Volume 11(3), 24–40. https://doi.org/10.18608/jla.2024.8483

# Students' Ethical, Privacy, Design, and Cultural Perspectives on Visualizing Cognitive-Affective States in Online Learning

Victor Manuel Corza-Vargas[1], Roberto Martinez-Maldonado[2], Boris Escalante-Ramírez[3], Jimena Olveres[4]

**Abstract**

While teachers often monitor and adjust their learning design based on students' emotional states in physical classrooms, synchronous online environments often limit their ability to perceive the emotional climate of the class. Drawing from the concept of *social translucence*, it is suggested that making students' emotional states "visible" in online settings can help foster empathetic interactions. Recent advancements in emotion recognition technology are enabling the creation of learning analytics (LA) systems that can estimate students' *cognitive-affective* states in real time. Yet, the adoption of these systems raises ethical, cultural, and practical concerns when implemented in learning environments, including potential challenges related to accuracy, privacy, and data integrity. To address these concerns, we conducted an in-depth qualitative study exploring the perspectives of 12 undergraduate students on modelling and visualizing their cognitive-affective states in the context of a Mexican higher-education institution. The study provides insights within a particular cultural context, which can guide the design of more human-centred emotion recognition–based LA tools for online educational contexts or contribute to informed decisions about the necessity of modelling and visualizing cognitive states.

**Notes for Practice**

- This paper describes an elicitation process with students of a higher-education institution in Mexico. The study is aimed at understanding the practical, ethical, cultural, and privacy perspectives that can inform the design of learning analytics (LA) tools based on cognitive-affective state (CAS) recognition.
- This study emphasizes the need for more human-centred LA studies that can serve as a reference for regulators in Latin America to create laws that ensure the development of safe LA tools for end-users.
- The paper also confirms that the six foundational emotions (anger, disgust, fear, happiness, sadness, and surprise) do not represent the emotional states that may be relevant in the synchronous online educational context from a student's perspective. A group of more complex states that blend cognition and affect can be more suitable.
- For designers of LA systems, this study provides a set of guidelines on practical, privacy, cultural, and ethical aspects that can be used as a starting point for the development of CAS-based LA tools.

**Keywords**
Human-centredness,vspace affective computing, online learning, emotions.

**Submitted:** 14/05/2024 — **Accepted:** 18/11/2024 — **Published:** 18/12/2024

**Corresponding author [1] Email: victorcorza@comunidad.unam.mx Address: Posgrado en Ciencia e Ingeniería de la Computación y Centro de Estudios en Computación Avanzada, Universidad Nacional Autónoma de México, México.*

*[2] Email: roberto.martinezmaldonado@monash.edu Address: Faculty of Information Technology, Monash University, Melbourne, Australia. ORCID iD: https:// orcid.org/ 0000-0002-8375-1816*

*[3] Email: boris@cecav.unam.mx Address: Facultad de Ingeniería y Centro de Estudios en Computación Avanzada, Universidad Nacional Autónoma de México, México. ORCID iD: https:// orcid.org/ 0000-0003-4936-8714*

*[4] Email: jolveres@cecav.unam.mx Address: Facultad de Ingeniería y Centro de Estudios en Computación Avanzada, Universidad Nacional Autónoma de México, México. https:// orcid.org/ 0000-0002-1514-4520*

## 1. Introduction

Emotions play a key role in influencing students' cognitive processes, including attention, learning, memory, reasoning, and problem-solving (Tyng et al., 2017). Conversely, the way a student thinks, perceives, or processes information can also shape their emotional responses. For instance, repetitive failure might lead to feelings of confusion and frustration, while the successful completion of tasks or the unveiling of new knowledge can result in delight and excitement (D'Mello & Graesser, 2011). This strong bi-directional interrelationship between students' emotions (affect) and cognition resulted in coining the term *cognitive-affective states* (CASs) (Baker et al., 2010). This notion characterizes student states that combine emotion and cognition, such as feelings of confusion, boredom, or deep focus, which students commonly experience during deep learning situations (D'Mello & Graesser, 2011).

In synchronous (online and physical) learning situations, it has been stated that the *emotional climate* of the learning environment must cater to the fundamental needs of students to keep them engaged and to mitigate disruptive behaviours (Brackett et al., 2011; Reyes et al., 2012; D'Errico et al., 2016). In physical classrooms, teachers play a key role in continuously monitoring perceived students' emotional states and tailoring learning activities accordingly to foster an emotional climate conducive to students' learning (Balaam, 2013; Beardsley et al., 2019; Weissberg et al., 2015). Moreover, students' awareness of each other's emotional states can also positively contribute to the emotional regulation of the class (Barsade, 2002). However, in synchronous online learning settings, perceiving the emotional climate can be more challenging for both teachers and students due to limited visibility of one another (Yarmand et al., 2021), often restricted to a camera feed at most. In such situations, a key challenge lies in understanding and recognizing students' emotional states (Baker et al., 2010) and discerning how these states influence their learning experience (Harley et al., 2015).

Although online classes offer accessibility and flexibility, they have inherent challenges in mimicking a physical classroom experience (Ali, 2020). The concept of *social translucence* was introduced to tackle this issue from a design perspective, highlighting reduced visibility and awareness of others online, affecting social interactions and group unity (Erickson & Kellogg, 2000). A central tenet of social translucence, when applied to the awareness of CASs in learning environments, would involve rendering students' emotional states *visible* in fully digital environments with the aim of promoting awareness and fostering empathetic interactions. Advancements in emotion recognition from video and audio are making it feasible to develop learning analytics (LA) systems that can automatically estimate students' varied CASs in real time (D'Mello & Jensen, 2022). This has enabled the creation of a number of teacher-facing (Beardsley et al., 2019; Zheng et al., 2021; Tarmazdi et al., 2015; Ez-Zaouia & Lavoué, 2017; Ez-Zaouia et al., 2020; GhasemAghaei et al., 2016; Wiedbusch et al., 2021; Alfredo et al., 2023) and student-facing (Derick et al., 2017; Ruiz et al., 2016) dashboards aimed at enhancing emotion awareness across different learning scenarios.

Yet, as emotion recognition algorithms improve, and interfaces based on them become more widespread (Cai et al., 2023; Boyd & Andalibi, 2023), there's increasing apprehension within the field of LA regarding the use of multimodal data collection approaches (e.g., video and audio) blended with AI techniques (Prinsloo et al., 2023; L. Yan et al., 2022). Evidence of this growing concern is in the Artificial Intelligence Act (Madiega, 2021), the world's first comprehensive law aimed at regulating the use of AI in the European Union. This categorizes AI-based systems according to the risk they pose to users. AI systems based on biometric data, such as some LA systems that assess affective states, can be classified as high risk. A further issue is that emotion recognition datasets commonly employed to train these AI models are grounded in a set of biological categories that overlook broader contextual factors such as cultural differences (Crawford, 2021), even though these are crucial in understanding emotions (Katirai, 2023).

To address these concerns, there's a growing interest in incorporating students' perspectives in the design of LA systems (Dimitriadis et al., 2021), recognizing design features rooted in their lived experiences (Martinez-Maldonado, 2023), and accounting for contextual and cultural factors (Viberg et al., 2023). In response, this paper presents a study examining students' perspectives on the practical, ethical, privacy, design, and cultural implications of modelling and visualizing their CASs during online classes. The study involved 12 undergraduate students enrolled in a fully online program at a Mexican higher-education institution. Drawing from the literature on CASs (Baker et al., 2010; D'Mello & Graesser, 2011), the study aimed to elicit

(i) students' perceptions of the emotions they believe might influence their performance in online classes;

(ii) potential design approaches for visualizing their CASs to enhance their visibility during online sessions; and

(iii) students' ethical, cultural, and practical concerns about sharing data modelled by contemporary algorithms capable of detecting CASs.

The findings may benefit LA researchers and designers looking to develop tools that enhance teacher or student awareness of CASs during synchronous online learning sessions and educational decision makers looking into making informed decisions about the need to model and visualize CASs in particular educational contexts.

## 2. Literature Review

### 2.1 Foundations of CAS Modelling

The relevance of Ekman's basic emotions (namely happiness, sadness, fear, anger, surprise, and disgust) (Ekman, 1992) in educational contexts has been continuously challenged due to the need for a more context-specific understanding of emotions, including a broader range of emotions, their complexity, and their long-term impacts on learning and development (Graesser et al., 2007; McDaniel et al., 2007). Instead of basic emotions, some researchers have examined CASs (Baker et al., 2010). These highlight the connection between cognitive processes and emotions in educational settings, namely boredom, confusion, pleasure, engaged concentration, frustration, and surprise (D'Mello & Graesser, 2011). D'Mello and Graesser (2012) explained that these states were placed within Russell's core affect framework (Russell, 2003), which juxtaposes valence (pleasure to displeasure) against arousal (activation to deactivation), positioning basic emotions based on their arousal and valence values.

Based on the above literature, some LA systems have been proposed to model students' emotions in educational environments. For example, using Russell's framework (Russell, 2003), Yan and colleagues (2022) employed speech data, facial expression recognition, and convolutional neural network techniques to visualize the emotional dynamics of individual students in an online class. This visualization was created by mapping the low-level data with arousal and valence. Gupta and colleagues (2023) introduced a deep learning–based method using facial recognition to detect online learners' engagement in real time. In a similar vein, Dawood and colleagues (2018) modelled students' CASs, such as confidence, uncertainty, engagement, anxiety, and boredom, using only a webcam.

However, some research has used multiple data sources or wearable devices, which might not scale well for online learning applications. For example, Mangaroska and colleagues (2022) combined brainwave signals, gaze data, and video to understand student states during programming activities. Likewise, Arroyo and colleagues (2009) suggested a machine learning model using wrist sensors and computer vision to infer US-based high-school students' complex emotions in the context of math education. These examples highlight the fact that the educational context of application imposes certain conditions that can influence the feasibility of modelling CASs.

### 2.2 Privacy Awareness and Human-Centred and Culturally Aware Design in LA

Since the inception of LA as a field of research, there has been an emphasis on addressing privacy concerns (Pardo & Siemens, 2014), yet there's growing interest in applying multimodal data collection methods, such as video (Roy et al., 2022; Savchenko et al., 2022) and audio (Son & Kwon, 2024; Madan & Kumar, 2024), as well as wearable approaches (Alwahaby et al., 2022), for CAS modelling. These methods can be seen as intrusive, capturing aspects of students not directly tied to their learning, thereby raising privacy and integrity issues (Prinsloo et al., 2023). Conversely, students are protective of personal data but take contradictory actions; therefore, another important aspect is to understand how students might perceive LA in terms of its privacy implications and the extent to which their beliefs in privacy are reflected through their actions (Tsai, Whitelock-Wainwright, & Gašević, 2020). Regarding the most common issues related to information privacy, several authors coincide in aspects related to purpose, access, and anonymity as benchmarks for privacy integrity (Liu & Khalil, 2023; Tsai, Whitelock-Wainwright, & Gašević, 2020).

In response to the increasing concerns about the design of LA systems that can be invasive or challenge human agency (Tsai, Perrotta, & Gašević, 2020), there is an emerging emphasis on integrating students' viewpoints and experiences directly into the system's design and functionalities (Dimitriadis et al., 2021; Martinez-Maldonado, 2023). Additionally, there's a rising awareness of the importance of considering broader contextual and cultural dimensions, ensuring that LA systems are sensitive to diverse student backgrounds (Viberg et al., 2023). As evidence of this, while large public datasets have shown potential for developing models to detect emotions or CASs (Mollahosseini et al., 2017; Goodfellow et al., 2013), they can be skewed toward specific demographics in terms of cultural representation. For example, the RAF-DB dataset (Li et al., 2019), sourced from diverse ages, genders, and races, may not fully encompass cultural particularities. Conversely, the JAFFE dataset (Lyons et al., 2019), short for Japanese Female Facial Expression, offers a regional perspective, showcasing facial expressions of Japanese females and emphasizing the need to consider region-specific facial features and cultural indicators. This underscores the necessity of region-specific datasets and designs that can account for Mexico's distinctive cultural characteristics (Cavazos et al., 2020), including those pertaining to facial features, in order to enhance the accuracy and inclusiveness of emotion detection.

### 2.3 LA Dashboards for Emotion Awareness

In LA, dashboards are commonly used as graphical interfaces that enable educators to adjust teaching strategies based on class analytics (van Leeuwen & Rummel, 2020). For instance, the ClassMood app (Beardsley et al., 2019) is an online classroom orchestration tool that identifies the aggregate "mood" of a class, suggesting activities to influence students' arousal. Tarmazdi and colleagues (2015) introduced a dashboard for analyzing students' online team discussions. It displays team mood, role distribution, and emotional climate, enabling educators to monitor teams in real time, give feedback on interactions, and spot problematic teams.

Another system, EMODA (Ez-Zaouia & Lavoué, 2017), monitors students' emotions during online synchronous learning activities using four different data sources: audio, video, self-reporting, and interaction traces. In contrast, EMODASH (Ez-Zaouia et al., 2020) explores the interactions of teachers and learners during teaching sessions, offering a general overview of learners and a detailed timeline that enables a replay of each session. GhasemAghaei and colleagues (2016) proposed a dashboard that supports educators to inspect and reflect on the emotional states of students using web learning applications. Similarly, Wiedbusch and colleagues (2021) reported relevant features of dashboards that allow teachers to explore real-time data visualizations of students' self-regulated learning processes.

In contrast, there are tools that provide some insight to *students* on their emotional states, often in the form of student-facing dashboards. An example of these is AffectVis (Derick et al., 2017), a visual learning dashboard for affective states and learning activities that includes four visualizations, with the objective of allowing students to reflect on their affective states and their connection to specific learning activities. Similarly, Ruiz and colleagues (2016) presented a visual dashboard that allows students to track their emotions and follow up on their evolution during the course.

In sum, although there is a growing proliferation of LA tools that aim at evaluating emotions, and some of them extend to CAS awareness, a close examination of these works reveals notable gaps: students' experiences and perspectives have not been considered in the design of such LA tools, including their perspectives on whether it is important for them to have their CASs modelled (gap 1) and, if deemed important, how the outputs from this modelling should be used or visualized to support their learning (gap 2). Moreover, student considerations of design, ethics, privacy, and culture remain unaddressed in the context of CAS modelling (gap 3). Therefore, many of these advances can fail to adapt to the real learning context.

### 2.4 Contribution and Research Questions

This paper presents a study examining students' perspectives on the practical, ethical, privacy, and cultural implications of modelling and visualizing their CASs during online classes. Results are anticipated to inform the design of more human-centred emotion recognition–based LA tools for online educational contexts. To guide this study, we formulated the following three research questions (RQs), each addressing our research gaps above:

**RQ1:** What are students' perspectives on the emotions they believe might influence their performance during an online class session (gap 1)?

**RQ2:** What are students' perspectives about visualizing evidence of their CASs for self-reflection, and the prospect of sharing this with their teachers (gap 2)?

**RQ3:** What are the ethical, privacy, and cultural considerations when using students' data (i.e., facial expressions or audio) to model and visualize students' CASs (gap 3)?

## 3. Methods

### 3.1 Participants

Twelve fifth-semester computer science students (ST1-12) from the faculty of sciences at National Autonomous University of Mexico (UNAM) participated in the study. Their average age is 22.5 years (std. dev. = 1.38). Of these, 10 identified themselves as male and two as female. They contributed their student experiences, basic to intermediate programming and software development skills, and introductory knowledge in AI and computer vision. The study was conducted in accordance with ethical research practices, involving the explicit, fully informed consent of all participating students, who voluntarily agreed to be part of the research.

### 3.2 Study Procedure

For this study, structured, individual interviews were conducted using videoconferencing software. A structured interview schedule was designed to facilitate in-depth explorations through a mix of open questions and creative drawing activities. The complete interview schedule is available at https://anonymous.4open.science/r/HCLA_elicitation-7708/README.md. We chose to conduct interviews over other methods due to their elicitation format, which encourages continuous openness and allows for a variety of interactive materials to be provided to students. Each interview lasted from 60 to 90 minutes. Each interview had three sections:

1. The first section addressed RQ1 and consisted of exploring the positive and negative emotions that students experience most frequently during their online courses and how they perceive that these emotions are addressed by their professors. The questions posed in this section were as follows:

   **Q1:** What **emotions do you commonly experience** during an online class, and how do you think they may impact your performance?

   **Q2:** Can you recall a situation when a positive or negative emotional state **influenced your performance** in online class activities?

Q2 was supplemented by a mapping exercise: students were given a brief explanation of the six CASs addressed in this study (listed in Section 2.1) and asked to identify the equivalence between their perceived emotions and the CASs.

Two additional questions were presented in this section to explore student's perception of their teacher's ability to attend to CASs and the potential benefits of making students' CASs visible to teachers:

**Q3:** Do you feel that your CASs are **recognized and addressed during your classes**?

**Q4:** Do you think that it may be beneficial that these CASs are **made visible** to teachers?

2. The second section addressed RQ2. Students were asked to assume that it is possible to obtain evidence of their CASs automatically through a system or application, and subsequently they were asked to imagine what that evidence would look like. To answer that question, students participated in two drawing tasks: (i) "Crazy 4," a design method in which students were challenged to sketch four different ideas in four minutes, and later (ii) "Solution Sketch," another design method in which students spent more time expanding on one idea that they were most interested in, and they also had the option to sketch a totally new idea or a combination of ideas.

   Both drawing tasks are part of Google's sprint design method (Banfield et al., 2015); we selected this framework due to its widespread adoption in the software design domain. Furthermore, we considered it ideal for leveraging the basic-to-intermediate software development abilities of the interviewed students while fostering their creativity. These two activities had students generate a variety of creative visual representations accompanied by verbal explanations by responding to the following question:

   **Q5:** How do you imagine this evidence about CASs can be **visualized or communicated to you or your teachers**?

3. In the final section, RQ3 was addressed. In this section, participants provided their opinions on ethical, privacy, and cultural implications of the monitoring of their CASs, framing all their answers in the particular context of their experiences at UNAM. Using a Likert scale, they expressed their level of comfort with the monitoring of their CASs during a class; afterwards, privacy, ethical, and cultural concerns were addressed individually. The particular questions students were asked are as follows:

   **Q6:** How comfortable are you with your CASs being monitored for the purpose of evaluating the classroom atmosphere?

   **Q7:** What concerns do you have regarding the potential **privacy issues** related to [this]?

   **Q8:** What **ethical concerns** do you have regarding the modelling and visualization of your CASs being shared with your teacher?

   **Q9:** Based on your own experiences as a student based at UNAM, what **cultural considerations** do you think should be taken into account in the design of a tool that supports awareness of CASs?

### 3.3 Data Analysis

For most of the questions, the analysis was inductive, with the exception of the complement of RQ1, question 2, and RQ3, question 6. We followed a structured, sequential methodology where each stage was built on the previous one. For each interview question, we followed the first four phases of the approach suggested by Braun and Clarke (2021): (1) transcription and familiarization with the data, (2) coding, (3) searching for themes, and (4) reviewing themes.

In phase 1, one researcher transcribed interviews using the Model Whisper-Large-V2-Spanish (Radford et al., 2022) and verified the data to ensure accuracy. In phase 2, the same researcher extracted quotes that may include potential topics and patterns (codes) and segmented them into spreadsheets, each associated with its respective interview question. The researcher then identified and created a preliminary list of codes and collated them with quotes. In phase 3, using spreadsheets as a collaborative board for analysis, four researchers worked together to identify and sort the final codes into potential themes, collating all the relevant coded quotes within the identified themes. In phase 4, the four researchers engaged in discussions to redefine and merge topics. These discussions were conducted simultaneously and through consensus during multiple sessions, adhering to recommended practices for qualitative analysis in human studies (McDonald et al., 2019). Kappa values are not reported in this work, because in our study there was no independent coding. By the end of this phase, a total of 38 quotes and 19 different themes were identified for RQ1, question 1; 29 quotes and 14 themes for RQ1, question 2; 12 quotes and three themes for RQ1, question 3; 12 quotes and two themes for RQ1, question 4; 42 quotes and 26 themes for RQ2, question 5; 12 quotes and five themes for RQ3, question 7; 18 quotes and 10 themes for RQ3, question 8; and 14 quotes and five themes for RQ3, question 9. RQ3, question 6, and the supplementary activity of RQ1, question 2, are discussed below.

Due to the nature of drawing activities in RQ2, question 5, thematic analysis employed an extra step: themes found were classified into five groups, namely data characteristics, reasons of visualization, visualization objectives, feedback, and regulate (Sedrakyan et al., 2019).

Deductive content analysis was employed in the supplementary mapping exercise of RQ1, question 2, where students were requested to map their emotions with six pre-established CASs, and in RQ3, question 6, where a Likert scale was presented to students.

## 4. Results and Discussion

From the analysis of Q1, 18 different emotions emerged. After aggregation, **boredom** was found to be the most common, with five occurrences. Three emotions occupied second place: **frustration**, **concentration**, and **stress**, with four occurrences each. In third place, with three occurrences, there was a tie between **relaxation**, **distraction**, and **pleasure**, while only two students mentioned **comfort**. Surprisingly, only one student mentioned **confusion**, despite the fact that this emotion is common in learning contexts (D'Mello & Graesser, 2012; D'Mello et al., 2014). Refer to Table 1 for the full list of mentioned emotions and their respective occurrences.

**Table 1.** Ranking of emotions experienced in online classes.

| Rank | Emotion | Occurrences | Rank | Emotion | Occurrences |
|---|---|---|---|---|---|
| 1 | Boredom | 5 | 10 | Fascination | 1 |
| 2 | Frustration | 4 | 11 | Curiosity | 1 |
| 3 | Concentration | 4 | 12 | Concern | 1 |
| 4 | Stress | 4 | 13 | Happiness | 1 |
| 5 | Relaxation | 3 | 14 | Confusion | 1 |
| 6 | Distraction | 3 | 15 | Interest | 1 |
| 7 | Pleasure | 3 | 16 | Disinterest | 1 |
| 8 | Comfort | 2 | 17 | Intrigue | 1 |
| 9 | Pressure | 1 | 18 | Anxiety | 1 |

**Perceived positive or negative influence of emotions in learning** From responses to Q2, we found 14 different emotions. We found eight emotions that were identified by students as having a negative impact on learning and six that were deemed to have a positive impact. **Boredom** and **concentration**, with five occurrences each, were the most common emotions. A total of four students mentioned **frustration**, and three students mentioned **stress**. The top four emotions in Q1 are consistent with the top four emotions in Q2, despite the fact that each question was asked in the context of a different situation. Additionally, we found that all top emotions are complex affective states close to the CASs that were described above. Only one student referred to a basic emotion, happiness. No other basic emotion was mentioned.

Regarding the top four emotions found in Q1 and Q2, participants agreed that **frustration** is commonly caused by difficult topics. ST8 explained this as follows: "Integral calculus is often frustrating." ST4 mentioned a negative consequence of this emotion. This was explained as follows: "Because I missed a class on angles, I felt frustrated and decided to drop it to focus on my other subjects." In contrast, **concentration** was related to addressing topics that students consider relevant. This was explained by ST6 as follows: "If a professor is explaining something that really catches my attention, I **concentrate** and **enjoy** the class."

**Stress** was associated with not being able to understand a topic. ST8 explained this as follows: "I feel **stressed** if I am not understanding a topic or I feel that it is becoming more complicated." Stress was also associated with answering a test poorly. Regarding this, ST7 mentioned the following: "When there are exams, I get stressed because I don't know some answers." **Boredom** was strongly related to deficient teaching methods. Respecting this, ST5 stated, "Teaching by reading slides doesn't encourage students to learn. It's boring." ST6 agreed with this view: "Sometimes it's **tedious** just reading. Students need to participate more, so that things are clearer."

For the supplementary part of Q2, **frustration** along with **engaged concentration** were the most common CASs mentioned, with seven emotions mapped for each. **Confusion**, **boredom**, and **pleasure** shared second place, with five emotions mapped for each CAS. Finally, **surprise** was not mapped by any student. The complete mapping results are shown in Table 2.

**Recognition of CASs by their teachers** For Q3, eight students agreed that their CASs are generally not recognized or addressed by their teachers. However, three students attributed part of the responsibility to students' reluctance to participate more actively in online sessions. ST2 described this as follows: "I usually keep the camera off because sometimes I don't dress up or I don't want to turn it on." ST5 elaborated on this matter as follows: "There are even students who adopt a somewhat aggressive attitude, becoming confrontational about 'why do they want us to turn on our cameras?'" However, ST3 mentioned that it is important to consider that not all students have the proper technical means to actively engage in online classes: "Not all students can have a good bandwidth; others don't even have a camera to be able to show themselves."

**Table 2.** Mapping between emotions and CAS.

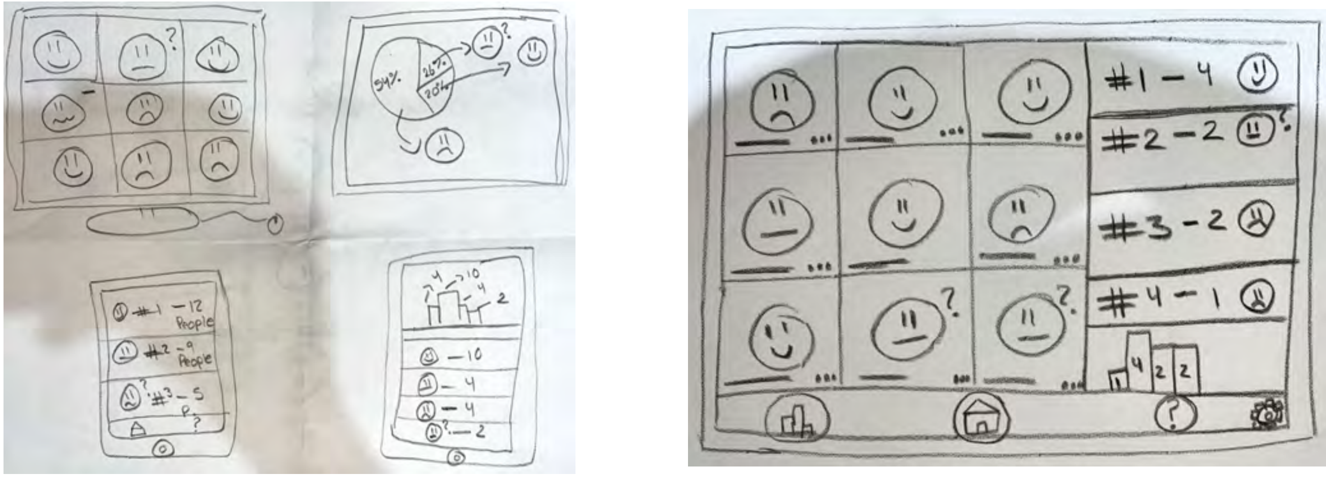
| Student | Named Emotion | Mapping | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Boredom** | **Engaged concentration** | **Confusion** | **Pleasure** | **Frustration** | **Surprise** |
| ST1 | Frustration | | | | | – | |
| | Concentration | | + | | | | |
| ST2 | Concentration | | + | | | | |
| ST3 | Boredom | – | | | | | |
| | Fascination | | | | + | | |
| | Concentration | | + | | | | |
| ST4 | Curiosity | | + | | | | |
| | Boredom | – | | | | | |
| | Frustration | | | | | – | |
| | Stress | | | – | | | |
| ST5 | Boredom | – | | | | | |
| ST6 | Concern | | | | | – | |
| | Pressure | | | – | | | |
| ST7 | Stress | | | – | | | |
| | Despair | | | | | – | |
| | Tranquillity | | | | + | | |
| ST8 | Frustration | | | | | – | |
| | Confusion | | | – | | | |
| ST9 | Anxiety | | | | | – | |
| | Excitement | | | | + | | |
| ST10 | Interest | | + | | | | |
| | Distraction | | | – | | | |
| | Boredom | – | | | | | |
| ST11 | Focus | | + | | | | |
| | Enthusiasm | | | | + | | |
| | Tranquillity | | + | | | | |
| | Disinterest | – | | | | | |
| ST12 | Frustration | | | | | – | |
| | Comfort | | | | + | | |
| | **Aggregation** | **5** | **7** | **5** | **5** | **7** | **0** |

Positive impact + Negative impact –

In contrast, three students mentioned that their teachers have addressed some of their CASs, mainly by asking continuously for doubts or by using some techniques to reduce stress. ST8 referred to this as follows: "Teachers constantly ask 'did you understand? how are we doing?' and so on. I feel that they are a bit more attentive to see if you are understanding the topic." ST7 also commented: "When teachers ask 'are there any questions?' or for example a teacher who manages the class using the pomodoro method, which was 25 minutes of work followed by a 5-minute break. I believe that it was a way to address some kind of stress." Yet, while these methods hint at recognizing students' CASs, they are broad and do not cater to individual needs.

Finally, just one student perceived that teachers have been attentive to students' CASs in the past. ST1 stated, "A teacher makes me realize they are truly interested in how I am reacting to their class by asking us to turn on our cameras to see our faces, checking if we are not falling asleep, if we are answering correctly, if there are questions about the topic." All the teaching strategies mentioned suggest some awareness of CASs and at the same time reflect a latent disposition of some teachers to potentially include LA technology in their classes.

**Perceived benefits of making CASs visible to their teachers** Regarding Q4, one student responded with "maybe," while the remaining 11 answered positively. All 12 agreed that visualizing CASs during online classes could enhance the quality of their online learning experience. ST9 said, "Teachers need to know what emotional factors are present in their students; whether they perceive them or not, emotions are there anyway." ST6 mentioned the importance of teachers' awareness of CASs: "This lets teachers know if their methods aren't working or if a student needs help." ST5 pointed out the possibility of personalizing learners' attention: "If teachers see that there are doubtful faces, they can ask directly to the students who have some expression




**(a)** Crazy 4's: four ideas in four minutes.

**(b)** Solution Sketch.

**Figure 1.** ST4's results of drawing activities.

of confusion." All these viewpoints suggest that students recognize the potential benefit of making their emotional states more visible to assist their teachers in tailoring learning tasks to students' needs.

### 4.1 RQ2: Students' Perspectives on How Evidence about Their CASs Can Be Visualized

Although at this point in the interview the students were familiar with CASs, all, without exception, interchanged the concept of CAS for the concept of emotion. To avoid confusion, in this section we will refer exclusively to the concept of CAS. Examples of the results of the Crazy 4's and Solution Sketch activities are illustrated in Figure 1(a) and (b), respectively.

All students proposed a solution resembling an LA dashboard interface, incorporating ideas they brainstormed in the Crazy 4's activity. For instance, Figure 1(b) displays an interface designed by ST4. It features a grid using emoticons to represent identified CASs in lieu of actual faces, a real-time ranking based on CAS occurrences, and a bar graph reflecting this ranking. ST3 suggested a distinct LA dashboard, segmenting class topics to provide specific statistics. The drafted dashboard also incorporated real-time suggestions based on a list of common issues, with the objective of enhancing immediate teachers' intervention, as well as a CAS ranking, a timeline detailing CAS occurrences, and an anonymous survey for assessing teachers at the end of each class.

At the end of the analysis, 21 different design features were found and classified into five groups, based on the literature as described in the previous section (Sedrakyan et al., 2019). Within the *Data features* group, all students mentioned, as the primary source of data for CAS recognition, the **acquisition of images** and the use of **datasets containing images of people expressing various emotions**. **Voice** was mentioned by two students, and **biometrics** was proposed by one student.

In the group *Reasons of visualization*, the most common interface element was **face grid**, proposed by six students, followed by **ranking of emotions**, mentioned by five students. Within the group *Visualization objectives*, **chart with percentage of emotions updated in real time** was the most common element, proposed by five students, while **a timeline with the count of emotions** was in second place with three occurrences. The complete list of classified design features is shown in Table 3. Within the first four groups the top two features have been designated with a ++ suffix and presented in bold. In the "Regulate Learning" group, only one feature was highlighted.

### 4.2 RQ3 Students' Ethical, Privacy, and Cultural Concerns

**Students' comfort regarding CAS monitoring** Using a five-level Likert scale, where level 1 indicated total discomfort and level 5 indicated total comfort with CAS monitoring, students generally accepted the use of technology for assessing their CASs. Four students chose total comfort (level 5), five felt comfortable (level 4), two were neutral (level 3), one felt uncomfortable (level 2), and none chose total discomfort.

**Privacy issues** This question elucidated four concerns related to data privacy: (i) information leakage, (ii) inappropriate use of data, (iii) loss of database, and (iv) inappropriate use of devices.

Two students mentioned **information leakage**. ST1 addressed the anxiety that inappropriate handling of data can cause students by explaining the following: "My biggest concern would be that those data and those images reach an inappropriate place, I would start to panic."

Four students expressed concern about **inappropriate use of data**. ST8 explained this as follows: "If these personal data are being used for another purpose, different from recognizing emotional states, I would feel scammed." In contrast, ST3

**Table 3.** Features classified by data visualization, design, and interaction paradigm.

| Concepts about visualization, design or interaction | Feature | Occurrences |
|---|---|---|
| **Data characteristics** | **Images ++** | **12** |
| | **Use a dataset of images expressing different emotions ++** | **12** |
| | Voice | 2 |
| | Smart watches | 1 |
| **Reasons of visualization (Explore, Discover, Summarize, Present, Enjoy)** | **Face grid (Explore) ++** | **6** |
| | **Ranking of emotions (Discover) ++** | **5** |
| | Use emoticons to depict emotions (Explore) | 2 |
| | Accompany questions with emotion at the time of asking them (Discover) | 1 |
| | Panel with list of students and emotion detected (Explore) | 1 |
| | Use colours to depict emotions (Explore) | 1 |
| | Digital whiteboard | 1 |
| **Visualization objectives (Relationship, Distribution, Trend over time, Composition)** | **Real-time charts with count or percentage of each emotion (Trend over time) ++** | **5** |
| | **Emotions count in a timeline (Trend over time) ++** | **3** |
| | Charts with distribution of answers of quick questionnaires about topics just seen in class | 1 |
| **Feedback** | **Anonymized survey at the end of class to asses teachers, students, or the class ++** | **3** |
| | **Divide the class into topics ++** | **2** |
| | Manual analysis after class | 1 |
| | Quick questionnaires about the topics just seen in class | 1 |
| **Regulate learning** | **Real-time suggestion to improve the class based on the emotion state ++** | **2** |
| | Set of solutions/recommendations for the teacher | 1 |
| | Emotion-based class meter | 1 |

mentioned that inappropriate use of data is not a concern: "In general, I don't have any concern; I mean, normally on the Internet, the sale of data is for targeted advertising, and that's not a concern for me."

On the other hand, two students mentioned **loss of database** as their main concern, and finally one student was concerned about **inappropriate use of devices**. ST4 explained this as follows: "Some apps use the camera without us knowing."

Finally, seven students said that they didn't have any concern about privacy implications as long as the purpose of data collection is clearly explained, and teachers and other stakeholders observe strict respect for those agreements. ST2 explained this as follows: "None in particular as long as the 'what is it for?' is well explained."

In addition to these opinions, an alternative to mitigate privacy concerns emerged. ST9 proposed erasing CAS data immediately after each class to help students feel more secure about their personal data, explaining as follows: "Something that could be applied is that each class is a fresh start; I mean, it's like, my information is being processed at the moment to give statistics to the teacher, and once the Zoom is closed, that information disappears."

**Ethical concerns** The analysis of this question allowed us to identify four possible ethical concerns: (i) prejudging students, (ii) unauthorized use of camera, (iii) wrong people using collected data for unethical actions, and (iv) crime profiling. The most common concern was **prejudging students**, mentioned by three students. ST1 addressed this issue as follows: "Maybe upon realizing that at a certain time of the day students tend to be more apathetic, some teachers might react negatively."

Two students were concerned about the **wrong people using collected data for unethical actions**; we found this ethical concern to be equivalent to the data privacy concern **inappropriate use of data**. This similarity reflected one issue that can be seen from two different perspectives. From the ethical point of view, ST5 addressed this concern as follows: "In the wrong hands even the Bible can be used for something unethical. So, in the end, it doesn't depend on the program or the developer; it depends more on the person who is going to use that program."

In contrast, two students mentioned **unauthorized use of camera**; again we found this ethical concern equivalent to the data privacy concern **inappropriate use of devices**. This time, the explanation given by ST7 in this section was very close to that given by ST4 for the same concern in the data privacy section: "Some apps continue to use the camera after the application is closed."

Finally, the ethical concern related to **crime profiling** was proposed by only one student. ST7 addressed this ethical concern as follows: "Taking it to a higher scale, it could even serve for something more, such as scanning the traits, gestures, or emotions of a person who is prone to committing crimes."

Moreover, four strategies to mitigate some problems related to the ethical concerns also emerged: (i) awareness courses, (ii) psychometric tests for the end-user, (iii) avoiding individual statistics, and (iv) prior consent. The first strategy, **awareness courses**, was proposed by two students. ST3 explained this strategy as follows: "Teachers must have professional ethics; I think they should take awareness courses on this." The second strategy, **psychometric tests**, was mentioned by one student. ST3 explained this strategy as follows: "You are going to use this system, well, you have to take this psychometric test so that at least initially, we can trust that you will not misuse this data."

The third strategy, **avoiding individual statistics**, was mentioned by one student. ST4 explained this strategy as follows: "Maybe it would be better if only a ranking of how many people show that emotion was displayed and not specifically who shows that emotion." Finally, the fourth strategy, **prior consent**, was proposed by two students. This strategy was explained by ST6 as follows: "It's paramount asking for prior consent to prevent issues; if something shady or crooked is discovered with the use of the data, action can be taken." Table 4 shows the results of aggregating all the occurrences of each concern and strategy proposed by interviewed students.

**Table 4.** Ethical issues and strategies.

| | Issue/Strategy | Occurrences |
|---|---|---|
| **Issues** | Prejudging students | 3 |
| | Wrong people using collected data for unethical actions | 2 |
| | Unauthorized use of camera | 2 |
| | Crime profiling | 1 |
| **Mitigation strategies** | Awareness courses | 2 |
| | Prior consent | 2 |
| | Avoid individual statistics | 1 |
| | Psychometric tests | 1 |
| Doesn't have any ethical issue | | 3 |

**Cultural considerations** The last question elucidated three cultural considerations: (i) diversity in lexical expressions, (ii) high cultural diversity in facial features in Mexico, and (iii) high expressiveness in facial expressions. Two students mentioned **the diversity of lexical expressions** used in Spanish spoken in Mexico as a critical cultural aspect to be taken into account. This concern was explained by ST2 as follows: "In the case of audio, I think there would be more considerations because here at UNAM people come from all over the country." In the same sense, ST5 explained, "The slang in Mexican Spanish, the fact that, even on a state-by-state basis, there are expressions used in Mexico City that are not used in the north; the accent could also be a matter to take into account."

The second consideration, **high cultural diversity in facial features**, was mentioned by six students. This cultural feature was addressed by ST3 as follows: "Mexico is a very diverse country; we have everything, there are a lot of people with very marked Asian features, with Indigenous features, with Caucasian features; at the end of the day, it is a super diverse population." In the same sense, ST4 mentioned the following: "One says well it's UNAM and one believes that almost everyone is from Mexico City, but since students also come from various states, even a change from one state to another makes a difference." ST6 outlined the importance of considering the diversity of students attending classes at UNAM in the design of what he identifies as an algorithm: "We live in a country that is ethnically very diverse. Some students don't completely match the features of 'Mexican people.' They might need a more specialized algorithm."

The last consideration, **high expressiveness in facial expressions**, was mentioned by two students. This concern addressed a very representative feature of Mexican culture that is shared in some parts of Latin America. ST1 explained this as follows: "At least here in Mexico City, we are very expressive. Our faces speak before our mouths do, and I consider myself one of those people." In addition, ST1 mentioned that due to this cultural trait, facial expressions should be considered above other types of features: "Anyone studying here shares that part of the culture where we are very expressive and you should, I believe, focus precisely on expressions; face is going to speak first." Finally, two students did not express any cultural consideration or concern. Table 5 summarizes the results of aggregating all the occurrences of each of the cultural considerations described in this section.

## 5. Discussion

**Table 5.** Cultural considerations.

| Cultural consideration | Occurrences |
|---|---|
| High cultural diversity in facial features | 6 |
| Diversity in lexical expressions | 3 |
| High expressiveness in facial expressions | 2 |
| No cultural consideration needed | 2 |

### 5.1 RQ1: Students' Perspectives on the CASs That Influence Their Performance

In addressing our RQ1, we discovered that the emotions students associate with their performance during online classes were boredom, confusion, pleasure, engaged concentration, and frustration. These states closely align with the major CASs that students naturally experience during deep learning sessions, namely boredom, confusion, pleasure, engaged concentration, frustration, and surprise (Baker et al., 2010; D'Mello & Graesser, 2011); the latter was not paired with any of the students' emotions. This is in contrast to Ekman's work, which focuses on a set of universal, biologically hardwired basic emotions, which include fear, anger, happiness, sadness, disgust, and surprise (Ekman, 1992). These emotions are expressed primarily through facial expressions and are hypothesized to be ubiquitous in everyday experience. In contrast, D'Mello and Graesser's work examines emotions as dynamic, context-sensitive phenomena that emerge in complex environments, such as learning or social interactions, emphasizing cognitive and social factors beyond Ekman's fixed categories.

In most instances, students found that linking emotions to CASs was intuitive, either due to identical naming or close meanings. Upon aggregation, frustration emerged as the dominant CAS, alongside engaged concentration. This was followed by confusion, which students linked with feelings of pressure or stress. This is consistent with recent findings that highlight the prevalence of frustration in higher education, especially in assessment-related scenarios (Wass et al., 2020). Boredom and pleasure also ranked second. The interplay between these two CASs has been examined recently, revealing that while pleasure or enjoyment positively influences the use of learning strategies, boredom does not (Obergriesser & Stoeger, 2020). Despite their significance, many students felt that their CASs often went unnoticed by their educators, with only a few dedicated teachers perceived to acknowledge and address these states. This points to the potential ethical application of LA dashboards, like those discussed in Section 2.3 (Beardsley et al., 2019; Tarmazdi et al., 2015; Ez-Zaouia & Lavoué, 2017; Ez-Zaouia et al., 2020; GhasemAghaei et al., 2016; Wiedbusch et al., 2021; Alfredo et al., 2023). The majority of students believed that making CASs visible to teachers would be beneficial. This can contribute to increasing *social translucence* in online learning settings (Erickson & Kellogg, 2000). This widespread acceptance signals a promising avenue for integrating multimodal LA tools into online higher-education courses at public Mexican universities, a region currently underrepresented (Yan et al., 2022).

### 5.2 RQ2: Students' Perspectives on How Evidence about Their CASs Can Be Visualized

For RQ2, students envisaged solutions that incorporated a variety of data sources to aid in emotion recognition, with a significant emphasis on facial recognition (as shown in Table 3, first row). This aligns with prior studies that have predominantly used video and voice to model CASs or other emotion-related constructs (Yan et al., 2022; Gupta et al., 2023; Dawood et al., 2018). In contrast, wearables, as explored by some researchers (Mangaroska et al., 2022; Radhakrishnan et al., 2023; Arroyo et al., 2009), may limit scalability (L. Yan et al., 2022). Predominantly, students conceptualized dashboard designs to visually represent data for teachers. These visualizations either depict individual students (using emoticons instead of actual faces) or rank emotions to provide an overview of the online classroom's emotional atmosphere in real time. Such designs resonate with genuine challenges teachers face in online settings (Yarmand et al., 2021). The comprehensive list of features derived from the students' prototypes (shown in Table 3) could inform the creation or evaluation of LA dashboards centred on CASs.

### 5.3 RQ3: Students' Ethical, Privacy, and Cultural Concerns

For RQ3, an initial point of discussion is the potential overconfidence of students regarding the topic of CAS recognition. Regarding data privacy, most students expressed no concerns at all. Although Mexico is not far behind in creating laws that ensure data privacy, their actual adoption is slower than in other countries or regions such as Europe (Carrillo & Jackson, 2022). It is therefore crucial to design LA systems with region-specific considerations. In regions where data privacy concerns may not be widely recognized due to a lack of awareness about potential risks, and in the absence of external oversight bodies to ensure proper implementation, tailored approaches to system design are necessary.

Nevertheless, students in the hosting university displayed a high degree of trust in the ways their university may use their data. Their primary concerns were associated with data leakage and potential consequential misuse. Interestingly, students' privacy concerns were focused on potential undesired marketing and potential scams, which may reflect the particularities of the context where the study was conducted. With a quarter of its young people being at risk of falling victim to scams, Mexico is in first place among OECD countries (Jerrim, 2023). This underscores the importance of conducting studies that consider the local context, as this may ultimately influence students' perspectives (Mutimukwe et al., 2022).

Regarding wider ethical issues, elicitation with students may not aid in the definition of guidelines, due to their susceptibility to interpret privacy and ethics as equivalent concepts. In this regard, other sources need to be consulted (Katirai, 2023; Crawford, 2021; Banzon et al., 2023; Rets et al., 2023). Nonetheless, two students mentioned one ethical issue related to the recognition of their affect states, the potential prejudging of students encouraged by long-term analytics/statistics that could be shared with teachers. These kinds of concerns, related to individual profiling, are increasing all over the world as affective computing systems spread. The emergence of the Artifical Intelligence Act (Madiega, 2021) underscores the importance of conducting research that enables regulatory bodies to understand the perspectives and concerns of key educational stakeholders. Such studies are crucial for proposing laws that prevent ethical harms while facilitating the safe use of emotion-based technologies.

Finally, regarding cultural implications, students strongly emphasized how the specific area of emotion recognition can be very sensitive to the cultural characteristics of Mexico. This supports the growing interest within the LA community in creating culturally aware LA solutions (Viberg et al., 2023). Indeed, the emotional response to environmental stimuli involves several crucial cognitive components, each significantly influenced by culture (Schrauf & Sanchez, 2004). Students highlighted the multicultural aspect of the university where they study, the rich variation in people's facial features in Mexico, and the various ways emotions are expressed in Mexican Spanish. At UNAM, people from all over the Mexican Republic are served, and each state has certain representative lexical features; even the tone of speech can be highly distinctive. This variability in the recognition of emotions in the particular context of Mexico has long been identified and extensively studied using acoustic modelling (Caballero-Morales, 2013). In summary, there are two main considerations for other LA researchers and designers working in the area of culturally aware emotion recognition in online environments: considering the potential high cultural diversity in facial features and the high expressiveness in both facial and verbal expressions.

### 5.4 Implications for Research and Practice

For LA researchers, this study provides practical confirmation that the six foundational emotions proposed by Ekman (1992) do not represent the emotional states that may be relevant in the synchronous online educational context. A group of more complex states that blend cognition and affect may be more suitable. Although it was relatively easy for students to map their emotional states with the six CASs addressed in this study, the list of CASs can be adjusted to cover a larger number of states.

On the other hand, this study can contribute to the growing interest and emerging developments in LA in Latin America (Hilliger et al., 2024) by providing a foundation for further elicitation studies aimed at understanding the practical, ethical, cultural, and privacy perspectives that should inform the design of LA tools based on CAS recognition. Alongside other much-needed human-centered LA studies, this work can also serve as a reference for policy makers and designers to ensure the development of safe LA tools for users, without the overly restrictive measures that, arguably, can be seen in the European Union.

In Section 5.5, a set of guidelines for LA systems based on CAS recognition in Latin America is provided. These guidelines can be used as a starting point for the development of CAS-based LA tools. Furthermore, they can serve as a reference point for supporting the requirement-gathering process of CAS-based LA systems.

Additionally, this study suggests that incorporating students' concerns regarding data privacy, culture, and ethics can aid in the adaptation of CAS-based LA tools to the regulatory framework of the region in which the LA system will be used.

### 5.5 Limitations and Future Work

Our study had several limitations. Firstly, only computer science students participated in the study. This means that the students had some basic data/AI literacy that enabled them to provide technical details about their envisioned LA solutions. At the same time, they may have been biased as they all proposed a dashboard interface, which they may have already been familiar with as part of their studies, potentially limiting creative thinking. Similarly, the demographic profile of the study population was characterized by a male-dominated cohort, which reflected the gender imbalance observed in the computer science degree program at the university where the study was conducted. The program had a 27% female to 73% male student ratio.

In future studies, to obtain more diverse points of view, it would be beneficial to prioritize the design needs of underrepresented groups in order to improve diversity and inclusivity (Martinez-Maldonado, 2023). This can lead to breakthroughs that are beneficial to both minority and majority cohorts (Nielsen, 2019). Finally, this strategy could be complemented by fostering robust relationships with underrepresented educational stakeholders, in this case female students, offering compensation for their time and using inclusive design kits (Martinez-Maldonado, 2023). Future work could also explore interviews with students from other areas of study.

Secondly, the Internet connection of two of the interviewees was intermittent; therefore, their transcriptions were not entirely accurate. However, this also highlights one concern that was precisely flagged in the study: poor Internet connection can be a significant obstacle to the adoption of any LA system relying on a continuous audio or video feed. Thirdly, the sample of students was small. Nonetheless, qualitative studies and design studies prioritize quality and rigour over quantity. Therefore, the results remain relevant and can be considered as one of several studies necessary to understand the specifics of the educational contexts where LA tools can be deployed. Additionally, we only considered the perspectives of students.

Interviews with teachers could provide valuable insights to enhance the design of a CAS-based LA dashboard and elucidate the level of acceptance of this kind of technology among the teaching staff.

Finally, in consideration of the findings reported in this study, we propose a series of guidelines for the development of CAS-based LA tools in Latin America as potential avenues for future research. The guidelines have been classified according to the research questions that they address.

**RQ1: Students' perspectives on the CASs that influence their performance** (1) When designing LA tools based on affect states, designers should consider modelling complex states that are common in the learning context. (2) Eliciting students' academic emotions for explicit mapping with CASs is useful for defining the list of CASs to be considered in the LA tool.

**RQ2: Students' perspectives on how evidence about their CASs can be visualized** (3) In modelling CASs, the data modalities that are feasible for synchronous online learning include facial expression, gaze data, corporal movement, speech, and text analysis. The scalability of wearable devices such as smartwatches, EEG, and wrist and ear sensors in online settings may be limited. (4) Unobtrusive visual aids can facilitate rapid evaluation of class affective state by teachers, such as an affective class meter, a ranking of states, real-time charts and timelines, emoticons, and suggestion messages for teachers. (5) For CAS modelling verification, surveys can be conducted to allow students to self-evaluate their top two or three states experienced during a class.

**RQ3: Students' ethical, privacy, and cultural concerns** Regarding privacy concerns: (6) To establish a trustworthy relationship with end-users, designers should provide a comprehensive privacy policy that outlines the data collected, its intended usage, and the measures taken to ensure its protection in accordance with the privacy laws and regulations of the region where the LA tool will be used. (7) It is recommended that video and image data be deleted on a class-by-class basis or stored for a limited period of time.

Regarding ethical concerns: (8) Access to cameras and microphones should be requested at the point of use, explaining the need for permission. (9) Psychometric tests should be adminstered to teachers to identify potential data misuse. (10) Cohort-level data should be collected to avoid prejudging students. (11) Both teachers and students should be made aware of privacy and ethical guidelines and their consent obtained before first use.

Regarding cultural considerations: (12) Designers should take into consideration high cultural diversity in facial features and the high expressiveness in both facial and verbal expressions. (13) Region-centric databases for both facial and verbal data are highly recommended to avoid demographic bias introduced by the use of large public databases.

## 6. Concluding Remarks

This paper presented a study that addresses the increasing concerns about data privacy, ethics, and culture related to the design of multimodal LA tools, in the particular context of emotion recognition in online learning sessions in a Mexican university. The study responds to the emerging interest in integrating students' perspectives into the systems design. The findings may guide the design of more human-centred LA tools to enhance *social translucence* of students' CASs during synchronous online learning sessions.

## Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The publication of this article received financial support in part by Universidad Nacional Autónoma de México by means of the Programa de Apoyo a Proyectos de Investigación e Innovación Tecnológica (PAPIIT), grants IT101624 and IN108624. Victor Manuel Corza-Vargas acknowledges Consejo Nacional de Humanidades Ciencias y Tecnologías (CONAHCYT).

## References

Alfredo, R. D., Nie, L., Kennedy, P., Power, T., Hayes, C., Chen, H., McGregor, C., Swiecki, Z., Gašević, D., & Martinez-Maldonado, R. (2023). "That student should be a lion tamer!" StressViz: Designing a stress analytics dashboard for teachers. In *Proceedings of the 13th International Conference on Learning Analytics and Knowledge* (LAK 2023), 13–17 March 2023, Arlington, Texas, USA (pp. 57–67). ACM. https://doi.org/10.1145/3576050.3576058

Ali, W. (2020). Online and remote learning in higher education institutes: A necessity in light of COVID-19 pandemic. *Higher Education Studies*, *10*(3), 16–25. https://doi.org/10.5539/hes.v10n3p16

Alwahaby, H., Cukurova, M., Papamitsiou, Z., & Giannakos, M. (2022). The evidence of impact and ethical considerations of multimodal learning analytics: A systematic literature review. In G. Michail, S. Daniel, D. M. Daniele, K. Sharma, O. Xavier, & H. Rawad (Eds.), *The multimodal learning analytics handbook* (pp. 289–325). Springer International Publishing. https://doi.org/10.1007/978-3-031-08076-0_12

Arroyo, I., Cooper, D. G., Burleson, W., Woolf, B. P., Muldner, K., & Christopherson, R. (2009). Emotion sensors go to school. In V. Dimitrova, R. Mizoguchi, B. du Boulay, & A. Graesser (Eds.), *Artificial intelligence in education*, Vol. 200 of *Frontiers in artificial intelligence and applications* (pp. 17–24). Ios Press. https://doi.org/10.3233/978-1-60750-028-5-17

Baker, R. S., D'Mello, S. K., Rodrigo, M. M. T., & Graesser, A. C. (2010). Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive–affective states during interactions with three different computer-based learning environments. *International Journal of Human-Computer Studies*, *68*(4), 223–241. https://doi.org/10.1016/j.ijhcs.2009.12.003

Balaam, M. (2013). A part practical and part conceptual response to orchestration. *Computers & Education*, *69*, 517–519. https://doi.org/10.1016/j.compedu.2013.04.009

Banfield, R., Lombardo, C. T., & Wax, T. (2015). *Design sprint: A practical guidebook for building great digital products*. O'Reilly Media, Inc. https://www.oreilly.com/library/view/design-sprint/9781491923160/

Banzon, A. M., Beever, J., & Taub, M. (2023). Facial expression recognition in classrooms: Ethical considerations and proposed guidelines for affect detection in educational settings. *IEEE Transactions on Affective Computing*, *15*(1), 93–104. https://doi.org/10.1109/TAFFC.2023.3275624

Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, *47*(4), 644–675. https://doi.org/10.2307/3094912

Beardsley, M., Vujovic, M., Portero-Tresserra, M., & Hernández-Leo, D. (2019). ClassMood app: A classroom orchestration tool for identifying and influencing student moods. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming learning with meaningful technologies. EC-TEL 2019. Lecture notes in computer science* (pp. 723–726, Vol. 11722). Springer. https://doi.org/10.1007/978-3-030-29736-7_75

Boyd, K. L., & Andalibi, N. (2023). Automated emotion recognition in the workplace: How proposed technologies reveal potential futures of work. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1). https://doi.org/10.1145/3579528

Brackett, M. A., Reyes, M. R., Rivers, S. E., Elbertson, N. A., & Salovey, P. (2011). Classroom emotional climate, teacher affiliation, and student conduct. *The Journal of Classroom Interaction*, *46*(1), 27–36. https://www.jstor.org/stable/23870549

Braun, V., & Clarke, V. (2021). *Thematic analysis: A practical guide*. SAGE Publications.

Caballero-Morales, S.-O. (2013). Recognition of emotions in Mexican Spanish speech: An approach based on acoustic modelling of emotion-specific vowels. *The Scientific World Journal*, *2013*, 162093. https://doi.org/10.1155/2013/162093

Cai, Y., Li, X., & Li, J. (2023). Emotion recognition using different sensors, emotion models, methods and datasets: A comprehensive review. *Sensors*, *23*(5), 2455. https://doi.org/10.3390/s23052455

Carrillo, A. J., & Jackson, M. (2022). Follow the leader? A comparative law study of the EU's General Data Protection Regulation's impact in Latin America. *ICL Journal*, *16*(2), 177–262. https://doi.org/10.1515/icl-2021-0037

Cavazos, J. G., Phillips, P. J., Castillo, C. D., & O'Toole, A. J. (2020). Accuracy comparison across face recognition algorithms: Where are we on measuring race bias? *IEEE Transactions on Biometrics, Behavior, and Identity Science*, *3*(1), 101–111. https://doi.org/10.1109/TBIOM.2020.3027269

Crawford, K. (2021). Affect. In *The atlas of AI: Power, politics, and the planetary costs of artificial intelligence* (pp. 151–180). Yale University Press.

Dawood, A., Turner, S., & Perepa, P. (2018). Affective computational model to extract natural affective states of students with Asperger syndrome (AS) in computer-based learning environment. *IEEE Access*, *6*, 67026–67034. https://doi.org/10.1109/ACCESS.2018.2879619

Derick, L., Sedrakyan, G., Munoz-Merino, P. J., Delgado Kloos, C., & Verbert, K. (2017). Evaluating emotion visualizations using AffectVis, an affect-aware dashboard for students. *Journal of Research in Innovative Teaching & Learning*, *10*(2), 107–125. https://doi.org/10.1108/JRIT-05-2017-0011

D'Errico, F., Paciello, M., & Cerniglia, L. (2016). When emotions enhance students' engagement in e-learning processes. *Journal of e-Learning and Knowledge Society*, *12*(4). https://doi.org/10.20368/1971-8829/1144

Dimitriadis, Y., Martínez-Maldonado, R., & Wiley, K. (2021). Human-centered design principles for actionable learning analytics. In T. Tsiatsos, S. Demetriadis, A. Mikropoulos, & V. Dagdilelis (Eds.), *Research on e-learning and ICT in education: Technological, pedagogical and instructional perspectives* (pp. 277–296). Springer International Publishing. https://doi.org/10.1007/978-3-030-64363-8_15

D'Mello, S., & Graesser, A. (2011). The half-life of cognitive-affective states during complex learning [PMID: 21942577]. *Cognition and Emotion*, *25*(7), 1299–1308. https://doi.org/10.1080/02699931.2011.613668

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction*, *22*(2), 145–157. https://doi.org/10.1016/j.learninstruc.2011.10.001

D'Mello, S., & Jensen, E. (2022). Emotional learning analytics. In C. Lang, G. Siemens, A. F. Wise, D. Gašević, & A. Merceron (Eds.), *The handbook of learning analytics* (2nd ed., pp. 120–129). SoLAR. https://doi.org/10.18608/hla22

D'Mello, S., Lehman, B., Pekrun, R., & Graesser, A. (2014). Confusion can be beneficial for learning. *Learning and Instruction*, *29*, 153–170. https://doi.org/10.1016/j.learninstruc.2012.05.003

Ekman, P. (1992). An argument for basic emotions. *Cognition & Emotion*, *6*(3-4), 169–200. https://doi.org/10.1080/02699939208411068

Erickson, T., & Kellogg, W. A. (2000). Social translucence: An approach to designing systems that support social processes. *ACM Transactions on Computer–Human Interaction (TOCHI)*, *7*(1), 59–83. https://doi.org/10.1145/344949.345004

Ez-Zaouia, M., & Lavoué, E. (2017). EMODA: A tutor oriented multimodal and contextual emotional dashboard. In *Proceedings of the Seventh International Conference on Learning Analytics and Knowledge* (LAK 2017), 13–17 March 2017, Vancouver, British Columbia, Canada (pp. 429–438). ACM. https://doi.org/10.1145/3027385.3027434

Ez-Zaouia, M., Tabard, A., & Lavoué, E. (2020). EMODASH: a dashboard supporting retrospective awareness of emotions in online learning. *International Journal of Human-Computer Studies*, *139*, 102411. https://doi.org/10.1016/j.ijhcs.2020.102411

GhasemAghaei, R., Arya, A., & Biddle, R. (2016). A dashboard for affective e-learning: Data visualization for monitoring online learner emotions. In G. Veletsianos (Ed.), *Proceedings of the 2016 World Conference on Educational Media and Technology* (EdMedia+ 2016), 28–30 June 2016, Vancouver, British Columbia, Canada (pp. 1536–1543). Association for the Advancement of Computing in Education (AACE). https://www.learntechlib.org/primary/p/173153/

Goodfellow, I. J., Erhan, D., Carrier, P. L., Courville, A., Mirza, M., Hamner, B., Cukierski, W., Tang, Y., Thaler, D., Lee, D.-H., Zhou, Y., Ramaiah, C., Feng, F., Li, R., Wang, X., Athanasakis, D., Shawe-Taylor, J., Milakov, M., Park, J., ... Bengio, Y. (2013). Challenges in representation learning: A report on three machine learning contests. In M. Lee, A. Hirose, Z. Hou, & R. Kil (Eds.), *Neural information processing.* ICONIP 2013. *Lecture notes in computer science* (pp. 117–124, Vol. 8228). Springer. https://doi.org/10.1007/978-3-642-42051-1_16

Graesser, A., Chipman, P., King, B., McDaniel, B., & D'Mello, S. (2007). Emotions and learning with AutoTutor. *Proceedings of the 2007 Conference on Artificial Intelligence in Education: Building Technology Rich Learning Contexts That Work*, 9–13 July 2007, Los Angeles, California, USA, 569–571. https://dl.acm.org/doi/10.5555/1563601.1563699

Gupta, S., Kumar, P., & Tekchandani, R. K. (2023). Facial emotion recognition based real-time learner engagement detection system in online learning context using deep learning models. *Multimedia Tools and Applications*, *82*(8), 11365–11394. https://doi.org/10.1007/s11042-022-13558-9

Harley, J. M., Bouchet, F., Hussain, M. S., Azevedo, R., & Calvo, R. (2015). A multi-componential analysis of emotions during complex learning with an intelligent multi-agent system. *Computers in Human Behavior*, *48*, 615–625. https://doi.org/10.1016/j.chb.2015.02.013

Hilliger, I., Ceballos, H. G., Maldonado-Mahauad, J., & Ferreira, R. (2024). Applications of learning analytics in Latin America. *Journal of Learning Analytics*, *11*(1), 1–5. https://doi.org/10.18608/jla.2024.8409

Jerrim, J. (2023). Who responds to phishing emails? An international investigation of 15-year-olds using PISA data. *British Journal of Educational Studies*, *71*(6), 701–724. https://doi.org/10.1080/00071005.2023.2234456

Katirai, A. (2023). Ethical considerations in emotion recognition technologies: A review of the literature. *AI and Ethics*, *4*, 927–948. https://doi.org/10.1007/s43681-023-00307-3

Li, S., Deng, W., & Du, J. (2019). Reliable crowdsourcing and deep locality-preserving learning for expression recognition in the wild. *IEEE Transactions on Image Processing*, *28*(1), 356–370. https://doi.org/10.1109/TIP.2018.2868382

Liu, Q., & Khalil, M. (2023). Understanding privacy and data protection issues in learning analytics using a systematic review. *British Journal of Educational Technology*, *54*(6), 1715–1747. https://doi.org/10.1111/bjet.13388

Lyons, M., Kamachi, M., & Gyoba, J. (2019, September). *The Japanese Female Facial Expression (JAFFE) Dataset*. Zenodo. https://doi.org/10.5281/zenodo.3451524

Madan, A., & Kumar, D. (2024). CNN-based models for emotion and sentiment analysis using speech data. *ACM Transactions on Asian and Low-Resource Language Information Processing*, *23*(10). https://doi.org/10.1145/3687303

Madiega, T. (2021). Artificial intelligence act. European Parliament: European Parliamentary Research Service. https://www.iisf.ie/files/UserFiles/cybersecurity-legislation-ireland/EU-AI-Act.pdf

Mangaroska, K., Sharma, K., Gašević, D., & Giannakos, M. (2022). Exploring students' cognitive and affective states during problem solving through multimodal data: Lessons learned from a programming activity. *Journal of Computer Assisted Learning*, *38*(1), 40–59. https://doi.org/10.1111/jcal.12590

Martinez-Maldonado, R. (2023). Human-centred learning analytics: Four challenges in realising the potential. *Learning Letters*, *1*, 6. https://doi.org/10.59453/FIZJ7007

McDaniel, B., D'Mello, S., King, B., Chipman, P., Tapp, K., & Graesser, A. (2007). Facial features for affective state detection in learning environments. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, 1–4 August 2007, Nashville, Tennessee, USA (Vol. 29). Cognitive Science Society. https://escholarship.org/uc/item/9w00945d

McDonald, N., Schoenebeck, S., & Forte, A. (2019). Reliability and inter-rater reliability in qualitative research: Norms and guidelines for CSCW and HCI practice. *Proceedings of the ACM on Human–Computer Interaction*, *3*(CSCW). https://doi.org/10.1145/3359174

Mollahosseini, A., Hasani, B., & Mahoor, M. H. (2017). AffectNet: A database for facial expression, valence, and arousal computing in the wild. *IEEE Transactions on Affective Computing*, *10*(1), 18–31. https://doi.org/10.1109/TAFFC.2017.2740923

Mutimukwe, C., Viberg, O., Oberg, L.-M., & Cerratto-Pargman, T. (2022). Students' privacy concerns in learning analytics: Model development. *British Journal of Educational Technology*, *53*(4), 932–951. https://doi.org/10.1111/bjet.13234

Nielsen, J. (2019). Usability for senior citizens: Improved, but still lacking (2013). *Nielsen Norman Group*. https://www.nngroup.com/articles/usability-seniorsimprovements

Obergriesser, S., & Stoeger, H. (2020). Students' emotions of enjoyment and boredom and their use of cognitive learning strategies—How do they affect one another? *Learning and Instruction*, *66*, 101285. https://doi.org/10.1016/j.learninstruc.2019.101285

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*, *45*(3), 438–450. https://doi.org/10.1111/bjet.12152

Prinsloo, P., Slade, S., & Khalil, M. (2023). Multimodal learning analytics—in-between student privacy and encroachment: A systematic review. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13373

Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C., & Sutskever, I. (2022). Robust speech recognition via large-scale weak supervision. *arXiv*. https://doi.org/10.48550/ARXIV.2212.04356

Radhakrishnan, M., Kandappu, T., Gulati, M., & Misra, A. (2023). Wearables for in-situ monitoring of cognitive states: Challenges and opportunities. In *2023 IEEE International Conference on Pervasive Computing and Communications Workshops and Other Affiliated Events (PerCom Workshops)*, 13-17 March 2023, Atlanta, Georgia, USA (pp. 671–676). IEEE. https://doi.org/10.1109/PerComWorkshops56833.2023.10150270

Rets, I., Herodotou, C., & Gillespie, A. (2023). Six practical recommendations enabling ethical use of predictive learning analytics in distance education. *Journal of Learning Analytics*, *10*(1), 149–167. https://doi.org/10.18608/jla.2023.7743

Reyes, M. R., Brackett, M. A., Rivers, S. E., White, M., & Salovey, P. (2012). Classroom emotional climate, student engagement, and academic achievement. *Journal of Educational Psychology*, *104*(3), 700. https://doi.org/10.1037/a0027268

Roy, M. L., Malathi, D., & Dorathi Jayaseeli, J. (2022). Facial recognition techniques and their applicability to student concentration assessment: A survey. In G. Manogaran, A. Shanthini, & G. Vadivu (Eds.), *Proceedings of international conference on deep learning, computing and intelligence. Advances in intelligent systems and computing* (pp. 213–225, Vol. 1396). Springer. https://doi.org/10.1007/978-981-16-5652-1_18

Ruiz, S., Charleer, S., Urretavizcaya, M., Klerkx, J., Fernández-Castro, I., & Duval, E. (2016). Supporting learning by considering emotions: Tracking and visualization a case study. In *Proceedings of the Sixth International Conference on Learning Analytics and Knowledge* (LAK 2016), 25–29 April 2016, Edinburgh, UK (pp. 254–263). ACM. https://doi.org/10.1145/2883851.2883888

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, *110*(1), 145–172. https://doi.org/10.1037/0033-295x.110.1.145

Savchenko, A. V., Savchenko, L. V., & Makarov, I. (2022). Classifying emotions and engagement in online learning based on a single facial expression recognition neural network. *IEEE Transactions on Affective Computing*, *13*(4), 2132–2143. https://doi.org/10.1109/TAFFC.2022.3188390

Schrauf, R. W., & Sanchez, J. (2004). The preponderance of negative emotion words in the emotion lexicon: A cross-generational and cross-linguistic study. *Journal of Multilingual and Multicultural Development*, *25*(2-3), 266–284. https://doi.org/10.1080/01434630408666532

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages*, *50*, 19–38. https://doi.org/10.1016/j.jvlc.2018.11.002

Son, G., & Kwon, S. (2024). Spontaneous speech emotion recognition based on spectrogram with convolutional neural network. *The Transactions of the Korea Information Processing Society*, *13*(6), 284–290. https://doi.org/10.3745/TKIPS.2024.13.6.284

Tarmazdi, H., Vivian, R., Szabo, C., Falkner, K., & Falkner, N. (2015). Using learning analytics to visualise computer science teamwork. In *Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer Science Education* (ITICSE '15), 4–8 July 2015, Vilnius, Lithuania (pp. 165–170). ACM. https://doi.org/10.1145/2729094.2742613

Tsai, Y.-S., Perrotta, C., & Gašević, D. (2020). Empowering learners with personalised learning approaches? Agency, equity and transparency in the context of learning analytics. *Assessment & Evaluation in Higher Education*, *45*(4), 554–567. https://doi.org/10.1080/02602938.2019.1676396

Tsai, Y.-S., Whitelock-Wainwright, A., & Gašević, D. (2020). The privacy paradox and its implications for learning analytics. In *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK 2020), 23–27 March 2020, Frankfurt, Germany (pp. 230–239). ACM. https://doi.org/10.1145/3375462.3375536

Tyng, C. M., Amin, H. U., Saad, M. N., & Malik, A. S. (2017). The influences of emotion on learning and memory. *Frontiers in Psychology*, *8*, 1454. https://doi.org/10.3389/fpsyg.2017.01454

van Leeuwen, A., & Rummel, N. (2020). Comparing teachers' use of mirroring and advising dashboards. In *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK 2020), 23–27 March 2020, Frankfurt, Germany (pp. 26–34). ACM. https://doi.org/10.1145/3375462.3375471

Viberg, O., Jivet, I., & Scheffel, M. (2023). Designing culturally aware learning analytics: A value sensitive perspective. In O. Viberg & Å. Grönlund (Eds.), *Practicable learning analytics* (pp. 177–192). Springer International Publishing. https://doi.org/10.1007/978-3-031-27646-0_10

Wass, R., Timmermans, J., Harland, T., & McLean, A. (2020). Annoyance and frustration: Emotional responses to being assessed in higher education. *Active Learning in Higher Education*, *21*(3), 189–201. https://doi.org/10.1177/1469787418762462

Weissberg, R. P., Durlak, J. A., Domitrovich, C. E., & Gullotta, T. P. (2015). Social and emotional learning: Past, present, and future. In J. A. Durlak, C. E. Domitrovich, R. P. Weissberg, & T. P. Gullotta (Eds.), *Handbook of social and emotional learning: Research and practice* (pp. 3–19). The Guilford Press.

Wiedbusch, M. D., Kite, V., Yang, X., Park, S., Chi, M., Taub, M., & Azevedo, R. (2021). A theoretical and evidence-based conceptual design of MetaDash: An intelligent teacher dashboard to support teachers' decision making and students' self-regulated learning. *Frontiers in Education*, *6*, 570229. https://doi.org/10.3389/feduc.2021.570229

Yan, L., Zhao, L., Gasevic, D., & Martinez-Maldonado, R. (2022). Scalability, sustainability, and ethicality of multimodal learning analytics. In *Proceedings of the 12th International Conference on Learning Analytics and Knowledge* (LAK 2022), 21–25 March 2022, online (pp. 13–23). ACM. https://doi.org/10.1145/3506860.3506862

Yan, Wu, N., Iliyasu, A. M., Kawamoto, K., & Hirota, K. (2022). Framework for identifying and visualising emotional atmosphere in online learning environments in the COVID-19 era. *Applied Intelligence*, *52*(8), 9406–9422. https://doi.org/10.1007/s10489-021-02916-z

Yarmand, M., Solyst, J., Klemmer, S., & Weibel, N. (2021). "It feels like I am talking into a void": Understanding interaction gaps in synchronous online classrooms. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (CHI 2021), 8–13 May 2021, Yokohama, Japan. ACM. https://doi.org/10.1145/3411764.3445240

Zheng, J., Huang, L., Li, S., Lajoie, S. P., Chen, Y., & Hmelo-Silver, C. E. (2021). Self-regulation and emotion matter: A case study of instructor interactions with a learning analytics dashboard. *Computers & Education*, *161*, 104061. https://doi.org/10.1016/j.compedu.2020.104061