating racialized inequities in STEM belonging more broadly (Nuñez, 2009; Museus, 2014; Ong *et al.*, 2018; Rainey *et al.*, 2018). However, much of this earlier research focused on students' overall sense of belonging in STEM, or on campus, rather than on specific classroom experiences. Our findings add to and refine this literature by showing that the effects of racism varied considerably depending on the component of classroom belonging and intersecting identities. For example, although Native American, Latiné, and Black/African men *and* women reported lower than average connectedness to peers, men in these groups described greater comfort sharing ideas in class than their women peers. Among Asian Group 1, the pattern for comfort sharing ideas was similar, but men reported considerably lower connections to classmates than women.

We also see differences at the intersection of racism and classism. Racism reduced connectedness to classmates among first- *and* continuing-generation students for Native American, Asian Group 1, and Black/African students, but only among first-generation Latiné and Asian Group 2 students. We see similar reductions among first-generation students in their comfort sharing ideas and seeking instructor help for Native American, Asian Group 1, and Black/African students,

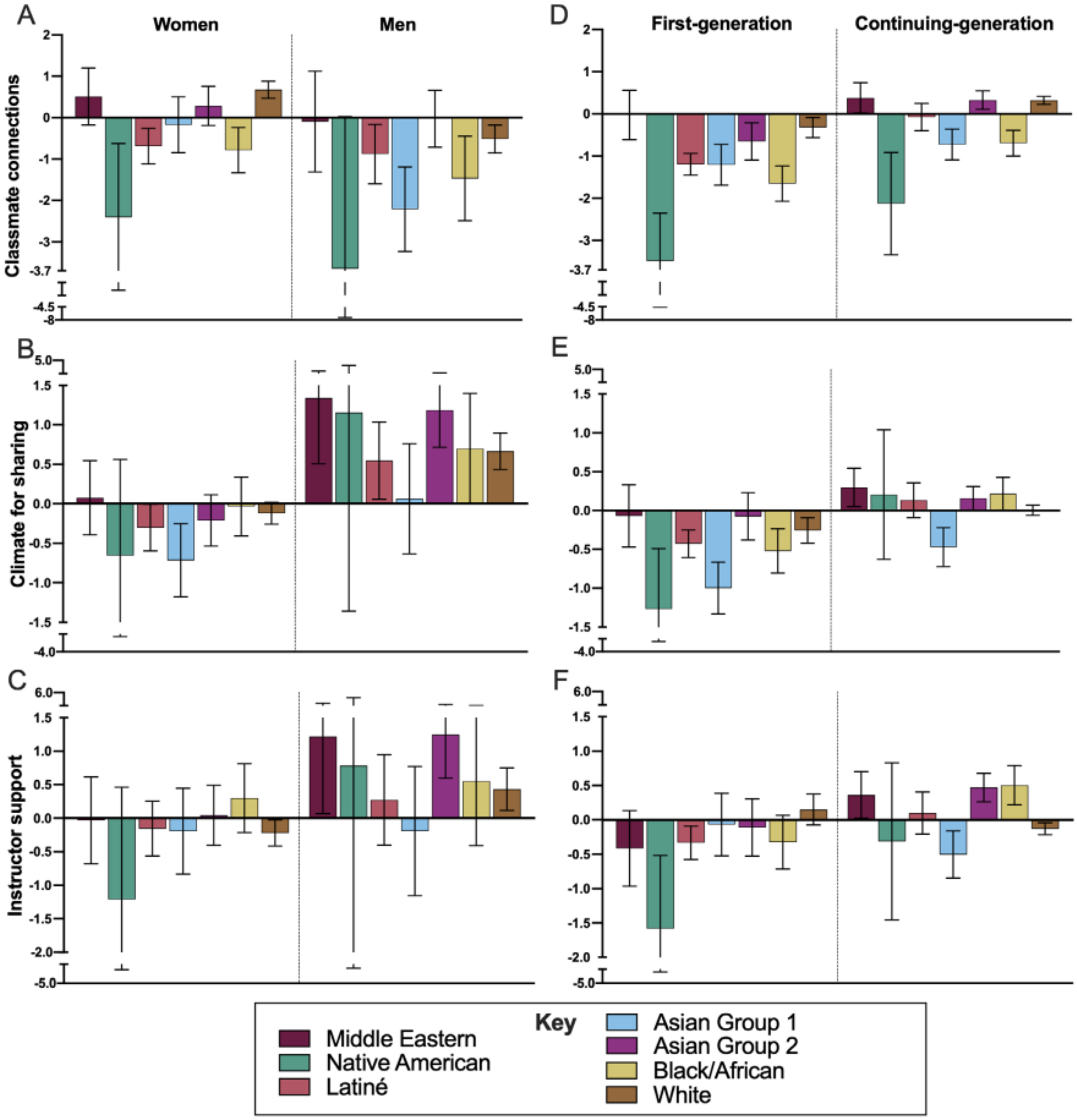

FIGURE 2. Estimated differences in sense of belonging between the average student and 14 intersectional identities. Zero on the *y*-axis represents belonging for the average student. Bars represent the average weighted effect for an intersectional identity, which is the difference between the group's mean belonging score and the average student's belonging, with a 95% confidence interval. (A–C) examine belonging at the intersection of race/ethnicity and gender. (D–F) examine belonging at the intersection of race/ethnicity and generation status. (A and D) show results for classmate connections; (B and E) show results for climate for sharing; (C and F) show results for instructor support. We include breaks in the *y*-axis to fully represent the range of uncertainty while also visually spreading out the data to aid in interpretation. Supplemental Tables S10–S12 include the full regression output.

but among continuing-generation students, the toll of racism is only readily apparent in our data for Asian Group 1 students. These findings extend prior work showing that belonging is not a unitary experience but is shaped by how structural forces manifest differently across classroom dimensions and students (Solanki *et al.*, 2019; Wilton *et al.*, 2019). By documenting group differences across multiple components of belonging, our work supports calls to distinguish between different aspects of student experiences and interrogate how systemic racial oppression maps onto specific classroom dynamics (Van Dusen and Nissen, 2020; Museus and Chang, 2021). We interpret these differences as expressions of how racism becomes embedded in institutional routines and everyday interactions in STEM classrooms. This framing aligns with research on racialized social dynamics and microaggressions in science education that shape students' perceptions of inclusion and support (Ong *et al.*, 2018; Stanton *et al.*, 2022). By centering oppression in our analysis, we move away from framing group differences as individual deficits and instead highlight the institutional forces that shape students' sense of belonging.

Students from socially dominant groups, including Middle Eastern, Asian Group 2, and White students, generally experienced average to higher-than-average levels of belonging, and this tended to be true for men and women and for first- and continuing-generation students (Figure 2). These trends reflect how college classrooms often embody unspoken cultural norms such as language use, behavior expectations, and communication styles, which align more closely with white, Western experiences (Gutiérrez and Rogoff, 2003). This alignment can give some students an advantage, as they may more easily recognize what is expected, feel comfortable speaking up, or trust that they will be taken seriously when they do. For example, an Asian Group 2 or Middle Eastern student may be more likely to be viewed as competent, even without saying much (Lee, 2015; Fisk e *et al.*, 2018). This reflects what scholars call *proximity to whiteness*, which is not being white, but being perceived as closer to white norms in ways that offer social and institutional advantages (Tehranian, 2008; Gillborn, 2010; Maghbouleh, 2020; Museus and Chang, 2021). These dynamics may not be visible on the surface, but they can shape whose ideas are affirmed, whose questions are welcomed, and who feels like they belong.

Sexism Undermined Comfort, Sharing Ideas, and Seeking Instructor Help

Although there were more than twice as many women in our sample as men (Table 1), their numerical majority did not shield them from the effects of sexism. Representation alone does not eliminate oppression, as power in educational settings operates through institutional norms, cultural expectations, and everyday interactions (Ong *et al.*, 2011). Women still face persistent gendered assumptions about competence, authority, and legitimacy, and these dynamics shape how students experience academic spaces and influence who feels safe, supported, and seen.

Sexism negatively impacted women's comfort sharing their ideas in class and seeking instructor help, though it did not have the same effect on their connections to classmates (Figure 2). This pattern may reflect how different components of belonging relate to different classroom dynamics. Sharing ideas publicly and approaching instructors often involve risk from public visibility, which can trigger academic anxiety and stereotype threat among women, perhaps especially in men-dominated STEM environments (Cooper *et al.*, 2018; Schussler *et al.*, 2021). This trend reflects how sexism can operate not only through overt exclusion but also through everyday interactions and institutional norms that undermine women's academic legitimacy and visibility. Even in inclusive classrooms, gendered assumptions about competence and authority can erode women's sense of recognition and value (Carlone and Johnson, 2007; Ong *et al.*, 2011). In contrast, peer relationships for women may be more accessible and affirming, especially in STEM classrooms, where women often form supportive, collaborative bonds and engage in more egalitarian peer interactions that may deepen connectedness (Araújo *et al.*, 2017; Huber *et al.*, 2023).

At the same time, men tended to experience lower-than-average connectedness to their classmates, a pattern that may align with broader research on the "loneliness epidemic" among men (Botha and Bower, 2024). Scholars have documented that men, particularly in Western contexts, often experience socialization that discourages emotional openness and reliance on peer support, leading to more fragile or surface-level friendships (Mahalik *et al.*, 2003; Way *et al.*, 2014). In academic environments, this may translate into fewer sources of affirmation or camaraderie, even in the absence of structural barriers. The result may be that men, though socially dominant in many contexts, may nonetheless experience diminished peer belonging due to gendered norms that constrain vulnerability and connection (Levant and Wong, 2017).

Classism Consistently Diminished Students' Sense Of Belonging

Classism diminished students' sense of belonging across all three components, regardless of race and ethnicity (Figure 2). In fact, this is one of the most consistent patterns in our findings, and it reflects how academic spaces often privilege continuing-generational norms, leaving first-generation students to navigate unfamiliar expectations, hidden curricula, and assumptions about competence that can signal they do not belong (Yosso, 2005; Jack, 2019). Classism operates through both structural barriers and cultural invalidation, shaping how students perceive their place in higher education. Even classrooms that adopt inclusive teaching practices often assume prior exposure to college environments or inherited academic knowledge (Stephens *et al.*, 2012). First-generation students may not have yet been given a chance to learn when or how to approach instructors, participate in office hours, or interpret feedback, which are practices that are often known to continuing-generation students and are essential to academic success (Cooper *et al.*, 2021). As a result, class-based disparities in belonging are not simply about financial hardship, but also about *whose* ways of knowing, being, and interacting are validated in academic spaces. Yet, first-generation students often bring deep connections to family and community, strong motivations to succeed not just for themselves but for others, and the ability to navigate unfamiliar systems, which are all strengths that can enrich classroom learning when they are recognized and supported by instructors and institutions (Yosso, 2005; Kiyama and Rios-Aguilar, 2018). Our findings align with scholarship calling for a broader understanding of inclusion, one that explicitly addresses class-based cultural mismatches in order to support belonging for first-generation students (Stephens *et al.*, 2014; Means and Pyne, 2017).

Patterns Of Exclusion For Native American Students Are Clear Even Without Statistical Power

Findings related to Native American students in this study highlight how overreliance on traditional statistical thresholds can obscure structural inequities. Traditional statistical practices often rely solely on p value cutoff values to interpret results. However, data and methods are not neutral and cannot "speak for themselves" (Tenet 3, Gillborn *et al.*, 2018), and this binary approach can lead us to overlook useful data. This issue is especially critical when studying groups where marginalization has led to underrepresentation, and it is difficult or impossible to achieve sufficient statistical power for comparisons with reach conventional thresholds for significance (Carter and Hurtado, 2007; Zuberi and Bonilla-Silva, 2008). Throughout the findings, uncertainty was high for estimates for Native American students, especially men, as seen in the wide span of confidence intervals in Figure 2. Though our sample overrepresented Native American students relative to their representation in higher education, their marginalization has been so extreme that our sample sizes were still very small, with 62 women and 17 men. This reflects how centuries of settler colonial violence, including cultural erasure, genocide, and the brutal history of colonization and compounding effects of classism and racism, have shaped the educational trajectories of Native American communities (Cech *et al.*, 2017; Masta, 2018). As a result, some of the most extreme estimates in our data, such as Native American men's low sense of connectedness to classmates, had 95% confidence intervals that crossed zero and p-values that did not reach traditional cutoff values. Nonetheless, the larger patterns in the data paint a picture that demands further investigation. In this sample of students, racism appears to sabotage Native American students' sense of belonging in introductory biology classes, and this effect seems to be magnified by sexism and classism. At the same time, we must recognize the considerable uncertainty in these estimates and the fact that sampling error has a larger potential impact on small samples. Particularly among Native American men, these findings could be due to sampling error if the 17 men shared something that affected their belonging but was not captured in our study, such as major, disability status, or prior educational experiences. We cannot generalize beyond such a small sample, and we also interpret these data as meaningful signals that warrant further investigation.

The legacies of cultural erasure and violence are embedded in institutional structures and continue to marginalize Native American students (Pandey and Mohanty, 2024). Data practices often render the experiences of Native Americans statistically invisible, even when they are present in the data at similar or higher frequencies than they are represented in higher education (Brayboy, 2005; Shotton *et al.*, 2023; Lomawaima and McCarty, 2025). Ignoring or dismissing the results of this work on the basis of non-significance would reinforce the structural erasure of these communities. Our approach, grounded in QuantCrit, treats these patterns as meaningful and interpretable, recognizing that the absence of statistical significance does not mean the absence of inequity.

Disaggregating Racial And Ethnic Groups Revealed Important Findings

In line with QuantCrit's assertion that groups are neither natural nor inherent (Tenet 2), disaggregating students' racial identities revealed distinct and critical patterns that would have otherwise been invisible. Most notably, we disaggregated Asian students into two groups because the common aggregation of students from diverse Asian backgrounds masks significant variation in experiences. Students in Asian Group 2 typically had average or higher-than-average belonging, whereas Asian Group 1 students often had lower-than-average belonging and never had higher-than-average belonging (Figure 2). Based on these findings, researchers should be skeptical of work that aggregates all Asian students and draws conclusions about their collective experiences.

Examining Identity Intersectionally Illuminated Uneven Patterns Of Support And Exclusion

Taking an intersectional lens (Tenet 4) showed how systems of power operate together to shape students' belonging. For instance, although classism broadly reduced classmate connections for first-generation students, the magnitude of this effect varied considerably across racial groups (Figure 2). Though men generally reported greater comfort sharing ideas in class and seeking instructor help, Asian Group 1 men had comfort levels more similar to women than other groups of men (Figure 2). These results align with prior work on intersectionality, which highlights that the experiences of students with multiple marginalized identities cannot be understood by simply adding the effects of race, gender, or class. Instead, these systems interact in complex ways to deepen exclusion or, in some cases, amplify support (Crenshaw, 1989; Zuberi and Bonilla-Silva, 2008; Van Dusen *et al.*, 2021). Our findings reinforce the need for research and interventions that account for the compounded impact of multiple identities, rather than assuming that broad demographic categories tell the whole story.

Implications For Researchers

Our findings contribute to a growing body of research that seeks to name and address the systemic forces shaping inequity in STEM education. We highlight how racism, sexism, and classism shape students' classroom experiences in ways that are often obscured by traditional research practices. Even without adopting a QuantCrit framework, researchers can take steps to better capture this complexity. Disaggregating identity categories (Museus and Kiang, 2009; Takahashi, 2024), analyzing intersections rather than additive effects (Crenshaw, 1989; Collins, 2015), and interpreting uncertainty in light of structural exclusion (Gillborn *et al.*, 2018; Van Dusen *et al.*, 2021) are critical practices. Treating findings that don't reach typical statistical cutoff values for marginalized students as unimportant, or as evidence that inequities do not exist, risks reinforcing their statistical erasure (Carter and Hurtado, 2007; Zuberi and Bonilla-Silva, 2008). Methodological choices also matter, and using approaches like effect coding, rather than reference group comparisons, can avoid positioning dominant identities as the norm (Mayhew and Simonoff, 2015; Ro and Bergom, 2020). Small shifts in methods and interpretation can lead to more accurate and equitable understandings of STEM education.

Treating sense of belonging as multiple components that capture different aspects of students' experiences also proved important in our findings, as different systemic forces impacted these experiences. For example, though men tended to report higher belonging for climate and instructor support, they reported lower peer connectedness than women. Therefore, our data do not support the claim that women experience lower belonging in biology classrooms writ large, but rather that they feel less comfortable sharing their ideas with the class and seeking instructor help. That distinction is meaningful and may also have more actionable implications for instructors.

Implications For Instructors

As instructors, a primary implication that we take away from these findings is that we cannot assume our students experience our classrooms similarly, or that any strategy we use, regardless of its evidentiary basis, will equitably impact all students. In this work, many instructors used evidence-based active-learning methods and approaches to foster belonging, such as positive Instructor Talk (Jackson *et al., in review*; Seidel *et al.*, 2015), yet students had widely variable experiences of belonging. Some students felt comfortable participating and asking for help, whereas others did not. These differences reflect classroom, disciplinary, and institutional norms, as well as peer dynamics, not just instructional strategies (Ong *et al.*, 2018; Canning *et al.*, 2019; Dewsbury and Brame, 2019).

Our findings also more specifically point to the need for instructors to think carefully about how their instructional decisions contribute to cultivating or diminishing students' sense of belonging in the classroom. Every day choices regarding how we structure active learning matter. For example, group work that lacks clear roles, facilitation, or accountability can reproduce gendered and racialized exclusion (e.g., Eddy *et al.*, 2017; Ong *et al.*, 2018). As another example, discussion structures that rely on rapid whole-class call-and-response, cold calling without wait time, or competitive volunteering can privilege fast-thinking or extroverted participation, shaping who feels invited to contribute (Cooper *et al.*, 2018). Additionally, thoughtfully-structured active learning might enhance belonging and reduce inequities, particularly for students historically marginalized in STEM (Eddy and Hogan, 2014). Together, this work reinforces that belonging is shaped not only by the activities we use but also by the way we implement them. Our findings suggest that strengthening belonging takes more than using active learning, as all instructors in this study had class time when they stopped lecturing, and students worked on questions. Fostering belonging likely requires close attention to how power and expectations play out in daily interactions. Instructors can begin to shift classroom culture by affirming students' identities, making expectations clear, and creating spaces where diverse perspectives are not only welcomed, they are expected (Dewsbury and Brame, 2019). These efforts are particularly important in introductory STEM courses, where early signals of exclusion can push students away from fields in which they could otherwise thrive (Meaders *et al.*, 2020).

Limitations

Although we aimed to disaggregate student identities more than traditional quantitative studies, our categories still grouped together students with diverse experiences. The groupings we made undoubtedly hide important differences in students' experiences of belonging in introductory classrooms (Gándara and Contreras, 2009; Museus and Truong, 2009). For example, we combined Black and African students into a single category. Immigrant African students may encounter different forms of privilege and marginalization than African American students (Awokoya, 2012). Similarly, students from many different nationalities and ethnicities are aggregated together in the Latiné group. National origin, migration histories, and cultural contexts can shape educational access, racialization, and identity development in distinct ways (Gándara and Contreras, 2009; Kasinitz *et al.*, 2008; Museus and Truong, 2009). Additionally, although we excluded gender-spectrum students from our analyses due to small sample sizes, it is important to recognize that students with these identities also experience distinct and significant forms of exclusion in STEM learning environments (Cech and Waidzunas, 2011; Casper *et al.*, 2022). Future work should prioritize further disaggregating and including identities wherever possible to better reflect this complexity.

Our decision to disaggregate Asian students into two groups allowed us to highlight variation that is often unrecognized, but it also carries important limitations. Asian Group 1 in our dataset was numerically dominated by Filipino and Vietnamese students, meaning that the patterns we report for this group may primarily reflect the experiences of these two subgroups. Students from other Asian backgrounds in this category, while included, were represented in much smaller numbers, limiting our ability to capture their unique experiences (Museus and Kiang, 2009). Additionally, different ways of grouping Asian subpopulations, such as by migration history, histories of colonization, language background, or other markers of racialization, could reveal different patterns of belonging (Sakamoto *et al.*, 2009). As with all socially constructed categories, the boundaries we drew inevitably shape the findings, and future work should explore alternative groupings and further disaggregation to better represent the diversity of experiences within Asian student populations (Dolly Nguyen *et al.*, 2015; Teranishi *et al.*, 2015).

We also caution readers about generalizing these findings to all introductory biology classrooms. The classes included in this study likely vary from typical classrooms in at least two ways. First, every class used active learning. Although the models controlled for active learning use, the range of instructors in this study does not fully represent biology faculty, about half of whom spend more than 80% of class time lecturing (Stains *et al.*, 2018). Instructors who use active learning may also use other evidence-based strategies, which might positively impact students' sense of belonging. It is possible that belonging is higher in the classes in this dataset and/or that differences in belonging among students are larger or smaller than they would be in other classes. Second, the instructors of the courses in this study willingly participated in an intensive study that collected data beyond what is presented here. This suggests that they are especially invested in the teaching component of their job and possibly their professional identity as a teacher (Brownell and Tanner, 2012). Furthermore, most had participated in 40+ h of teaching professional development, further suggesting they are highly invested in being effective teachers. Courses taught by faculty who invest less time in their teaching might have lower belonging and/or larger differences between students.

The modest R^2 values of the models we fit (Supplemental Table S12) underscore that many additional factors influence students' belonging. Outside factors could include prior educational/social experiences, institutional context, experiences in degree programs, student interests, and more. These unmeasured influences highlight the complexity of belonging and represent an important limitation of this work.

Additionally, this quantitative study identifies differences among students and attributes them to forms of systemic oppression, but it cannot reveal the specific ways in which racism, sexism, and classism undermined students' sense of belonging in the classroom. There are many factors that could affect students' sense of belonging, and we hope that future research takes up the challenge of further exploring patterns revealed in this study with a qualitative study of students' experiences.

CONCLUSIONS

Our findings underscore that a sense of belonging in biology classrooms is not equally accessible to all students. Racism, sexism, and classism shape classroom dynamics in ways that advantage some students while undermining others. Even in courses taught by experienced instructors using active-learning strategies, students from marginalized backgrounds reported lower levels of belonging. By applying a QuantCrit lens and disaggregating intersectional identities, we revealed patterns that would have remained hidden in traditional analyses. These insights highlight the need for the biology education community to go beyond thinking about instructional strategies to seriously consider the deeper power structures and cultural norms that determine who feels welcome, valued, and ultimately able to thrive.

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