

Enabling Investigation of Impacts of Inclusive Collaborative Active Learning Practices on Intersectional Groups of Students in Computing Education

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Abstract—This full paper presents the Collaborative Active Learning and Inclusiveness (CALI) inventory, and an analytical model using the CALI inventory, demographic data, mindset surveys, and knowledge mastery assessment, to explore relationships between classroom climate and student experiences. The CALI inventory enables the investigation of the impact of the student experience in an active learning classroom by distinguishing the factors that characterize the structure, social learning, and inclusive practices. The Structure Index includes components related to course setup, organization, assessment, grading, and communications. The Sociality Index includes components related to opportunities for students to interact with each other. The Inclusiveness Index includes components related to how the instructor communicates a sense of belonging to the students through a growth mindset and inclusive policies and practices. A CS Mindset Instrument was developed based on research that measured students' self-efficacy by evaluating the extent of variation in their self-perceived ability to accomplish a task, sense of belonging in computing, and professional identity development. Demographic data is collected that allows for an analysis using an intersectional lens to acknowledge the complexity of social and cultural contexts. The knowledge and mastery assessments capture changes in competency through pre-post mastery quizzes. The combination of CALI with other instruments, including those that characterize student mindset, identity, and levels of mastery, enables investigation of how various practices of inclusive and collaborative active learning have differential effects on students with different identities in computer science.

Index Terms—Active Learning, Student Engagement, Diversity, Sense of Belonging, Faculty Engagement.

I. INTRODUCTION

Despite the rising enrollments in national collegiate computing, achieving gender and racial parity remains a significant

challenge. Many investigations have focused on addressing the challenge of broadening the student diversity “pipeline” in computing, with a particular emphasis on innovative co-curricular activities [1], [2] and exploration of psycho-social constructs that impact academic outcomes [3], [4]. Prior studies have indicated the importance of classroom climate in retaining students from underrepresented groups [5]–[8]. This paper continues this research direction by examining the factors that characterize classroom climate and their association with the experience of students with different intersectional identities.

As computing education reckons with its past, present, and future in meeting the demands of a global, digital economy reliant on a diverse and technologically-literate workforce and public [9], the call to democratize computing education [10] has been embraced and pursued by many computing educators. However, the typically ad hoc, localized, and individual nature of computing education interventions poses a challenge to a true sense of coherence and impact across the discipline. Therefore, interconnected and evidence-based approaches that leverage collaborative partnerships across institutions and encourage replication are necessary to manifest systemic change at scale.

The pathways to earning an undergraduate degree in computing are often non-linear and complex, as a recent report on STEM degree barriers and opportunities highlights [9]. Institutional policies and structures significantly influence student success in computing, affecting both the speed and likelihood that students earn a STEM degree. These policies

and structures are most directly encountered by students in their classrooms, where the organizational climate intersects with teaching practices. However, there is an implied goal in some institutions that STEM gateway courses serve to distinguish between students who have the ability to succeed in STEM and those who do not, often resulting in a culture of competition in the classroom [9], [11]. Empirical studies suggest that such competitive classrooms lead to negative outcomes for underrepresented students, although the number of these studies is small and outdated with limited samples [12], [13]. Hence, additional research is needed to critically examine how current STEM teaching practices cultivate the classroom climate, particularly with larger, more representative student samples.

In this paper we describe how the CALI inventory characterizes classroom climate, along with instruments for characterizing the student experience through demographic data, mindset constructs, and knowledge mastery, providing a basis for an analytical model of the impact of classroom climate on students with different identities. The paper reports on initial data collection in introductory CS courses at two universities in the US.

II. LITERATURE REVIEW

Classrooms are a reflection of society [14], and similar to how society has various stakeholders with their own independent interests, goals, and privileges, so does a classroom. A classroom or course has multiple stakeholders such as the teacher, the student, and the institution. Researchers can examine the interactions between the three but typically focus on one. Research that looks for associations may choose to study two proxies for stakeholders such as students and faculty, faculty and institutions, faculty and pedagogy, students and pedagogy, and students and institutions. There is a social contract tying the selected stakeholders together evidenced in documents such as the syllabus, degree requirements, performance reports, and exams [15]. Researchers analyze how the stakeholders interact with one another in different contexts at a broader level by considering, assuming, or limiting the attributes of one as constants with the other being a variable. This is done to limit the complexity of the analysis. It is crucial to observe and explore systemic level factors that influence how a course is designed and how students experience the course through patterns in their perception with an intersectional lens [16]. In the current context of computer science education, it has become common to focus mainly on the surging number of students reached. However, it is increasingly important to consider not just the quantity, but also the qualitative characteristics of the teaching that students are receiving and how that affects students differently.

A. Active Learning & Flipped Classrooms in CS

According to research conducted by Latulipe in 2018, when first-year computing students from underrepresented groups, such as women and students of color, are exposed to computer programming through a flipped, active learning

classroom, they are less likely to switch majors the following year [17]. While there could be several factors contributing to this retention increase among diverse students, the results of the Connected Learner studies are consistent with recent research that highlights two particularly significant aspects: course structure and social learning [18], [19]. Eddy and Hogan found that course structure, such as schedules, grading, attendance, and participation, is the critical component in flipped classrooms that closes the achievement gap for underrepresented students [18]. The highly-structured format in many flipped courses provides a level of support that all students, particularly those from underrepresented groups, require to succeed in higher education. In addition, Deil-Amen's socio-academic integrative moments theory emphasizes the importance of providing in-class opportunities for students to socialize and form a community [20], [21]. Underrepresented students, who have fewer connections to their peers in the major, competing obligations, and stronger social ties off-campus, require socio-academic integrative moments. Several types of activities used in active learning environments, such as think-pair-share and lightweight teams, provide opportunities for socio-academic moments in the classroom and a foundation for forming relationships and community within the major. Prior studies have shown mostly positive effects on student attitudes towards flipped classes and their learning [22] and increased retention among first-year computing majors [17].

Further investigation is needed to identify the theoretical scope conditions [23] in which flipped, active learning pedagogy leads to positive student outcomes in terms of both knowledge and mastery of curricular content and personal and professional mindset.

B. Measuring CS Student Mindset

Mindset about learning plays an important role in promoting student success [24]. Students who believe that they can acquire an ability and cultivate their intelligence are said to have a growth mindset that can positively shape their academic achievement [25]. Additionally, students' self-efficacy or beliefs in their ability to accomplish a task and reach a goal can impact their academic performance [26]. Grit, or motivation to persist through challenges [27], has been shown to positively predict computer science course grades [28]. A student's sense of belonging is shaped by their experiences and defined by the extent to which they feel that they are an integral part of the system [29]. Students' sense of belonging can lead to increased student retention, academic motivation, and success [30], [31]. In turn, a sense of belonging drives one's professional identity which reflects on a person's technical competency [10]. While we do not typically expect students' mindset to be significantly impacted by a single course, we hypothesize that the learning climate in a single course may have a measurable impact on students' mindset within a course topic that can be further compounded over time.

C. Intersectional Analytics

The social, political, and economic structures of the US are organized through the historic mechanisms of race, sex, and social class [32]. These mechanisms function via “assigned” categorical identities that shape the life experiences and outcomes of all individuals, such that some are systemically conferred advantages (white people, men, high socioeconomic status) while others are systemically conferred disadvantages (people of color, women, low socioeconomic status). This inter-categorical approach to identity-based on one’s intersectional location of social experiences lays the foundation for understanding the intersectional identity of an individual. Studying intersectional identities [33] is especially important to acknowledge and capture a deeper understanding of how the intertwined complexities of race, gender and social class relate to student learning outcomes [34]. For example, a female student of color in the computing classroom is simultaneously carrying her race and gender with her; her experiences as a person of color cannot be separated from her experiences as a woman, just as her experiences as a woman cannot be separated from her experiences as a person of color. That critical junction between students’ singular categories—the intersection—is rarely measured in STEM education research [35].

Intersectional identity is known for the inherent challenges of studying complexity in quantitative approaches. The ‘additive assumption’ can incorrectly stack race, ethnicity, gender, and class [36] and fail to address the nuances of multiple and intertwined identities. There are specific challenges to studying intersectional identity within computer science, due to small populations of women and people of color in the field [37]. This context has produced many studies where certain groups are treated monolithically, e.g Asian, Black, Hispanic, and White women as one, with noted criticism [38]–[41]. Despite these challenges, the need to explore how race, gender and social class relate to student learning is critical to understanding how patterns of advantage or disadvantage persist in computer science education [42], [43].

III. CLASSROOM CLIMATE - STUDENT IDENTITY ANALYTICAL MODEL

We developed an analytical model (Figure 1) to triangulate the impacts of classroom climate on content mastery and mindsets of students from different intersectional groups. The model uses data from multiple sources: climate classroom characterizations measured through the CALI inventory [44], student knowledge mastery measured through test scores, student attitudinal constructs measured through a composite CS Mindset instrument, and student demographic data. This a more comprehensive approach to understanding classroom climate based on previous models that focused on combinations of one or two components like classroom instruction and student evaluation [45]; active learning and student performance [46] [47]; student knowledge mastery with inclusivity [48]; educator evaluations and student performance [49] [50]; course contentment and inclusiveness [51]. The

scope of measurement is a single CS course in a single semester, with mastery and mindset data being collected both at the beginning (pre) and at the end (post) of a given semester. The demographic identity data is collected at the beginning of the semester, and the CALI inventory is scored mid-semester by researchers external to the course. Figure 1 shows an overview of how these data sources are conceptually linked. Each aspect of the model is further detailed in the following subsections.

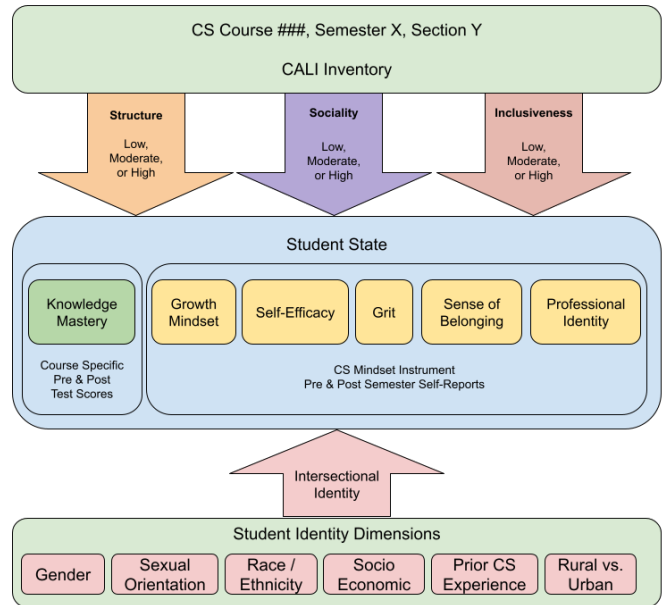


Fig. 1. The Classroom Climate - Student Identity Model

A. CALI

The Collaborative Active Learning and Inclusiveness (CALI) Inventory was developed as a research tool to investigate how classroom instruction and course design impact the student’s ability to engage with introductory computer science (CS) course materials. The inventory consists of three indices: Structure, Sociality, and Inclusiveness. The Structure Index includes components related to course setup, organization, assessment, grading, and communications. The Sociality Index includes components related to opportunities for students to interact with each other. The Inclusiveness Index includes components related to how the instructor communicates a sense of belonging to the students through a growth mindset and inclusive policies and practices. By categorizing courses along the three dimensions of structure, sociality, and inclusiveness, researchers can analyze correlations between course sections with student success and engagement ratings. For the purposes of the model proposed here, we use the CALI data to categorize courses as having low, moderate, or high structure; low, moderate, or high sociality; and low, moderate, or high inclusiveness. Figure 3 presents a visualization and description of the categorical labels in which a single course can be placed to indicate how that course presents a classroom climate

	# of courses		
	low	med	high
Structure	0	2	9
Sociality	7	4	0
Inclusivity	3	4	4

TABLE I
SUMMARY OF CALI DATA

with respect to course structure, sociality, and inclusiveness. Characterizing the data collected for each course in this way allows us to group courses that have similar characteristics in classroom climate, even if the topics or content being taught is different.

In Fall 2022, we administered the CALI instrument to characterize 15 sections of 3 courses (equivalent to CS1, CS2, and CS3). To characterize each section, a member of the research team performed a course observation and documented their findings. As part of the observation, the researcher reviewed the course syllabus, including attendance, assignment submission, and grading policies; reviewed course assignments posted on the learning management system; observed an in-person or recorded class session; and conducted an interview with the instructor to discuss their approach to teaching the course and to clarify scoring of any CALI items. A research team of two members reviewed the collection of CALI items associated with a course, and determined a categorical score in each of the three CALI dimensions: high, medium, or low. Of the 15 courses that were included in our data collection efforts, researchers were able to complete individual course observations using the CALI instrument and determine a score for 11 course sections. Table I shows a summary of the data collected for Fall 2022 sections. The majority of sections (9 of 11) were identified as "high" in structure, and the majority of sections (7 of 11) were rated low in the sociality dimension. With respect to the inclusivity index, there was a more even distribution across the high, medium, and low categories.

B. Student Identity Dimensions

Student identity dimensions play a crucial role in shaping the experiences and outcomes of computer science students. Recognizing the importance of intersectional identities, the CS Mindset Instrument includes demographic items that aim to capture the multidimensional aspects of students' identities. A total of 27 items were designed to collect descriptive information about students' academic background (institution, level, prior computing, first generation college student), race, ethnicity, gender, sexual orientation, community orientation (rural, urban), caregiving responsibilities, and sources of financial support (employment, scholarships, loans, grants). These items are optional but can be utilized to construct meaningful intersectional identity groups, when provided. We used the data of 274 students who answered combined the Pre and Post CS Mindset Instrument in fall 2022 for preliminary analysis.

When examining intersectional identities in computer science education, it is important to consider specific combinations that can impact students' experiences. These items go beyond traditional demographic characteristics and encompass a range of intersectional identities that are relevant for computer science education. Here are some examples of relevant intersectional identity combinations in the context of computer science that we observed were underrepresented based on the data we collected in the fall 2022:

- **Race/Ethnicity and Gender:** Exploring how students of different racial or ethnic backgrounds, such as Black women(6 students), Asian non-binary individuals(9 students), or Hispanic women (8 students), navigate the computer science learning environment and any unique challenges they may face.
- **Gender and Sexual Orientation:** Understanding the experiences of LGBTQ+ students (50 students) in computer science, such as lesbian women, transgender men, or bisexual individuals, and how their gender identity and sexual orientation intersect with their academic journey.
- **Academic Background and First-Generation Status:** Investigating the experiences of first-generation college students (90 students) from diverse academic backgrounds, including those with no prior computing experience, as they enter the computer science field.
- **Gender and Caregiving Responsibilities:** Examining how female-identifying students who are also caregivers(8 students), such as mothers or primary caregivers for family members, balance their caregiving responsibilities with their pursuit of computer science education.
- **Community Orientation and Socioeconomic Status:** Analyzing the experiences of students from different community orientations (rural (101 students) or urban (158 students)) and their socioeconomic backgrounds to understand how access to resources, support systems, and opportunities can influence their computer science education.
- **Race/Ethnicity, Gender, and Disability:** Examining the experiences of students with disabilities who identify as women of color(6 students), LGBTQIA+ individuals with disabilities (6 students), or disabled students from different racial or ethnic backgrounds. This intersectional lens can shed light on the unique challenges and opportunities faced by individuals with disabilities within specific racial or gender contexts.
- **Disability, Academic Background and First-Generation Status:** By examining the experiences of students with cognitive or tangible disabilities who are first-generation college students (6 students), researchers and educators can uncover important factors that influence their academic journey in computer science. This includes understanding the specific accommodations and support systems needed to ensure equal access and participation in computer science courses and activities. It also involves recognizing the potential impact of limited family

knowledge or support related to both the disability and the pursuit of a computer science education.

It is essential to recognize that these are just a few examples, and there can be numerous other intersectional identity combinations that impact computer science students. By considering these combinations, researchers and educators can gain insights into the unique challenges, barriers, and opportunities faced by students from different identity intersections, ultimately fostering a more inclusive and supportive learning environment.

By collecting this information, researchers and educators can gain a more comprehensive understanding of the diverse backgrounds and experiences of computer science students. It allows for the construction of meaningful intersectional identity groups, enabling deeper analysis and insights into how different aspects of students' identities interact and influence their experiences in CS education. By considering the intersectionality of students' identities, educational institutions can strive for greater inclusivity and equity, addressing the unique challenges and needs of various student populations.

C. CS Mindset Instrument

The CS Mindset Instrument was developed to address the complexity of psycho-social constructs that have been demonstrated to correlate with student learning success. The instrument contains 31 items adapted from well-known and validated measurements of growth mindset, self-efficacy, grit, sense of belonging, and professional identity. These constructs are crucial in understanding students' attitudes, beliefs, and perceptions related to their computer science education. Three growth mindset items were adopted from Dweck's Mindset Questionnaire [24]. Self-efficacy items originated from Schwarzer [52]. The Grit scale was included [53]. Sense of belonging items were adopted from Anderson-Butcher [54]. Professional identity items were adopted from Chemers et al [55]. Table III-C displays sample survey items, their origin, and the reliability coefficients from a pilot administration of the instrument during the Fall 2022 across 13 introductory courses. A total of 338 students responded, with 276 pre-survey and 62 post-survey responses. Twenty-two responses were able to be matched between pre and post-surveys. All alpha coefficients were strong, above .70. Figure 2 is a visualization of the ranges and means for pre- and post-mindset data collected in Fall 2022 courses that are categorized as low (left) and moderate (right) course sociality in the CALI inventory. The visualization suggests that low sociality may have a negative impact on student mindset. The data visualization in Figure 2 demonstrates the associations we can analyze, and does not indicate that we have significant results.

D. Knowledge Mastery Instruments

To understand student learning within and across classroom settings, students' academic performance variables are measured and tracked as indicators of student knowledge and mastery. Academic performance variables include persistence in

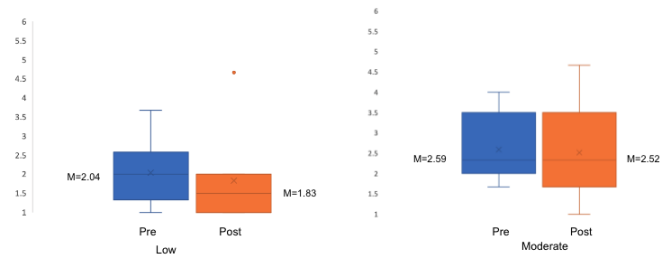


Fig. 2. A visualization of the ranges and means of pre- and post-mindset in courses that have low and moderate sociality.

the degree (retention), course grade performance, and knowledge acquisition. In this study, knowledge acquisition and mastery are measured by rubrics and assessment instruments developed in consultation with faculty to evaluate student learning outcomes within and across the curriculum.

To examine knowledge mastery, five multiple-choice questions were created for each course level (CS1, CS2, CS3). Questions were limited in number to five so that they could be easily incorporated into various instructors' current course content. Having the questions in the form of multiple choice questions as opposed to open-ended questions makes it more objective and consistent when assessing mastery.

The pre-knowledge mastery questions were administered at the beginning of the semester and did not affect the student's grades. The post-knowledge mastery questions were embedded in the final exams for the class. A common final exam was given at each of the course levels at both institutions.

Mastery questions were chosen to be representative of the topics that students would encounter in a typical course at each of the course levels. The questions were designed to test multiple concepts at different levels of Bloom's taxonomy. Table III shows a mapping of the courses to topics and their tested level of Bloom's taxonomy. Appendix A shows an example of a mastery question for a CS2 course.

E. Analysis Methodology

The analytical model relies on the collection of a significant amount of data in order to explore associations and significant relationships between course climate and the student experience. With the limited data we collected in Fall 2022, we were able to identify an analysis methodology. Once the data has been collected, a process of data cleaning, de-identification, and linking is conducted to create a dataset that comprises pre and post-mastery learning as well as pre and post-CS mindset survey responses from all the students in a specific class, or all the students in a set of classes that have similar CALI inventory characteristics. This dataset also contains the demographic characteristics of each student. Figure 3 provides a visual depiction of how classes can be clustered by the three dimensions of the inventory, with binary categories within each dimension.

After data cleaning, de-identification, and linking, the data can be analyzed in many different ways, including:

TABLE II
CS MINDSET INSTRUMENT ORIGINS

Construct	Origin	Sample Item	Total Items	Cronbach Alpha
Mindset	Dweck, 2006	Your intelligence is something about you that you can't change very much.	3	0.904
Self Efficacy	Schwarzer, 1995	I am confident that I could deal efficiently with unexpected events.	9	0.865
Grit	Duckworth & Quinn, 2009	I finish whatever I begin.	8	0.707
Belonging	Anderson-Butcher, 2002	I can relate to people around me in this course.	5	0.823
Professional Identity	Chemers et al., 2011	In general, being a computer scientist is an important part of my self-image.	6	0.900

TABLE III
KNOWLEDGE MASTERY TOPICS BY COURSE AND BLOOM'S TAXONOMY LEVEL

Class	Topic	Knowledge	Comprehension	Application
CS1				
	Data types	x	x	
	Conditionals	x	x	
	Loops	x	x	
	Parameters and methods/functions	x	x	
CS2				
	Conditionals	x	x	
	Loops	x	x	
	Objects	x	x	x
	Arrays	x	x	
	Inheritance	x	x	x
CS3				
	Linked lists	x		x
	Stacks	x	x	
	Queues	x	x	
	Recursion	x	x	
	Trees	x	x	

- Examine associations between each of the three dimensions of classroom climate with student mindset overall, by examining mindset deltas for all students taking courses that are high in structure, high in sociality, or high in inclusiveness.
- Examine associations between each of the three dimensions of classroom climate with student mindset deltas for students in particular intersectional identity groups, by identifying students of that intersectional identity group in classes with particular levels of structure, sociality, or inclusiveness.
- Examine associations between each of the three dimensions of classroom climate with knowledge mastery, by examining knowledge mastery deltas for students in courses with particular levels of structure, sociality, or inclusiveness.
- Examine associations between mindset deltas or knowledge mastery deltas for clusters of courses within the three-dimensional space of structure, sociality, and inclusiveness as depicted in Figure 3.

We note that it is also possible to look at associations within the Student State component of the conceptual model and examine how knowledge mastery impacts various mindset constructs.

With enough data collected over multiple courses at multiple institutions with large numbers of students, we anticipate using structural equation modeling to determine the size of the impacts of structure, sociality, and inclusive classroom

climate, and we anticipate that the equations will be different for different intersectional groups of students.

IV. DISCUSSION

A. Strengths of the Model

Identified strengths in the model include the study design and the approach to data collection. The study design takes into account the intersectional identities of students, including race, ethnicity, gender, sexual orientation, and other salient socio-economic features. This approach allows for a more comprehensive understanding of how classroom climate affects students from a complex set of group memberships. Examining multiple data sources, including the CALI inventory, student knowledge mastery assessments, CS Mindset instrument, and student demographic data, provides a broader perspective on the classroom climate and its impact on student experiences. By collecting data at the beginning and end of the semester, the study captures changes in student attitudes, knowledge, and experiences over time. This longitudinal analysis allows for a deeper understanding of the effects of classroom climate.

B. Implementation Challenges and Solutions

Implementing a study of this scale across two institutions and multiple courses presents inherent challenges, particularly for instrumentation, collection, and overall data fidelity.

Instrumentation: Some data, such as the CALI inventory and course observations, rely on subjective assessments by

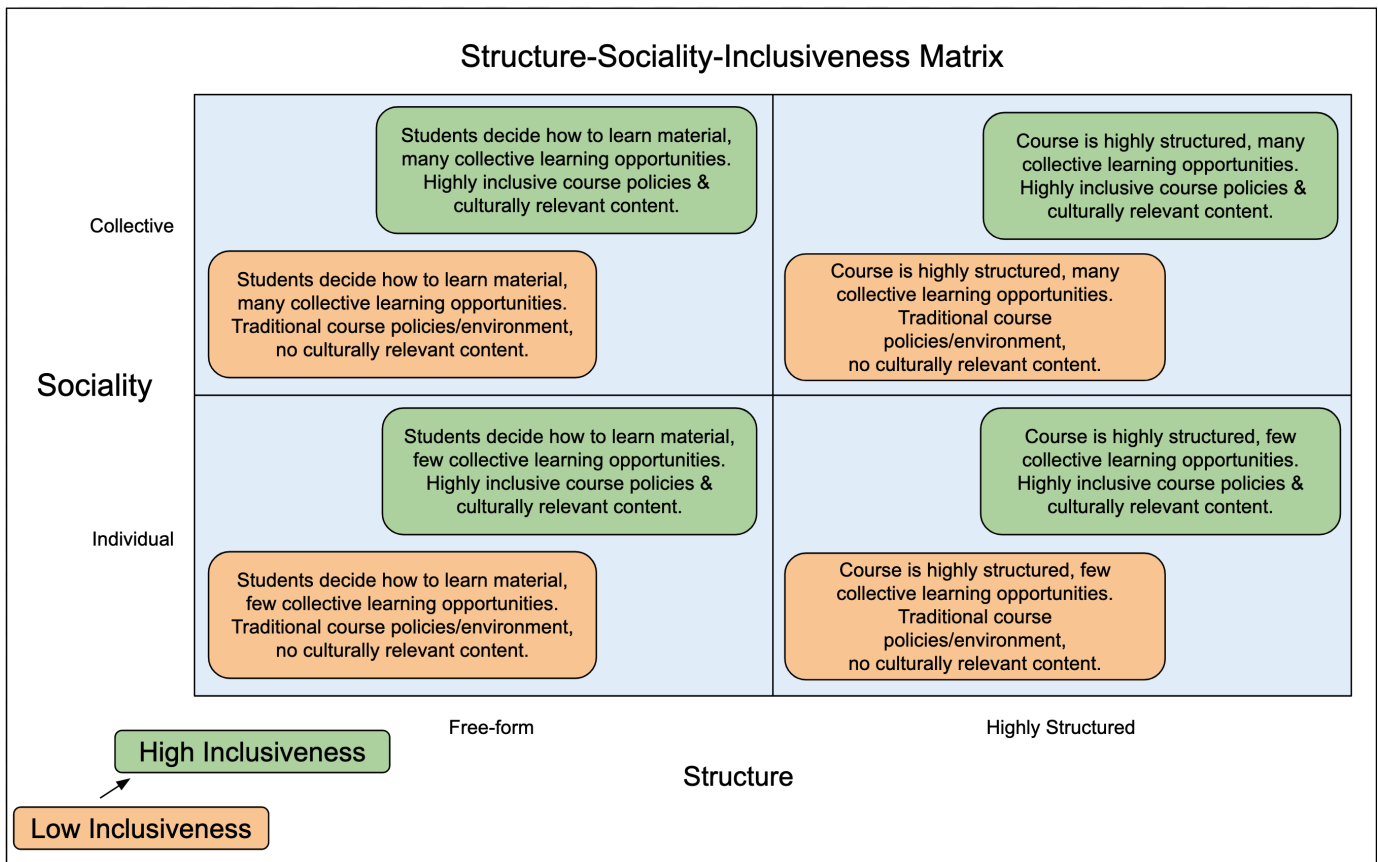


Fig. 3. Matrix for clustering courses by structure, sociality, and inclusiveness.

researchers. This subjectivity introduces the potential for bias and may affect the reliability of the findings. In our study, we minimize subjectivity with the assessments performed independently by multiple researchers using a standardized process that they are trained to conduct. Self-reported data from students, such as the CS Mindset instrument, may be subject to social desirability bias, where students provide responses they perceive as favorable. The CS Mindset Instrument included reliable and validated items, which will be continually examined throughout this study.

Data Collection: Administering multiple surveys to both faculty and students can lead to survey fatigue, where participants become overwhelmed or disengaged due to the frequency or length of the surveys. Mitigating survey fatigue requires careful consideration of survey length, timing, and the overall burden placed on participants to ensure high response rates and data quality. Sampling for diversity within a student population is an inherent limitation of any computer science education study. Applying an intersectional lens to examine student experiences by a myriad of groups enables a richer look at demographic descriptions. Additionally, there are logistical details that require alignment, such as coordinating different academic calendars, human subjects research approvals, and participant recruitment and retention. Ensuring an adequate sample size and participant retention throughout the study

can be challenging, especially when dealing with multiple courses and institutions. We have developed the following strategies to engage and motivate participants: obtain faculty buy-in through department meetings, embedding assessments into learning management systems, and address any concerns or barriers to participation on an ongoing basis.

Data Fidelity: Managing the accuracy, consistency, and timelines of data collection across institutions and courses is complex. Ensuring data quality, compatibility, and security across different systems and formats requires robust data management practices. Additionally, analyzing the data considering the variations in course timelines and institutional contexts requires careful consideration and appropriate statistical techniques. Our approach is to use a single collection point for CS Mindset, and to copy a learning management module for Knowledge Mastery, to ensure data fidelity. Data integration and analyses are copiously documented and are cross-checked by the research team.

V. CONCLUSION

In conclusion, this study contributes to the growing body of knowledge in computer science education by highlighting the significance and impact of creating supportive and inclusive classroom environments. The examination of classroom climate dimensions, such as structure, sociality, and inclusiveness, has provided valuable insights into their relationships

with student mindset, knowledge mastery, and intersectional identities.

The implementation of the CALI inventory, a comprehensive measurement tool for assessing classroom climate, offers educators and researchers a framework to evaluate and improve the learning environment. By utilizing knowledge mastery tools, educators can assess students' proficiency and understanding of CS concepts, leading to the design of more effective curricula and instructional strategies.

Moreover, the study emphasizes the importance of incorporating an identity analysis approach. By collecting demographic data and considering intersectional identities such as race, ethnicity, gender, first-generation college student status, and disability, a more nuanced understanding of the experiences and challenges faced by diverse students in CS education is obtained. This approach allows for the development of targeted interventions and support systems, ensuring that all students have equal opportunities to succeed.

Practical applications for educators and administrators include implementing the CALI inventory and related instruments to assess and improve classroom climates, designing effective and inclusive CS curricula and programs, and promoting diversity and equity in CS education. Policymakers can utilize these recommendations to shape policies and initiatives that foster inclusivity and support underrepresented students in pursuing and persisting in CS fields. By prioritizing diversity and equity, we can work towards a more inclusive and representative computer science community.

In summary, this study highlights the importance of classroom climate, knowledge mastery, and intersectional identities in computer science education. By utilizing the CALI inventory, knowledge mastery tools, and an identity analysis approach, educators, administrators, and policymakers can gain comprehensive insights into the factors influencing student experiences and outcomes in computer science education. These tools and approaches enhance our understanding of the learning environment, promote effective pedagogical strategies, and contribute to a more equitable and inclusive CS education system.

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APPENDIX

Below is an example of one of the mastery questions for a CS2 object oriented programming course using Java. The question tests students on the topics of object instantiation, inheritance and arrays. In this question students are required to understand object instantiation and the fact that a variable of the subclass can be assigned to an instance of the superclass. Students are also required to understand that an array of the super class can hold instances of the superclass or any of its subclassess. This understanding needs to be applied to determine which of the array declarations is legal.

```
class Animal {
    public String toString() {
        return "Animal";
    }

    public String f() {
        return "Animal f";
    }

    public String g() {
        return "Animal g";
    }
}

class Mammal extends Animal {
    public String g() {
        return "Mammal g";
    }
}

class Dog extends Mammal {
    public String f() {
        return "Dog f";
    }
}

class Reptile extends Animal {
```

```

    public String toString() {
        return "Reptile";
    }
}

class Lizard extends Reptile {
    public String g() {
        return "Lizard g";
    }
}

```

Which of the following are legal declarations?

- A. Lizard Godzilla = **new** Reptile();
- B. Animal Simba = **new** Mammal();
- C. Reptile Rango = **new** Lizard();
- D. Animal []Ark = {**new** Animal(),
 new Reptile(),
 new Lizard()};
- E. Lizard []Hatchlings = {**new** Animal(),
 new Reptile(),
 new Lizard()};