Sensing Affect to Empower Students: Learner Perspectives on Affect-Sensitive Technology in Large Educational Contexts

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ABSTRACT
Large-scale educational settings have been common domains for affect detection and recognition research. Most research emphasizes improvements in the accuracy of affect measurement to enhance instructors' efficiency in managing large numbers of students. However, these technologies are not designed *from* students' perspectives, nor designed *for* students' own usage. To identify the unique design considerations for affect sensors that consider student capacities and challenges, and explore the potential of affect sensors to support students' self-learning, we conducted semi-structured interviews and surveys with both online students and on-campus students enrolled in large in-person classes. Drawing on these studies we: (a) propose using affect data to support students' self-regulated learning behaviors through a "scaling for empowerment" design perspective, (b) identify design guidelines to mitigate students' concerns regarding the use of affect data at scale, (c) provide design recommendations for the physical design of affect sensors for large educational settings.

Author Keywords
Affective computing; Education; Design; Privacy; Self-regulated Learning; Sensor Design;

CCS Concepts
•Human-centered computing → Empirical studies in HCI; Ubiquitous and mobile computing;

INTRODUCTION
Emotion plays a vital yet complex role in students' learning processes and outcomes. Positive emotions such as happiness, delight and flow have been commonly associated with academic success [43, 15], and negative emotions like frustration and boredom are significantly related to poor learning outcomes [5], increased dropout rate [15, 20], and problem learning behaviors [5]. These emotional states, such as boredom and confusion, could lead to better learning outcomes when properly regulated and resolved in a timely manner [5, 22, 34]. Detecting and recognizing learners' affective states thus become critical in building a positive learning process and optimal learning outcomes for students.

Expert instructors are skilled at recognizing and addressing students' emotional states accordingly. In small, in-person classrooms, instructors can clarify class content when students seem confused and alert students when they seem distracted. However, as education and learning increasingly take place at a larger scale (e.g., online learning and large in-person classes), instructors are no longer able to intervene in timely manners by observing students' emotions. Students are also expected to take more control of and responsibility for their own learning process, due to the lack of close interactions with instructors.

To help provide the emotional context that is considered lost in large-scale learning environments, affect-sensitive technology has attracted attention from both academic research and real-world classroom implementations. Some research efforts have sought to develop methods to detect students' affect or emotions. For example, researchers claim they are able to detect and measure emotions with reasonable accuracy, through collecting and analyzing learners' electrodermal activity [40, 19], eye gaze [25, 32], body language such as posture and movement [47, 21], facial expressions [2], or multi-modal physiological sensing [23]. Some of these technology have already been implemented in traditional classroom setting. For example, facial recognition technology is already deployed in a high school in Hangzhou, China to detect students' emotion and behavior in the classroom [10].

However, we argue that existing work on affect-sensitive technology in educational settings has two important gaps. First, most work tends to focus on *"what can be done"* rather than *"what should be done"* [55]. Prior research efforts emphasize improvements in the accuracy of the detection and recognition of students' affect, or better display and communication of the results to various stakeholders, other than students. To date, there has been little research on students' preferences for the physical design of affect sensors in large educational settings, nor has there been attention paid to students' concerns about the use of affect sensors at scale, or effective use of student affect data to support their learning process.

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Second, research on affect-sensitive technology seems to be solely designing from a *"scaling through efficiency"* [39] perspective—that is, aiming at improving the efficiency of teachers to educate more students—rather than a *"scaling through empowerment"* perspective [39], to involve more stakeholders other than the instructors in assisting learners' education. We recognize the importance of allowing teachers to detect students' affective states to provide learning interventions. However, given that students must take additional efforts in regulating their own learning processes in large educational context, we want to highlight the potential in leveraging affect data to assist students with their own learning.

The goal of affect-sensing technology in this domain is to support and augment students' learning experiences. Overlooking students' attitudes and opinions about affect sensors poses risks of negative effects on them, such as physical discomfort caused by poorly-designed sensors or mental distress of privacy and security concerns related to affect data. Both of these effects can also interfere with learning. Taking the alternate perspective of "scaling for empowerment" also presents opportunities for design that enables students to leverage their affect data to support their own learning process. We thus seek to explore these issues by asking three research questions:

1. How can students leverage their affect data to support their learning processes?

2. What are students' concerns regarding the use of affect sensors at scale?

3. What are students' preferences for the physical design of affect sensors when used in large-scale educational settings?

This paper examines these research questions in large-scale educational environments, in which affect-sensitive technology is urgently needed. In this paper, we contextualize these environments and explore our research questions from the perspectives of both students enrolled in large, in-person classes and online learners. We conducted in-class observations and semi-structured interviews with 10 undergraduate and graduate students, all recruited from large, campus-based computer science classes, to understand their perspectives on the use of affect sensors, drawing on their experience wearing non-intrusive wrist watch devices in our observational study. We later distributed an online survey to understand online learners' opinions about the use of affect sensors in online learning environment. We collected 301 survey responses from online students in a large computer science graduate program at a public institution in the USA. Through the interviews and survey, we identified students' attitudes toward the use of student affect data at scale, their concerns about using affect-sensitive technology in large educational environments, and their preferences for the design of physiological sensors.

The contributions of this paper are three-fold: (1) Adopting a "scaling through empowerment" design perspective [39], we identify a new research direction in the design of affect-sensitive technology for students to leverage their affect data in support of their self-regulated learning processes; (2) Building upon students' attitudes about using affect-sensitive technology to improve teaching efficiency, we outline design guidelines to mitigate students' concerns; (3) Based on students' preferences, we provide design recommendations for the physical design of affect sensors when used in large educational contexts, both in-person and online.

RELATED WORK

From mental health tracking [4, 42, 35] to text communication [27], various research has sought to understand human perspectives about sharing affect data. These studies suggest that the collection and sharing of affect or physiological data could act as a double-edged sword: while affect data could provide more social context [27] and emotional support [28, 42, 30], it could also have repercussions on user privacy [42] as well as social images (e,g., displaying emotions that users don't want to share with others) [65, 27, 30]. Prior research thus suggests that affective systems should prompt for consent before sharing, giving users more control, and be mindful about the role affect data plays in shaping users' self-presentations in social contexts [30, 27]. However, these studies were often conducted in small-scale, informal social interactions, in which sharing affect data rarely has long-term consequences. In large-scale, formal educational settings, students could be more willing to provide their affect data due to the potential learning benefits and social invisibility they feel [68] in large-scale educational context; or students might be more reluctant to having their emotional and physiological data collected, analyzed, then shared, due to the potential negative consequences on their grades, class evaluations, or even career opportunities.

In the remaining portion of this section, we first highlight the potential of designing affect-sensitive technology to support learners' self-regulated learning process. We then present prior work on the privacy and ethical issues related to data use in the field of learning analytics and affective computing. Finally, we review existing work on the design and acceptance of sensing technology in the classroom.

Self-Regulated Learning in Education at Scale

Self-regulated learning (SRL), defined as student's ability to plan, monitor, regulate, and control their own learning process, independently, to achieve their learning goals [52, 72], is highly correlated with level of engagement [66] and academic achievement [72, 53]. Considering contextual constraint and viewing learners as active participants in their learning process, one of the most well-established SRL models proposed by Pintrich [52] suggested that the SRL process consists of four *learning phases*: planning, monitoring, control, reflection, and four *areas of regulation*: cognition, motivation/affect, behavior, and context. They provide directions for designing educational technology to support specific areas of regulation during different phases to enhance students' SRL processes.

SRL is especially important to learners in large-scale educational settings. In online learning, where students have to self-pace their learning with little guidance and structure, SRL has proven to improve students' course satisfaction and performance [67], academic self-efficacy [12], motivation, and effective use of learning strategies [67]. In large in-person classrooms, students are usually provided with some level of structure and guidelines, however, instructors can offer limited support and guidance due to the large number of students enrolled in the class. Students in large in-person classes thus also need to apply SRL strategies to meet their learning goals [46].

The majority of SRL scholars all agree that SRL is not a fixed personal trait, but instead a skill that can be developed over time[38, 7]. Prior research suggested that an individual's awareness of their motivation and affect could be viewed as the first step towards self-monitoring [54, 52]. Self-monitoring could also inform and facilitate a number of SRL strategies such as goal setting, planning, self-evaluation that are related to academic achievements [38, 71]. Designing systems that can provide timely feedback of students' affect to them directly thus has the potential of supporting students' SRL processes.

Privacy and Ethical Issues of Student Data

The use of student affect data falls under a broader field called learning analytics, defined as "the collection, analysis, and use of large amounts of student data and information to better understand learner behaviors and contexts (both digital and analog) to improve learning outcomes and increase institutional efficiency and effectiveness."[58] Generally, the goal is to improve individual student's learning experience and outcome, which is why many consider identifiable student data as more useful than de-identified data [58]—it preserves the ability to tailor experiences to individual student. However, retaining identifiable data raises privacy and security challenges.

While students exhibit a high level of trust in the school's use of their data [64], existing work on student perspectives about the ethical implications of learning analytics found that students have concerns about their learning data being collected and used [64]. For example, students are concerned about inaccurate and outdated information, lack of transparency of the purpose in data use, negative consequences due to generalization and errors, and inappropriate measures regarding data collection and analysis storage [63].

To address these issues, learning analytics researchers have presented several general guidelines, principles, and frameworks to ensure the ethical use of student data. Some research emphasizes the importance of a student-centered approach by involving students in the entire process of data collection, analysis, and use [64]. Other work stresses the importance of transparency and obtaining consent from students throughout the entire process [62, 13, 16, 44].

In the field of affective computing specifically, various scholars have expressed concerns about the collection, annotation, and exploitation of people's affect data [60, 55, 14, 50]. Many consider the ethical questions regarding affect-sensitive technology as "imperative to solve" before putting the technology into use [50, 49]. Specifically, Reynolds et al. [55] proposes the use of an ethical contract between users and designers to avoid the perception of privacy invasion.

While affect-sensitive technology provides benefits in enhancing the interaction and communication between humans and technical systems, it is clear that system designers and developers should strive to maintain a balance of the potential harm and benefits during the process [14, 50, 57, 49].

With the advancement of affect detection and recognition technologies in recent years, more and more scholars acknowledge the importance of using such technologies ethically in educational contexts. For example, Aslan et al. [3] found that some students feel uncomfortable about their engagement levels being monitored by their instructors. They urge researchers to look into students' privacy perceptions and the impact of these perceptions on technology design; DiLascio et al. [19] also recognize the potential negative consequences of leveraging students' affect data, even in an anonymized format.

In large-scale educational environments, where data collection is the norm, students must already share a large amount of their data. Though prior work in learning analytics suggests various measures to mitigate students' privacy and security concerns (e.g., proper anonymization, obtaining consent, transparency about collection process and purpose), due to the private and sensitive [1] nature of affect data, students could be more resistant to share it. The research we present here thus seeks to identify students' concerns regarding affect-sensitive technology and provide recommendations to alleviate those concerns.

Designing Sensing Technology in the Classroom

The usability of physiological sensors has been extensively studied, especially with wearable technology. To assess the acceptance and adoption of wearable technology, scholars proposed various general design guidelines and models for on-body sensors, most of which built on the general Technology Acceptance Model (TAM) [17]. To encourage better adoption and persistent user engagement [45], these models often include constructs such as physical comfort [24, 26, 45], visible feedback [70], aesthetics [24, 45, 69], level of distraction [26, 8], cost [36, 26], privacy and security [26, 45], social acceptability [69, 8, 26], as well as two constructs in TAM — perceived usefulness [36, 26, 8], and perceived ease of use (e.g., low effort to learn, use, and maintain) [45, 36, 8]. Guidelines typically do not suggest a one-size-fits-all design for sensing technology, because the design of sensors is largely dependent on specific contexts and constraints [24, 70].

In recent years, the body of literature on detecting and displaying students' affective states in educational contexts has grown. Most of the design work surrounding affect-sensitive technology in educational contexts emphasizes the design of technology to *display* students' affect data to instructors and educational institutions [59, 29, 3]. However, little is known about the design of technology to *detect* students' affect—specifically, the effective physical design of affect sensors in educational contexts. Beyond general design rules such as"[make it] easy to wear" and "align with proper ergonomic design" [48], students' preferences and factors that may impact their willingness to wear on-body sensors—in both large-scale traditional and online classrooms—remains unexplored.

For learners in large-scale settings, especially online learners, the context of use may frequently change as they carry their learning platforms through public places (e.g., large in-person classrooms, library, coffee shops), semi-private places (e.g., workplaces), and private places (e.g., learner's own home). To date, research has not examined implications for student adoption and use of sensors in such a complex set of contexts. While general guidelines about usability may be helpful, it is unclear if students' preferences for affect sensors are unique to the large-scale learning context. Motivated by this gap, our paper explores students' preferences for the physical design of affect-sensing technologies in large-scale educational settings.

STUDY OVERVIEW

To summarize, current work seeks to fill in the gap present in the existing literature on the design of affect sensors in large-scale educational settings. In order to identify students' concerns, preferences, and the potential of affect sensing technology, we conducted two studies, separately, in two large-educational contexts— large in-person classrooms and an online, for-degree, learning program. In the following sections, we present our methodology and findings of each study, separately. We first present study 1 that aimed at understanding the perspective of on-campus students enrolled in large in-person classes, then study 2 that sought to understand online learners' perspectives of affect sensors. Both studies were approved by our Institutional Review Board (IRB).

STUDY 1: PERSPECTIVE FROM ON-CAMPUS STUDENTS

There were two portions of this study. First, to provide students with actual experience of wearing on-body sensors and having their physiological data knowingly collected by others, we conducted in-class observations in two large, lecture-based classes with on-campus students who wore on-body sensors measuring their physiological data during class. Second, we conducted semi-structured interviews with those students to understand their attitudes about affect sensors in large, in-person classrooms, based on their experience wearing the sensors we provided in class.

Study Material and Procedure

In-Class Observation

We conducted in-class observation sessions with 11 on-campus students from two large, lecture-based classes at a U.S. public institute. There were 200 students enrolled in one class and 350 students enrolled in the other class. We distributed the recruitment message through the class Canvas pages and announced the message in person at the beginning of the lecture. Students who were interested in participating reached out to the corresponding researcher voluntarily.

Before in-class observation sessions started, we met with each participant face-to-face and introduced the study procedure, obtained consent, gathered participants' demographics and asked about their past experience with using on-body sensors and sharing physiological data.

During the observations, we collected three types of data: students' physiological data, self-reported affect data, and observer-annotated student affect data. During in-class observations, we asked each participant to wear the Empatica E4 (wrist-worn) device, to collect their physiological data during class. Students' self-report affect data were collected before and after class through an adapted five-point likert scale Self-Assessment Manikin (SAM) [6]. Researchers sat in the front of the classroom to observe and annotate participants' affective states throughout class with participants' knowledge. The data we collected from the in-class observation was also used to explore the feasibility of inferring student affect from physiological data. All participants completed at least four observation sessions each.

Semi-Structured Interview

After each participant completed all the in-class observation sessions, they participated in semi-structured interview[1]. We conducted semi-structured interviews with all 11 participants from the in-class observations in person. However, one participant (P9)'s interview audio file was corrupted and thus resulted in ten post-observation interviews included in our analysis.

Each participant was compensated with a USD$25 electronic Amazon gift card. A detailed breakdown of the interview participants' information is shown in Table 1. All the interviews were audio-recorded and later transcribed.

ID	Gender	Level	Major
P1	M	UG	Computer Science
P2	M	G	Human-Centered Computing
P3	F	UG	Computer Science
P4	F	UG	Biomedical Engineering
P5	F	UG	Computer Science
P6	M	UG	Math & Economics
P7	M	UG	Computer Science
P8	F	UG	Computer Science
P10	M	G	Computer Science
P11	M	UG	Business

Table 1. Interview participant information. "M" stands for "Male", "F" stands for "Female". "UG" stands for "Undergraduate", "G" stands for "Graduate". Note that P9's post-interview audio file was corrupted and therefore excluded from our interview data analysis.

The interviews focused on participants' experience wearing physiological sensors during class, their opinions towards the use of affect-sensitive technology in large classroom, and the use of student affect data inferred from sensor data.

To probe for students' general attitudes on affect-sensitive technology, we first showed and explained five types of physiological data (accelorometer, skin temperature, altimeter, blood volume pulse, galvanic skin response).

We then asked about their general attitudes towards these data being measured from them and the types of data they believe to be useful in educational context. Later, we showed participants two kinds of devices: on-body sensors [2] and embedded sensors [3], then inquired about their device preferences and occasions (private vs. public) they would wear the devices.

[1]Interview protocol: https://tinyurl.com/y8lvk2kq

[2]On-body sensors: Apple Watch Series 3, Garmin Forerunner 35, Fitbit Charge, Google Glass Gen 2, Wrist Mount GoPro Hero 3, In-ear thermometer, Galvactivator skin conductivity sensor glove [51], Mindfield eSense Skin Response

[3]Embedded sensors: Pressure sensor on chair [33], pressure mouse [18]

In the last part of the interview, participants were prompted to talk about their opinions on the usage, access, and attitudes on using student affect data in large educational context.

Data Analysis

Two researchers coded all interview transcripts through open-coding [11]. We went through three iterations of coding and collaboratively distilled themes that emerged throughout the process. In the first iteration, two researchers coded all the interview transcripts in a line-by-line fashion, resulting in 49 low-level codes. First-iteration codes stayed close to the original meaning of each sentence, such as "concern about data being used against me" and "discrepancy between self-perception and data". In the second iteration, we arrived at seven categories, for instance "data use", "data collection", "device design factors". Finally, we identified five themes that highlight students' preferences for the device's physical design, and their attitudes on the use of student affect data. The two researchers met and discussed the codes and resolved conflicts throughout each iteration of the data analysis process.

Findings

Through our analysis, we found that on-campus students were receptive of using their affect data to help instructors improve future class and inform curriculum design, yet were not sure how affect data could be used to assist their own learning. Students expressed concerns regarding the accuracy, validity, privacy and security of affect data measured. We found that on-campus students prefer on-body sensors that would cause minimal distractions yet provide adequate level of information feedback for system transparency. Even though general sensor design guidelines still applied, students especially valued aesthetics and social acceptability of the sensors if they were to wear them in the classroom. Below we discuss these findings in more details.

Student Attitudes on the Usage of Student Affect Data

Help Instructors Improve the Class. More than half of the interview participants (P2, P4, P7, P8, P10, P11) believed that the inferred affect data could help instructors better understand students' reactions to different parts of the course, and therefore enabling instructors to tailor course materials based on students' needs. Students believed their affect data could help instructors infer students' learning processes and make proper adjustments accordingly.

For example, P7 commented on the possibility of allowing instructors to identify and re-explain concepts that might cause confusion, suggesting that *"The instructor can compare different days [of students' affect data]. If something they were talking about wasn't explained very well, it would probably show up in that data. They could probably spend ten minutes on the next lecture trying to close some loose ends up. It might be useful for them to see what we actually understood."*

P8 also believed that students' inferred emotion data could help instructors adjust their teaching style to engage students: *"If the instructor went through an example during the middle of the lecture, noticed students were not engaged, the instructor would know not to present that example anymore."*

Help Inform Curriculum Design. Students also commented on using student affect data to inform future curriculum design, saying that *"Maybe that (student affect data) can give the instructors an idea of what specific topics are of interests or are engaging to students, whereas what topics alienate some students. And they would potentially help inform future class preparations for the teachers."* (P2)

P7 pointed out that data could inform future class administration such as number of spots in each class: *"I guess if the class is gaining a very positive reaction, they may open up more spots for that class, which would be useful."*

Using Affect Data to Support Student Learning. When asked about potential usage of the affect data for themselves, some participants pointed out several potential usage of students' emotion data to aid students' self-learning (P4-P6, P8, P10, P11).

Some students believed that the affect-sensing wearable could alert students when they were too stressful or when they zoned out (P5, P8). P5 said *" If someone's really freaking out then that device would be able to alert you and tell them to calm down and take a break from learning. "*

P6 and P11 also mentioned the possibility of assisting students to selectively review course materials based on students' affect data: *"Students could use that as a study tip. If everyone seem real sad during this topic, maybe they need to go back and review that material."* (P11)

Though students generally agreed that their own affect data would be interesting to review, some students were not sure how they could act on the data (P1-P3, P7, P10, P11). When asked about potential usage of their own affect data for themselves, P2 said *"Having a repository of my own attentiveness or my own emotional states in other classes is useful insight. But I don't know how it will help me change in future classes. It's out of my hands because I might prefer certain teaching styles than others. Therefore I will not really be more interested or more attentive in some classes than others."*

Students' Concerns about Affect Data

Data Accuracy and Validity. In the interviews, students expressed doubts about the accuracy of data collected—both the self-reported affect data and the raw physiological data.

Half of the interview participants (P1, P2, P5, P6, P10) believed that affect measurement scale could not meaningfully speak for their affect throughout the class due to the lack of contextual information and the ambiguous rating system, which could lead to different interpretations.

Besides the self-reported affect data, students didn't trust the accuracy of the raw physiological data collected either. P5 commented on the skin conductivity sensor glove that was shown to him *"If you put something on your hand that might cause a variation of sweat that isn't natural."*

All the interview participants expressed doubts about the validity and accuracy of the inferred affect data from raw physiological data. Many participants (P1, P2, P4, P5, P7, P8, P11) believed students' affect measured during studying might not be about the class at all. P11 said *"Maybe I wasn't upset about the class, I was just upset that day."*

P1 was also concerned that the inferred affect data wouldn't take into account individual differences *"Different people act differently. Some people can work fine even when stressed they can still just be as efficient. Other people completely shut down. Though there are definitely person-by-person correlations but I think it would be hard to find population-wide."*

Mitigating Privacy Concerns in Data Sharing. The majority of the interview participants (P1-P3, P7, P8, P10, P11) emphasized the importance of anonymizing students' data due to privacy concerns. P2 said that sharing raw physiological data risked the danger of revealing private health information: *"Having access to how my body is naturally behaving could disclose some health conditions that I probably would not want to disclose to anyone."* P4 believed that inferred emotional states is private data because *"not everyone would want anyone to know their emotional states."*

Proper anonymization or aggregation of affect data could help ease students' privacy concerns. When asked about sharing his inferred affect data, P7 said he *"wouldn't have a problem with that as long as it's all anonymous."* Some students also said that aggregated data would make them more comfortable about sharing. P3 said *"I don't personally mind sharing my data with anyone really. But I can see why other people would, and so this is the place where generalized data would be more comfortable to share."*

P7 also mentioned that aggregated data would be more useful for instructors, *"If you have two hundred student class, it might be a little hard to go through all that data and trying to figure it out. So if there is a way to get general consensus of most of the students in the class, maybe the instructor could compare different days, and that might be useful too."*

Data Security Concerns. Several students (P2, P6, P8, P10, P11) also expressed their concerns about the security of students' physiological and inferred emotion data. When asked about the drawbacks of measuring and sharing students' affect data, P8 said, *"This data is like personal or medical information. So whenever there is data like that, it needs to be very secure and handled in a positive way."* P10 said, *"I don't mind as to the data being collected, so much as where it's going and at least knowing what sort of lock and key it's under."*

P6 was especially concerned, given the recent data leak incidents happened among universities, *"Someone may steal your data illegally. I think I saw the news that over one million student data was leaked in some universities? I trust our school is not going to sell our data, but we don't know if someone would sell the data for their own benefits."*

Student Preferences of Sensor Design in the Classroom

Minimize Distraction. On-campus students expressed concerns that certain features of commercially-available wearable technology could be a potential source of distraction during class. Several on-campus students (P8, P10, P11) worried that these "mini smartphones" with screens, push notifications, and various functionalities might cause unnecessary distractions while students were trying to engage with the lecture.

Students also showed strong preferences towards Empatica E4, the wrist watch device with almost no information feedback that they wore during observations. P2 said, *"It (Empatica E4) didn't distract me from class because it has no screens and there is nothing that tells me what it's doing for me to understand, or for me to even look at that data and try to make sense of it. It stopped being exciting after putting it down."*

Information Feedback to Foster Transparency. One might thus conclude that wearable devices in the classroom should minimize information feedback as much as possible to avoid causing distractions. However, we found students also valued an adequate level of instant information feedback to provide transparency into the device's activity. i.e. to let the users know what the device is doing at all time.

Several students (P2, P7, P8, P10) commented that this kind of system transparency could mitigate their privacy concerns, considering the device would be collecting sensitive physiological data. P10 commented on Apple Watch, saying that *"The only thing I don't like is it (Apple Watch) has so many features. Sometimes I don't know what it is recording or if it is recording."*

Aesthetics and Social Acceptability are Important. Many participants (P1, P2, P4, P8, P10, P11) also connected the aesthetic design of wearable devices with social acceptability. For example, P3 said she felt embarrassed when wearing the device we provided for observation, *"I found myself kind of embarrassed sometimes wearing it because it was just such a bulky device."*

P10 also pointed out that making wearable devices less visible on the body might make it more socially acceptable, *"I guess the other is also in making something that isn't very visible to others... Something that provides the users as much information as they would want inside the lecture setting, but at the same time isn't obvious enough to make other people be like 'oh that person's using technology and possibly taking pictures that I wouldn't want them to take' things like that."*

General Sensor Design Guidelines Still Apply. Through our interviews, we found that the majority of the general sensor design guidelines are still valued by students in physical classrooms, especially physicality, ease of use, and perceived usefulness. Students consider physicality to be the most important factor in the design of on-body sensors (P1-P10), with a particular emphasis on devices not obstructing them from their normal learning activities such as taking notes.

Given that on-campus students often have little time between classes, the device should also be easy to use and carry around (P3-P8, P10, P11). One of students' primary considerations is the perceived usefulness of sensing devices, with half of them emphasizing the importance of "value of information provided."

STUDY 2: PERSPECTIVE FROM ONLINE LEARNERS

Our second study aimed at understanding the perspectives of online learners regarding the design and use of affect sensors in online educational setting. We thus conducted a Qualtrics survey with current and former students in an online computer science graduate degree program at a U.S. public institute.

Study Material and Procedure

Participants were recruited either from social media platforms (e.g., Facebook group, Reddit) or directly from online classes through convenience sampling. For students recruited from the online classes, we offered a small amount of participation points (which students could earn in other ways as part of the standard class structure). We received 301 complete and valid responses over two weeks.

The survey[4] consisted of both closed-ended and open-ended questions. In the survey, we collected participants' basic demographic information, past experience using on-body sensors, sharing physiological data with others, and their experience in online classes. Participants then answered a set of questions regarding their attitudes toward using a wearable device during their study sessions, which can include doing homework or watching video lectures. The survey then presented participants with a short scenario to probe their attitudes about the sharing and using their affect data. The scenario described a voluntary school program where students could provide class feedback to instructors through short, mobile surveys about satisfaction and affect, and directly sensed data about movement and stress levels from physiological sensors.

Survey participants came from 30 different countries, with the majority of students from United States (55.81%), followed by India (21.59%), China (9.97%), and Canada (2.33%). 63 students self-identified as female (20.93%), 229 students self-identified as male (76.08%), nine students didn't specify. Participants were spread out in various age groups: 38 students were between 18 to 24 years of age (12.62%), 177 students were between 25 to 34 years of age (58.8%), 71 students were between 35 to 44 years of age (23.59%), 13 students were between 45 to 54 years of age (4.32%), and two students were between 55 to 64 years of age (0.66%).

Data Analysis

We analyzed the single and multiple choice answers using descriptive statistics. One researcher independently coded the answers to the two open-ended questions in the survey regarding online students' challenges in the program and their comments to our study using thematic analysis. A second researcher then went through the codes, verified and discussed conflicts with the researcher who conducted initial coding.

Findings

Through the survey, we identified challenges online learners faced in online learning and their attitudes about the potential usage of affect data. Online learners had concerns about affect data regarding its secondary use, privacy, security, as well as accuracy and validity. We also found that online learners considered the social acceptability of on-body sensors less important yet they still valued device transparency and physicality of the device. In the rest of this section, we provide a detail account of our findings.

How to Use Online Learners' Affect Data?

In this section, we first describe online learners' current experience, emphasizing on the challenges online learners encountered that could be resolved by affect sensing technology. We then discuss online learners' perspectives on the appropriate usage of their affect data.

Challenges in Online Learning. We found online students faced challenges in all stages of SRL— planning, monitoring, control, and reaction, across multiple areas of regulation— motivation, behavior, and context. Through survey comments, online students reported time management as one of the biggest challenges since many of them often struggle between schoolwork, full-time jobs, as well as families and kids. Other challenges include social isolation, procrastination, lack of motivation, and low engagement.

Online learners also reported difficulty in getting feedback from instructors. More than half of the online students said there was a lack of emotion feedback to instructors (58.81%), lack of immediate feedback on learning progress (53.82%), lack of personalized feedback (51.17%), and lack of real-time communication with instructors (48.5%).

However, online learners seemed to be relatively satisfied with the current evaluation and feedback system for classes and instructors— only 14.28% students felt the current course evaluation system didn't work well for them and only 13.29% students felt the current instructor evaluation system didn't work well for them.

Potential Usage Suggested By Online Learners. We found that online learners were generally open to the idea of using their affect data for legitimate purposes. Students reported that they would be willing to participate in the voluntary school program in the survey scenario if the goal was to improve future class or curriculum (78.41%), assist student learning with course materials (68.77%), or facilitate instructor-student communication (51.5%).

We also noticed that online learners felt strongly about using their affect data for improvement instead of evaluation. When asked about how should school or instructors use their affect data, majority of the students believed it should be used to improve future class design and content (78.41%) or to improve future curriculum design (75.08%).

Few students thought it should be used to evaluate instructor performance (45.51%) or to monitor each student's study progress (34.88%). One student commented *"Emotional data should not be used alone to assess. Emotional data can be the students' fault, not just the teacher."* Another student also commented, *"I'd want to stress that the data tracked through the wearables shouldn't be adversely used to determine the performance of teachers and TAs"*

Online students, though majority of whom would love to share their affect data if the goal was to help students learn better (68.77%), in general didn't bring up ways that their emotion

[4]Survey instrument: https://tinyurl.com/y8f7mbr6

data could be used to help themselves. Yet some students were excited about the potential of using affect data to cultivate solidarity among the learners: *"I would feel great if I knew others were frustrated with the same thing as me. This is a killer idea!"*

Online Learners' Top Concerns about Affect Data

We found that online learners have different levels of concerns regarding affect data collected, with 15.28% students being very concerned about sharing their affect data, 40.53% students having some concerns, and 30.23% not very concerned. Among those students who reported very and somewhat concerned about sharing their affect data, we identified three major concerns online learners had about the use of their affect data: secondary use, privacy and security, and data validity and accuracy.

Secondary Use. The majority of the students were concerned about their data being collected for one purpose but used for another (67.86%), while 27.98% worried their data might be used against them.

One student commented *"I would definitely be concerned if the data was used to track when, where, or how often students were studying and used as a grading/performance metric."* Another student also said *"As long as the data is only used for purposes that are made clear to the student, I am okay with it. The problem comes when data is collected and then used behind the scenes for other things."*

Privacy and Security. Online learners also showed significant concern about the security (66.07%) and privacy (57.74%) of their affect data. One student commented *"Emotional data seems to be on a higher level than physiological data. I would not like the possibility of someone else knowing my mood."*

When we asked whether students would be willing to share their affect data if they chose to participate in the voluntary school program presented in the survey scenario, 69.23% students were only willing to share their data with others under certain circumstances or conditions and 10.03% students were not willing to share at all.

Proper anonymization and aggregation of students' affect data would make them feel more comfortable about sharing. Among those students who were willing to share their data, 67.29% students would like to share their data anonymously, 20.45% students were only willing to share in aggregated format, and only 12.27% students were willing to share identifiable individual data. One student commented *"The challenge is not with collecting the data. It is with securing and using the data as promised. We have seen a lot of precedence in data breaches due to naive setup or process."*

Data Validity and Accuracy. Even though we didn't explicitly ask online learners' attitudes about the validity of inferring affect from physiological data in our survey, many students left comments throughout the survey to express their doubts about the validity and accuracy of inferred affect data.

The majority of the students who were skeptical about affect data validity all pointed out that physiological data doesn't necessarily map to students' emotions related to learning. One student said *"The source of emotion could come from a variety of sources and not just from the lectures or homework, even if it is during the same period of time."* Another student suggested to let students themselves confirm the data validity: *"I just hoped what is inferred is actually correct from the student's perspective and student has a say in what gets said."*

Student Preferences of Sensor Design in Online Learning

Social Acceptability Less Important. We found that online learners were less concerned about the device being socially acceptable among other common wearable design factors. In our survey, only 13 students (4.32%) picked "wearing the device doesn't make me self-conscious (i.e., other people won't judge me for wearing the device)" as part of their top three considerations if given an opportunity to choose wearable devices to wear while studying. In a multiple choice question which we gave examples of wearable device students could choose to wear during study sessions, devices that are more visible such as earpiece (28.57%) and smart glasses (33.89%) were also among online learners' top three choices.

Information Feedback. To our surprise, when asked to pick the three most important design factors of a wearable device, more online students chose transparency of device mechanism (19.27%) than other factors that are usually ranked higher in general wearable technology design guidelines, such as aesthetics (14.62%), ease of use (14.29%), and social acceptability (7.31%).

Physicality as Most Important. As expected, we found *physicality to be the most important factor* students consider in the design of on-body sensors. Physical comfort (69.44%) and that the device doesn't impede body motions (54.82%) are the two most important factors for students when asked about their preferences for wearable technology in online education. Vast majority of online learners also picked wrist watch (87.71%) as one of their top choices if they could pick a device to wear while studying.

DISCUSSION

These findings highlight the various perceived risks and benefits of affect-sensitive technology from the perspective of students in two large-scale educational contexts. In our study, we investigated students' current challenges encountered in SRL and their attitudes on the usage of their affect data. We also identified students' concerns regarding affect data and preferences on the physical design of affect sensors, which though were not unexpected, but helped ground our design guidelines in empirical evidence.

Based off of these findings, we first take the design perspective of "scaling for empowerment" [39] and propose using students' affect data to support their SRL process. We then discuss students' attitudes and concerns in leveraging student affect data to improve teaching efficiency at scale and provide design guidelines to mitigate their concerns. Finally, we describe design priorities for affect-sensitive wearables in large-scale educational settings.

Scaling for Empowerment: Support Students' SRL

We found that on-campus and online students encountered various challenges with self-regulation during their learning. Consistent with prior literature [37, 41], we found that online students especially face difficulties in various phases of SRL—self-planning, self-monitoring, self-control, and self-reflection [52]. For example, lack of motivation potentially caused by failure in planning and reflection, challenges in time management possibly caused by difficulty in self-planning and self-monitoring, procrastination potentially caused by challenges in self-monitoring and self-control, as well as low engagement possibly caused by the lack of self-reflection. On-campus students also encountered problems with SRL such as low self-control, but were less commonly mentioned during the interviews.

Helping students be aware of their affect during their learning process may be beneficial for their SRL. As mentioned in Related Work, affect plays a key role in informing students' self-monitoring behaviors, which helps facilitate students' SRL processes [52] and inform students' SRL learning strategies [38]. Students are open to the use of affect sensors if it could help improve students' learning processes and outcomes. Many participants in our study were eager to suggest ways affect sensors could help support their individual learning process, such as alerting students when the sensors detected that they were distracted. Yet some students were not sure how they could act on their own affect data to improve their learning.

Taking the design perspective of "scaling for empowerment" [39], we argue that designing affect-sensitive technology for students to support their SRL process is a promising direction for future research. For example, to encourage SRL self-planning practices, data from affect sensors could provide students with summaries of their own daily affect, for students to adjust their study schedule to ensure effective learning during optimal affective states. To facilitate self-monitoring, affect data could help students become more aware of their level of motivation and affect, by providing visualizations of their affect data during studying. To support self-reflection, affect data can be used as an opportunity to prompt students to think about why their affect might have changed and how it might impact their learning, encouraging students to conduct self-data analysis.

Using student affect data to support their SRL process also aligns with students' privacy and security concerns regarding their affect data. Students may feel more empowered and secure if data is only being generated for their use. Overall, based upon the findings presented here, there is greater promise and lower risk in using affect-sensitive technology in large educational contexts if they are designed to give feedback to students directly, rather than using affect data for institution or instructor change.

Scaling for Efficiency: Usage and Concerns

We found that students are also receptive of the idea to use affect data in improving class design and providing feedback to instructors for timely learning interventions. Though prior research suggested the potential use of student affect data to redesign future class content [31], provide feedback to instructors' teaching [31, 40], and customize learning materials accordingly [61], our studies provide evidence that students are open to these proposed usage.

However, though supportive of using their affect data to improve teaching efficiency at scale, students also expressed concerns regarding sharing their affect data with schools and instructors. We identified that these concerns are similar with student concerns regarding the use of their learning analytics data [63]. Specifically, students were concerned about the accuracy of inferred emotion data, the goal of using their affect data, the privacy issues of data sharing, and the security issues regarding data access and storage. Based on these concerns, we outline below several design guidelines to help mitigate students' concerns in sharing their affect data.

Students' affect data should be shared in anonymized and aggregated format only. Students feared that their affect data could be used against them by the school or instructors, for evaluation or grade assessment, which echos similar concerns about potential negative consequences in leveraging student affect data in educational settings [19]. Thus, students are more comfortable and more willing to share if they remain "invisible"— the data cannot be traced back to them individually. Majority of the participants also considered their data to be personal and private, thus their affect data should warrant proper security measure to guard students' privacy.

We also urge designers to consider different protocols and measures for students' affect data, compared to data collected in traditional learning analytics. Affect data is considered more personal and private, and thus needs to build upon the ethical perspectives of affective computing. **We thus recommend schools and instructors to provide an ethical contract [56]** that details the collection, analysis, use, and access of affect data at the very beginning of the process. In order for students to make an informed decision, detail should be provided along with proper consent procedures and seeking ongoing assent throughout the data collection.

Findings indicated that **schools and instructors should give students full control of their affect data**. Participants showed a high level of distrust in the accuracy of inferred affect data due to various confounding factors that could cause changes in emotion unrelated to their learning. Validity is a legitimate concern and it is a largely unsolved challenge in current affect detection and recognition technologies due to the lack of contextual information [9]. Consistent with related literature outside of educational setting [27], we also encourage system designers to give students the freedom to confirm their affect data, to share their affect data with parties of their choosing, or to annotate and provide more contextual information themselves. Considering affect data during learning could influence their academic evaluation, owning control of their affect data might be highly valued by students, comparing to users outside of educational context.

Yet with further comparison of our findings with relevant literature that investigated people's perspectives of affect sensors in other contexts such as in-person social interactions, *we* *didn't find students expressing similar concerns of sharing emotion data might affect their social images [27, 65].* We believe the scale of large in-person classrooms and online learning environment makes students feel "invisible" and thus are not concerned about their emotion data affecting their self-presentations in the learning environment.

Design Priorities for Affect Sensors in Education

We found that the general design guidelines on wearable technology still apply to large educational contexts, as does the technology acceptance model [17]. Across the on-campus and online settings, students viewed physical comfort, unobtrusiveness, and absence of impediments to body motion as vital attributes for the design of wearable sensors.

However, we also identified several design elements that are unique to educational context. In this section, we highlight these two design elements and provide suggestions to sensor designers based on students' preferences.

Distraction and Transparency in Educational Context

We found that learning context poses a tension between minimizing distraction and transparency of device mechanisms; which is usually provided through instant information feedback and display on the device. Students believed it was important that the device do not distract them from their learning, but also showed concerns about not knowing what and when the device is measuring data they considered to be sensitive.

Online learners in particular, ranked transparency of device mechanisms as more important than factors such as aesthetics [24, 45, 69] and social acceptability [69, 8, 26] which previous studies ranked higher in consideration. Therefore wearable designers should balance providing instant feedback to students so that they feel comfortable about the data collected, while not providing too much information feedback, which might cause unnecessary distraction during students' learning.

Aesthetics and Social Acceptability

We argue that students' perceived importance of affect sensors' appearance is highly dependent on their studying environment. In our study, online learners ranked aesthetics and social acceptability as less important, which contradicts with on-campus students' reports.

On-campus students told us they were self-conscious when wearing sensors in the classroom, and preferred options that were common accessories and less noticeable (e.g., smart watches), which aligns with general design guidelines of sensing technologies [69, 8, 26].

The perspective of online learners, their lack of concern with the aesthetics and social acceptability of sensing technology, is not surprising considering that students in the online programs have the freedom to study anywhere, including private settings such as their own home rather than public spaces. This suggests that designers may have more leeway with the aesthetic design of sensors for learners with more flexibility in choices of their learning environment, and could look to design sensors that are more visible and less like traditional wearable technology.

Yet, designers should keep in mind that, depending on the scale of affect data collection, if students need to wear sensors during informal learning activities (i.e., outside of attending video or in-person lectures), on-campus students might choose to study in more private settings; online learners could also need the flexibility to study in more public spaces.

LIMITATIONS AND FUTURE RESEARCH

There are limitations in current study. First, both of our interview and survey study used convenience sampling. Our findings are thus prone to self-selected bias— participants in both of our studies might be more open and ethusiastic towards physiological sensing or surveillance technology. Second, all the participants—both survey and interview— were recruited through computer science classes in a U.S. public technical institute. These students are thus likely to be more familiar with technology-related issue and more open to the use of physiological sensors comparing to students across all disciplines. Third, all the survey participants were in an online graduate degree program in computer science. Thus, our results may not be generalizable to other non-CS online degree programs, especially less structured online learning environment such as MOOCs. Finally, we focused on exploring the design of on-body affect sensors in the current study, yet future work is needed to explore student perspectives of other affect sensing technology such as facial recognition.

We urge future research to examine the design of prototypes of affect-sensitive systems for in-the-wild evaluation. Future work is also needed in exploring the influence of students' studying contexts on the design of affect sensors. For example, for online students, a key research question is how to design affect sensors that are suitable for constantly changing learning contexts.

CONCLUSION

This study is the first of a larger research program that is exploring students' perspectives on the use of affect-sensitive technology in large-scale educational settings. Current work examined this question through two studies with students in large in-person classrooms and online learning context. We conducted observation sessions and semi-structured interviews with 10 on-campus students in two large in-person classes, and a survey filled out by 301 online students to understand their perspectives and needs regarding affect-sensitive technology. Based on students' perspectives, we identify a new direction to design affect-sensitive technology in using affect data to empower students in their own self-regulated learning process. We also outline design guidelines to mitigate students' concerns when their affect data are used to improve teaching efficiency at scale, and present design recommendations on the physical design of affect sensors in large-scale classrooms.

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