"An Instructor is [already] able to keep track of 30 students": Students' Perceptions of Smart Classrooms for Improving Teaching & Their Emergent Understandings of Teaching and Learning

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ABSTRACT

Multi-modal classroom sensing systems can collect complex behaviors in the classroom at a scale and precision far greater than human observers to capture learning insights and provide personalized teaching feedback. As students are critical stakeholders in the adoption of smart classrooms for the improvement of teaching, open questions remain in understanding student perspectives on the use of their data to provide insights to instructors. We conducted a Speed Dating with storyboards study to explore student values and boundaries regarding the acceptance of classroom sensing systems in STEM college courses. We found that students have several emergent beliefs about teaching and learning that influence their views towards smart classroom technologies. Students also held contextual views on the boundaries of data use depending on the outcome. Our findings have implications for the design and communication of classroom sensing systems that reconcile student and instructor beliefs around teaching and learning.

CCS CONCEPTS

• **Human-centered computing → User centered design**.

DIS '23, July 10–14, 2023, Pittsburgh, PA, USA

ACM ISBN 978-1-4503-9893-0/23/07.
https://doi.org/10.1145/3563657.3596079

KEYWORDS

smart classrooms, speed dating, learning analytics, teaching, learning

ACM Reference Format:
Tricia J. Ngoon, David Kovalev, Prasoon Patidar, Chris Harrison, Yuvraj Agarwal, John Zimmerman, and Amy Ogan. 2023. "An Instructor is [already] able to keep track of 30 students": Students' Perceptions of Smart Classrooms for Improving Teaching & Their Emergent Understandings of Teaching and Learning. In *Designing Interactive Systems Conference (DIS '23), July 10–14, 2023, Pittsburgh, PA, USA.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3563657.3596079

1 INTRODUCTION

Over the past few years there has been significant research into building smart classroom sensing systems to improve teaching, with the promise of providing meaningful insights not possible from digital interactions or human observations [11, 12]. Classroom sensing systems (*i.e.* wearable wristbands, eye-tracking devices, microphones, and cameras), which we use interchangeably with smart classroom systems, can capture a breadth of multi-modal data such as gaze, facial expressions, and speech. These data can provide insights into instructor and student behaviors, immediacy, and engagement [1, 10, 77, 80, 107, 137]. Compared to traditional learning analytics that use student-generated data to understand student performance and optimize learning environments and outcomes [26, 115], multi-modal learning analytics (MMLA) and classroom sensing systems focus on monitoring engagement and behavior for instructor reflection and improvement in what might be more appropriately termed, *teaching analytics* [1, 10, 77, 80, 137]. In this work, we focus on classroom sensing systems for the improvement of teaching through teaching analytics, which enable instructors to use both their own and their students' data to make decisions about teaching. This differs from work focusing on student performance and personalized learning because though student data is sensed and tracked, instructors are the primary system users.

Though teaching analytics and smart classroom systems are designed for the instructor, students are important stakeholders in the design of these systems as it is primarily their data tracked and sensed. While recent work has examined student perspectives in MMLA systems that assess student cognition and performance [32, 74], there is limited understanding of student perspectives for instructor-focused smart classroom systems as these often involve instructor perspectives [95, 128]. Most studies also focus on K-12 classrooms [49, 51, 95], which differ from college settings because undergraduate students are not required to attend class and more often self-regulate their own learning [13, 130]. These systems may be especially useful in improving college STEM teaching as prospective STEM students, especially from underrepresented groups, continue to leave STEM fields due to reported negative learning experiences and inconsistent quality of teaching [34, 111, 112]. As smart classrooms for improving teaching are not yet widely prevalent, the actual impact of classroom sensing systems on quality of teaching or student learning and the broader ethical implications of mainstream implementation are not yet understood [3, 21, 53].

Prior work on students' comfort and expectations with traditional learning analytics systems found that students were generally accepting of sharing their data for educational purposes or to the benefit of their grades [54, 57, 65, 125]. Students were mostly unaware of how their data was used and maintained by institutions and were hesitant to share any personally identifiable data [57, 65, 125]. Factors such as instructor and institutional trust also impacted students' propensities to consent to learning analytics [65]. However, generalized survey and interview techniques could not capture potential contextual factors or granularity of student responses [57]. For instance, students report intuitive feelings of discomfort with online data collection, but behave in ways that contradict this discomfort such as providing online data in exchange for course credit [94]. These nuances point towards a need to consider contextual integrity, a view of privacy in accordance to social norms and context [84, 85]. In instructor-focused smart classroom systems, students receive no direct benefit, and they may have different views towards sharing their data in these scenarios. Considering the debate around the potential moral "obligation to act" on student data to provide the best possible learning and teaching experiences, understanding student perspectives is crucial [92, 100].

We conducted a Speed Dating study with storyboards [25, 143] with undergraduate STEM students to examine students' values and boundaries, their desires and fears, with regards to the uses of classroom sensing systems. Through iterative brainstorming, we developed 27 storyboards of imagined futures with hypothetical sensing systems in college STEM courses. Based on prior work and discussion, these storyboards varied the level of data identifiability and the directness of impact to understand contextual factors in accepting the use of student data from classroom sensing systems [3, 21, 57, 65, 99]. From our study, we found that students held several assumptions about instructors' abilities and emergent beliefs about learning and teaching, which impacted their views towards classroom technologies and giving their data for the purposes of improving teaching. For example, students believed technology might standardize teaching or decrease student and instructor autonomy. Although we expected that students would not share personally identifiable data, we also saw surprising contextual nuances. For instance, some students were willing to share personally identifiable data if it would improve an instructor's awareness of students' emotional well-being.

We make two primary contributions. First, through our Speed Dating study, we demonstrate students' values and boundaries for which students find the use of their data from classroom sensing technologies appropriate. Second, we contextualize students' nuanced views by situating these views within their emergent beliefs about teaching and learning. Our findings show the relationship between students' beliefs about teaching and learning and their willingness to share data for smart classroom technologies for improving teaching. We conclude the paper with future opportunities and cautionary considerations for the design of smart classroom technologies.

2 RELATED WORK

2.1 Multi-modal Learning Analytics (MMLA) & Teaching Analytics

Learning analytics is broadly defined as the use of student-generated data to derive educational insights, primarily focused on interactions in virtual environments such as Learning Management Systems to predict and enhance student performance [63, 115]. Student-generated data consists of interactions recorded through digital actions in online learning environments [26, 89]. Yet much of teaching and learning involves the physical. Teachers use both verbal and nonverbal behaviors (*i.e.* gaze, gestures, tone, etc.) to foster student engagement and rapport with students [4, 5]. MMLA and a more teacher-focused subset, teaching analytics, take advantage of physical, in-class behaviors using a variety of sensing devices to capture both teacher and student behaviors rather than only student-generated data [11, 12, 81, 110, 136]. Classroom sensing systems, or smart classroom technologies, can capture complex data beyond that of traditional online analytics or human observation by generating insights from physical traces of activity [76, 89]. In particular, classroom sensing systems can capture ephemeral nonverbal behaviors or interactions for precise recollection and reflection [11, 12]. There are several types of sensing systems that can capture different types of data. For example, prior work explores collecting "under the skin" biometric data such as heart rate variability and electrodermal activity [31, 37, 76] and neural activity through electroencephalography (EEG) devices [74, 95, 96]. Location-tracking badges to track instructor movement throughout a classroom to assess spatial pedagogy [77, 80]. Unobtrusive sensors that do not require users to wear or carry sensor devices can track student engagement with classroom materials [107] or collect and analyze a variety of audio [19, 39, 108, 117] and video [1, 16, 27, 71, 88, 126] data to record verbal and nonverbal behaviors in the classroom. This breadth of multi-modal data can provide new educational insights that link behavior to learning.

Prior work has also examined the use of teaching analytics data to improve teaching based on pedagogical interventions and learning theory. Several systems aim to assist teachers' reflections on their own teaching behaviors [59, 81, 95, 96, 105, 110]. For example, Prieto et al [95, 96] examined the use of classroom sensing to create automated graphs of a teacher's activity to aid their in-class orchestration. Holstein et al [49, 51] addressed design challenges in using AI-supported systems for classroom orchestration. Some systems also aim to help improve a teacher's spatial pedagogy [69] by visualizing how a teacher uses a classroom's physical space [77, 80, 139]. While instructors may gain insights from seeing visualizations of their own data, they may also be interested in seeing their students' behaviors and reactions to their own teaching behaviors [105, 138]. Smart classroom systems can utilize both student and teacher data for instructors to understand the impact of their teaching behaviors. For example, Gerritsen, Zimmerman, & Ogan [38] presented a smart classroom system for helping teaching assistants reflect on their teaching behaviors and their students' reactions to these behaviors and provided scaffolds based on active learning practices and pedagogical theory (*i.e.* using wait time after questions to promote student engagement). Xhakaj et al [138] visualized multi-modal data for instructors to better utilize nonverbal behaviors for improving immediacy, the interpersonal closeness between instructors and students [4, 5]. This data can give instructors additional information of their classroom behaviors to improve their pedagogical practice beyond content-based changes.

Awareness of what is happening in the classroom and student engagement and attention are also major aims of smart classroom systems. Rodriguez et al [105] used a customizable MMLA system to help teachers monitor their students' attendance and participation in class. Similarly, behavior management systems make handling student behaviors more efficient and simpler [24, 119]. Systems can use overt student behaviors such as hand raises or posture as signals of student engagement [1, 16, 39, 82, 142]. They can also attempt to detect student emotions while performing complex learning tasks [33, 40] through measuring latent states of engagement, attention, or affect through biometric data [31, 37, 74, 127] and gaze tracking [10]. Predictive analytics to estimate domain expertise can help instructors give personalized feedback [7, 47, 87, 88]. For example, Ochoa et al [88] used audio and video sensors to give students feedback on oral presentation skills. Recent work additionally examines collaboration analytics and collaborative learning processes to support active learning [19, 31, 79]. At the institution level, smart classrooms can also provide data to better determine resource allocation and optimize classroom space [126]. While instructors (and sometimes institutions) are the primary users of teaching analytics smart classroom systems, student data contributes to these systems. For this reason, we focus on student perspectives on the use of their data in these systems.

2.2 Importance of Student Perspectives for Classroom Sensing Systems

A large concern with ambient sensing devices such as microphones and cameras that collect student data in the classroom is over-surveillance and vulnerability that can make the classroom an uncomfortable environment [91, 99]. Pervasive monitoring technologies commodify surveillance in "surveillant consumerism" [122]. As technology in the classroom becomes increasingly common, teachers themselves might be thought of as surveillant consumers who use technology to monitor and generate data about students' learning and behaviors [61]. Complex and sensitive multi-modal data (*e.g.* facial expressions, gaze, biometric data, etc.) also bring up questions of data control, access, and use (or misuse) [21, 57, 99, 106]. There is an ethical tension between the "obligation of act" on student data to improve teaching and learning and the importance of considering student perspectives [100]. Most prior studies of student perspectives focus on traditional online learning analytics [54, 57, 65, 67] or systems that focus on assessing student performance and learning [50, 74, 97]. In these cases, students are also users of analytics systems and can keep track of their performance and receive more personalized learning. Students were generally accepting of using their data in online learning analytics to improve learning outcomes and education, but there were boundaries of what data they were willing to share, such as digital data trails (*i.e.* time spent online, download frequencies) though this data might be used to create more adaptive and personalized learning experiences [54]. Students also had differing propensities to consent to learning analytics depending on their levels of institutional trust or their own values around privacy and potential data use [65, 67, 106]. Importantly, students in these studies did not have awareness of the full extent of what data was collected, how it was used, and the outcomes of data use from the institution, complicating the issue of informed consent [57, 125]. One gap in this prior work is that students did not (and could not) share their preferences with any granularity. Students could not provide specific scenarios where they would approve of their data use because these scenarios are impossible to imagine in the abstract [57]. In practice, students may sometimes demonstrate a privacy paradox in which they behave in ways that conflict with their stated privacy preferences depending on the context [86]. For example, students might express an intuitive concern that online browser tracking is "creepy," but felt no concern in installing an online browser tool that monitored web activity in exchange for course credit because of the perceived benefit for themselves [94]. This calls for a need to consider contextual integrity in the design of multimodal analytics systems, which views privacy as something dynamic that changes in accordance with social norms [84, 85].

For smart classroom systems that focus on improving instructor teaching, instructors are the primary users and viewers of data. Student data is tracked and sensed, but they themselves do not receive direct benefits, which emphasizes the importance of student perspectives. Prior work in teaching analytics systems focus on the instructor's perspective [95, 128]. For example, Prieto et al [95] conducted a deployment of a MMLA system and interviews with teachers to uncover the value of these systems for teachers. Holstein et al [49, 51] do take into account both student and teacher perspectives in co-designing real-time intelligent tutoring aid in K-12 classrooms. K-12 classrooms differ from college classrooms as undergraduate students are not required to attend class and are more self-regulated in their motivation to go to class [13, 36, 130]. While students are not experts in learning theory or pedagogy, their lived experiences within the classroom affect their agency and motivation in their learning. We build upon the prior literature by examining student perspectives in undergraduate STEM courses for smart classroom systems for improving teaching.

2.3 The State of College STEM Education

We chose to focus on STEM college courses because many research efforts in education demonstrate that active learning is beneficial for improving student learning and experiences, particularly in STEM [35, 43, 60, 98]. However, implementing active learning practices is challenging. STEM college instructors report issues of scale, poor student evaluations, and prioritizing research activity as primary reasons that hinder the application of active learning [6]. Several factors such as race, gender, and other personal characteristics can bias student evaluations [9, 93, 120], which may influence how instructors choose to implement class activities. Despite the benefits of active learning, students often report more negative attitudes towards active learning methods, citing more discomfort and anxiety at discussion activities [18, 22, 118] and even feeling as though they learn more from lecture-based methods [29, 121, 132]. As a result, much of STEM teaching remains lecture-based and didactic teaching [62, 83, 121]. This may contribute to STEM college instructors' hesitancy to use active learning strategies [23, 113]. Furthermore, faculty and teaching assistants do not have consistent time nor opportunities to participate in teaching professional development activities in general [14, 45, 46]. Thus, they may not have the professional development to learn to implement active learning practices [135]. At the college level, the most common forms of personalized professional development and feedback are through consultations or observations [14, 17, 123], but these methods do not scale. The lack of teaching training may contribute to the uneven and inconsistent quality of teaching in college STEM classes, which prospective STEM students cite as reasons for deciding to leave STEM fields altogether [111, 112]. These pedagogical issues make exploration of classroom sensing systems in STEM classrooms timely.

3 METHOD

Students are critical stakeholders in smart classrooms meant to improve teaching. These systems collect data on students' in-class actions and reactions to an instructor's teaching actions. Depending on how they are implemented, they can collect either de-identified and aggregated information or identifiable data on individual students. They can directly impact students' grades and in-class experiences or indirectly impact students through longer-term teaching changes. We wanted to understand how students in STEM classes perceive these types of potentially invasive system functions within their assigned classrooms both in terms of values and boundaries. Did they have concerns about their privacy? Did they view data collection as a fair trade if it resulted in better teaching? Did they have fears and desires that should be considered in the design and implementation of this emerging technology? These questions have been raised in prior work as salient issues the use of smart classroom systems that measure student performance [3, 21, 57, 99], and we wanted to examine student perspectives in systems that provide no direct benefit for themselves.

It is hard to imagine what potential futures with these systems might look like without widespread adoption. While co-design methods such as those described in [50, 78, 97] are useful for eliciting student wants and preferences, they do not specifically test boundaries of what students do not want. We conducted a Speed Dating study in the form of needs validation using storyboards [25, 143]. Speed Dating is a method specifically designed to investigate people's acceptance of future technology, a way to conduct "fieldwork on the future" [90]. As Speed Dating is a future-oriented method, participants do not need to have experience with the systems or ideas being probed in order to share deep insights [143]. Much like romantic speed dating, participants go on many short encounters or "dates" with possible futures. At the end of the session, participants know little about any specific date (future), but they have gained insights on what they really want and what they find disturbing or troubling [143]. When conducting needs validation with storyboards, researchers show participants a number of storyboards that first situate the participant in a familiar situation and then exposes a possible technology intervention that is often provocative and controversial to uncover participant desires and boundaries. Researchers then scaffold participants in critically reflecting, encouraging participants to clarify their reaction and working to understand the rationale for why they seem to be having this reaction. Speed Dating has been used in a range of socio-technical contexts including family smart homes [25], privacy behaviors [55], automated in-class orchestration tools [51], and even boundaries of social robots [73, 104]. It can include large-scale online deployments for testing hypotheses [25, 55, 104] or semi-structured interviews and focus groups with smaller sample sizes for more in-depth responses [30, 73, 109, 128, 133, 141]. In the domain of learning, the predominant form of Speed Dating has been small samples or focus groups where needs validation is the primary or sole contribution [51, 109, 128, 133]. For example, Tenorio et al [128] used needs validation with storyboards to investigate teachers' use and acceptance of gamification analytics with 15 teachers and 20 storyboard concepts. We follow a similar model.

3.1 Participants

As our study is focused on technologies for college STEM classes, our participant scope was undergraduate students who took STEM classes. We recruited participants through convenience and snowball sampling by advertising on undergraduate research program listservs and Slack and through word of mouth recruitment. Participants were undergraduate students majoring in primarily technical fields from 11 universities in the United States participating in a research program at the institution of the first author. Recruiting students from a diverse set of universities allowed us to generalize potential findings across different higher educational settings. We conducted sessions with 14 participants (8 female, 6 male) was sufficient for data saturation [41]. 6 students identified as White, 5 students identified as Asian-American or Pacific Islander, 2 students identified as Black, and 1 student identified as Hispanic. 5 students completed one year of college, 6 completed two years, and 2 completed three years, and 1 completed four years. 2 students attended large universities where large STEM lecture courses are common, 9 students attended mid-size universities where large STEM courses are common for first-year students, and 3 students attended small universities where large STEM lecture courses are uncommon. School size was determined according to the National Center for Education Statistics' College Navigator database[1]. See Table 1 for participant demographics.

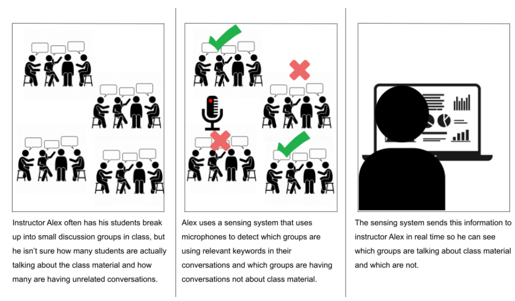
[1]https://nces.ed.gov/collegenavigator

Student ID	Years completed in college	School size	Major	Gender
S1	2	Large	Computer Science and Linguistics	M
S2	4	Medium	Electrical Engineering	M
S3	2	Medium	Computer Science	F
S4	2	Small	Computer Science and Mathematics	M
S5	2	Small	Computer Science and Philosophy	F
S6	1	Medium	Computer Science	F
S7	2	Medium	Computer Science and Cognitive Science	M
S8	3	Small	Math/Computer Science and Physics	F
S9	2	Large	Computer Science and Mathematics	M
S10	1	Medium	Human-Computer Interaction	F
S11	3	Medium	Computer Science	F
S12	1	Medium	Computer Science	M
S13	1	Medium	Computer Science	F
S14	1	Medium	Computer Science	F

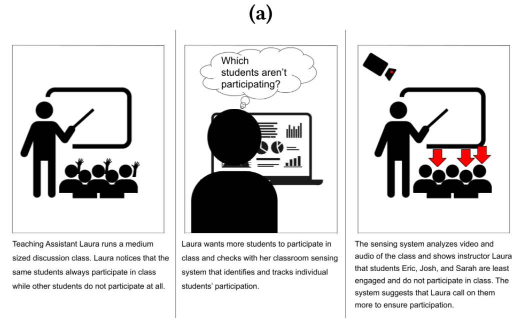
Table 1: Demographics of student participants.

3.2 Storyboard Generation

Our research team consists of 4 faculty members, 1 postdoctoral researcher, 1 doctoral student, and 3 research assistants with experience and expertise in ubiquitous sensing, learning science, and design. We have previously deployed instructor-focused smart classroom systems in college classrooms and conducted interviews and co-design with college instructors. These previous experiences informed the topics we brainstormed in the generation of storyboard concepts. All members of the research team brainstormed potential storyboard scenarios over the course of several months. Some of the topics we brainstormed included the identifiability of data, teaching evaluations, instructor awareness, evaluating student participation, real-time notifications, and post-class reflection. The first and second authors generated an initial set of 35 storyboards depicting various sensing systems with the goals of awareness of instructor and student behaviors and evaluation of teaching and learning. These storyboards explored conditions such as identifiability of data and impact of data as these are among the important issues identified in prior work [3, 21, 42, 57, 65, 99]. *Identifiability* refers to the degree to which student data was could be identified. This ranged from individual personally identifiable information (*i.e.* per individual student), grouped anonymity (*i.e.* left side of the class versus the right side of class), to fully aggregated and anonymous (*i.e.* entire class as a whole). *Impact* refers to whether outcomes directly impact the student's academic or in-class experience (*i.e.* grades or being called on to participate) or indirectly impact the students' learning experience (*i.e.* feedback to the instructor). Table 2 describes example storyboard scenarios along these dimensions, and Figure 1 shows two example storyboards. We designed the storyboards to be provocative, with some meant to push past expected comfort levels such as instructors analyzing the content of group discussions (Figure 1a) or tracking student engagement to select students to cold-call (Figure 1b). After discussion with the rest of the research team and pilot sessions with 3 STEM undergraduate research assistants who were part of the research team and 4 sessions with undergraduate STEM students who were not familiar with the research, we refined the storyboards to a total of 27 finalized storyboards[2]. The first and second authors led data collection and data analysis with input from the other authors. All authors took part in the writing and review process of the paper.



(a)



(b)

Figure 1: Two example storyboards. a) (Grouped anonymity, indirect impact) The instructor wants to know which groups in a collaborative activity are having on-topic class discussions. b) (Identifiable, direct impact) The sensing system identifies students who participate less for the instructor to cold call.

[2]All storyboards used in this study are included as supplementary material.

	Impact	
Identifiability	Direct	Indirect
Individual	An instructor uses a camera-based sensing system to track individual student engagement to determine which students to encourage to participate more in class (Figure 1b).	An instructor uses a camera-based sensing system and sees that a student is stressed and less engaged than normal. The instructor recommends the student speak to a school counselor.
Grouped	An instructor uses a location-tracking sensing system to analyze in-real time where in the classroom she spends the least amount of time. She then moves to that part of the classroom.	An instructor uses an audio sensing system to see which groups of students are staying on task by tracking keywords said in their discussion (Figure 1a).
Aggregate	An instructor uses an audio sensing system to measure the proportion of instructor and student speech. The system suggests that the instructor give time for students to participate in discussion more.	A school decides to use camera-based sensing system data to evaluate teaching based on teaching practices and student engagement.

Table 2: Example storyboard scenarios based on the dimensions of Identifiability (Individual, Grouped, and Aggregate) and Impact (Direct and Indirect). Two storyboards from these scenarios are shown in Figure 1.

3.3 Procedure

Study sessions were conducted with one researcher and one participant either in-person or on Zoom depending on the comfort of the participant and local health guidelines regarding the ongoing COVID-19 pandemic. The researcher first asked the participant about their background and prior experiences in college STEM classes. The researcher then gave a brief introduction to classroom sensing systems and presented storyboards to the participant. For each storyboard, the researcher asked open-ended questions to get the participant's opinions and impressions on each storyboard scenario. Participants were asked to assume that all students and instructors consented to using the technology described in each storyboard, the technology was capable of doing what was described, and all data was secure. This was to probe on their thoughts without the limitations of real-world technical capabilities. Storyboards were presented on a computer screen and in random order to each participant to prevent order biases. Lastly, the researcher asked general concluding questions regarding the use of classroom data. Study sessions lasted between 45-90 minutes, and participants were compensated $20USD. All interviews were audio recorded and transcribed via Zoom or by a researcher when transcription quality was low. This study was approved by the institutional IRB.

3.4 Analysis

We analyzed student responses using affinity diagramming, an analysis technique for exploratory design research which reveals higher-level ideas and commonalities in qualitative data [52]. Our affinity diagramming sessions took place in the web application Miro[3]. Through several interpretation sessions, the research team compiled relevant quotes (840 in total) and labeled them based on participant, storyboard, and data dimensions (identifiability and impact). These quotes were iteratively grouped based on emerging affinities based on a three-level grouping approach described in Holstein, McLaren, and Aleven [49]. Level-1 grouping consisted of grouping quotes based on content similarity and labeling clusters. Level-2 grouping consisted of grouping level-1 clusters into larger themes and labeling these clusters as well. We then repeated this grouping for level-2 clusters to find and label higher-level insights as level-3 themes. We continued iterating on these affinities until we reached a consensus through discussion and critique.

[3]https://miro.com

4 FINDINGS

Here we describe common patterns that emerged regarding students' perceptions classroom sensing systems that collect and process student behavioral data to improve an instructor's teaching. Overall, we found that students' emergent beliefs about learning and instructors' abilities impacted their divergent views of classroom sensing technologies (Table 3).

4.1 Students Value Connections with Their Instructors & Peers

4.1.1 Connections with Instructors. Students desired a connection with their instructors, expressing that they wanted to "*make a good impression on my professor*" (S14) and "*care a lot about what teachers think about me*" (S5). In turn, students wanted instructors to show they cared for students. Many students expressed a concern that though smart classroom technologies might improve teaching, they would create a disingenuous relationship between instructors and students: "*I think I care so much about [teaching] being genuine, that I would take subpar teaching with like a genuine relationship and connection...I know that seems kind of like an ideal world, and my school really does work like that*" (S5). Some students also believed that instructors might "game the system." In response to a scenario in which instructors used smart classroom systems to track their behaviors towards teaching goals, S9 stated: "*It wouldn't impact me directly, it would impact the teacher more, but I think that would make teachers fairly unhappy...if they try to game the system, I can see the classroom experience being a lot worse*" (S9).

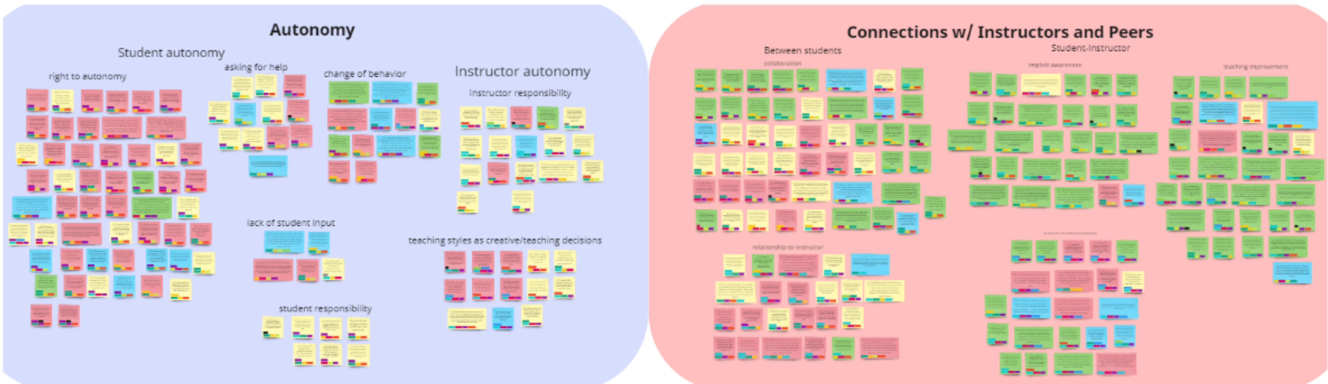


Figure 2: A partial view of the affinity diagram, showing how participant quotes were grouped within themes.

Instructors using technologies to monitor student affect also received many negative reactions. Many students were highly uncomfortable with the idea unless they already had a good relationship with their instructor: "*If an instructor needs the sensing system to tell them that a student has been less engaged over the past week then I don't think they have kind of a close enough relationship to recommend that kind of thing*" (S10). S14 also added that it was dependent on her relationship with an instructor for them to know her emotional status: "*Like I just don't feel comfortable with every single one of my teachers, for them to know like I'm not really doing good right now...I wouldn't be comfortable with that.*" S5 believed that classroom sensing technologies would "*[compromise students'] privacy and [turn] them into these data points every class period by monitoring them.*" We were surprised to find contextual views regarding emotional awareness and about the use of personally identifiable data. For example, S8 said, "*I think for me personally it would be helpful because if someone else brings your attention to something objective that is different, it could verify suspicions that you're not doing well...I think there could be benefit to the professor seeing the data and making sure it's consistent to what they perceived.*"

4.1.2 Students Want Implicit Awareness, but Have Assumptions about Instructors' Abilities. For scenarios that provided instructors with implicit awareness, such as those that give instructors information about which students need attention, received mixed opinions. Some students saw them as unnecessary because they assumed instructors already had full awareness of their class: "*It wouldn't really be saying anything that one couldn't figure out for themselves...whatever this can accomplish, there are much less invasive ways of doing so*" (S10). S1 further added, "*You're just recording everything that everybody is saying for the hope of doing something that is already handled pretty well...I think you're getting too much data for very little benefit.*" S8, who attends a school with small STEM classes, mentioned that smart classrooms for implicit awareness seemed unnecessary: "*If the class is small enough, the professor should have an accurate view of [engagement] without a computer system.*" S9, who attends a university where large STEM classes are common, said the following in response to the storyboard shown in Figure1b where an instructor wants to use cold-calling to get more students to participate:"*In large classes, I think it's impossible to make everyone participate in the first place so I feel like you really want this in a small class, and in a small class, it's realistically possible for the instructor to see who's participating and who's not so I'm just like questioning the usefulness of such a system...in general, an instructor is able to keep track of 30 students.*" S14 also thought instructors could keep track of "*upwards of like 20 or 30*" students. Students also assumed that instructors had training for teaching and would not need additional help: "*[Instructors are] regularly evaluated for how well their teaching and given tips in terms of how to teach the topic*" (S13) and "*Teaching is [the professor's] primary job, and they've been training for this*" (S11). They saw teaching ability as somewhat innate, believing that some instructors were naturally "*better at [teaching] than others...a good professor will naturally be engaging because they are excited about what they're teaching*" (S12). Despite students' beliefs that instructors are trained in teaching, prior work shows that college instructors rarely receive teaching training [6, 14], which may lead to different expectations about what instructors can and cannot do.

Some students did see value in systems that provided implicit awareness for instructors. S11 thought these scenarios were most useful for students who were not always comfortable asking for help or giving feedback directly. For example, S10 stated, "*If there was a way to kind of indicate to professors like 'hey this lecture was boring,' and have someone else notify them, I think I would be in favor of that because I could see it having a ton of positive outcomes.*" S11 also thought, "*It takes the pressure off of students to like actively say 'hey I don't know what's going on' and just gently nudge the professor so they can use that information to subtly walk over.*" S8 saw a benefit of implicit awareness in larger classes, "*In a big environment, that would be especially helpful when...the instructor can't engage with everyone for a significant amount of time, and they need to prioritize who they go to.*" Some students also reacted positively to scenarios where instructors were made aware of their implicit biases: "*most of the times professors want to not be biased, but there's just some things that they do unconsciously and having that information explicitly telling them ... would help them see what they are doing and then they could think about how to improve that*" (S7). Students' perceptions of instructors' awareness and abilities influenced whether smart classroom technologies were even necessary for instructors.

4.1.3 Connections with Peers. Students saw themselves as a collective and valued connections with other peers. Students were more favorable towards scenarios that had "*a net classroom benefit*" (S9) that promoted greater equity in discussions even if it would not impact their own individual experience. For instance, a student who identified as White and a male (S1) said about scenarios to reduce implicit bias, "*I would like everybody regardless of their race and whatnot to be treated appropriately and fairly. I mean I guess as a White guy it wouldn't help me, but it would help the student body.*" Students also expressed nuanced views about technologies that would monitor and assist instructors with managing collaboration among students. Some thought that technology would be helpful in mediating communication with other students, especially in uncomfortable situations: "*It's hard for even a student who talks too much to recognize that they are not letting other people speak ... other students might not want to say something to them because they don't want to be rude*" (S14). However, some students were concerned that technology that attempted to improve or measure collaboration would take away from important learning aspects of collaboration. In one scenario in which classroom data is used to assign students to collaborative groups based on their interactions, S3 commented, "*Collaboration is about hearing other people but also presenting your own opinions and ideas in a more accepting way, and when you use technology to reassign groups, it's just really troublesome.*" Students generally liked ideas towards communication mediation rather than resolution or forced collaboration.

4.2 Students Value Autonomy in Teaching & Learning Experiences

Students had strong opinions about what learning and what the learning experience meant to them. We presented several storyboard scenarios of classroom sensing systems measuring proxies of student engagement and participation to help instructors manage engagement in their classrooms. These elicited responses divided along the lines of objectivity and subjectivity. Students viewed engagement to be "*a subjective statistic*" (S12) that "*cannot be quantified*" (S9). In one example, S7 thought that overt student behaviors typically thought of being associated with participation and engagement like hand raises or speaking in class do "*not mean that you're engaged or you're actually participating and paying attention in class.*" These perceived definitions of engagement related to students' thoughts about autonomy and comfort in the learning environment.

4.2.1 How Students View Autonomy. Students strongly desired autonomy in shaping their own learning experiences. Many were concerned that classroom sensing systems would cause an unnatural change in behavior and loss of such autonomy. S10 believed this change in behavior would lead to a negative learning experience: "*if all of a sudden kids are getting called out to participate when they hadn't been [before], then I get less out of it because then we're kind of focusing on what other people are confused about rather than what I'm confused about.*" S5 worried that engagement would no longer be authentic: "*Maybe [engaging] makes me a person who gets better grades but I don't think that makes me a better person, I'm not interested in school at that point, like I'm doing it for the credit.*" Scenarios in which technology suggested ways to encourage students to participate (such as cold-calling, as seen in Figure 1b) received mostly negative reactions because students saw engagement (and disengagement) as a conscious choice: "*I feel like the professor should kind of just do their part in meeting students halfway, but if students choose not to take initiative I don't feel the professor should kind of force them to participate...If I don't sit in the front, I know I'm making the conscientious decision that like I'm not ready to be fully engaged, and sometimes I'm pretty okay with that*" (S14). Students had somewhat differing views in terms of who bore the responsibility of engaging students. Some felt it was their own responsibility to adapt and engage in class in their role as students, "*If other students in the class aren't paying attention that's their problem*" (S12). Others thought "*more of that responsibility [in engaging students] tends to kind of fall on the professors* (S11).

In general, students were more favorable towards use cases where they were rewarded for effort rather than being used in a formal evaluative or punitive sense. Students expressed concern that classroom sensing systems would need identifiable data in order to assess learning and engagement: "*I don't like individualized student tracking...if it would be more aggregated or maybe like a group, like this group of students in this area are participating less than students everywhere else...that would be better as long as it's not individual scores or rankings kept per individual*" (S2). This view was also contextual as use cases where identifiable data would reward students for effort were seen more favorably. S6 said, "*The engagement part of it, where you're actually able to keep track of like individual students and then there's some sort of incentive so there's like actually a reason for students to care.*" S14 thought classroom dynamics could change in a positive way: "*I think most people who don't discuss don't want to because they're too shy, but it's like a useful life skill to step out of your comfort zone and then once a teacher kind of forces that initial step...those students who are initially shy...kind of ease into the conversation and start to participate on their own.*" These students perceived classroom technologies as more objective: "*it implements more objectivity to [showing effort] because it's not just what the professor kind of internally perceives as people who speak up the most*" (S11). However, S5 saw this objectivity as a negative: "*it's adding more of that scientific objective rationality into the classroom environment that...I personally don't like...the more that you have a system that you put a lot of trust in...then you're likely to just listen to that and abandon your own potential for judgment.*" Students brought up the idea of "gaming the system" as well: "*If I had access to the algorithm, I could literally just analyze the algorithm and then see what will give me a higher score so it's gonna result in like social inequality or some other big issues*" (S3). These differences in views were tied to students' beliefs about their own individual choices about engagement.

4.2.2 Students Want Comfort in the Learning Environment. Related to autonomy, students also wanted to feel safe and comfortable in the classroom. Many students expressed concerns that classroom sensing systems would reduce comfort. Students felt that "always on" sensing systems in the classroom were "*unnerving*" (S5) or "*distracting*" (S8). They worried that these systems meant to improve teaching could potentially make instructors more authoritative or supervisory in the classroom. For example, in response to a scenario where an instructor monitors group conversations, S11 said: "*Not a fan of this one, this is directly analyzing every little conversation you're having and then sending it [to the professor].*" S5 thought that sensing systems would make "*students into the teachers' 'zoo'*" and felt "*offended*" at the feeling of being under surveillance. Several students mentioned feeling "*self-conscious*" (S13). S9 said, "*I think people would be less inclined to answer questions...it's difficult to dispel the social anxiety of something watching me. As a result, that would change the classroom dynamic in a negative way.*" These views on how technology might affect students' comfort were also related to their views of autonomy and the role instructors had in engaging students.

4.2.3 How Students View Instructor Autonomy. Students were concerned about the loss of instructor autonomy. They worried that technology for measuring or suggesting teaching practices would lead to standardized or routine teaching: "*There's different teaching styles, it's not so black and white...they wouldn't be able to teach in a way that they like to teach*" (S12). S7 elaborates, "*The cost of not letting professors try new things is more important than kind of incentivizing a specific way of teaching...All the classes would be the same way and it wouldn't have as much space for professors to innovate the way they teach.*" Students were also against technology-generated suggestions for this reason. For example, in one scenario where an instructor is notified of the time spent lecturing in class, one student thought the system was "*trying to standardize how much each professor should talk… like percentage of professor talk versus student talk… and I don't think that should be standardized*" (S3). In another scenario where a system provided a suggestion to the instructor to engage students, S5 responded, "*This is like 'okay professor, you should ask more questions', which I think is already kind of biasing what [an instructor] could possibly think about as an array of solutions into this particular one.'*"

Scenarios that probed on whether classroom sensing systems should be used to evaluate teaching received universally negative reactions. Students valued the subjectivity of teaching evaluation surveys because they felt that technology would not be able to capture student sentiment: "*A genuinely good teacher is going to be based off of the outcomes of the students, rather than [the] every day being like...where the learning goals are being like achieved...If people make bad mistakes you will hear it from the students and not necessarily from the machine*" (S1). Though students acknowledged evaluations could be biased, they thought these surveys were still valuable to give students a voice: "*Of course student surveys are biased. They're opinions, student surveys are opinions. The perception from students is what matters the most. It doesn't matter if it's biased*" (S8). S5 added, "*I get the appeal, it could be beneficial like teachers, avoiding like the really negative unhelpful feedback and getting like a more objective analysis of their teaching... I don't know if having a system prevent instructors from receiving [unhelpful] surveys is really worth it...I think we should work on refining that practice like maybe asking better questions or finding a way to still have students give their input.*" S3 stated that teaching evaluations are helpful for deciding which classes to take: "*When you sign up for a course, you know what kind of professor you're signing up for.*" For students, teaching evaluations evaluate the *teacher* rather than the teaching.

4.3 Student Views on the Role of Technology in the Classroom

4.3.1 Students' Views Towards Smart Classroom Technologies Depend on the Types of Data & Context. Though students generally objected to classroom sensing in situations where they expected privacy, these expectations varied between students. For example, S1 thought "*a small class discussion is not a public thing*" while S13 said they "*wouldn't mind [audio recording] if it's limited to a small group discussion.*" S4 considered the classroom a public space: "*If [students] are in class, and they talk about something private, it's going to be their problem.*" Students also had different comfort levels depending on the types of data collected. For example, biometric data was seen as both "*very innocent data*" (S4) because such data is "*the kind of information that my smartwatch can tell me*" (S11) and on the other hand, "*an entirely new dimension of tracking, and it feels a little invasive*" (S10). Gaze and facial recognition or emotional expression analysis were especially contentious: "*It's different if you're looking at someone's attendance because you only need to see that instance one time or like a hand raise you only need to see that body part go up, but with gaze you're analyzing not only where they're looking, but what they're looking at, kind of almost trying to figure out what's going on inside their head*" (S14).

In some cases, students mentioned how technology would impact their academic decisions. Though most students often preferred taking a class with no smart classroom system if possible, the system was not a deal breaker in itself: "*If there were two classes, and I wanted to take them on an equal level, and one had [this system] and one didn't have this, then I would take the class that didn't have this, but if I really want to take a class it's not going to be a huge impact*" (S12). S6 also mentions that the prestige of the school would affect their views of smart classroom systems, "*Depending on how good the school is...yeah I'll [consent], but I mean if it's just a regular school...and I find out that they have [smart classrooms] then like no.*" These statements may represent a privacy paradox [86] where students have an intuitive concern about sensing systems, but considered assessments of benefits and risks may override the intuitive concerns. In another example, though S11 reacted negatively towards audio data recorded in the storyboard in Figure1a, she reacted more positively towards audio data recorded as a way to provide the instructor with implicit awareness of when students were confused, "*I appreciate the concept of this.*" These student conceptions of privacy expectations based on context of use and the types of data collected spark questions about activity-based classroom sensing.

4.3.2 Opportunities for Human-Computer Collaboration. Participants primarily majored in technical STEM fields. Based on their knowledge, many thought "*computers are stupid...they are very just rigid and not as flexible as human beings*" (S3). As technical STEM majors, they were cautious about smart classroom systems making decisions that seemed more appropriate for the instructor. Students were generally favorable towards using classroom sensing data as supplemental information: "*[The data] is just like supplemental information, it would help the professor to have a more informed decision...instead of having something fixed that they need to do it in a certain way*" (S7). Though S5 was generally against technology-provided teaching suggestions, she mentioned, "*It would also be interesting if [the system] gave them options like 'here are five ways* *that you can improve engagement*." Students also saw value in providing data alongside subjective surveys: "*I think [data] should be used with other information like surveys and feedback from the students,...but I think in general it could help to encourage the professors to be better teachers and make the students more engaged so they could go to a better classroom*" (S7). S11 acknowledged how data might reduce potential bias in student evaluations, "*[Data] could be used in conjunction with [student evaluations] to determine the level of bias of those student evaluations*." Instructor-focused contexts for instructor reflection and improvement received mostly positive reactions because "*presumably, it really only impacts the instructor*" (S9). S11 supported such systems for improving teaching: "*This is more what I was thinking...of systems that are aiming to help the professor, like directly improving learning outcomes*." S10 adds, "*I think if the professor just gets all the metrics in one cute little package instead then they might know what's best for the material that they are teaching and be able to switch it up*." Students thought classroom data and smart classroom systems could be beneficial as long as they did not solely direct instructors' decisions in class.

5 DISCUSSION

We set out to understand students' values and boundaries – their desires and fears – about smart classroom technologies. We wanted to understand barriers to adoption and situations where sensing systems might inflict unintended harm. In general, students strongly desired and valued autonomy (both for themselves and for their instructors) and comfort in the classroom. Indeed, prior work cautions against MMLA technology leading to less creativity in how students learn [74, 92]. The commonality amongst all student views is that they did not want to be viewed as "data points" to their instructors (Table 3). Here we discuss the implications and potential directions from these views.

5.1 Reconciling Student Views with Instructors & Learning Theory

Our findings showed that students had emergent beliefs about active learning and learning science. As we found, students thought active learning methods that increased discussion and participation might cause discomfort. Their hesitancy to accept active learning points to an emergent belief that the default lecture-based teaching, the idea of instructors pouring content into students' minds, is better for learning [29, 62, 83, 121]. Students also mentioned that instructors have unique "teaching styles," and saw idiosyncratic qualities of instructors' teaching methods as beneficial. Indeed, Brewer & Burgess [13] found that an instructor's personal qualities were the main factors in motivating continued class attendance. Students may see the primarily lecture model of teaching as a "teaching style" rather than a teaching practice. They were especially concerned that both students and instructors would optimize behaviors towards captured metrics (an intuitive sense of Campbell's Law [15]), and that this would lead to less "innovative" teaching and a worse learning experience.

Though smart classroom systems promise to be helpful for improving teaching practices, we need to address students' beliefs and attitudes towards learning. Do we first educate students about effective teaching and learning or do we design these technologies to reshape student beliefs around learning? Prior work has emphasized the need to consider students' privacy in the development of MMLA and other types of smart classroom systems [3, 140]. Our findings add an additional layer, that there is also a need to understand student beliefs around what "good" teaching and learning are and whether these align with researcher or instructor goals. We found that student discomfort with certain smart classroom system scenarios may be due to privacy concerns coupled with their resistance to changing the learning environment. Smart classroom technologies will fundamentally change the student experience whether through instructional changes or the mere presence of a sensing system. However, there is limited understanding of the real-world impact and long-term use of these systems [3, 75, 140]. Martinez-Maldonado et al's [75] reports from a 2-year deployment of a MMLA system that issues of continuous informed consent and practicalities with integration into regular practice are ongoing challenges. From our findings, students wanted demonstrated value from smart classroom systems and greater transparency about their data use. Instructors themselves may also require demonstrated value of these systems as they may not want to commit time to incorporate complex technology [2]. If institutions choose to adopt smart classroom systems, they should be scaffolded and integrated slowly, allowing both instructors and students to adapt and understand the technology before it is fully implemented. Institutions could also invest in combining these systems with PD programs to show a dedicated initiative to better training instructors and providing better value to students.

5.2 The Role of Computer-Augmented Teaching & Learning

Student concerns of technology in the role of teaching are situated within a larger debate about human-AI collaboration and open a space for future questions about technology and learning theory. Are computers capable of complex thinking and creativity? If computers are thought to be deterministic and rigid, what role do they play in teaching and learning? Can teaching and learning behaviors be measured, and if so, what are these metrics? Hybrid intelligence models suggest that machines and humans provide complementary roles that augment human decision-making [28, 134]. Rodriguez et al [105] proposed a "teacher-in-the-loop" model to bringing in teachers to the design of MMLA tools. We also suggest that both instructors and students could be involved in the ongoing implementation and adaptive use of smart classroom systems through a "computer-in-the-loop" model where humans have high levels of control and ultimate agency in making decisions [114]. In this section, we describe potential directions for future research that empower both students and instructors in these teaching-focused systems.

5.2.1 Supporting Students' Agentic Engagement. All students acknowledged that classroom sensing systems for improving teaching would cause a change in their own behavior in class. For some, this change in behavior was welcomed as a way to motivate greater engagement. For others, this change in behavior was associated with a loss of autonomy. Unlike K-12 classes, college students are not required to attend class. Students may feel that instructors have a responsibility to engage and motivate them to attend class while

	Values	**Boundaries**
Autonomy	Smart classroom technology might encourage students to participate more and can give objective data to the instructor about their efforts.	Smart classroom technology would impede on both student and instructor autonomy, leading to potential "gaming of the system."
Connections	Students value implicit awareness from their instructors so the instructor can be proactive in providing help for students.	Smart classroom technology could lead to disingenuous connections between instructors and students.
Role of Technology	Smart classroom technology could provide additional data to help instructors make decisions for their classroom.	Smart classroom technology could cause instructors to treat students as "data points" and remove the human aspect of decision-making.

Table 3: Summary of key findings from student participants, showing both their values and boundaries around the primary themes.

students have more of a responsibility to self-regulate their own learning both in and out of class [13, 36, 130]. From these findings, we suggest that smart classroom technologies should help instructors support students' agentic engagement, an aspect of engagement in which students proactively contribute to shaping their learning environment in a way that supports their own motivation [101, 103]. Interventions that helped teachers use non-controlling, supportive language and acknowledge student perspectives were effective at supporting student autonomy and led to greater student engagement [102, 124]. Connecting these forms of interventions with those that improve student-instructor immediacy through nonverbal behaviors and body language [4, 5] is a potential direction forward that considers students' agency and autonomy in learning. Similarly, instructors could implement their own experimentation, using sensing data to try out different pedagogical strategies to see their effects and communicating these findings to students, similar to A/B testing methodologies. Vermette, McGrenere, & Chilana [131] present a way for instructors to experiment with different LMS configurations in an exploratory sandbox interface. Such exploratory and experimental mechanisms could also be incorporated in smart classroom systems. Students might also participate in deciding which learning and teaching metrics would better motivate them and effectively demonstrate effort both on the part of the students and the instructor. This way, smart classroom technologies for teaching do not provide a prescriptive solution, but rather more information that instructors and students can adapt to their own needs.

5.2.2 Supplementing Teaching Evaluations. Teaching evaluations are another area for classroom sensing augmentation. We found that students valued subjective evaluations perhaps because they represent their perceived autonomy in shaping their learning experiences even if the evaluations are not objective. They felt that subjective evaluations were opportunities for their voices to be heard even if they were not objective towards the instructor or their teaching. In their comments, students did suggest that sensing system data could provide supplemental information for teaching evaluations so long as instructors did not over-rely on data to make decisions or changes to their teaching. Prior work has argued that nonverbal behaviors, teaching practices, and external factors such as class size be incorporated into student teaching evaluations [8, 68, 116]. Teaching analytics data could provide a longitudinal approach to combining quantifiable and subjective data to better improve teaching evaluations for both students and instructors. As many students in our study said they used teaching evaluation scores to decide which classes to take and with which instructor, there is opportunity for a different form of personalization as well. Teaching analytics data that shows an instructor's teaching practices and behaviors could allow students to decide which teaching environment best suits them in deciding which classes to take.

5.3 Contextual Boundaries of Data Use

Consistent with prior work in traditional learning analytics [54, 57, 67], students had multi-faceted views about the use of their data for classroom sensing systems for improving teaching. These views may stem from prior learning experiences or thoughts about technology in general. Students saw value in smart classrooms if it meant that their efforts and their voices were seen and heard by instructors. The complexity in designing such systems is that students' views were shaped by what their individual views of what good teaching are and how technology would support (or not support) those views. Our participants were technical STEM majors, which may impact their knowledge and views of technology. Students expressed nuances with regards to their intuitive privacy concerns and their considered assessments of risks and benefits [86, 94]. We found several value propositions where students saw a considered value that outweighed the potential intuitive concerns about sensing systems. Instructor-focused scenarios that gave instructors implicit awareness to improve their teaching and connections with students received the most positive views though some students worried about artificial connections with instructors. Unsurprisingly, students were more favorable towards aggregated or grouped data that gave instructors an overview of the class rather than personally identifiable or sensitive data. However, one instance where some students were more accepting of using personally identifiable data was in scenarios where the use of their data rewarded them for their effort and could only benefit them such as in providing extra credit or incentivizing participation. The most objectionable scenarios were those in which students felt they could be punished in terms of their grades or where the instructor or institution played a more authoritative role. In these instances, many students felt as though they were being "watched" or "picked on."

There lies a balance between instructor monitoring for the purposes of understanding students' learning behaviors and instructor monitoring for behavioral accountability [61]. Finding this balance is perhaps the largest tension in the ethical debate of acting in students' best interests and promoting equitable learning and teaching in the classroom. Smart classroom systems have the potential to bring awareness to instructors' biases, but even with the use of classroom data as a form of supposed objectivity, human bias in interpretation can lead to reinforcing harmful biases and assumptions that place students on a behavioral or intellectual binary (*i.e.* "being respectful" or "not being respectful"; "high achieving" or "low achieving") [67, 72]. Our student participants also saw the potential of smart classroom systems for both reinforcing and reducing biases. Institutions looking to adopt smart classroom systems should provide regular evaluations from both students and instructors of how these technologies and the data collected are used to ensure continuous ethical practice. Instructors should also be trained in interpreting multimodal sensing data and in communicating data use practices and the outcomes of data use to students. Researchers should also consider how privacy and data collection norms and perceptions change and adapt smart classroom systems to these norms. Ifenthaler and Schumacher [54] suggested that consent be a fluid, ongoing process. Maintaining informed consent across contexts is an open challenge for the implementation of classroom sensing systems. Privacy techniques such as privacy nutrition labels [64] and privacy dashboards [56] can better communicate privacy choices to students, but these strategies need careful choice architecture in order to keep from overwhelming or biasing student choices similar to problems in the European Union cookie consent notices [44, 129]. Another direction is co-opting registrar data that students voluntarily share or students' own devices such as laptops or mobile phones to allow them to consent to what data to share and when [32, 92, 137]. However, the challenge still remains for ambient sensing systems that collect data from the entire classroom such as through cameras or microphones. An individual student opting out seemingly means the entire class opts out since removal of individual data points requires some level of identification. This is an open area for privacy-preserving learning analytics and data visualization [66].

5.4 Smart Classrooms & Technosolutionism

Smart classroom systems are also situated within a larger debate around pervasive surveillance technology in general. As online data collection and tensions around ubiquitous monitoring technology rise, there is growing concern about growing surveillant consumerism and datafication, both in and out of the classroom [20, 61, 122]. In particular, the issue of technosolutionism, in which technology is thought to be able to solve complex societal problems, is reductionist of the root causes of these problems [70]. We as researchers see opportunities to gain insights about teacher and student cognition with classroom sensing systems that were not previously possible [21, 92]. But how do we reconcile these scientific ambitions with students' thoughts about intrusiveness of data and discomfort in the classroom? How do we utilize data in a way that improves teaching that aligns with all students' moral and ethical boundaries [99, 100]? How, and more critically when, do we design technology to alleviate rather than amplify inequities [48, 106]? These are critical questions for HCI researchers in designing AI and complex MMLA tools in education. Lindtner et al [70] argue for a reflexive-interventionist approach that critiques the present and anticipates speculative futures when designing these socio-technical systems. We hope that this work in understanding student perspectives will contribute to answering these challenging questions about the role of technology in education.

5.5 Limitations

There were several limitations of this study. The first is that in utilizing convenience and snowball sampling, our student participants were primarily engineering and computer science majors. Their backgrounds in technical fields may give them different viewpoints regarding technology and privacy than students in other types of STEM fields. However, engineering fields in particular have low implementation of active learning in college courses [58]. Having participants from various universities enabled us to get a diverse set of student perspectives, but targeting institutions that are particularly under-resourced in implementing technology or active learning may provide additional insights about the challenges in incorporating smart classroom technology. The second limitation is that with unknown technology, students may not be able to accurately judge their feelings or needs in these uncertain scenarios. Our study elicited student beliefs and desires that generalized to their overall learning experiences regardless of technological implementation. Third, there are several other dimensions that we did not explore in this study. For instance, we did not vary conditions of data storage, sharing, and selling. We also did not explicitly examine other demographic contextual factors such as gender, race, and culture. These other dimensions remain open questions for future research. While our exploration was around smart classroom technologies for improving teaching, we did not explore sensing systems that provide feedback to instructors and students to optimize students' own learning, which likely would have garnered different responses.

6 CONCLUSION

With growing interest in classroom sensing technologies, there is a need to understand student perspectives on the use of their multimodal data for improving teaching. In this paper, we used Speed Dating to uncover undergraduate students' values and boundaries about smart classroom technologies and the use of their data. We found that students' desires and fears of these systems were largely driven by their beliefs about learning and their assumptions about instructors' training and abilities. Our findings contribute a nuanced understanding of the value propositions that students find favorable or objectionable for the adoption of classroom sensing systems for the improvement of teaching. These findings have implications about the transparency and communication of the specific outcomes of multi-modal data use and contribute to the larger question of designing ethical and equitable technology in education.

ACKNOWLEDGMENTS

We thank our participants for their time and participation. We also thank Longjie Guo and Annie Karitonze for their efforts in piloting this study and insightful feedback on the paper. This research was funded in part by NSF award #1822813 and NSF STEM Education Postdoctoral Fellowship #2222530.

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